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The impact of emotional images on motivation, attention and decision making

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Summary

The level of meaning towards images is defined by numerous constructs. From an individuals knowledge of the object the image portrays to the emotion that the object elicits. A vast amount of work has been conducted to look at the interplay of objects representations and the resultant impact upon performance and learning. Within this thesis, the aim was to add further depth to our understanding of these representational impacts. In a series of ten experiments we looked at the role of meaningful images in decision-making, time perception, and inhibitory control. Within the decision-making experiments we found that meaning and its subsequent representations impacted upon the way we perform and learn during emotional decision-making paradigms. In particularly we find that the information that the object gives can bias the decision of participants even if unrelated to the actual task in hand; a form of incidental impact on the way that behaviour can be shaped. Within the time perception experiments we found that at the low-level these objects and their meaning impacts not wholly on the way that we perceive a perceptual event. Indeed it was only during the most meaningful images that we found an effect of perceptual acuity. Within the inhibitory control experiments, we showed that the overlap between an objects familiarity and emotionality hinders the way in which we can study meaning. However, what it does suggest is that the two effects drive in the same direction. Furthermore when looking at the neural correlates of meaning we found a suggestion of prefrontal and subcortical networks that strive to represent the anticipatory reward of an objects meaning, and specifically differ in their activation during various states of motivation. In conclusion, we suggest that measuring the level of meaning towards an object is important and that the persuasive nature of meaningful images can differ as a function of personal relevance.

Chapter 1: Introduction

As humans we are confronted with a multitude of images each day. If we take the average number of saccades that we make each second as about three, and suggest that each of these saccades leads to us seeing a new image, then every day we see approximately 2.8 million images. Multiply this by our lifetime and the extent of the bombardment of these images is very apparent. To create some form of structure in this bombardment (or some may say noise) then we must attend, filter, and act upon these images. As we do this, we impose structure on the visual inputs and, over time, some of this structuring becomes more and more automatic. For example, while our own name used to require effort to see/understand it is now effortless for us to recognize it (even in noise) and to understand its meaning and personal relevance to us. This same type of effortless meaning-extraction occurs for a myriad of visual stimuli: from words, to stop signs, to facial expressions, to flags. Through the development of this automated structuring we can extract and impose meaning on vast ranges of visual inputs: whether that be the meaning of a mother's face to a newborn or the picture of a grandchild to a grandparent, we are constantly updating and integrating visual imagery into a construct and in turn are able to interact with these constructs every second. At perhaps its highest level, this thesis is intended to help understand how meaning influences risk, cognition, attention, inhibition, and even action. How, for example, will the sight of a loved person, flag, or brand influence our willingness to take risks? Or, how might they impact one's ability to inhibit responding? To this end, before we start to discuss the experiments that have investigated these and related questions, it might first prove useful to briefly review some of the philosophy of meaning and the known neuronal correlates of meaning.

Philosophy of Meaning in Visual Images

Understanding why some images are more meaningful than others is, in some sense, a philosophical question. In fact, the nature of "meaning" has been the subject of philosophical investigations for quite some time. We first begin with a discussion of the broader sense of meaning and how meaning is formed, and in particular how visual images differ in their power to evoke meaning.

Research on semiotics and linguistics has provided the 20th century with the majority of concepts on the nature of meaning. In 1916 Saussure proposed a framework to understand meaning from a linguistic point of view. He put forward the concept of a sign ("the basic unit of language") that denotes meaning through its own structure and a "code" that is shared between the speaker and the listener. The existence of a shared code is essential and, without this, the meaning of the word is lost, and consequently there is no sign without the shared code. Research into the production of meaning though verbal communication is well defined (Putman, 1996) and is based primarily on the sign/code philosophy and on an analysis of automatic exchanges between authors and the readers. For meaning to be conveyed by language it is important to have a common ground (the shared code), so that messages can be transferred and understood accurately. However, for non-verbal *visual* communication, the exchange between the author and the reader can differ drastically and as such the actual meaning produced and received can differ.

If we return to the concept of signs within the domain of visual communication several interesting issues arise (Belova, 2006). For example, in visual communications the code to convey the meaning can be adaptive, and at times the sign itself needs no code. One example of such code-less visual communication can be found in well-designed road signs (for example, see the left image in Figure 1), or indeed a smiling human face. Other visual communications require greater understanding of the codes – built up over time through cultural, political, socio-economic, and other means that lead to organically developed shared codes (for example, see the middle and right images in Figure 1). This type of visual communication (and meaning exchange) is often adaptive because there are often multiple mediums through which the visual information can, or must, be filtered. Belova (2006) gives the example of a photograph within a newspaper: firstly there is the photographer who took the image, then there is the publisher who prints the image, and then finally there is the reader who sees the image in print. At each one of these stages the meaning of the image might be altered.

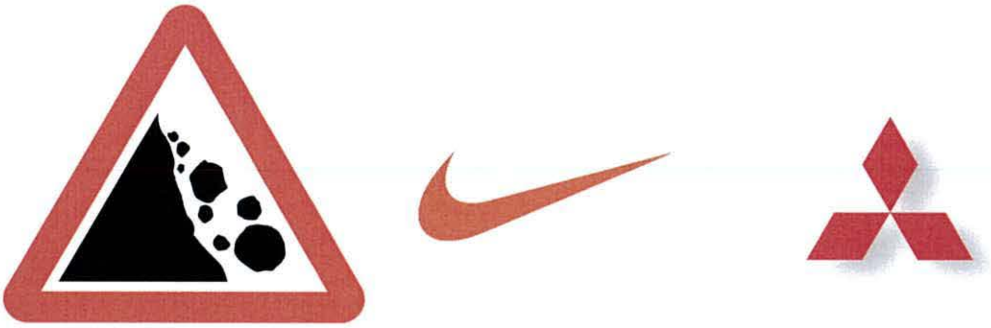

Figure 1: This UK road signs meaning requires no code, it is signalled purely by the imagery. Whereas the logo in the middle requires some code (although there is a signal of the tick) to produce meaning, and finally the final logo on the right requires code to produce meaning.

The importance of these codes, and whether they are shared amongst people, is crucial for meaning and the communication of meaning. Brand logos for example are often meaningless without a code (again, see Figure 1). It is the power of marketing that allows the code to be formed and allows the meaning of the brand logo to be developed and shaped in the minds of a cultural subset (or subsets) of individuals. While some codes are created or develop late, other codes develop very early on (Smith, 1999). One example of a code that is developed early on is a smiling face, which has shown categorical perception in 7-month-old infants (Kotsoni, de Haan, & Johnson, 1997). What is also generally common amongst these early codes is the general universal structure of their perceived meaning, across ages and cultures. Such 'early' codes are in marked contrast to other signs and symbols and even aesthetic conventions. For example, consider the aesthetics of landscapes and in turn the meaning individual landscape paintings – the codes and understandings of which are not universal (Phan, Taylor, Welsh, Ho, Britton, & Liberzon, 2004). In many cases such as these the code is held only by a (perhaps small) set of receivers and is typically not entirely shared between individuals.

Osgood (1971), in his discussion of meaning, outlined how it can be seen as a representational mediation process. More specifically, he discusses how meaning can be either a "conditioned" or "unconditioned" reflex. When considering meaning in this framework we can say that the smiling face is an example of a "wired-in" connection, with its evoked unconditional reflexes. The example he uses is food-powder and its ability to create a response when placed in a receiver's mouth.

Indeed, it is issues around visual images and their differences in the production of meaning that is one of the core explorations of this thesis. How does the way in which meaning is produced and exchanged effect the interactions and influences that they can impart?

Representations

Within typical frameworks of cognitive psychology and cognitive neuroscience, we understand "meaning" to be related to activity in different regions of the brain. And, one common way of discussing how different objects (words, images, sounds, etc) are processed by the human is through the term "representation." Of course, we know that the brain does not operate on or with images/words in the world. Instead, we believe that the brain works on/with representations of the images/words. Such representations begin very early in neural processing:

photons hit the retina and they ultimately lead to activity in primary visual cortex. This activity is, in some sense, one of the earliest neural *representations* of the visual object.

This early visual representation (in area V1 for examples) is then processed by numerous other neural areas which, in some sense, *enrich* the representation of that physical object. Thus, areas such as MT add to the representation of the object's motion. It might prove helpful to use a computer/hypertext/XML/markup metaphor. And, using such a metaphor we can say that area MT adds "motion tags" to this representation ('upwards', 'leftwards', 'slow). Similarly, areas like V4 add "colour tags" to the representation ('red', 'green specks') and area IT adds "shape tags" to the representation ('round elongated'). Presumably, higher-level areas will add more and more "tags" to this representation ('food', 'strawberry', 'yummy'). Many of these tags will arise nearly automatically and be fairly universal across people (e.g. those that originate in lower visual areas). However, other tags will arise with more effort ('organic strawberries') and with greater variability across individuals ('reminds me of grandma's jam').

If we employ a neuroscience/XML-inspired view of objects – as representations and their associated tags – then we might ask how "meaning" fits within this framework. In this thesis we see meaning as a creation formed from the representation of an object. And this level of meaning changes as a function of the strength and size of this representation.

Evaluative Conditioning

One area that has looked in depth at the growth and formation of meaningful representations is Evaluative Conditioning (EC) as such I will give a brief review of this topic. Evaluative conditioning a term used to describe one of the processes of preference formation and in particular how one comes to like an object (for review of theory see de Houwer (2007), and De Houwer, Thomas, & Baeyens (2001) for a review of the studies). Essentially what the studies show is that by pairing a negative or positive stimulus with a neutral stimulus you can alter the way in which the observer judges the value of the neutral stimulus. It is this pairing of the *unconditioned stimuli* (US, the neutral stimuli) with the *conditioned stimuli* (CS) that is a driving force in the way that we form positive and negative meaning towards an object. There are numerous explanations as to why this valance shift occurs, one such explanations is the propositional models of EC. Within these models, the effect of EC is thought to occur based on the acquisition of knowledge between the stimulus regularities (e.e. Corneille, Yzerbyt, Pleyers, & Mussiler, 2009). More specifically, it is the knowledge that, for example, an electric shock will be negative and this will be associated with a stimulus pairing. This accounts for two ways in which confounds about the knowledge formation could occur: firstly, the model presumes that both direct and indirect pairings can lead rise to a switch in valance (i.e. EC), and secondly, why participants quite rapidly experience this EC effect with prior knowledge (Field & Lawson, 2003).

Throughout the thesis as we talk about meaning and its influence on performance in learning it is important to understand that there are different levels of how this formation occurs. For example, the brand images induce a positive valance because they have experienced EC towards them throughout the consumer decision-making process (from advertisements, to consumption the brand is paired with a CS). We will not directly measure the processes in which these formations occur, we will look purely on their impact.

Meaning and Behaviour:

There are many different areas of human behaviour that could be investigated, in relation to meaning. I have chosen to look at three primary areas: Decision making, time perception, and inhibitory control. I chose these areas for three reasons. First, they are areas where, at least intuitively, 'meaning' may have a large role to play. For example, recent research in decision-making (Damasio, 1994) has suggested that we often make decisions not based on rational/cognitive information, but instead we often base decisions on the emotional 'tags' that are evoked by objects/events/choices in the world. Additionally, I chose these areas because they are ones that have a clear and strong connection to applied issues. For example, understanding the role of meaning in decision making or in inhibitory control is clearly relevant for issues such as compulsive shopping and brand loyalty. And finally, these three areas and more specifically the paradigms we use to investigate these three areas are implicated in slightly different systems of cognition. That is: the decision-making component encompasses both the 'hot' and 'cold' processes; the time perception look at low-level 'hot' processes; and, finally inhibitory control looks primarily at the 'cold' inhibitory process. Indeed the neural correlates of these three components differ: Decision-making and in particular the emotional decision making within this thesis has been shown to predominately involved ventral medial prefrontal cortex and subcotical limbic structures; Time-perception and in particular the paradigm put forward here seems more driven by sub-cortical bodies; and finally, inhibitory control has been shown to predominately involved in supralateral prefrontal cortex. These points will be discussed further at the beginning of their respective sections.

Meaningful Images

Now we have discussed the concept of meaning from both a philosophical and neural perspective and also the different cognitive/behavioural domains of interest. It is also important to understand the particular image sets that will be used throughout this thesis. Of course, when investigating a topic as individualistic as 'meaning', it is difficult to decide on one set (or even several sets) of images to employ. However, thankfully, I was able to identify several classes of images which seemed like good choices to evoke 'meaning' from a large number of people.

The sets of images that were used throughout the experiment were human faces (Ekman & Friesen, 1976), affective images (International Affective Picture System (IAPS)(Lang, Bradley, & Cuthbert, 1997)), and common brand logos, and food. The reason that such a range of meaningful stimuli was choosing was because of there *a prior* differences in meaning. This idea will be developed further as we examine each of the stimuli sets individually, and then finally contrast them.

From a methodological perspective it was of course important to ensure that the images presented to any participant had meaning (or lack thereof) *to/for that individual.* Thus, as will be seen in later chapters, all the experiments either began or ended by asking participants to rate the images. Typically, the way we preceded was by starting with a large set of images, asking participants to rate them on various dimensions, and then selecting a set of appropriate images based on their ratings. For example, they would rate a series of 120 brands on familiarity, and we would then select the highest-rated brands to use in the next phase of an experiment. This approach allowed us to measure levels of meaning for the images and implement this into experimental analysis.

Faces

Human faces are incredibly complex objects as such it has even been suggested that there is a specialised brain region that is used in the perception of faces (Kanwisher, McDermott, & Chun, 1997). The evidence of the importance of face perception and recognition being separate from object recognition and perception stems from a wide range of fields, for example neurophysiology (Perret, Hietanen, Oram, & Benson, 1992), cognitive psychology (Yin,1969), and neuropsychology (Damasio, Tranel, & Damasio, 1990). This is important to note, however what is more important to understand within the context of this thesis is the evidence of emotional processing of faces.

Faces emotions are displayed through their expressions, and research on facial expressions has been extensive and long-standing. Take for example the simple smile, in the 19th century French physicist Duchenne discovered two different physiological smiles. One of these smiles involves two major facial muscles (zygomatic and orbicularis oculi), now known as a Duchenne smile, whereas the other involves purely the zygomatic major muscle. The difference of these smiles are not just physical, or physiological, but the interpretation of the observer of the meaning of the smiles. The Duchenne smile is a genuine emotional response and cannot be generated by the individual on demand, primarily due to lack of control of the orbcularis oculi. As such much research has been conducted on the perception of emotion of a facial expression based on these two types of smiles. With observers showing great accuracy in identifying between a Duchenne and non-Duchenne smile, both explicitly and more implicitly altering subsequent actions upon it. This example highlights the accuracy of perception of smiles and the subsequent encoding of their meaning. Within this thesis we will use the intrinsic meaning evoked by faces and their subsequent impact on in particular decision-making and learning. Due to the level of previous research using faces only one experiment uses them, however throughout research gained via the use of this stimulus set makes an important contribution. We will use a commonly used set of facial expressions the Ekman and Friesen (1976) facial affect data set.

International Affective Picture System

Released in 1997 the International Affective Picture System (IAPS) is a large set of normative emotional stimuli that have been used to investigate a variety of phenomena (Lang, Bradley, & Cuthbert, 1997). To standardize the emotions three primary dimensions were used to define each individual image. The three dimensions were pleasure, arousal, and dominace. These three dimensions were chosen due to the seminal work by Osgood (Osgood, Suci, & Tanenbaum, 1957), which outlined them as the three main dimensions of emotions when making a verbal judgement towards an emotional assessment. Lang et al. (1997) see the primary dimensions to be the pleasure and arousal scales, with the "less strongly-related" dimension of dominance being secondary. The three dimensions were assessed with the Self-Assesment Mankin (SAM), which is a rating system that was developed by Lang (1980).

The IAPS set has been used extensively within research, with a GoogleScholar citation count above 800 (Google Inc., 2011). This gives the added benefit of contrasting results to previous uses', which will be done throughout the thesis.

Brand Logos

Another one of the stimuli sets that we use to understand meaning is brand logos. Brand logos are the visual archetype of a brand. One of the core-marketed materials of a company is its brand. With the brand logo being the visual form of the brand. Much research has been conducted on brands and their associated logo. We process their meaning from a very young age, for example one study in the US demonstrated that children as young as 3 are able to recognize and associate logos with their products, and 91.3% of 6-year olds were able to indentify Camels cigarette logo (Old Joe) with a cigarette picture (Fischer, et al., 1991). With such early onset of representations the meaning they can evoke in an individual can be strong. Added to this they have a somewhat unique position (along with for example famous faces) as being recognized by a large set of a population but this population would differ on their liking towards this brand. This point makes them an interesting stimulus set to measure when looking at meaning, as there is a shared recognition but not a shared emotion evoked by the brand. This for example is opposed to the facial dataset used within the thesis that has a shared emotion as evoked by the facial expression.

Food

The final stimuli set that will be used to understand meaning is food. Food is a widely studied stimuli set within emotion and motivational research. Its biological importance makes it highly salient affective stimuli, and the altering of the physiological states of hunger means it can also be state manipulated. For these two reasons they add another element to the level of meaning that a stimulus can evoke, whereby the motivational relevance of the stimuli can alter the evoked meaning by the item. This is important within the context of the thesis as it allows us to separate the way in which meaning demands attention and performance differences dependent on state manipulations, which will be demonstrated in two experiments during the thesis.

Overview of the Experiments

This thesis is divided into six main parts. The first part is this introduction. In Chapter 2 we shall explore how meaningful images impact decision-making. We explore this question using a series of four different experiments. The first experiment looks at whether images that evoke feelings/meanings of "trust" can guide decision-making. We look at this using brands and a version of the Iowa Gambling Task (Bechera et al., 1994). In this experiment we superimpose brands on various decks and end up showing that brand logos can influence decision-making. In the second experiment we look at whether images that evoke feelings/meanings of happiness/sadness can guide decision-making. And, similar to Experiment 1, we do this by superimposing images of happy/neutral/sad faces on decks in an IGT. Surprisingly, we find out that these images do impact on decision-making but also the inability to adapt the meaning of the emotion of the face creates learning deficits within some of the conditions.

In the third experiment we decided to look for a task that could better "tap into" the tags associated with object representations. Specifically, we wanted to find a task that was similar to the IGT, but which could allow participants to make more rapid (and, ideally, less cognitively-led) decisions. After numerous pilot experiments, we developed a novel task: Bangor Learning Intuitively Non-verbal Keleidiscope (BLINK). In this experiment we compare performance between the normal IGT and the BLINK. Using a variety of analysis (EV modelling; time duration; standard) we demonstrate that the decision-making systems can be pushed quicker and it is the sample rather than the time taken that is a large factor in decision-making. This task help to probe the underlying mechanisms involved in the IGT and help understand how the impact of meaningful images on the IGT may manipulate these mechanisms.

In the fourth experiment we revisit the question of whether trust can guide DM using brands within the BLINK paradigm. Here, in support of our results from Experiment 1, we again find that brand logos impact on decision-making and that this impact requires little exposure towards the brand.

In Chapter 3 of the thesis we investigate how meaningful images can impact time perception (TP). We do this primarily using a variation of the temporal oddball paradigm employed by Tse et al (2004). In a series of four experiments using meaningful images within this paradigm we investigate the following questions: Does emotionality influence TP? By using IAPS images within the temporal oddball paradigm we are able to show that the emotional meaning of an image does not influence TP. Does motivation influence TP? By using images of furniture and food within this paradigm we show that hungry people (who should be motivated by the images of food) do not experience any greater temporal distortion than other people. And our final questions is: Does brands influence TP? By using images of pre-rated brands within the paradigm, we show that one of the derived psychometric measures is influenced by an individuals preference towards a brand.

In Chapter 4 I investigate how meaningful images impact inhibitory control (IC). I used a variation of the standard go/no-go (GNG) paradigm to investigate the following four questions:In Chapter 5 of this thesis I investigated the neural correlates of meaning, motivation, and behavior. Using an fMRI study we looked at the GNG task within the food stimuli domain and manipulated a variety of state measures.

Chapter 6 and final part of this thesis provides a general discussion of these findings and tried to relate them applied and theoretical issues.

Chapter 2: Decision Making and meaningful images

As a whole the thesis will focus on the impact of meaningful images on cognitive and attentional processes the first process that we will explore is decision-making. The rationale behind the exploration of decision-making stems from its importance as a fundamental human act and one, which is clearly heavily influenced by information in the world and as a result seems apt when examine the influence of meaningful images of performance. As choices are made from the various options available to us in the outside world. Indeed it seems obvious that meaningful images should bias decision-making. But, at the same time, most classic theories of decision-making have looked at decision making either like a rational decision or an emotional decision. Meaningful images are interesting in that they span both rational and emotional content.

Decision-making is a diverse research domain, studied at multiple levels throughout varying approaches. It is the selection of one action when other possible actions are available, ultimately resulting in a final choice. Decision-making is one of the central phenomena studied in human performance. As such it has a long history of various research avenues that have examined it from alternative perspectives. From the decision-making made during saccadic eye movements (Carpenter & Williams, 1995) to theories on decision-making under risk (Kahneman & Tversky, 1979), decision-making is at the forefront in psychological, economics, game theory neuroscience and many other research domains.

One of the core challenges to understanding decision-making is the way in which the computations between alternatives occur. Take the classical example of two alternatives lottery: Option A: 100% chance of £1million; or Option B: 50% chance of £3million. One of the initial theories put forward to explain the choice a person would make is expected value theory (EVT), which stems from theories of probability. EVT says that each alternative should be assessed on the possible net gain from the choice outcome. So in this example the rational decider should choose option B (a value of £1.5million i.e. 50% of £3million), however in reality a number of participants would choose choice A. Clearly, EVT sees decision-making as overtly rational, however in reality there is more variables than the mere gain probability. As such EVT fails to fully capture real-world decision-making, and thus an alternative theory was put forward in the early 20th Century.

One alternative towards this expected value theory is expected utility theory (von Neumann & Morgenstern, 1944), which takes into account individual differences for example the assets of the individual (e.g. a person with no money would take choice A, whereas a billionaire is more likely to take choice B). A more psychological perspective for this was put forward by Kahneman & Tversky's (1979) in seminal work on decision-making under risk 'prospect theory', a descriptive approach alternative to expected utility theory, which looked at (amongst other things) the underlying pattern of response during the evaluative period of decision-making. Theses theories on decision-making are only a snapshot of the research that has been undertaken, and further theories exists to understand the more variant multi-criteria decision-making where more large alternatives and stratagies are implemented, however within the context of this thesis these non-multi-criteria decision-making theories (i.e. EV, expected utility, and prospect theory) are the most parsimonious examples and thus the ones which will be used to explain the underlying psychology within the experimental procedures outlined.

The above theories highlighted the understanding of the processes that occur during one decision-point. That is, they look at the decision primarily as if it happens once and then the person moves on, and that they choose between alternatives and then the decision-making ends.

In reality, we are often confronted with decisions repeatedly, and that as a result from this repeated selection we learn about the alternatives and update the contigencies that form the weightings of the decision moment. In a sense when looking at these types of decisions one must not only look at the decision-making theorem, but also at the learning that occurs between decision points. There are many theories on these learning aspects towards decision, and these are explored further in the introduction to experiment 2 (Faces and the Iowa Gambling Task).

The Iowa Gambling Task (IGT; Bechera et al., 1994) is the decision-making paradigm that is used throughout these decision-making experiments, and this will now be briefly introduced. The IGT was designed to explore emotional aspects of real-world decision-making. Specifically, in this laboratory-based procedure, participants are required to make decisions that maximize their long-term rewards (e.g. monetary rewards) under conditions of uncertainty. In the classic version of this task, subjects are presented with four identical stacks ("decks") of cards and are asked (on each trial) to choose one deck to draw from. Each card drawn has a different amount of monetary win and/or loss. For example, one card might say "Win $100, Lose $50". Unbeknownst to the participants, each of the four decks has a different long-term pay off structure. Specifically, two of the decks are "good" (i.e. continued selection will lead to long-term winning), and two are "bad". Typically the subjects do not know how many draws they will get from the decks, but the experiment ends after 100 draws.

There are two key ways that we will look at these repeated decisions within the IGT, one looks merely at the choice over time and uses a general linear model to asses these decision over time, whilst the other approach uses a cognitive model approach to quantify the decisions made and the underlying mechanism resulting in net choice outcome. The general linear model is more simplistic in its approach, as it relies on the choice outcome trial by trial normally dividing the choices into sections, for example looking at 100 trials broken into 5 blocks of 20, as such this approach will be discussed within the context of the experiments below. However the cognitive model approach is more complex and as such a brief overview will follow.

Cognitive Modelling

Cognitive models stem from the cognitive sciences, and are used to understand cognitive processes and interaction between different processes during the execution of a task (Buysemeyer & Diederich, 2009). These models are mathematic and these mathematic descriptions are formed from knowledge of the underlying cognitive process (Anderson & Lebiere, 1998). Used within various domains, they apply a specific descriptive model to each individual task rather than using more generic statistical models. They have been used within decision-making research extensively (Buysemeyer & Diederich, 2009), and due to the complexity of decision-making and competing models of cognitive processing involved in decision-making, when using cognitive models within decision-making, multiple models are often tested on a data set and it is the best-fitting model which is then used to understand the underlying mechanisms involved in the task.

The model that will be used throughout the decision-making experiments below is the Expectancy Valance Learning Model (EVL) (Buysemeyer & Diederich, 2009). This model was shown to best explain the underlying mechanisms within the IGT. Two other models were proposed, one which is a Bayesian Utility Model which uses a Bayes rule to update the expectancies of the deck, however one flaw with this model is the clarity of the winnings presumes a speedier learning pattern than that observed within normal IGT performance (Buysemeyer & Diederich, 2009). The other model proposed was a strategy-switching model that saw 3 branches of the decision making procedure; this again was shown not to explain the data as well as the EVL model. These three models were compared using a quantitative method. This method employs a chi-squared statistical test and highlighted the benefit of the EVL to explain the data (Buysemeyer & Diederich, 2009).

The EVL model sees the choice outcome coded as either a positive or negative affective reaction based on the gains and losses received. For example, if you received £50 and lost nothing on a trial this would elicit a sensation of "positive" valence, as in a feel good effect, whereas if you lost an amount during a trial then this would elicit a sensation of "negative" valence, as in a feel bad effect. These positive and negative emotions are the fundamental signals towards your learning, and the learning follows a reduction of prediction error similar to a Rescorla &Wagner (1974) model of learning. To explain this in more detail the model uses three parameters.

The attention-to-reward (*w)* parameter arises from the weight that an individual gives to wins (*R*) and losses (*L*) during a trial (*t*), and is formulated from the valance (*v)* equation (see Equation 1). The (w) parameter can range between 0 (where no weight is given to losses) and 1 (where losses are maximally weighted).

$$v(t) = \{(1 - w) \cdot R[d(t)] + w \cdot L[d(t)]\}$$

Equation 1

The updating-rate parameter (phi) is the previous expectancy plus an adjustment resulting from the prediction error (see Equation 2). This is commonly known as the delta-learning rule. This rule relies on the notion that one updates their knowledge each trial based on their prediction to the outcome and the resulting choice outcome, and subsequently alter their prediction based on the error term between prediction and outcome (Rumelhart & McClelland, 1986). The parameter can range between 1 and 0 (a weight of zero indicating that no attention is given to learnings from previous trials).

$$E_d(t) = E_d(t-1) + \phi \cdot [v(t) - E_d(t-1)]$$

Equation 2

The final parameter is the choice consistency parameter, which is the consistency that the participants makes their decision based on the expectancies of each of the deck. It is the probability of choosing a deck, as determined by the strength of that deck in contrast to the sum of all other decks (see Equation 3).

$$\mathrm{P_r}[G_d(t+1)] = \frac{e^{\theta(t)-Ed(t)}}{\sum_k e^{\theta(t)-Ed(t)}}$$

Equation 3

The consistency-parameter c, is the power function of theta over trials, varying between 0 and 5: the higher the number the more consistent the responses (see Equation 4).

$$\theta(t) = (t/10)^c$$

Equation 4

From these parameters we will be better able to explore the types of effects the meaningful stimuli within the following experiments. More specifically with the model having the affective response caused by the choice outcome as a key component we will be able to relate this more directly to the effect of stimuli on the perceived valance weighting given throughout the tasks. That is, the key domain of decision-making that will be tested experimentally within this chapter will be the role of cues when exposed to multiple alternatives on decision-making, and how in turn each choice outcome leads to a better decision in the future. These two domains are very important when looking at meaningful stimuli, how does a superimposing of meaningful stimuli on an object effect the final decision choice, and as a result how does the congruency with the meaningful stimuli and the choice outcome effect subsequent decision towards that object.

Section Overview

Within this section we will be employing the IGT to asses the effects of meaningful images in decision-making, in Experiments 1 & 2 we will use a traditional form of the paradigm, and in Experiments 3 we will outline a novel adaptations of the IGT to understand if the role of speed plays any part. In Experiment 4 we utilise the novel task outlined in Experiments 3 to explore meaningful images in decision-making once again. Throughout all of the experiments we try to understand the underlying mechanism being affecting the decision, in particular using cognitive models to try and establish a variety of parameters than alter decisions in the context of meaningful images.

Experiment 1: Decision Making is Biased by Pre-Existing Emotional Information: Brand Logos and the Iowa Gambling Task

Within the world of business and marketing, the creation of a strong brand is one of the core goals to which any brand owner aspires. In fact, financial data (Barth, Clement, Foster, & Kasznik, 1998) suggest that a strong brand can be one of the most valuable assets possessed by a company. For example, strong brands help improve perceived quality (Aaker, 1991), help companies recover from negative publicity (Monga & John, 2008), and may make consumers less risk-averse (Erdem & Keane, 1996).

Although a great deal of research has demonstrated the value of a strong brand, one important question that has not been fully examined is how brands can influence decision-making towards novel stimuli. For example, when a new product is introduced to the market it often carries a brand name or logo. Although the product may be novel, the association with a familiar brand will likely trigger brand-related associations and the branding (or the associations) will likely bias subsequent decision-making.

Our question here is: when confronted with novel objects carrying brand information, how is new learning about the object (e.g. through purchase or use) influenced by the pre-existing brand and associative values?

This question is important from an applied perspective as it can help us better understand how brands influence decision-making, purchase, and use. However, it is also important from a broader and more theoretical perspective. Specifically, as we will discuss in greater detail below, a known brand (particularly as encapsulated by its logo) is only one example of a broader class of stimuli: stimuli that have pre-existing cognitive and emotional information. Thus, at this more abstract level, the deeper question of interest here is: how does pre-existing cognitive and emotional information influence learning about novel objects. This is a fundamental question since it may help us understand the interplay between cognition, emotion, and learning in decision-making.

Research on the influence of affective stimuli has started to explore this question, and one prominent researcher Winkeilman suggests these stimuli sets (e.g. happy faces) only require unconscious processing for a reaction to occur, and that they predominantly influence motivationally relevant behaviours (Feldman-Barrett, Niedenthal, & Winkielman, 2005). This influence of affective stimuli has been studied within the consumer domain, take for example the influence of mood states on consumer behaviour (Lee & Sternhal, 1999); or the influence of incidental affect in status quo biases (Yen & Chuang, 2008). However, these studies larger look at the role of unrelated emotions on consumer decisions, the question that seems somewhat unexplored is the role of consumer related emotions on unrelated decisions.

Brands and emotions

Brands are "multidimensional constructs, matching a firm's functional and emotional values with the performance and needs of consumers" (de Chernatony & Riley, 1998). Often brands are represented by a logo that is used as a visual shorthand intended to call to mind the entire abstract brand. Individuals can develop strong preferences and affinities for specific brands and their associated logos. Recently, researchers have looked into the emotional connections that consumers have with brands (e.g. Lindstom, 2008), and there are some who now claim that emotional branding is the key way to improve the customer value proposition (Shiv & Bechera, 2010). Part of this so-called "third-wave" approach to branding is the belief that the best way for brands to build affinity, and even long-term loyalty, is through their emotive properties. Within research on brand loyalty this notion is not particularly new (Copeland, 1923;

Guest, 1944). However with advances in online, implicit, and neuroscience techniques the links between emotions and brands have garnered more empirical evidence (see for example Mclure et al., 2004; Lindstrom, 2008).

There are now several lines of converging evidence that suggest a deep link between emotions, experience, and brands. For example, Gobe (2001) has talked about the importance of building emotional relationships with brands through the use of sensory experience. In fact, earlier work has discussed the importance of brand-related emotions on consumer decisions (Miniard, Sirdeshmukh, & Innis, 1992). And, more recently, researchers have studied links between brands and emotions more directly by using neuroscience techniques (Mclure et al., 2004; Koenigs & Tranel, 2007; Lindstom, 2008).

There are numerous ways of conceptualizing the emotional relationship that a consumer might have with a brand. One such concept is "brand loyalty", which is a high-level construct that likely is based on a combination of brand strength, brand commitment (Fourier, 1998) and brand preference (for literature related to brand loyalty, see Jacoby & Chestnut, 1978; Mower & Minor, 1998).

The consensus seems to be that brands sometimes evoke emotions and, when they do, they may impact subsequent brand-related decision-making. While this "direct effect" seems fairly clear, one question that seems largely unanswered is how this effect may influence other (non-brand-related) decision. The nature of such "indirect effects" is important, as it may have direct bearing on issues such as the success of brand extensions, the resilience of brands in the face of negative information, and the positivity of consumption/post-consumption evaluation.

It has traditionally been difficult to measure the brand's indirect-effect on decision-making. One reason this has been so difficult to capture is because a large part of the <u>direct</u> and indirect impact that brands have on decision-making happens at an emotional level. Thus, any decision-making task that relies on purely rational decisions (e.g. price-related or preference-related information), will fail to capture the indirect effects of brands on decision-making. Thus, a more appropriate decision-making task is one that is influenced by emotional (or "hot") processes. One such task is the gambling task developed by Bechera et al (1994). It will be this task – the so-called "Iowa Gambling Task" (IGT) - coupled with measures of brand loyalty that we will employ to quantify the indirect effects of brand emotions on decision making.

The Iowa Gambling Task (IGT)

The IGT was designed to explore emotional aspects of real-world decision-making. Specifically, in this laboratory-based procedure, participants are required to make decisions that maximize their long-term rewards (e.g. monetary rewards) under conditions of uncertainty. The process through which participants learn about rewards and punishments is argued to be implicit – based on 'gut-feelings' – and so captures the influence that emotions and feelings may have on otherwise 'cognitive' decisions (Damasio, 1994). The role of emotions within the task was further clarified with the use of skin conductance response (SCRs). The results from such studies have suggested that normal participants elicit anticipatory SCRs even before they have any explicit knowledge of risk–suggesting that an emotional 'gut-feeling' guides choice behaviour before cognition (Bechera, Damasio, Tranel, & Damasio, 1997)

In the classic version of this task, subjects are presented with four identical stacks ("decks") of cards and are asked (on each trial) to choose one deck to draw from. Each card drawn has a different amount of monetary win and/or loss. For example, one card might say "Win $100, Lose $50". The subjects are given a certain amount of money to start with and are asked to try and win as much money as possible by simply drawing from the different decks across a long series of draws/trials. Unbeknownst to the participants, each of the four decks has a different long-term pay off structure. Specifically, two of the decks are "good" (i.e. continued selection will lead to long-term winning), and two are "bad". Typically the subjects do not know how many draws they will get from the decks, but the experiment ends after 100 draws.

Healthy controls will, after 50 or 60 trials, learn which decks are "good" and tend to gravitate towards them. There is a large range of individual differences that affect task performance, for example certain clinical populations (patients with damage to the ventral-medial prefrontal cortex and schizophrenics) fail to exhibit this type of emotion-based learning (for a review, see Dunn et al., 2006).

Aims of the present study

One of the key features of brands is the influence they have over decision-making. For example, brand loyalty tends to bias behavior towards preferred brands and seems to reduce the impact of negative information related to a loyal brand (Monga & John, 2008). Each of these processes can be explored using an adapted version of the IGT. For example, by associating a particular brand with one of the decks, it should be possible to bias responding toward (or away from) that deck (brand preference) and to influence the speed of learning about that deck (brand commitment). The presentation of a group of branded items accompanied by an instruction to "choose one" represents an analogy of real-life decisions a consumer makes. That is, a consumer is often presented with a number of products from one category and selects one of them (e.g. based on brand). The outcomes (rewards and losses) may influence later decisions when the consumer is again presented with a similar array of choices. By using the IGT we will be able to ascertain how brand preference and brand commitment influence decisions over time and in response to varying reward structures (wins/losses).

Thus, we had two hypotheses: first, brands will have an effect on emotional-based decision making. Specifically, we hypothesize that superimposing brand images onto card decks within the IGT will alter the speed at which a participant learns the task. And second, the speed of learning during the IGT will be affected by the strength of brand preference and commitment that a participant has towards the superimposed logos. Specifically, the rate of learning will be faster when a preferred brand is superimposed onto a "good" deck and slower when a preferred brand is superimposed onto a "bad" deck.

EXPERIMENT 1 A&B

Methods

These experiment was conducted in two phases. In phase one, the participants rated their preferences to a wide variety of everyday brands (see Figure 2). Results from these ratings were used to determine which logos would be used in the second phase of the experiment (see Figure 3). The first phase was the same for both experiments however the second phase altered for the two experiments. In Experiment 1A were three conditions "preferred good", "preferred bad", and "neutral". In the "preferred good" condition, the logo of the highest-rated (most preferred) brand was superimposed on one of the "good" Iowa decks. The other three decks contained logos of the three most neutral-rated brands. In the "preferred bad" condition, the logo of the highest-rated (most preferred) brand was superimposed on one of the "bad" Iowa decks and again the other three decks contained logos of neutral-rated brands. We also had a control in the "neutral" condition in which a generic "card-back" image was presented on all four decks (similar to the standard IGT procedure). In Experiment 1B the second phase of this experiment, the three conditions were: "adverse-on-good", "adverse-on-bad", "neutral". In the "adverse-on-good" condition, the logo of the lowest-rated (most dis-loyal) brand was superimposed on one of the "good" Iowa decks. The other three decks contained logos of the three most neutral-rated brands. In the "adverse-on-bad" condition, the logo of the lowest-rated brand was superimposed on one of the "bad" Iowa decks and again the other three decks contained logos of neutral-rated brands. The 'neutral' condition was the same participants for both Experiment 1A & 1B.

Figure 2: Part I: The brand loyalty rating. During this phase participants saw an image that was located in the centre of the screen and they were required to respond from 1-5 on a Likert scale. Each item was rated four times and, although presented in a random order, the brand images were kept in the same position and size. An average rating was calculated from these four responses and was used to select the images used in Part 2 of the experiment (the IGT).

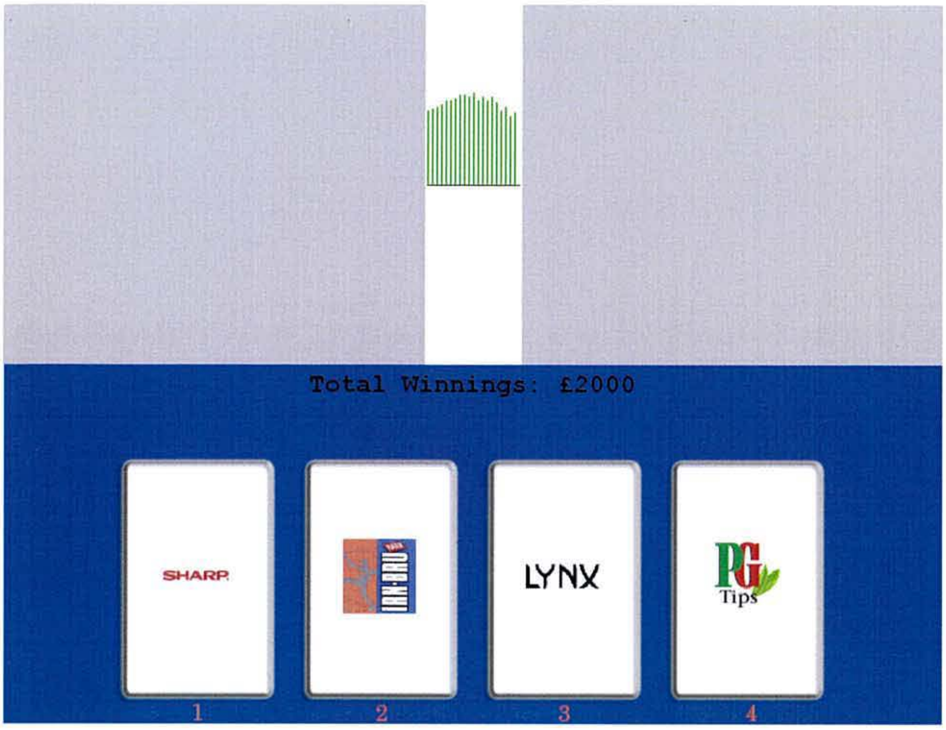

Figure 3. Part 2: The Branded Iowa Gambling Task. The chart at the top shows the participant their running total of winnings. The participant was able to see how this had altered over the last 20 trials (this was slightly different from the method used by Bechera et al. (1994)). The four decks (bottom half) had their corresponding number placed underneath, the brand images themselves were located in the centre of the decks and the images did not change location or size. A smiley presented itself below where the total winnings were displayed after a participant made a choice of a deck. The smiley was either a smile or a frown.

Participants

158 participants (104 female, 54 male); ranging in age from 19-32 (Mean= 20.35) from Bangor University volunteered to participate through an online experimentation booking system (SONA). The entire procedure took approximately 45 minutes and participants received course and printer credits for their participation. The School of Psychology ethics committee approved the research.

Apparatus

E-Prime experimentation software (Psychology Software Tools, 2002) was used to conduct both parts of the experiment. The software ran on Windows XP with a Pentium 4 (3.06 GHz) processor. The stimuli were displayed on a 17" CRT monitors (1076x768 resolutions, 85Hz, 32bit). The participants' made all responses via a keyboard with the primary responses being the keys 1 through 5 (during the brand preference rating phase) and the keys 1 through 4 (during the IGT).

Stimuli

Brand logos were presented as 24-bit bitmap files with dimensions of 80x80 pixels (subtending approximately 8 degrees of visual angle) throughout the IGT. The same logos were used in the rating (first) phase of the task with a 20% scaling increase (96x96 pixels). The brand logos were from the UK market and were either fast moving consumer good brands (e.g. drinks or chocolates), or UK service brands (e.g. banks or newspapers). This mix and variety of brands was used to increase the likelihood of identifying a range of brand preferences within the specific experimental population. During the neutral "no logos" condition the stimuli were similar to previous IGT stimuli (images of traditional card backs).

Measures

The first phase was a computer-based rating questionnaire where the participants were asked to rate their familiarity, preference, and loyalty to 40 different brand images. These were presented one at a time in a random (self-paced) order – each image was presented a total of four times, thus participants made 160 responses. Each image remained on-screen until a rating was indicated via a keypress, with possible ratings being: 1 = "very disloyal"; 2 = "disloyal"; 3 = "neutral"; 4 = "loyal"; 5 = "very loyal", with the same Likert-scale used for familiarity and preference. The measure of loyalty was used as the criteria for inclusion in the IGT, with the preceding question used to ensure consistency of preferred brand.

Design

Each participant was randomly assigned into one of the three conditions. Due to the nature of the task (discovering a hidden rule), we decided to be conservative and had each of the participants only perform the IGT once. Consequently a between subject design was necessary to answer the research hypotheses. For the second phase of the experiment (the IGT) the independent variable was the location of the brand image (or lack thereof, within the neutral "no logos" condition) on the decks, this was different in each condition (loyal good, loyal bad, neutral). The dependent variable in the second phase is the deck chosen: A,B,C,D further classified as "good" (decks C or D) or "bad" (decks A or B).

Procedure

The participants were run in groups of four to six. Initially the participants were given a broad outline of the study. After the brief introduction, the participants were given an information sheet and a consent form that they were asked to complete. The experiment lasted approximately 30-45 minutes with a timeline as follows: 5-10 minutes for the first phase (the brand loyalty rating); and 25-35 minutes for the second phase (the IGT). Participants sat in one of two rooms where six identical computers, desks and chairs were. The rooms were dimly lit and the participants sat on a chair approximately 60 cm away for the computer monitor, which was positioned at eye level. Dividers and headphones ensured that adjoining participants did not influence performance.

Part one preceded as follows: Participants rated brand images that were presented; each of the images was shown at screen centre and remained visible until a response was made. An average of the score for each brand image was calculated. Four brand images were forwarded into the second phase: the highest average rated (and always above a rating of 4.5) and three with averages closest to a neutral rating (between 2.5 and 3.5,). These images were used as either the 'target' brand (highest rated) or as the neutral 'non-targets'.

The second phase of the experiment (the IGT) began with an explanation of the game. Participants were shown a sample of the IGT display (including the decks, generic logos, and the reward feedback/graph). They were told that while there were going to be brand logos present during the task, they should ignore these logos – as they were simply distracters that were irrelevant to the main (money-earning) task. The task they performed required the participant to make a selection of one out of the four decks every trial. Thus, across the 100 trials, the participant made a total of 100 deck selections. Once the participants made a deck selection, they were presented with two pieces of information: the monetary winnings, and losses. The winnings after a deck selection was either £100 or £50, A loss did not always occur, but when it did, the loss ranged from £25 - £1250. The winnings and losses are paired together so that they stay the same for each type of deck. The participants were told that the aim of the game was to make as much money as possible, and that they may choose whichever deck they feel like. At the start, they were given £2000. Ultimately, some decks are advantageous (i.e. have a long-term net gain) and some are disadvantageous (and have a long-term net loss) (See Table 1 for a summary of the deck win/loss statistics).

During the task, the participants were also given information as to their overall running total and their performance over the last 10 selection outcomes in the form of a sliding bar chart (See Figure 2 for an example). It is important to note that although the decks are referred to as A, B, C, and D, the physical positions on the screen were randomized across participants. The deck positions remained constant for each participant across the entire course of their IGT experiment.

Table 1

How the IGT rules work so as give rise to "good" and "bad" decks

	Bad Decks		Good Decks	
	A	B	C	D
Winnings/Deck:	£100	£100	£50	£50
Loss/10 Cards	£1250	£1250	£250	£250
Net Gain/10 cards	-£250	-£250	£250	£250
Frequency of Rewards/ 10 cards	5	1	5	1

Participants could take breaks at any part of the experiment, and all of the trials were self-paced. After the conclusion of the experiment (after 100 deck selections), the researcher debriefed and thanked the participant and answered any questions that they had.

Statistical Analysis

There are numerous techniques that have been used to analyse the performance within the IGT. The expectancy-valance model (EV) was suggested as the best-fit model for performance on the IGT (Busemeyer & Stout, 2002): combining the processes of the individual decisions (trial-by-trial) with the process of learning and adapting these decision through experience. One advantage of the EV model is that it allows researchers to assess the weightings individual participants give to each of the three different (model fit) decision parameters. This further allows researchers to make meaningful comparisons with typical performance during the IGT. The three parameters are: attention-to-reward; updating-rate; and, choice consistency.

The attention-to-reward parameter is formulated from the idea that for each trial the participant incorporates their "recent" wins and losses into a single value of the valance equation. This parameter can range from 1 to 0, where 1 suggests that losses are given the maximum weighting, and 0 suggests that losses are given no weight.

The updating-rate parameter (phi) is the previous expectancy plus an adjustment resulting from the prediction error, it is the speed in which information is incorporated. The parameter can range between 0 and 1. A value of one suggests a sensitivity to recent trials, and the forgetting of older trials (myopic), whereas a figure close to 0 suggests more sensitivity to older trials.

The final parameter is the choice consistency parameter, which is an indication of the consistency to which a participant makes their decision based on the expectancies of each of the decks. It is the probability of choosing a deck, as determined by the strength of that deck in contrast to the sum of all other decks. The consistency-parameter c, is the power function of theta over trials, varying between 0 and 5: the higher the number the more consistent the responses

The final component of the model is the model fit statistic G^2, which is the extent to which the model fits the data better than a baseline model, which assumes a random selection of decks. Using the EV model we will be able to estimate the specific impact that brands have over decision-making. We can do this by comparing the derived parameters across our various conditions (and with values reported in the literature from similar tasks).

Experiment 1a: Results

Ten participants were removed from analysis due to ambiguous responses during the initial rating task. Specifically, five showed no brand loyalty (all responses were near neutral), and five participants had no brands that they rated neutral. All Iowa trials from the remaining participants were analyzed using two different approaches: the traditional analysis method (described earlier) and also using an expectancy valence model approach (described in more detail below). We turn now to the results of these analyses.

Block Analysis

Initial analysis of the IGT split the trials into 5 blocks of 20 trials (draws 1-20, 21-40, 41-60, 61-80, and 81-100). Within each block of trials, the participant's selections were analyzed with a simple computation of the mean number of bad decks selected per block (A+B) subtracted from the mean number of the good decks selected per block (C+D). Thus, the net score can range between -20 (chose a bad deck on all twenty selections) and +20 (always chose a good deck) for each block. Negative scores indicated that the participants were selecting the "bad" decks more, whereas positive scores showed that participants were selecting the "good" decks more. The target brand (single preferred brand) could be located on either one of the "good" decks (i.e. deck C or D) for condition preferred-on-good or on one of the "bad" decks (i.e. deck A or B) for the preferred-on-bad condition.

These scores were analyzed using a 5 (block) X 3 (conditions: preferred-on-good, preferred-on-bad, and control) repeated measure ANOVA[1]. We found an overall main effect of block (F (2.38,121.38)=11.403, p= . 000, $f^2=0.42$), which is expected in all normal-population IGTs, but no interaction between group and block (F (4.86, 126.26) =1.142, p=.342, $f^2=0.21$).

[1] Mauchly's Test of Sphericity tested significant to the null hypothesis, so Greenhouse-Geisser correction was used for degrees of freedom.

This main effect is expected since participants who are learning will select advantageous decks a greater proportion of the time as the task progresses (see Figure 4). A within-subject contrast revealed that the relationship was significantly linear ($F(1,51)=19.992$, $p= .0001$, $f^2=0.56$) showing that the mean score increased linearly across blocks. There was a significant effect of the between-subject factor (condition) ($F(2, 52) = 3.982$, $p=.025$, $f^2=0.40$), and the between group intercept ($F(1,52) = 6.350$, $p= .015$, $f^2=0.35$).This suggests that although an overall difference between groups was present, the nature of this difference did not differ block by block. Tukey post hoc tests revealed that there was a significant difference between preferred-on-good vs. preferred-on-bad (*MD*=+/-5.72, *SE*=2.06, p=. 028) showing that those in the preferred-on-good condition choose the good decks more often than those in the preferred-on-bad condition, the post hoc test also revealed no significance between preferred-on-good vs. control (*MD*=+/-1.59, *SE*=2.06, p= .744) and preferred-on-bad vs. control (*MD*=+/-4.13, *SE*=2.09, p=. 152).

We conducted further analyses on the overall deck selections (percent of time selecting Deck A, Deck B, etc..) that a participant made during the 100 trials of the experiment, however no significant differences were discovered (all ps = >.05). In summary, as can be seen in Figure 3, the logo presence/positioning effected overall participants performance. However, this was not apparent in the "learning" (block x condition RM ANOVA) measure. Moreover, it was an initial preference for the high-valence brands that primarily effected participant performance.

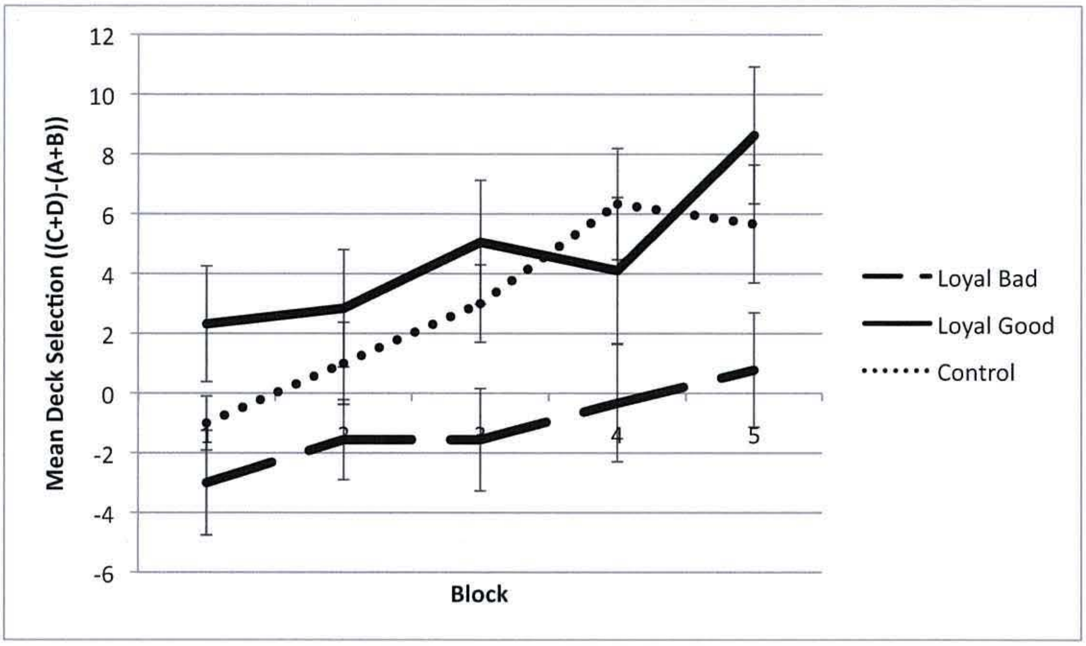

Figure 4. Graph displaying estimated means for the different groups. The horizontal line represents trials over the course of the experiment split into 5 blocks of 20. Note the smoothness of the disadvantageous and neutral condition and the jagged nature of the advantageous.

Expectancy Valence Model

Since Busemeyer and Stout (2002), researchers have attempted to model trial-by-trial deck selections in the IGT task using an Expectancy Valence model (EV). This model looks at the performance of participants trial by trial, and incorporates a dynamic updating of the different deck representations (probabilities, etc) after each trial. The model was fit to the data with the G2 statistic revealing that the data only just fit to this model (M=14.72, SE=5.17), a one-way ANOVA revealed between group significance, $F\ (2,51) = 4.079$ p=.023, with Tukey post-hoc tests revealing significance between preferred-on-good vs. preferred-on-bad (MD=+/-3.41, SE=11.99, p=. 017), suggesting that the EV model better explains the performance during the preferred-on-good condition than in the preferred-on-bad condition, there was no significance between the other comparisons (ps = >.05) .

Three primary decision-making parameters are generated from the EV model; the Recency parameter, which measure how much the participant attends to recent vs. distant gains; a Win vs. Losses parameter, which measures how much the participant attends to loses vs. wins; and finally, the Choice Consistency parameter, which measures how much the participant is consistent with their decision-making based upon the expectancies learnt throughout the task. A one-way ANOVA showed a between-subject significance for the recency parameter, $F(2,51) = 3.093$ $p=.054$, Tukey post-hoc revealed no significance when comparing experimental conditions (ps = >.05). The two other parameters revealed no significance differences (ps = >.05). In this type of model, the actual values of the parameters are also of interest. For example, the attention parameter value would be 0.5 if participants were weighting gains and losses equally (Stout et al., 2004) however, in both the preferred-on-good and the preferred-on-bad condition the scores are below this value (see Table 2).

Table 2

Expectancy Valence Model Value Means for Experiment 1 ---Means(SE)

	Loyal-on-Good	Loyal-on-Bad	Control
Model Fit (G2)	31.22(11.32)	-2.12(3.00)	15.91(8.44)
Attention-to-win (a)	.32(.078)	.26(.08)	.50(.094)
Recency-of-update (w)	.31(.08)	.26(.07)	.09(.02)
Response Consistancy (c)	0.68(0.58)	0.17(0.57)	1.09(0.60)

Experiment 1B: Results

Nine participants were removed from analysis due to ambiguous responses during the initial rating task. Specifically, four showed no brand adversity, and five participants had no brands that they rated neutral .

Block Analysis

The target brand (single adverse brand) could be located on either one of the "good" decks for condition adverse-on-good (i.e. deck C or D) and likewise on one of the "bad" decks for the adverse-on-bad condition (i.e. deck A or B).

Analysis for the second experiment followed the same approach as the first experiment, that is the scores were analyzed using a 5 (block) X 3 (conditions: adverse-on-good, adverse-on-bad, and control) repeated measure ANOVA. We found a main effect of block ($F(2.96,153.81)=10.666$, $p=.000$, $f^2=0.45$) which is expected in all normal-population IGTs. This main effect is expected since participants who are learning will select advantageous decks a greater proportion of the time as the task progresses, see Figure 5. A within-subject contrast revealed that this relationship was again significantly linear ($F(1,52)=22.39$, $p=.000$, $f^2=0.65$) showing that as the block increases (over time) the mean selection score increases with it. There was a significant effect of the between-subject factors (condition) ($F(2, 52) = 4.511$, $p=.016$, $f^2=0.42$), however there was no significance for the between group intercept ($F(1,52) = 1.351$, $p=.250$, $f^2=0.16$) and the interaction between group and block ($F(5.92, 153.81) =.567$, $p=.567$, $f^2=0.15$) meaning that although an overall difference between groups was present, this could not be seen block by block. Tukey post hoc tests revealed that there was a significant difference between adverse-on-good vs. control (*MD*=+/-5.21, *SE*=1.83, p= .017) showing that those in the control condition choose the good decks more often than those in the adverse-on-good condition.

The post hoc tests also revealed a trend towards significance in the adverse-on-bad vs. adverse-on-good (*MD*=+/-4.03, *SE*=1.83, p= .079) and added to this no significance in the averse-on-bad vs. control (*MD*=+/-1.18, *SE*=1.85, p=. 801).

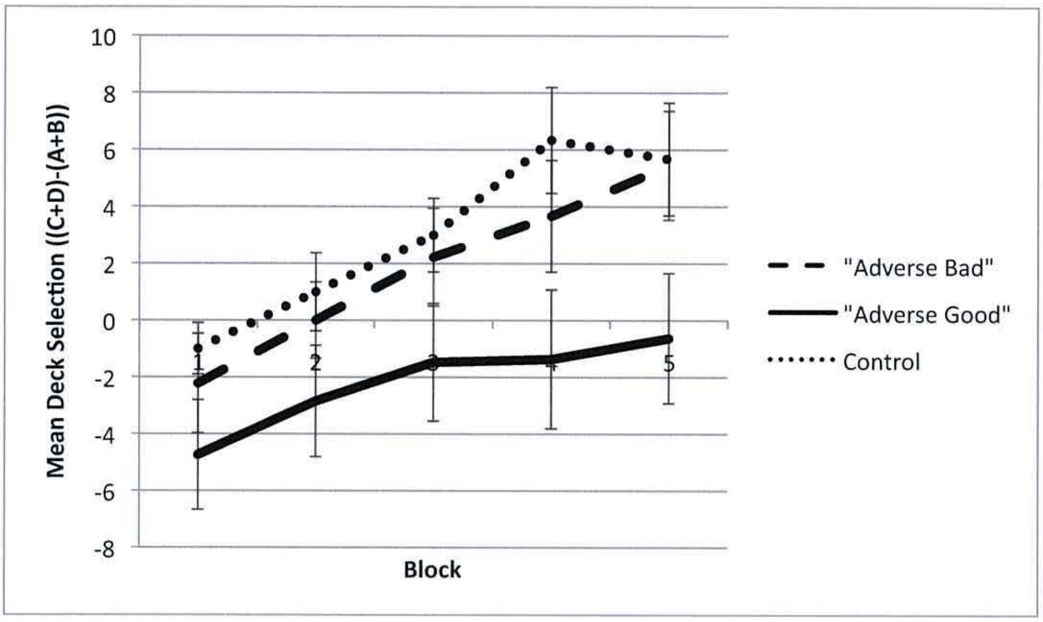

Figure 5. Graph displaying estimated means for the different groups. The horizontal line represents trials over the course of the experiment split into 5 blocks of 20. Note the smoothness of the disadvantageous and neutral condition and the jagged nature of the advantageous.

Once again we conducted further analysis on the overall deck selections that a participant made during the first 100 trials of the experiment. A one-way ANOVA looking at deck selections by condition revealed a between subject effect of Deck B[2] ($F(2,52)=5.193$, p= .009) with all other decks being non-significant. Tukey post-hoc tests revealed that this difference was significant between the adverse good condition and the control condition (*MD*=+/-13.21, *SE*=4.26, p=. 009). Additionally, the comparison between the adverse good condition and the adverse bad condition also trended towards significance (*MD*=+/-9.66, *SE*=4.26, p=. 069), and

[2] "Deck B" is one of the "bad decks". Specifically, it is the deck that has an occasional large loss card.

there was no-significance between the adverse bad condition and the control condition (*MD*=+/-3.56, *SE*=4.31, p=. 690).

<u>Expectancy Valence Model</u>

The data were fitted to the EV model (Busemeyer and Stout, 2002). The G2 statistic revealed that the data only just fit to this model (*M*=4.03, *SE*=1.56), a one-way ANOVA revealed no between group significance, (ps = >.05). For the three other parameters, a one-way ANOVA showed a between-subject significance for the recency parameter, F (2,50) = 6.506 p=.003, Tukey post-hoc revealed significance when comparing conditions adverse-on-good vs. control, (*MD*=+/-.41, *SE*=.14, p=. 002) see Table 3. The other comparisons revealed no significance (ps = >.05). The higher value of the adverse-on-good suggests that they are more reliant on recent trials to guide their behaviour during the task. The two other parameters revealed no significance differences (ps = >.05), however it must be noted that, as with experiment one, participants seemed to pay more attention to the gains than the losses during the experimental conditions.

Table 3

<u>Expectancy Valence Model Value Means for Experiment 2 ---Means(SE)</u>

	Adverse-on-Good	Adverse-on-Bad	Control
Model Fit (G2)	5.62(8.46)	-2.98(4.02)	15.91(8.44)
Attention (a)	.34(09)	.37(.07)	.50(.094)
Recency (w)	.49(.11)	.31(.09)	.09(.02)
Response Consistancy (c)	0.47(0.60)	0.82(0.41)	1.09(0.60)

Discussion

In these studies on the way in which brand valence may influence performance in the IGT, we began by investigating whether brands to which one is loyal can influence performance and learning in the IGT. Further, we also asked whether brands to which one is adverse can also affect performance and learning in the IGT.

Seen together, the results from these experiments suggest a shifting of the initial baseline for performance primarily based on the preference towards the depicted brand. That is, when the deck's brand-valence is congruent with the deck's reward structure, there is a baseline shift in performance (e.g. preferred-on-good and, adverse-on-bad). Conversely, when the deck valence is incongruent with the deck's rewards structure there is an impairment of performance (e.g. preferred-on-bad and, adverse-on-good). It is the initial preference towards the brand that creates the primary performance difference between the conditions: participants chose the brand they liked irrelevant of the IGT outcomes. By doing this during congruent conditions they were aided in their selection and performance and their performance suffered for the incongruent condition.

Another crucial finding is the effect that the brands have on learning during the task. Even though ANOVA failed to detect any overall learning effect (based on traditional IGT scores), the more subtle analysis based on the EV model did reveal such an effect. Specifically, when looking at the recency parameter of the EV model, otherwise known as the learning-rate parameter (Yechiam, Busemeyer, Stout, & Bechera, 2005), we find an overall effect of the experimental conditions in comparison to the control. These results suggest that when brand information is present, participants give more weight to their recent trials and discounting the long-term payouts, which leads to a selection of the disadvantageous decks,. During Experiment

1B this effect is also apparent between the experimental conditions, with participants in the adverse-on-good condition being myopic towards past rewards and punishments.

Finally, the lack of fit of the EV model for two out of the four experimental conditions highlights that the two effects outlined above lead to abnormal decision making. In other words, the mere presence of brands can lead to irrational decisions that ultimately result in thwarted performance and learning. That is, if participants were making normal decisions, then the model values would be as those seen in the control condition. These values however could stem from a different approach to decision making within the task rather than purely irrational decisions.

These findings demonstrate the profound effect brands can have on decision-making. Specifically, these data appear to reflect the two essential components of loyalty: brand preference and brand commitment. Furthermore, these results demonstrate that the behavioural effects of brand loyalty can be measured in an objective way within a laboratory context. During the task, brand preference lead to an initial bias of selection, followed by the commitment towards the brand leading to discounting of information and impaired learning.

Not only are these results important in terms of understanding the nature of brands, but they are also fundamentally important in terms of understanding the emotional nature of decision-making. As proposed by Damasio (1994), the somatic marker hypothesis provides a theoretical interpretation of the IGT. This theory proposes a physiological driver that aids the participants in choosing the "good" decks and staying away from the "bad" decks. So how might this influence performance in our version of the IGT? In our IGT the levels of brand loyalty played an integral role in a participant's selection of decks. This may seem bizarre within the context of the IGT (where payout information should, logically, drive performance regardless of the superimposed brand information). However, this phenomenon perhaps makes more sense in real world contexts: For example, in a shopping environment, a consumer may feel less anxious when buying products that are made by a liked, respected, or "loyal" brand. In fact, this could be a largely unconscious drive that may, over time, create or reinforce brand loyal consumers. That is, through emotional-based learning, your body unconsciously adds positive somatic markers to the representations of brands with which you have had positive experiences, and so these brands become less "risky" and more preferred. As a result, one becomes less anxious whilst purchasing these brands, which further adds to the likelihood of brand loyal behaviours. This could be exaggerated even further when a consumer makes an impulse purchase. Further research into this area would add greatly to the understanding of brand loyalty and may even help further our understanding of normal decision making and such theories as the somatic marker hypothesis. One possible way to do this would be by using the same methodology in this research, but with the addition of physiological measures (e.g. skin conductance) being recorded.

Jacoby and Chestnut (1978) argued that there was more to loyalty than just behaviour. The present data clearly support their claim, indicating that there is a multi-faceted impact that brand loyalty has on cognition and with a resultant impact upon decision-making. With both the attraction and commitment elements of brand loyalty clearly demonstrated from this study, we can think more about how these effects present themselves in consumer behaviour. At this point, it would be beneficial to conduct further research that could demonstrate these phenomena in a more real-life setting.

Research by Harris & Murawski (2009) provides another example of the way that brands may influence incidental learning, and they provide a discussion of the possible mechanisms underlying this. Specifically, they point towards the modulation of the affective system by the brands that in turn shape the decision-making. Using a discounting task they found that an immediate reward was preferred when primed by a desired brand, and in light of research on discounting behaviour this could stem from a transient increase of affective state (McClure, Laibson, Lowenstein, & Cohen, 2004). This concept is backed up by the EV data, which suggest participants gave greater weight to more recent trials during all of the experimental conditions.

Future research needs to be conducted on the psychological factors driving brands. The area of social neuroscience gives some indication as to the possible neuronal substrates for this. A recent study by Koenigs and Tranel (2008) has looked at the brand-based decision-making within ventral prefrontal cortex patients (VMPFC), an area implicated in blunted learning in the IGT, finding that these patients disregarded brand information. Added to this McClure et al. 2004 conducted an fMRI study with a similar experimental design to Koenigs and Tranel (2008), the results of which highlighted the role of dorsolateral prefrontal cortex during the brand-based decision-making – another area implicated in learning during the IGT. More recently Plassmann and collegues (2008) looked at choice ambiguity and brand information and highlighted once again the possible role of the VMPFC, clearly further research must be conducted to understand the relevance and implications these findings have for branding research. Furthermore, the role of the VMPFC in the IGT suggests that the behaviours found in the present study may be related to activity in this brand information-processing centre.

One limitation of the experiment is the possible confound of "demand characteristic" present in the IGT phase. In its strongest form, the argument goes like this: participants remember that they liked/disliked a brand in phase one (the brand ratings) and they felt compelled to continue to select/not-select that brand in the IGT. In other words, this argument would suggest that their selections in the IGT were not reflective of true emotional preference, but instead were based on a desire to maintain consistency in their responding. Thus, they would be initially drawn towards their previous positively rated brand and away from their negatively rated brand simply for consistency's sake. However, for this to happen they would have to remember and be guided by their previous rating for that specific brand logo from phase one. While possible, this seems very unlikely. We say this because of the number of ratings that the participants made in phase one. Remember that in phase one they were asked to rate 40 brands, three times each, on four different dimensions (in total they made 192 ratings). It seems highly unlikely that the participants remembered and were motivated by one or two of their 192 ratings in phase one. It seems far more likely that it was their true rating of the brand (i.e. their emotional commitment to it) that guided their selections in phase two and led to the found effects. That is, if there is any consistency in responding, then it is based on the participant's true emotional connection with this brand. Furthermore, if participants were asked to rate the brands after the IGT we would suffer from two major problems. Firstly, choosing the actual brands to present, and how these would match up with the participant's subjective ratings, would course a lack of control of the conditions. For example, you may present four brands that they are 'adverse' to. This would result in high levels of variance and harder to compare experimental effects. Secondly, the actual selection and outcomes that a participant receives towards a particular brand during the IGT may impact on the way that an individual rates that brand in a subsequently.

The practical implications of these study stem from the information that branding can have on indirect decision-making, and the resilience of brands to negative information and biasing of decisions. Firstly, the results highlight the importance and the impact that adversity towards a brand has, indeed marketers often focus on the capture and retention of consumers, but with the resounding effects of brand non-preference perhaps marketers should also ensure that consumers do not develop this feeling towards their brands.

The aim of the study was to investigate and explore brands with the desire to gain a deeper understanding of their nature and impact on decision-making and learning. Specifically, the question we addressed was whether brand logos could influence learning and performance on an emotion-based decision task (the IGT). The findings demonstrated that brand preferences shifted participants' performance from the outset, and that brand commitment led participants to discount information about rewards and punishments across the task. In essence it led to non-normative decision-making performance that could be described as irrational in so far as responding did not appropriately reflect the reinforcement structure of the task. The seemingly blinded nature of the participants was quite surprising: they would infrequently choose a "good" deck if it also had an incongruent brand placed on it. Suggesting that once a consumer has formed their loyalties a great deal of persuasion is necessary to change their mind. Similarly, as suggested by the results and previous marketing research (Jacoby & Kyner, 1974), the cost of keeping a loyal consumer is less. Finally, our results demonstrate that the mere presence of an incidental stimulus (here, a brand logo) can produce performance that fails to take into account task-critical information.

Interlude

In Experiment 1 we showed that superimposing brands onto decks during the IGT affected. The next question we wanted to look at is how faces superimposed onto the deck would effect performance on the task. Previous research has clearly showed the biasing effect that faces can have on decision-making (e.g. Plassmann et al. (2008)), and so a question that we felt was still unanswered was how the meaningful nature of the unknown faces develops during the IGT. Another question is that instead of merely guiding behaviour through different types of emotional information, for example placing happy faces on 'good' decks and sad faces on 'bad' decks, we wanted to understand the effect of unguided performance during the task. As a result we choose to have just happy, neutral or sad faces on duing the task.

Experiment 2: Emotion and Faces within the Iowa Gambling Task: The role of learning, subjective evaluations, and biases.

In Experiment 1 we demonstrated that emotional responses to irrelevant stimuli (e.g. brand logos) could bias decision-making. This impact on task performance could stem from multiple factors. For instance, it could be that the initial biasing effect of the emotional stimuli could have contributed to the learning effects observed. In other words, it could be that the initial "draw" one feel to emotionally relevant stimuli leads – over the course of the experiment – to biased decision making. However, there are two other important questions raised by Experiment 1. The first question is: are these effects somehow specific to brands or might they also apply to other types of emotional stimuli. One could hypothesize that brands might be unique in that they are typically seen "on" items (e.g. products) and that they typically convey something about the products themselves (e.g. the quality). Thus, it could be that brands are special in having this ability to bias decision-making. A second question left unanswered by the previous research is how might continued selections over time alter the conditioning of the stimuli themseleves. In other words, if a particular deck were chosen again and again (e.g. because it led to higher payouts) might it subsequently acquire an emotional tag itself? And, if there were an image atop that deck, might it also acquire the same tag?

One important way to look at the role of learning during tasks is through models of *classical conditioning.* Most theories of conditioning put forward the notion that it is the fact that there is a reliable association formed between the stimuli and the reinforcement that leads to subsequent learning or conditioning (Pearce & Bouton, 2001; Rescorla & Wagner, 1972). Within the Iowa Gambling Task (IGT) this association might well be seen as the relationship between selection of the stimulus (in our case the image superimposed onto the decks) and the resultant outcome of that trial. This outcome might be positive, negative, or neutral, and the subsequent reinforcement might increase, decrease, or have no effect on the evaluative valance of the stimuli chosen. If we hypothesize that such conditioning should occur during performance of the IGT, then one might wonder what implication this might have to the data from Experiment 1. In Experiment 1 we used stimuli that already had evaluative valances attached to them (e.g. positive valance towards liked brands). This pre-existing evaluative valence might have been either lessened or strengthened over the course of performing the IGT as a result of selection and reinforcement outcomes. Following this line of reasoning, stimuli associated with the 'good' decks should, if selections are made from them, experience a strengthening of their overall evaluative valance. So for example, if a neutral brand were put on a 'good' deck, then over the course of the experiment the evaluative valance of this brand should increase as the participant receives positive reinforcement to it's associative contingency.

Bechera, Damasio, Damasio, and Lee (1999) looked directly at the role of conditioning within the IGT by assessing the performance differences between patients with brain lesions either in the Ventromedial Prefrontal Cortex (VMPFC) or in the Amygdala. These two groups were used as they exhibit different profiles of emotional regulation deficits.

With VMPFC patients exhibiting an inability to engage in emotions that require a level of complexity, for example the inability to experience embarrassment in social contexts (Damasio & Anderson, 1993). Whereas Amygdala deficits exhibit an inability to process the affective attributes of rewarding stimuli (Bechera, et al., 1999). Both structures are seen as necessary components of the neural system implicated in the somatic marker hypothesis and deficits in these regions should ultimately lead to failures to make advantageous decisions (Damasio, 1994). As predicted, both groups failed the task, however skin conductance response (SCR) measures highlighted the ability of VMPFC patients to have intact associative conditioning abilities (as demonstrated in a Pavlovian conditioning experiment), whereas amygdala patients were unable to show the effects of conditioning or have a conditioned SCR response. This study highlighted the role of associative learning within the IGT, but also suggested higher-level processes are necessary to perform the task optimally. In addition, it suggests that the two regions are not mutually exclusive, and that both may be necessary for satisfactory IGT performance. More specifically, it is the integration of the emotional response into a representation of the deck values that leads to failure within VMPFC groups, and for the Amygdala patients it is the failure of an emotional response to the deck selection which leads to a lack of representation of deck values.

Indeed the Expectancy-Valency Model (EV) (Busemeyer & Stout, 2002), uses parameters that were formulated from models of *classical conditioning.* For example, the learning parameter uses the delta-learning rule, which stems from the Rescorla-Wagner model (Rescorla & Wagner, 1972) and models of neural networks (for example, Buysemeyer & Diederich, 2009). This model stipulates that learning is based on the a-priori predictions that an individual has to the outcome of the input. And, as a result of the outcome, the prediction shifts (i.e. the errors are "back propagated"). The speed of this learning is a function of the rate of the updating of these predictions. As such, within these sets of experiments it will be important to assess these updating rates to understand the learning parameters at play.

Numerous learning paradigms have used face stimuli to examine such things as the role of facial expressions in associative learning. Such paradigms have quantified the impact of emotion on learning using a variety of dependent measures including the strength of the response, the time taken to learn, and the effects on extinction (Lanzetta & Orr, 1986). An important finding is that fearful faces show greater speed in conditioning to negative reinforcement (by the process of an aversive unconditioned stimuli, e.g. loud buzz, electric shock), than do happy faces (Orr & Lanzetta, 1980). Likewise fearful faces reduce the speed of extinction of an aversive conditioning, whereas happy faces increase the speed of extinction in comparison (Orr & Lanzetta, 1984). From these series of experiments it became clear that it was fearful faces that had the most excitatory strength (Lanzetta & Orr, 1986), to a degree that removed the normal progression of extinction. These findings demonstrate the ability of faces to impact associative learning.

Research within the domain of emotion has classical involved faces, and with good reason, they are an essential component of social interactions. The ability to judge the expression and intentions of another can be informed by multiple signals. The face is one such signal and, as such, much attention is given to a face. Indeed we are so well able to understand these facial expressions that we can make judgements of expressions within 100 msec (Willis & Todorov, 2006). The dimensions that are used when making these judgements differ between emotions (e.g. liking, happiness; Ekman (1992)) and more trait specific judgements (e.g. trustworthiness; Todorov (2008)), and normal participants are well able to make these judgements (Todorov, Said, Engell, & Oosterhof, 2008). Within the context of this study we decided to have judgements of two different trait dimensions: trustworthiness and honesty.

Additionally, we have decided to assess subjective awareness towards the faces across the trials of the IGT. Judgements towards the faces will follow the same experimental procedures that have been previously employed to understand the role of subjective awareness in the IGT. That is, judgements towards faces will be made every 20 trials. Assessing subjective awareness will let us ascertain whether there is cognitive penenatrability within the IGT. This is an important question because if participants are able to cognitively comprehend the outcomes of the decks before the somatic representations guide behaviour then this would directly undermine the somatic marker hypothesis as the underlying mechanism in IGT performance profiles (Dunn, Dalgleish, & Lawrence, 2006).

The aforementioned research highlights the importance of associative learning within the context of the IGT. But, does such associative learning also happen with items "on" the decks (such as the brands we used in Experiment 1)? Or, will the associative learning simply happen to the deck "as a deck" and within the context of the IGT. To answer this question we needed to employ images that had a known and robust valence. We decided to use faces. This also helps address the "is it only brands" question. The overall flow of the experiment runs as follows: first we have participants rate faces, then we superimpose some of these faces (either happy, neutral, or sad) on various IGT decks, then the participants perform the IGT and at various points in time we ask them to re-rate the faces. Our question is: will the associative learning that we know to be active in the IGT influence participant's ratings of faces over the course of performing the IGT.

Method

Participants

84 Participants (28 in NeutralFaces, 28 in HappyFaces, and 28 in SadFaces) ranging in age from 19-26 (Mean= 20.35) from Bangor University volunteered to participate through an online experimentation booking system (SONA). The entire procedure took approximately 30 minutes and participants received course and printer credits for their participation.

Apparatus

E-Prime experimentation software (Psychology Software Tools, 2002) was used to conduct both parts of the experiment running on Windows XP operating system platform with Pentium 4 3.06 GHz. The experiment was displayed on 17" CRT monitors (1076x768 resolutions, 85Hz, 32bit). The participants' interaction with the keyboard was recorded during the experiments. With the primary responses being keys 1 through 5 both on the numeric keypad and main keyboard section during the brand loyalty rating task, and the primary responses being 1 through 4 during the IGT.

Stimuli

For the NeutralFaces condition four neutral female Ekman faces were used. Similarly, in the HappyFaces condition four happy female Ekman faces were used and for SadFaces four sad female Ekman faces were used. When appearing on the decks, each face was presented as 96x96 pixels. When presented for ratings, the faces were enlarged to 200x200 pixels. These faces were converted to grayscale images and normalized (equating overall contrast and mean luminance).

Measures

The four images of faces were rated twice every 20 trials. The ratings were made on a 7-point Likert scale with two prompted questions: "How trustworthy do you think this face is?" and "How honest do you think this face is?".

Design

The face locations were randomized within condition. That is, the faces would be randomized between the types of decks (i.e "Good", "Bad") and also their spatial location (i.e. the good and bad decks would not always appear in the same location; e.g for each participant a good deck could appear at any one of the four possible deck locations). The IV was the location of the faces on either the good or the bad deck. There were two DVs: the IGT score and the rating giving to the face on the 7-point Likert scale. The IGT score was computed as per traditional techniques used in the literature. This technique is the preference of good versus bad deck selection and is computed as; ((Deck C Count + Deck D Count) – (Deck A Count + Deck B Count)) this formula is calculated for 5 blocks of 20 trials (100 trials), however as we conducted 200 trials, we also grouped results into 10 blocks of 20 selections (200 trials). The rating responses will be analysed using the participants first rating as a baseline and then looking at the variation from that point during the subsequent 9 ratings.

Procedure

The participants were run in groups of six, and firstly a presentation of the outline of the study was given to them. After the brief introduction, the participants were given an information sheet and a consent form that they were asked to complete if they were willing to take part in the experiment. The experiment lasted approximately 30 minutes. The participants would start with the "Autism Quotient Questionnaire"(AQ) that takes approximately 5 minutes, then a further 25 minutes for the IGT. Participants sat in one of two rooms where 6 identical computers, desks and chairs resided. The rooms were dimly lit and the participants sat on a chair approximately 60 cm away for the computer monitor, which was positioned at eye level. Dividers and headphones ensured that adjoining participants did not influence performance.

After signing the consent form, the experiment proper began. First, the AQ was conducted and this required a mouse click response to 50 questions (see Appendix for further details of the AQ). The IGT began with an explanation of the game. The task they performed required the participant to make a selection of one out of four decks every trial. There were 200 trials meaning the participant made a total of 200 deck selections during the experimental procedure. Once the participant made a deck selection, they were presented with two pieces of information: the winnings gained and the loss on the card. The winning after a deck selection was either £100 or £50, with two decks giving £100 winnings and the other two decks giving £50 winnings. A loss did not always occur, but when it did, the loss ranged from £25 - £1250. The position of these winnings and losses was counter-balanced so as to remove order effects, the winnings and losses were paired together so that they remained the same for each type of deck. The participants were told that the aim of the game was to make as much money as possible, and that they may choose whichever deck they feel like, they were given £2000 to start with. The participants were told that ultimately some decks will be advantageous and some will have a disadvantageous net gain. Decks A and B gave out the winnings of £100 yet the penalties were higher. So, for example, during 10 selections of deck A the participant would make 10 winnings totaling £1000 and five loses totaling £1250 resulting in a net loss of £250 (the same occurs for deck B but only one selection contains a loss) – these decks are referred to as the "bad" decks. Decks C and D gave out winnings of £50, yet the penalties were lower. So, for example, during

10 selections of Deck C the participant would make a total winning of £500 and the five selections where losses occurred would total £250 meaning a net gain of £250 (the same occurs for deck D but only one selection contain a loss) – these decks are referred to as the "good" decks (See Table 2 for reference). During the task, the participants were also given information as to their overall running total and their performance over the last 10 selection outcomes in the form of a sliding bar chart (See Figure 4 for an example).

Participants could take breaks at any part of the experiment, and all of the trials were self-paced. After the conclusion of all three phases, the researcher debriefed and thanked the participant and answered any questions that they had.

Table 4
How the IGT rules work so as give rise to "good" and "bad" decks

	Bad Decks		Good Decks	
	A	B	C	D
Winnings/Deck:	£100	£100	£50	£50
Loss/10 Cards	£1250	£1250	£250	£250
Net Gain/10 cards	-£250	-£250	£250	£250
Frequency of Rewards/ 10 cards	5	1	5	1

Results

Nine participants were removed from the neutral faces and sad faces condition (N = 19 for both), and five participants were removed from the happy faces condition (N = 23). This was due to random deck selection, that is, each deck was chosen 25% of the time, and they also fell below the standard IGT criteria for inclusion as outlined in Experiment 2. The results are presented in two sections: Firstly, we will describe the IGT performance as measured by the standard blocking analysis; and secondly we present the EV model results. When looking at the subjective rating scores by deck selection over time we found no significant effects, and as a result we show no results here, however we will discuss possible reasons for this in the discussion.

Behavioural IGT

Initial analysis of the IGT closely followed the original procedure (Bechera et al., 1994) however trials were split into 5 blocks of 20 selections (20, 40, 60, 80, 100). The selections were analyzed with a simple computation of the mean number of good decks (C+D) selected per block subtracted from the mean number of the bad decks (A+B) selected per block. Thus, for each block the net score could be between -20 (always chose a bad deck) and +20 (always chose a good deck). Negative scores indicated that the participants were selecting the disadvantageous decks more, whereas positive scores showed that participants were selecting the advantageous decks more.

Using repeated measures ANOVA of the 5 blocks with factors of block (5 levels) and condition (3 levels: happy, neutral, and sad). As expected, there was a significant effect of Block, ($F(3.217, 186.604)=3.606$, $p = .012$). And this effect was significant by a linear contrast, ($F(1, 58)=7.164$, $p = .010$), meaning that over time participants selected more from the good decks than the bad decks (see Figure 6). There was no BLOCK by CONDITION interaction ($p = .423$), meaning that the different conditions did not have any differential impact on the learning. However, when looking at Figure 5 there is a suggestion of a difference, and when conducting the ANOVAs separately for each condition only the HappyFaces condition showed a significant effect of block.

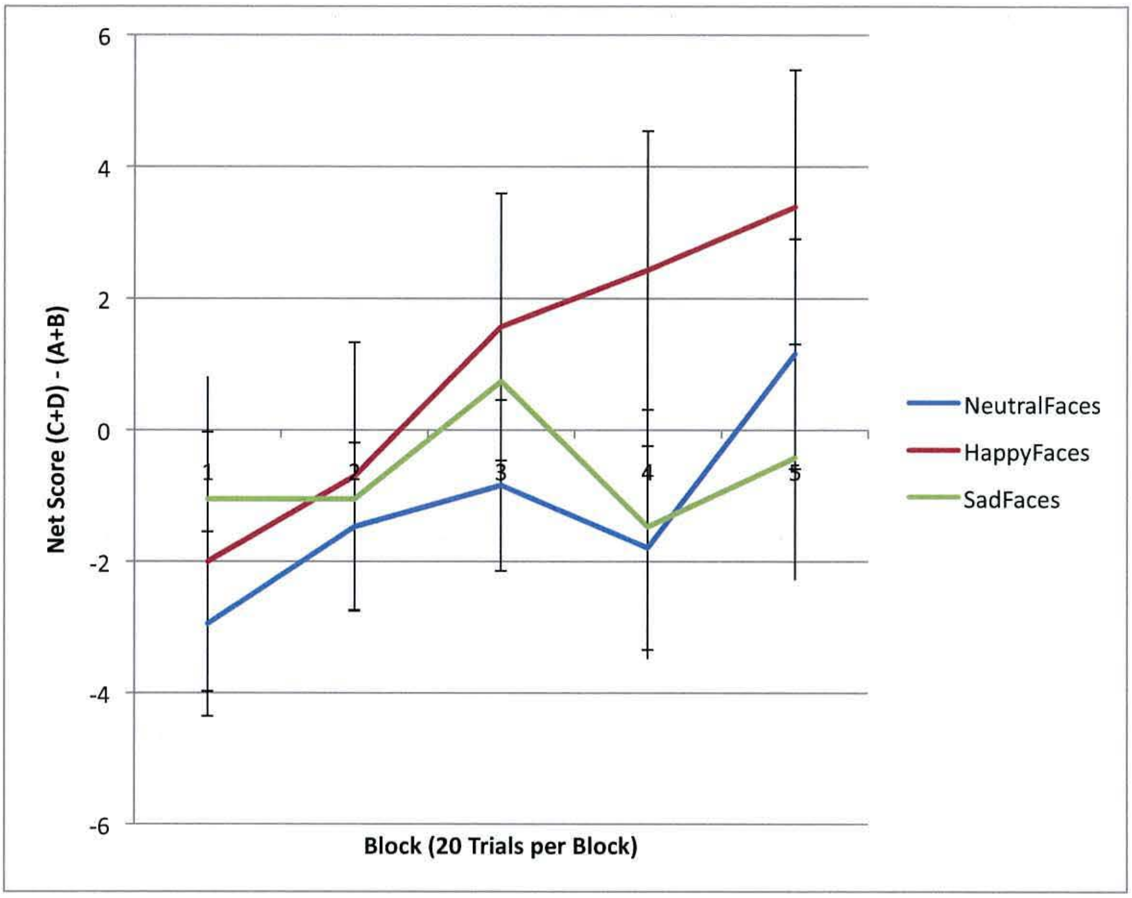

Figure 5. Graph displaying estimated means for the different groups. The horizontal line represents trials over the course of the experiment split into 5 blocks of 20.

<u>Expectancy Valence Model Analysis</u>

The three conditions were compared within the EV model. The data were fitted to the EV model (Busemeyer and Stout, 2002). The G2 statistic revealed that the data only just fit to this model (*M*=2.27, *SE*=1.88), a one-way ANOVA revealed no between group differences, (ps = >.05). For the three other parameters, a one-way ANOVA showed a between-subject significance for the consistency parameter, F (2,85) = 3.570 p=.034 , with Tukey-HSD post-hoc comparison showing significant difference between HappyFaces and NeutralFaces (*MD*=+/-1.45, *SE*=0.57, p=. 038) with the value being higher in the happy faces compared to the neutral faces condition (*see Table 5*). The higher value of the happy faces condition suggests that they are more consistent in their deck selection during the task. The two other parameters revealed no significance differences (ps = >.05).

Table 5

Expectancy Valence Model Value Means for Experiment 2 ---Means(SE)

	NeutralFaces	HappyFaces	SadFaces
Model Fit (G2)	3.01(2.30)	1.30(3.69)	2.70(3.51)
Attention-to-win (a)	.44 (.09)	.37(.07)	.46(.09)
Recency-of-update (w)	.49(.09)	.33(.07)	.36(.09)
Response Consistancy (c)	-0.84(0.42)	0.60(0.32)	-0.51(0.50)

Discussion

In this experiment we examined two different questions. First, we wanted to see whether emotionality (as conveyed by a face) would influence IGT learnings. And, secondly, we wanted to investigate whether participants would altere their subjective ratings towards the meaningful images (faces) over the course of the IGT. Because there was no change in the subjective ratings of the faces over the course of the IGT we can conclude that the representations of the meanings of the faces are robust. Our second key finding was an interesting effect on learning based on the facial expression superimposed onto the decks. Specifically we found that during the condition with sad and neutral faces participants learning reached lower than expected values.

In terms of the robustness of ratings across learning, there are a few possible reasons why the perceived meaning of the faces did not shift. Firstly, perhaps the breaks in the IGT (to make the ratings) made the two tasks feel disconnected and participants were consistent with their responses due to the strong representations of the traits the questions probed. One way in which we could tackle this in the future is by leaving the images in location (e.g. on the decks) when the ratings occur. This finding also suggests that for effective evaluative conditioning (De

Houwer, Thomas, & Bauyens, 2001) to occur, the stimulus-response learning requires clear pairing between the two stimuli. One way that this might be addressed in future research is through a clearer pairing between the trial outcome and the face. It must also be noted that this effect would have only been applicable towards the neutral faces, as evaluative conditioning typically only occurs when it is in regard to an unconditioned stimulus.

Another variable worth considering is the reward values present in the task. Specifically, there were at least two rewards: the emotionality of the faces and the monetary payouts from the IGT. Previous work has suggested that such rewards may operate in different ways or may, at least, have different impacts on learning. For example Shore & Heerey (2011) have examined the intrinsic value associated with social and nonsocial feedback. They found that social feedback (e.g. facial expressions) carried more intrinsic value than the non-social feedback (e.g monetary reward). Within their study the feedback was directly linked to the expression. However, within our experiment the facial expressions were operating, in a sense, above or atop the monetary rewards and feedback. Thus, perhaps the reward values of the faces were not giving any value-added information to the participants and were being ignored or untouched. As a result, it could be that the representations of the different faces did not alter. This perhaps relates to our second finding. That is, it may have been this lack of connectedness between the rewards of the IGT and the emotional rewards of the faces that led to no difference in performance across the various IGT conditions.

The presence of the Neutral and Sad faces gave no added value towards the representations of the decks and misguided participants attention. Furthermore, the facial expressions for the HappyFaces condition did give the participants some information. The smiles seen in the HappyFaces have a general enhancement effect on the ability of participants to incorporate the trial feedback to guide future decisions (Averbeck & Duchaine, 2009), suggesting why there is more consistent responses within this condition. Why is it though that a smiling face can aid (or simply unaffect, i.e. there are no differences between HappyFaces condition and the control condition in Experiment 1) decision-making whereas neutral of sad faces hinder decision-making?

When comparing the two conditions of NeutralFaces and SadFaces, there is perhaps neutral faces are actually perceived as being mildly aversive, similar to the aversion towards the sad faces. This aversion leads to a desire to not continually select one of the faces (i.e. optimal task performance), continual selection of one of the faces would suggest an asocial performance. Or that this aversive nature of the neutral and sad faces led to an overall mood effect that the faces had on the participants. For example, a study by de Vies, Holland & Whitteman (2008) looked into the role of mood in the IGT finding that positive mood state boosts IGT performance, whereas a negative mood reduced performance. However, the effects shown in the de Vies et al. (2008) were pinned down to occur within only block 2 of the IGT. Whereas what we found was a prevalence of poor performance continually. However a further study to probe this via looking at the mood of participants and the performance in the different conditions, either by a state manipulation of mood or by assessing the mood of the participants throughout the task.

The lack of learning within the neutral faces, in a sense more interesting than the lack of learning that has been shown within the sad faces condition. What are the possible explanations does learning models give for this effect? One concept within associative learning that can explain the effect is latent inhibition. Latent inhibition is a theory stemming from models of animal cognition, and it follows thus: when a to-be-conditioned stimulus has been pre-exposed as a neutral condition, (or external unknown conditioning) the conditioning of the stimuli cannot take place (Lubow & Moore, 1959). This effect has been shown within both the human and non-human literature (see review Young, Moran, & Joseph, 2005) In a sense because the neutral faces are conditioned to be seen as neutral and have no affective value, participants are unable to associate the wins and losses to the decks. This effect is further highlighted in data from our lab that suggests the same can occur for neutral brands as well. In a sense, the irrelevance of the neutral faces and neutral brands brings about a form of learned inattention (Lubow, 1997). With the lack of attentional capture of any of the neutral faces, participants forget which deck goes with which condition and instead of learning the task they are inconsistent with their response. This is particularly apparent when comparing the neutral face and neutral brand results against the results when the backs of the cards are merely different shapes. Within this condition (see Experiment 1) participants are able to learn the task because the backs are unconditioned to a neutral inattentive response, rather they are just representations of the different decks. To further explore this question however future studies must be set up that control for the initial conditioning towards the deck objects prior to the administration of the IGT.

In sum there are a variety of explanations for why the effect occurred. One of the most persuasive is the lack of consistent choices formed by an inattentional effect created by the neutral and sad facial expressions. That is, participants did not want to select from the decks and to do so consistently because they were trying not to encode the information that these facial expressions gave them other than the value expressive meaning represented in their expressions. This suggests that meaning towards faces is intrinsic and the representation is not fluid to shift. This concept will be discussed further in the General Discussion of this thesis.

Interlude

In Experiment 1 & 2 we showed that meaning impacts the IGT. The next question we wanted to look at based around the actual IGT and the way in which it taps into the different decision making processes. To this end we decided to develop a new form of the IGT, after numerous pilot studies we decided on the design below. These pilot studies varied a number of parameters, for example the feedback given, time between feedback presentations, a forced speeded response (via losses if participants failed to respond within a time window), the shape of the feedback display, and the representation of the decks. We came to the below design because of a variety of reasons, in particular the closest IGT performance that could be achieved. As this experimental endeavour is not a central facet of the thesis we will not include the pilot data, but we felt it important to go through this paradigm because even though it doesn't use meaningful images in the task it discuss the decision-making systems at play when representations of meaning are formed.

Experiment 3: Quick as a BLINK: An ultra-rapid analogue of Iowa Gambling Task decision-making

Well over a decade ago, Bechara, Damasio, Damasio, and Anderson (1994) introduced a decision-making task. The measure, now referred to as the Iowa Gambling Task (or IGT), was designed to capture several important aspects of real-world decision-making under conditions of uncertainty. In the classic IGT, a participant is confronted with four decks of cards, and given the opportunity to select freely from any deck. With each selection, he or she either gains or loses (and in many cases both gains *and* loses) money -- for example, a card may read "Win \$100, lose \$50." The participant's goal was to continue selecting, at will, from the four decks to try to gain as much money as possible.

In the standard contingency design (Bechara et al., 1994), two of the decks were advantageous in the long-term (i.e. continued selections would lead to net gain), whereas the other two decks would lead to eventual net loss. The original study (Bechara et al., 1994), since widely replicated (see Dunn et al., 2006 for review of IGT), suggests that healthy participants show relatively systematic adaption to the contingencies, and they learn to reliably bias their decisions towards the 'advantageous' decks after roughly 30-60 selections.

Although many healthy participants perform the task well, researchers have reported that some clinical populations have extreme difficulty performing the task. Examples of neuropsychological populations who perform poorly on the task include patients with damage to the ventromedial pre-frontal cortex (VMPFC) (Bechara et al., 1994), patients with damage to dorsolateral pre-frontal cortex (DLFC) (Bechara et al., 1998), and patients who have frontotemporal dementia (Torralva et al., 2007). Clinical populations who perform poorly on the IGT include patients with schizophrenia and schizotypy (Bowman, Evans & Turnbull, 2005; Bowman & Turnbull, 2009: Evans, Bowman & Turnbull, 2005; Sevy et al., 2007), patients with major depression disorder (Must et al., 2006), and people with attention-deficit hyperactivity disorder (Toplak, Jain, & Tannock, 2005).

There is some debate as to why such populations experience difficulty with the IGT (Maia & McCelland, 2005). In fact, researchers have demonstrated that it is not the task in general that is overly challenging to these populations; instead it is specific aspects of the task that are problematic. For example, Fellows and Farah (2005) showed that it is the rewards and penalties experienced early in the standard IGT that lead to an early positive association with the 'disadvantageous' decks which VMPFC patients have difficulty unlearning (reversing). Fellows and Farah found that simply shuffling the order of these early rewards and penalties allowed

VMPFC patients to perform as controls (2005). The order of rewards is just one example of a broader theoretical debate around issues such as the role of somatic markers in IGT performance (Bechara, et al., 2005), the role of reversal learning (Fellows & Farah, 2005), and the neural substrates that support decision-making under conditions of uncertainty (Lin, Chiu, Cheng, & Hsieh, 2008).

Initial explanations of the underlying mechanisms driving performance in the IGT have primarily been framed in terms of the somatic marker hypothesis (SMH; Damasio, Tranel, & Damasio, 1991). The SMH suggests that integration of wins and losses within the task is initially driven by an emotion-based signal that is subsequently consolidated into higher cortical areas (e.g. VMPFC). Although initially theoretically motivated, the primary empirical support for the SMH explanation of performance in the IGT is participant's galvanic skin response (i.e. responses related to an emotional signal), and its apparent role in the guidance within task performance (Bechara, et al., 1999).

While the initial understanding, and broad story, underpinning IGT task performance was compelling, researchers have now called parts of this into question. For example, initially the "cognitive impenetrability" of IGT performance was fairly central to the SMH account - but has now been called into question (see the review by Dunn, Dalgleish, & Lawrence, 2006). Similarly, others have highlighted concerns and clarifications around many other mechanisms that have traditionally been implicated in IGT performance, including emphasising the role played by various psychological processes such as working memory, reversal learning and inhibition (e.g. Fellows & Farah, 2005), risk-taking behaviour, and apathy. Many of these theoretical and neural issues have been covered in various reviews (including Dunn et al., 2006; Clark & Manes, 2004).

Whatever the theoretical and neural underpinnings of the IGT, it has been used extensively and successfully within a wide range of healthy, clinical, and neuropsychological settings. A PubMed keyword search reveals that the task has been used in several hundred peer-reviewed publications (NIH Org, 2010). However, in the classic form of the IGT, certain aspects of the task make it difficult to use with some populations and in certain clinical settings. For example, some populations have difficulty with using hand-held cards, or might have difficulty focusing for the length of time required to administer the task (about 20 minutes).

Bechara and colleagues addressed the problems with hand-held cards early on, when they introduced a computerised version of the task (Bechara et al., 1999). Performance on this computerised version has been shown to be statistically equivalent to that found when using hand-held cards (Bechara et al., 2000a & 2000b). The majority of modern studies with neurologically healthy participants now employ such computerised methods. Bowman and Turnbull (2003) also addressed the concern about the motivational value of the winnings when they demonstrated that facsimile money did not appear to significantly alter IGT performance. Again, most modern studies use 'virtual' rewards.

There is also an issue of failure-rate. Most studies that use the IGT have found that a substantial fraction of non-clinical (i.e. healthy) participants are unable to learn the task. For example, Bechara, Dolan, Denburg, Hindes, Anderson & Nathan, (2001) reported that 32.5% of healthy controls performed within the range of patients with ventromedial frontal lesions [p384]. One hypothesis is that this could be partly due to individuals becoming frustrated and/or confused on the task.

This leads to a final concern, namely the time required to administer the task. This issue is clinically and pragmatically important, since the IGT typically takes over 20 minutes to administer. Given that many clinical populations may experience fatigue during neuropsychological assessment, any reduction in administration time would represent a substantial clinical gain.

Researchers have addressed some of the temporal aspects of the IGT. For example, a number of studies have required participants to wait for several seconds before permitting a response (Bowman, Evans, & Turnbull, 2005; Cella, Dymond, Cooper & Turnbull, 2007). Requiring a time delay does not appear to either improve or impair performance on the IGT (Bowman et al., 2005). However, forcing participants to perform very rapidly has been shown to lead to poorer performance. Specifically, Cella and colleagues (2007) required participants to respond either freely (take as long as they wish), within four seconds, or within two seconds. While performance was normal in the control and four-second conditions, they found that IGT performance deteriorated in the two-second condition. Perhaps surprisingly, they found this impacted upon performance even though the average decision-making time itself did not differ between the two-second and four-second groups, and was less than a second in both cases. This suggests that participants in the IGT require more than two seconds of deliberation time to perform successfully -- even if they do not necessarily use that time (on average). Thus, a deliberation time of somewhere between two and four seconds might be seen as representing the upper speed limit for the IGT. Adding a time-to-draw and an inter-trial interval of about two seconds (Cella et al, 2007) to this deliberation time suggests that the IGT could never be completed in less than about 10 minutes.

While learning and decision-making over the course of 10 minutes may seem fairly rapid, recently there has been growing interest in more rapid (perhaps emotion-based) decision-making. This type of decision-making, (popularized in Malcolm Gladwell's book "Blink", Gladwell,

2005) has also been referred to as "fast and frugal" decision making (Gigerenzer, 2004) and is closely related to the "associative system" within Sloman's two systems of reasoning (1997). Numerous lines of research have increased interest in this type of intuition-led, non-rule-based decision-making. Because the IGT is relatively slow, and uses a monetary/points win-loss framework that encourages reliance on rational-deductive (cognitive) decision-making, the IGT may represent a non-optimal means of measuring intuitive-based decision-making. Indeed, these issues may be intertwined – such that the method typically employed to display the win/loss information in the IGT not only extends the time required to complete the task, but also may encourage reliance on slower, more deliberate, and "non-intuitive" decision making systems. Specifically, using numeric and linguistic information (e.g. "Win $100/Lose $50") may force participants to engage in high-level information processing. In fact, it may be the engagement of such high-level processing which gives rise to poor IGT performance of DLPFC patients, rather than the emotional-based components that may lead to deficits in VMPFC patients (see Bechara et al. (2005) for further discussions on this point). We hypothesized that it should be possible to alter the IGT paradigm in order to allow participants to perform at a far greater speed and, critically, to solely (or predominantly) engage the intuitive associative system allowing a cleaner measure of this system.

Of course, when designing a new task to measure the type of decision making captured by the IGT (e.g. decision making under ambiguity and risk) it is important to assess the comparability of the different measures. That is, behaviour in both tasks must originate from similar mechanisms. One way to understand the psychological factors that contribute to performance in the IGT is by using equations to model the underlying learning processes on the task. One of the most frequently used models is the Expectancy-Valance model ("EV", Buysemeyer & Stout, 2002). Combining individual trial-by-trial decisions with the process of learning and adapting decisions through experience, the EV model allows researchers to assess the weightings participants give to three parameters as well as quantifying goodness-of-fit for the model. The three parameters are: attention-to-reward (a measure of the relative weight that an individual gives towards wins versus losses), updating-rate (related to the speed at which participants incorporate new information into their decision-making behaviour), and choice-consistency (a measure of the stability of decisions, i.e. how often a participant switches between decks).

Given these three primary parameters, each participant's trial-by-trial deck selections can be modelled quite accurately (via step-by-step maximum likelihood estimation). The final component of the model is the model fit statistic G^2 – a parameter that indicates how well or poorly the parameters model the actual data. Using the EV model we are able to estimate whether our new decision-making task relies on the same mechanisms as the IGT. Specifically, we will be able to use the EV model to identify the similarities and differences between our new task and the IGT, by comparing model fit as well as the three performance parameters (See Supplementary Material B for further details).

We have devised a task that relieves participants of some of the cognitive demands present during the IGT. In particular, during the IGT, participants are presented with numeric/linguistic information (e.g. "Win $100, Lose $50") that they must interpret and incorporate in their subsequent decision-making. Our new task presents this kind of win/loss information in a far more visual and simplistic valenced manner. This form of information presentation allows the participants to learn the deck contingencies far more rapidly, so that the overall time required to perform the task is reduced. Through a variety of metrics (EV and basic behavioural measures) we compared our new Bangor Learning Intuitive and Non-Verbal Keleidiscope task (BLINK task), with the IGT. Our comparisons are intended to demonstrate that our new task takes far less time to administer, has a lower failure rate in non-clinical populations, and taps the same decision-making processes that support performance on the IGT.

Method

Participants

60 students (38 female) from Bangor University volunteered to participate in the experiment through an online experimentation booking system (SONA). These were UK students in years one and two of their undergraduate psychology degree. The entire procedure took approximately 15 minutes and participants received course and printer credits for their participation. Half the participants took part in the new (BLINK) task, and the other half took part in a version of the standard IGT decision-making task. Previous research has shown that performance improves over multiple administrations of the IGT (Bechara, et al., 1994). Thus, even though BLINK and IGT appear very different on the surface, we decided to be conservative and employ a between-groups design to avoid any potential confounds.

Apparatus

E-Prime experimentation software (Psychology Software Tools, 2002), running on a Windows XP operating system platform with Pentium 4 3.06 GHz, was used to conduct both parts of the experiment. Stimuli were displayed on 17" CRT monitors (1076x768 resolutions, 85Hz, 32bit color). The participants' interaction with the keyboard was recorded during the experiments, with the primary responses being keypresses of the numeric digits 1 through 4 during both the IGT and the BLINK task.

Stimuli

The IGT used a standard display consisting of four “decks” (large white rectangles) presented on a black background. Numbers below the decks indicated the key-press required to select one of the decks (to “turn over a card”). Upon deck selection, participants were presented with win/loss information by means of on-screen text (e.g. “win £100/lose £50) and a schematic happy/sad face. The net wins/losses on each selection and a running total (in the form of a graph) was presented above the decks.

For the BLINK task, no decks were present. Instead, there were simply numbers presented along the bottom of the screen and a “feedback flower” (described below). The numbers indicated the key-press options and participants were required to continually use keypresses to “choose” one of these numbers and try to fill the feedback flower as quickly as possible. The feedback flower occupied most of the screen and was used to give participants several forms of feedback (see Figure 6). While initially appearing gray, the participant’s goal was to make all the petals of this kaleidoscopic flower turn blue through their responses. This feedback flower consisted of 336 small disc elements placed in 12 concentric rings with more elements in the outer ring than the inner ring. The individual disc elements began as gray and were colored (“filled”) to indicate the current total winnings as the trials progressed. Items were filled with either blue (indicating a positive/win) or red (indicating a negative/loss). The discs were filled from the outside inwards, meaning that the participants tried to fill the flower with “positive” blue discs from the outer ring, with completion moving inwards. In the centre of the flower there was a percent complete counter (e.g. “82%”). An online version of the task can be found here: http://tinyurl.com/24k5r4w.

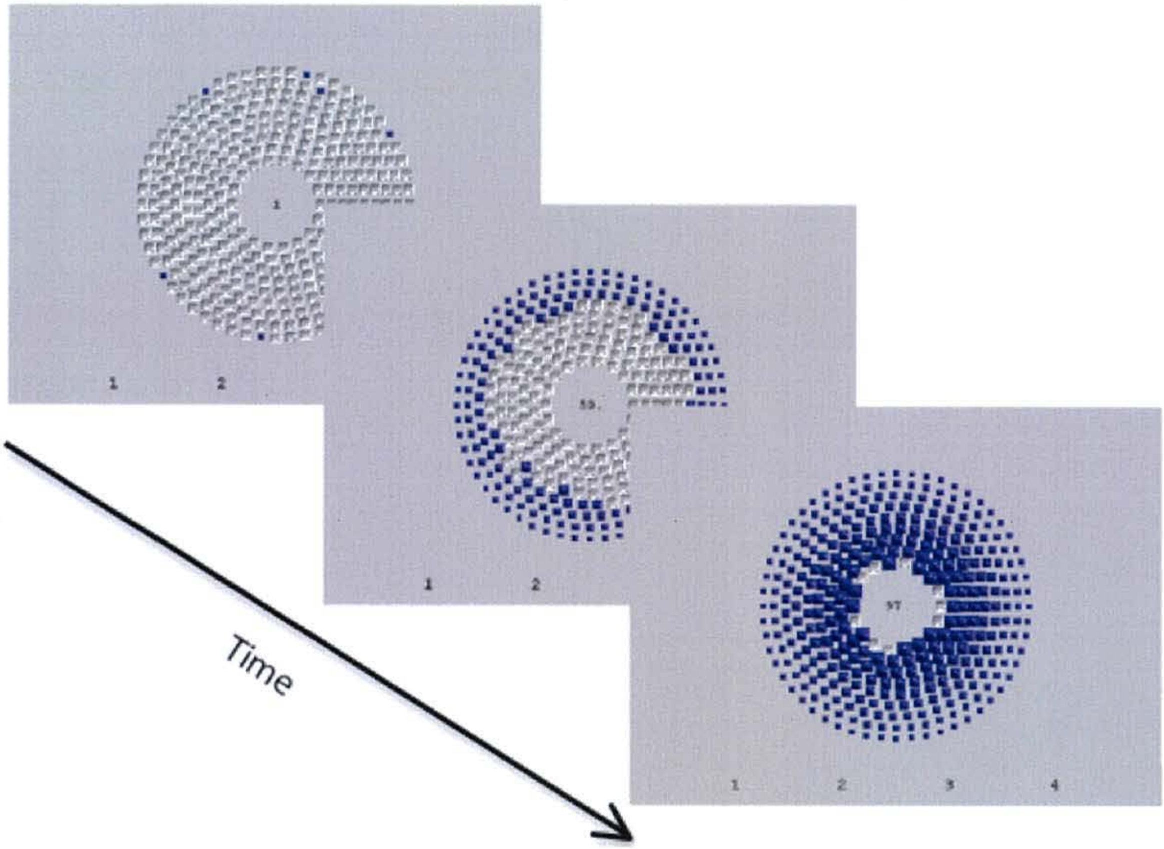

Figure 6: A schematic showing three screenshots of the BLINK task. These show what the participant would see when they had the feedback flower completed one, fifty, and ninety-seven percent. Note the small numeric counter in the centre that displays the percentage complete and the blue tokens that show the running total. The four numbers at bottom represent the deck, and after a participant pressed one of the corresponding numeric keys, the displayed number would increase in size and turn white, then fall back into its original colour and position (i.e. as displayed here).

Procedure

The participants were run in two batch testing rooms containing three computer booths in each room. After a thorough introduction to the running of the relevant task (IGT or BLINK), participants were given an information sheet and a consent form that they were asked to complete. Pilot data (not shown) highlighted the importance of participant information, with a lack of complete and clear instructions leading to abnormal participant performance in the BLINK task. Specifically, we found that it is essential to inform BLINK participants to:

Respond quickly and to take no more than about one-second in deliberation.

See the task as a "game" and aim to complete it as fast as possible.

And finally, to remember that recovery is possible from any position.

Participants sat in one of the two rooms and wore headphones throughout the procedure, which served to reduce background noise from fellow participants who were sat in the experimental room. The rooms were dimly lit and had a fan running to keep room temperature down. Participants sat on a chair approximately 60cm away from the computer monitor that was positioned at eye level. Dividers and headphones ensured that adjoining participants did not influence performance – and the experimenter remained present to monitor that no communication occurred between participants.

After signing the consent form, the experiment proper began. Firstly, a set of instruction screens was presented to the participants (two for IGT and three for BLINK, these were self-paced via keypress (see Appendix I). The IGT instructions were the standard ones employed in dozens of past experiments. The BLINK instructions (designed based on pilot data as described above) are presented in Supplementary Material A. After the final screen, the experiment began. In the IGT task participants were instructed to select decks (via keypress) and try to win as much money as possible. In the BLINK task they were told to press keys and try to completely fill the flower with blue tokens. Thus, during the IGT task, participants were required to select one of the four decks shown on the screen via a key press (1,2,3, or 4). Similarly, during the BLINK task they were also required to make a key press (1,2,3, or 4) to indicate a selection – however, this time the response was not linked to a "deck", but instead was simply linked to a number presented at the bottom of the screen. Selections (in both the IGT and BLINK) occurred every trial and were self paced. There was a maximum of 200 trials in the IGT and 1000 trials in the BLINK task. We used a greater number of trials in the BLINK task because we believed participants would be more carefree and rapid in this task and thus that they would go through the trials far more rapidly. In the BLINK task, as soon as the participant completely filled 100% of the feedback flower, the task ended. In terms of standard IGT payouts, completely filling the BLINK feedback flower would be equivalent to winning £3,360 in the IGT.

Once a participant made a selection in the IGT they would hear the sound of a card turning over, win/loss information would be displayed on top of the deck selected, a happy/sad face would be presented, as well as a "cheer" or a "boo" sound, and their overall winnings/losses would be updated. Once a participant made a selection in the BLINK task, they received four pieces of information: an auditory click that confirmed the response, the color and size of the chosen number would alter briefly (change to white and large font), the flower would alter to display the outcome of their choice (this is described in more detail next), and the current percent-filled would be updated in the centre of the flower. The selection phase was self-timed in both the IGT and the BLINK task, and the feedback sequence duration was about 2 seconds for the IGT and near instantaneous (under 100 msec) for the BLINK.

The feedback flower displayed two kinds of information: information regarding the most recent selection ("selection-impact") as well as their continual running score/total. Thus, after each keypress (selection) in the BLINK task, a visual "selection-impact" was presented (as tokens) and this information was subsequently and automatically integrated into the visual display of the participant's total score. The selection-impact tokens and total-score tokens differed in size (selection-impact tokens being larger). For example, in the BLINK task, if a participant pressed the key corresponding to selection 1, the participant would hear a click, the number "1" would be highlighted at the bottom of the screen, and if the outcome was, say, +5/-10 then for the selection-impact feedback, five large blue tokens and ten large red tokens would appear in the feedback flower briefly (500 msec or until a key was pressed). After this initial selection-impact disappeared, the net score (in this case -5) would be integrated into the total score which was represented both via the percent complete (at screen-center) and via the total number of small red or small blue tokens accumulating around the edges of the flower. Thus, if they currently had a positive total score (many small blue tokens in the flower) then to represent their loss of five points, five blue tokens would be removed. If the net score had been positive, five blue tokens would have been added. Similarly, if they currently had a negative score (many small red tokens around the edges) then five red tokens would be added. If the net score had been positive, then five of the red tokens would have been removed. The score was computed based on key/deck contingencies that were identical to those used in standard IGT tasks -- with the main difference being that in the BLINK task the values were associated with colored tokens (discs) instead of money or points. Furthermore, because the feedback flower used in the BLINK task was comprised of 336 elements, the base-rate of reward was scaled to ensure that rewards/losses were perceptible yet not too dramatic. It is worth noting that all this feedback (the click, the number changing size, the selection-impacts, and the total-score-integration) all took place in well under one second. In addition, unlike the IGT, in the BLINK there was essentially no inter-trial interval (as soon as one key was pressed, another key could be pressed).

Choices were made from two 'good' decks/keys and two 'bad' decks/keys, with the winnings from the 'good' ones being 5 points/tokens and the winnings from the 'bad' ones being 10 points/tokens. The order of the decks/keys (as presented on the screen) were randomized for each player. A loss did not always occur, but when it did it could range from 2 to 125 tokens. The order of losses was pseudo-randomised and comparative to previous IGTs, for example the 9th selection of deck/key B (a bad deck) would result in a loss for all participants irrelevant of task type. In both the IGT and the BLINK task, some decks/keys had an advantageous net gain and some had a disadvantageous net gain. For example, if a participant made 10 selections from a bad deck/key they would make a net loss of 25 points/tokens, whereas if they made 10 selections from a good deck/key they would make a net gain of 25 points/tokens. One of the differences between contingencies is the frequency of loss (see Table 1 for the ratios, which are identical to those used in a typical IGT). During performance of the BLINK task, the visual display of discs (the feedback flower) and the percent-complete counter represented the only feedback for the running total.

Table 6
How the BLINK rules work so as give rise to "good" and "bad" decks

	Bad Decks		Good Decks	
	A	B	C	D
Winnings/Key:	10	10	5	5
Loss/10 Selections	125	125	25	25
Net Gain/10 Selections	-25	-25	+25	+25
Frequency of Rewards/ 10 Selections	5	1	5	1

Results

The results have been divided into five sections. The first details the failure rate of participants in the two tasks; the second outlines the time benefit our new (BLINK) task has over the IGT; the third section compares task performance between the BLINK task and IGT using a traditional IGT analysis (based on Iowa Scores which quantify "good" minus "bad" deck selections) ; in the fourth section, we use the expectancy valance model (EV) to model performance and highlight the similarities between the mechanisms of learning in the two tasks; and finally, we take a closer look at some of the patterns of performance found in the BLINK.

Unlike the IGT (which has a set number of trials), the BLINK task continues until all cells have been filled (or until 1000 draws). This difference led to different numbers of trials between participants. Thus, to directly compare performance between tasks, we use only the first 100 trials of the IGT and the BLINK task. No participant took fewer than 100 trials to complete the BLINK task. One must note, thus, that these trials do not represent the experiment as a whole for each participant. Duration data, however, represent the total time taken to complete the entire BLINK task.

Failure Rate

As previously stated, we believe that the large failure rate on the IGT may be partly due to individuals becoming frustrated and/or confused during the IGT (as it does require some effort to perform such a task for 15+ minutes). Thus, in the BLINK task, we might expect fewer participants to fail in their learning.

Two types of failure rate criterion were defined; one which used the traditional Iowa-score approach and a second which used the EV model data. Based on previous findings with the IGT, participants should have learnt the tasks and maintained performance by trials 80-100. As such they should be selecting from 'good' decks more than 'bad' decks at the point. Therefore, we defined failure-to-learn as a greater selection of 'bad' decks over 'good' within this 20-trial period. Using this criterion of failure, there were 5 who 'failed' in BLINK and 10 who 'failed' in the IGT. A Barnard's exact test (Barnard, 1945) revealed a trend towards significantly different failure rates between the two tasks ($p = .07$, one-tailed).

Using the EV model procedures, we used the model fit statistic G^2 to classify participants as having failed to learn. Specifically, as is common in the literature, we classified any participant who had a score below -60 as having failed to learn. Such a low value does not necessarily represent negative learning, but is performance that cannot be explained by the EV model, for example participants could be using a baseline model of selections (deck selection by chance). Using this criterion of failure rate there was 4 who 'failed' in BLINK and 7 who 'failed' in the IGT. A Barnard's exact test (Barnard, 1945) revealed this difference in failure rates to be not significant (p =.26, one-tailed). We used this exclusion criterion to remove participants from all subsequent analysis, apart from those related to overall time benefits.

Further evidence of the low rate of failure on BLINK can be seen when comparing the running total between the two tasks. In the IGT participants are given a "loan" of $2000 dollars at the beginning, so when comparing the scores for the two tasks we will take their running total at 100 trials for the BLINK and IGT and subtract $2000 from the score of the IGT and multiply the BLINK by 10 (due to the 10 times smaller contingencies used). This like-for-like comparison yields significant differences, $t(47) = 3.11$, $p = .00$, with higher final scores for the BLINK (M = 683, SE = 266) than IGT (M = -270, SE = 122).

Time Benefit

The overall time to complete a gambling task was computed based on calculating the duration between the moment a participant sat down to the task and when they completed the task. As can be seen in Figure 7, the between task difference in time-to-complete was substantial. When looking at the time to complete just 100 trials, the time taken in the BLINK task was even more apparent: no participant took longer than 1 minute to complete the first 100 trails of the

BLINK task -- participants took, on average, 39 seconds (SD = 8 secs). Significant effects were found between the time to complete the BLINK task (M =4.4 mins, SD = 2.6 mins) and the IGT (M = 20.7 mins SD = 3.9mins), $t(58) = 18.89, p < .001$, one-tailed.

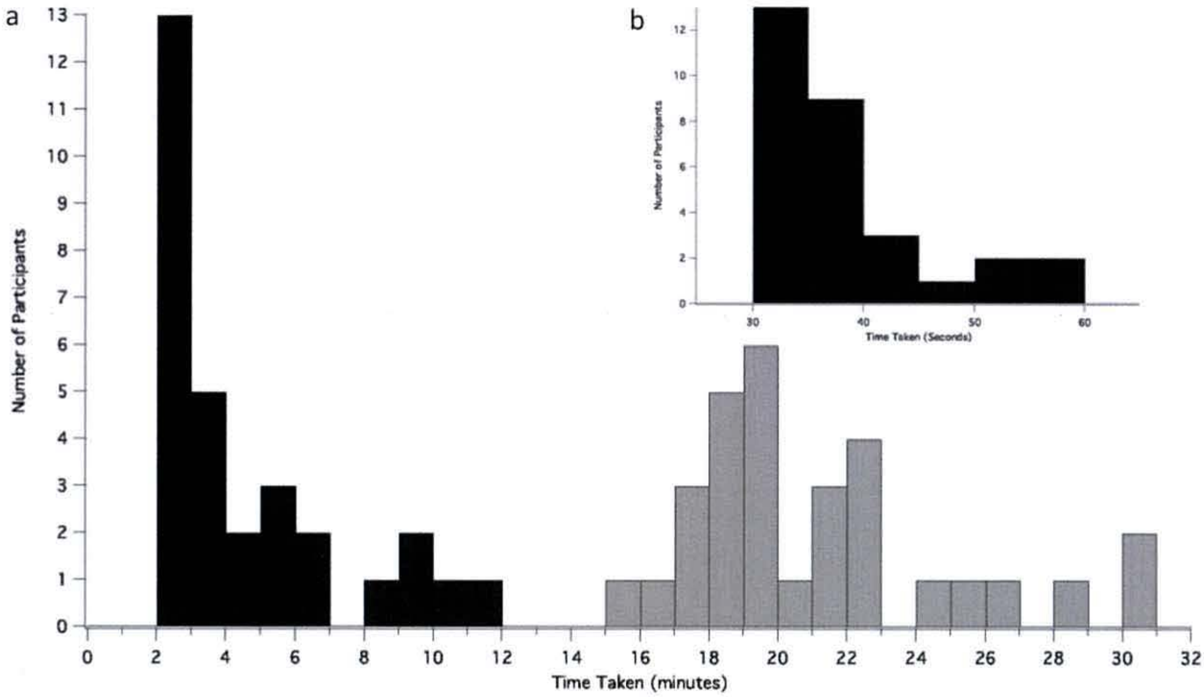

Figure 7: Time benefit. (a) Histogram (with one-minute bins) of the number of participants by the time taken. The black bars represent the BLINK task condition and the grey bars represent the IGT. (b) Histogram (with 5 secs bins) showing time to complete the first 100 trials in the BLINK task.

Learning Success Analysis

It is also possible to use the IGT learning performance calculations to compare conditions. The primary dependent variable in such an analysis stems from the standard approach of calculating the total number of "good" deck selections minus total number of "bad" deck selections within each block of 20 draws (ranging from -20, where each selection was from a bad deck, to +20 where each selection was from a good deck). Using this dependent variable, it is possible to compare the IGT to the BLINK task. Mean IGT scores (i.e. total "good" deck selections minus total "bad" deck selections) were calculated for the first five blocks of 20 trials. This score was used to compare the conditions: A 5 (BLOCK) x 2 (TASK) mixed-factor ANOVA was conducted resulting in a main effect of block [$F(192,4) = 8.180$, $p < .001$] but no interaction between block and condition, $p = .256$. A within-subject contrast of block revealed a significant linear trend [$F(48,1)=25.431$, $p<.001$] demonstrating that participant's selection from "good" decks increased over time. An overall significance of the between subject factor (TASK) was observed, $F(48,1) = 8.563$, $p < .001$, which was driven by an increased selection from "good" decks in the BLINK task (See Figure 8).

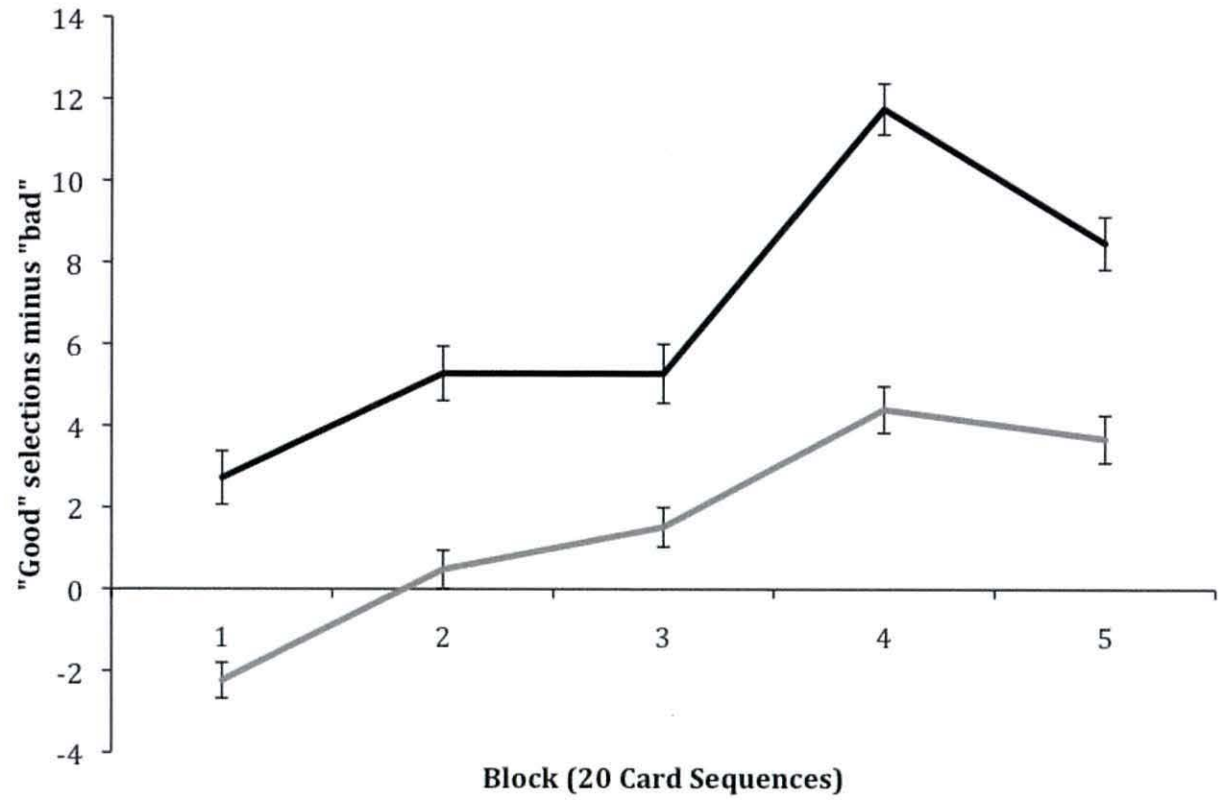

Figure 8: Line graph showing the mean "good" deck selections minus mean "bad" deck selections of participants in the BLINK task (black line) and IGT (grey line), split over 5 blocks of 20 trials. The bars represent standard error.

Evaluating Common Performance Parameters

A series of t-tests was conducted for the three expectancy-valence model parameters, with correction for equal variance indicated with degrees of freedom. The parameter of recency, which gauges information updating, differed between the groups, and was higher within the BLINK task. The response consistency parameters, which measures participant sensitivity to expectancies, was higher within the BLINK task, suggesting a more deterministic decision behaviour. The attention parameter, the weight given to wins versus losses, showed no difference between task types. Finally, and crucially, the model fit was similar between the BLINK task ($G^2 = 13.2$, SD = 32) and the IGT ($G^2 = 15.91$, SD = 8.4), see Table 7 for all measures. These results suggest two conclusions: first, that the EV model is a good fit to performance in both tasks (in comparison to a baseline model); and second, although the weighting of several subcomponents of the EV model (recency and consistency) did differ between the tasks as measured here, the similarity in overall model-fit between the two tasks, as well as the general agreement between our subcomponent measures in BLINK and those reported in the literature for EV models of IGT performance, suggests that both tasks rely on similar (or the same) underlying mechanisms.

Table 7

Expectancy Valance Model Means

	Group	Mean	Std. Error Mean	*p (2-tailed)*
ModelFit	BLINK	13.20	6.28	0.794
	IGT	15.91	8.44	
Recency	BLINK	0.31	0.07	0.004
	IGT	0.10	0.01	
AttendLoss	BLINK	0.43	0.05	0.817
	IGT	0.45	0.06	
Consistency	BLINK	2.27	0.36	0.042

IGT	1.07	0.45

BLINK and IGT performance patterns

Figure 9 illustrates several performance patterns found in the BLINK task and in the IGT. Each row contains two graphs: the histogram (left) displays frequencies of deck/key selections across the first 100 trials and the graph (right) shows trial-by-trial deck/key selections. The first two rows show data from the BLINK task (a participant who learned followed by one who did not), the second two rows show data from the IGT (learned followed by did-not-learn). The final row shows data from a VMPFC patient (adapted from Bechara et al., 1994). The particular participants displayed were chosen at random, but their performance patterns are quite representative of other participants. Thus, the participant shown in the first row is representative of the 94% of participants who learned the BLINK task, the second row is representative of the 13% who failed to learn in BLINK, the third is representative of the 82% of participants who learned in the IGT, and the fourth is representative of the 23% who failed to learn on the IGT. There are several important observations to make about these data. First, the overall performance pattern of our normal/healthy participants who failed to learn in the BLINK task (2nd row) is quite similar to that found for our normal/healthy participants who failed to learn in the IGT (4th row). Specifically, the performance differs not by the number of selections from the good/bad decks (which is almost at random with a 50/50 chance of a participant choosing a good or bad deck), but by the *consistency* of the selections, with a more consistent selection for the BLINK task in comparison to the IGT. This form of failure is quite different from how VMPFC patients typically fail on the IGT. For example, the data from the VMPFC patient (5th row) shows how these patients tend to be drawn towards the "bad" decks. The second important observation to make about Figure 9 is in regard to the similarities and differences in performance of participants who learned the BLINK and the IGT. The participant in the BLINK task (top row) has a far greater consistency in responding (much longer "runs"). This consistency in responding was apparent in the EV modeling. We further discuss the similarities and differences in performance patterns in the general discussion.

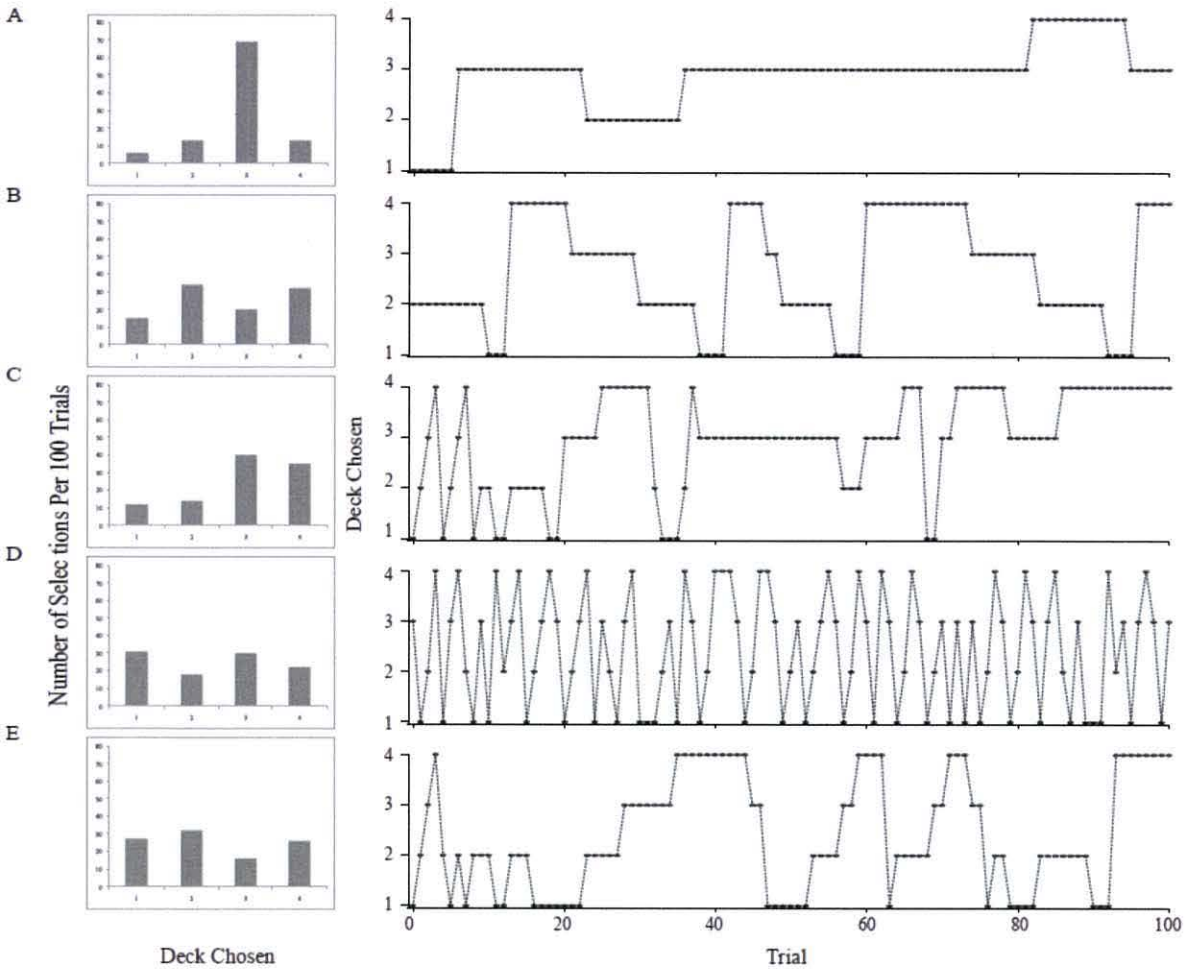

Figure 9: Performance patterns. Each row represents a different type of participant and task. Row A is a BLINK participant with good performance. Row B is BLINK participant with bad performance. Row C is a IGT participant with good performance. Row D is BLINK participant with bad performance. Row E is IGT participant with VMPFC damage (Bechera et

al., 1994). See results for detailed descriptions. Decks 1 & 2 are the 'bad' decks, decks 3 & 4 are the 'good'.

Discussion

The present study demonstrates a novel task that measures IGT-like decision making but which is *dramatically* speeded. This improvement in speed is apparent using a number of criteria. For example, participants completed the *complete* BLINK task (often several hundred trials) in an average of four minutes, with more than a third of participants completing the task in under two minutes. Indeed the first hundred trials were completed in less than *one* minute by all participants. By comparison, the average for the IGT was 20 minutes, and the range of task completion times for the two measures were entirely non-overlapping. Indeed the *fastest* performance on the hundred-trial task was (at 15 minutes) a full five minutes slower than the *slowest* participant for several hundred trials on the full BLINK task. Finally, we note that a smaller percentage of participants showed 'failure' on the BLINK task (13%) than our IGT (23%) or findings showed before (32.5% Bechara et al., 2001), which most likely stems from the ease of understanding.

In sum, on the assumption that the BLINK task measures the same psychological processes as the IGT, the BLINK task appears to represent a *dramatic* technical advance in the assessment of complex reward-based learning.

Similar Performance Characteristics

To compare the IGT to the BLINK task, we adapted the standard expectancy-valence model. This model incorporates parameters of attention, recency, and response consistency. When we modelled the performance of our participants in the BLINK task we found that they performed this new task at parameter values consistent with other researchers (Busemeyer &

Stout, 2002). Participants who performed the BLINK task also had parameters similar to those who performed the IGT, and differed from IGT in that they were *more* consistent in their choices, and took *more* information from previous trials (recency parameter). This is perhaps by virtue of faster learning on the task, as consistency parameter is driven by the participant's sensitivity towards the expectancies they have of the decks, in that a greater value shows more use of the deck C. It is worth highlighting that, as mentioned earlier, we had two different groups of participants perform the BLINK and IGT tasks. While a within-group comparison of task performance might well be informative, we chose to employ a between-group design to avoid the possible confounds (carry-over and learning effects) that have been documented in previous studies. As mentioned earlier, the experiential differences between the tasks might make a within-group design possible, and we might investigate this in future studies (e.g. by using an A-B Vs B-A design).

These data do not necessarily *confirm* that the BLINK task and the IGT assess identical psychological processes. However, the broadly consistent data suggest that there is substantial overlap in the response properties of the two measures – which supports the claim that the BLINK task measures the same psychological processes as the IGT. It is important to note that a variety of pilot studies led to the version of the BLINK task that we present here – studies that included numerous variations of the feedback display, the payout rates, and the instructions that were given to participants before they started the task.

<u>Advantages as a clinical and research tool.</u>

The BLINK task has potential advantages over the IGT in at least two domains. The first relates directly to the pace of performance. For example, for many clinical populations, issues of fatigue and concentration loom large when the clinician chooses which assessment tool to employ (see Lezak, Howieson, Loring, Hannay & Fischer, 2004, pp. 125-126). By reducing test performance time by some 80% or 95% (depending on whether one compares the first hundred trials, or time to BLINK task completion) the participant avoids fatigue, and can maintain attention. The clinician is therefore at liberty to use the saved assessment time to deploy other valuable measures. Speed of completion also opens the possibility of using the BLINK task as a screening measure – which is especially valuable since the original motivation for developing the IGT was the absence of neuropsychological tools to measure emotion-based learning (Bechara, Damasio, Damasio & Anderson, 1994). Other clinical populations that could benefit from the BLINK task include patients with Parkinson's disease, ADHD, and people with various forms of dementia. However, BLINK may prove difficult for some clinical populations that have a psychomotor impairment (e.g. Parkinson's disease). The large demands that the BLINK places upon psychomotor skills may require an altered methodology. For example, it might be possible to use a BLINK variant whereby the experimenter responds under participant instructions.

A further benefit may be found in the assessment of children. When the IGT is used with children researchers often reduce the number of decks to two (Kerr & Zelazo, 2004), however the BLINK task has no decks and the more "game" like appearance suggests that the BLINK task may be a more suitable measure for younger participants.

In a research context, speed of performance is also valuable: for example, one might take advantage of the opportunity to set up the task with different contingency mappings. This opens the possibility of *multiple* uses of the IGT even within a *single* session, such that one can more routinely measure effects such as set-shifting (Turnbull, Evans, Kemish, Park & Bowman, 2006).

A further advantage of the BLINK task lies in the well-established distinction between slow and thoughtful decision making over fast, automatic (intuitive) decision-making

(Kahneman, 2003). There is a longstanding debate in the emotion-based learning literature on the question of implicit awareness and the cognitive or emotional processes underlying performance on the IGT (Bechara, Damasio, & Damasio, 2000a; Bechara, Damasio, Tranel & Damasio, 1997; Bowman et al., 2005; Evans et al., 2005; Maia & McClelland, 2005; Turnbull, Evans, Bunce, Carzolio & O'Connor, 2005) and more generally the role of explicit emotion in complex decision making (Kahneman, 2003; Stanovich & West, 2001). By virtue of its rapid pace and non-linguistic feedback, the BLINK task seems to rely far more on rapid automatic choices, so this important issue can be addressed afresh in the context of this new tool. In terms of the dual system (Loewenstein and O'Donoghue, 2004) this BLINK task demonstrates the speed and integration between the two systems, and suggest that it is not the amount of time required to consider and make a slow deliberate decision, but it is perhaps instead the number of samples required for the fast and frugal decision making system to guide selections.

Indeed, the fact that participants can successfully learn response contingencies at a rate of more than one trial per second also has important implications for theories of decision-making. Specifically, our results suggest that the "bottleneck" found in most tasks that require decision making are perhaps less related to decision making *per se* (i.e. a central or executive process), and may be more related to information display issues, information acquisition, and perhaps working memory loads in top-down influence from "the rational system". These results may have particular relevance to classic models and theories of decision-making. Furthermore, recent research has suggested that, in some cases at least, very rapid (or "Blink") decisions may actually be more accurate and trustworthy (Gladwell, 2001; Gigerenzer, 2004; Sloman, 1997). The current results suggest that it might be possible to engender such rapid decision-making in other tasks, and in other domains, by modifying information display and response parameters.

Beyond the obvious feedback (non-verbal) difference between BLINK and IGT there is one other difference worth discussion. Specifically, this is the contrast in terms of the participant's understanding of the overall task goal/duration between measures. In the IGT, participants are simply told to "try and win as much as possible." They do not have any explicit sense of when the experiment will end (beyond the knowledge that their testing session has been scheduled to last no more than 30 minutes). In comparison, the BLINK task does present participants with an explicit goal/end: they know that it will end when they make the flower 100% filled with blue tokens. This difference may have some impact on the sense of reward and accomplishment associated with winnings (and losses). Because of the rapidity of learning (especially in the first 30 seconds of BLINK performance), we do not believe that this difference made a significant contribution to between-task differences. However, future experiments could help clarify the specific role played by these "goal-related" aspects of performance in both the BLINK and the IGT.

One issue worth discussing is the different durations used the feedback in the two tasks. In the IGT the auditory and visual feedback last for several seconds, whereas in BLINK the feedback is far more instantaneous. While these differences are substantial, they can not explain the order of magnitude decrease in task performance time between the two tasks. If we imagine that the IGT performance speed was limited by this required feedback delay, this limitation would have amounted to about 3 seconds per trial for the 100 trials, or about 300 seconds (5 minutes). Even if we disregard this five minutes from the overall IGT task performance time, the time to perform the tasks are still vastly different (2 minutes vs 10 mins).

In terms of the brain areas involved in performance of the BLINK task, the agreement between our expectancy-valence model and others reported in the literature for IGT performance suggest that the same cognitive-emotional processes may be involved in performance of both the BLINK task and the IGT. Thus, as a first hypothesis, we suppose that similar neural areas are involved in both tasks: namely, VMPFC and DLPFC. We are currently planning future research that will examine the performance of patients with damage to these areas. The results of such studies should help clarify the neural substrates involved in the performance of the rapid decision-making processes involved in the BLINK task.

In sum, the BLINK task appears to share many of the properties of the IGT, but has substantial advantages in terms of usefulness, for both the clinical and research worlds. The assessment of psychological function in neurological patients has long struggled to address potential confounds, such as time restrictions in assessment, fatigue, assessing executive function in the context of ecologically important issues such as complexity and ambiguity, and even the extent to which methodical and systematic decisions are open to manipulation by patients with pseudo-neurological disorders (i.e. transcranial magnetic stimulation techniques; Lezak et al., 2004, pp. 755-784). Furthermore, the BLINK task may provide a cleaner assay of the fast intuitive associative system that contributes to everyday learning and decision-making, enabling a more precise neuroscientific understanding. It is not yet clear whether the BLINK task can address all, or indeed any, of these issues. However, it does offer a tool that is based on a measure that is increasingly well-established in the scientific literature, but where the radically revised assessment format may well offer clinical and research advantages in a number of domains.

Experiment 4: Quick as a BLINK and Brand Logos

Within Experiment 1 we looked at how brand logos superimposed onto decks within the traditional IGT affected performance. Now that we have developed a speedier version of the task we wished to explore how these effects would appear. The basic premise of the task follows that of Experiment 1 as such I will not reiterate the points made in the introduction. The main empirical questions that this experiment questioned are as follows: 1) Does reducing the deliberation time, and as such exposure towards the meaningful image, impact in the learning and biased response towards congruent conditions; 2) Can we tie the concept of the meaningful image to abstract representations; 3) Finally, can we replicate the results seen in Experiment 1. To allow us to answer these questions we kept the procedure very similar as was in Experiment 1, with three main differences. Firstly, instead of the brands been placed on the backs of the decks continually, the brand only now appeared when participants pressed the corresponding "deck" key. Secondly, as a way to associate the different key presses with the different brand we added a learning phase pre-BLINK to the experimental design. And finally, we used the one "incongruent" condition (adverse-on-good) and one "congruent" condition (loyal-on-good), as well as the same pre-rating phase that selected the brands to be used within the BLINK.

There are multiple reasons why a replication will aide our understanding of the role meaningful images have in decision-making. Firstly, we believe that the BLINK task taps into more subconscious learning effects than the IGT (see discussion in Experiment 2), and if meaningful images guide subconscious learning we should find similar effects to Experiment 1 in this study. Furthermore, we have the added bonus of greater trials to analyze the data from; this allows us to better probe the decision-making profile of the participants until they reach more of a ceiling. Indeed in Experiment 1 the learning rate had not stabilized within the conditions (marked by a positive slope in the final two blocks) and with greater stabilization of the decision profiles we may get more information as to how performance alters over time. Finally, with the new presentation of the brands we can understand the object-marker representation further. That is, with an ability to disentangle the card from the brand representation a heightened form of associative learning may occur.

Method

Participants

48 participants (30 female, 18 male); ranging in age from 19-24 (Mean= 20.15) from Bangor University volunteered to participate through an online experimentation booking system (SONA). The entire procedure took approximately 45 minutes and participants received course and printer credits for their participation. The School of Psychology ethics committee approved the research.

Apparatus

E-Prime experimentation software (Psychology Software Tools, 2002) was used to conduct both parts of the experiment. The software ran on Windows XP with a Pentium 4 (3.06 GHz) processor. The stimuli were displayed on a 17" CRT monitors (1076x768 resolutions, 85Hz, 32bit). The participants' made all responses via a keyboard with the primary responses being the keys 1 through 5 (during the brand preference rating phase) and the keys 1 through 4 (during the IGT).

Stimuli

Brand logos were presented as 24-bit bitmap files with dimensions of 200x200 pixels during the BLINK IGT, these images only appeared during the selection of a deck (i.e. if an individual selected deck 1 the brand associated with that deck would appear at the centre of the screen and grow slightly (see Figure 10:Panel e). The same logos were used in the rating (first) phase of the task with a 20% scaling increase (96x96 pixels), as well as the BLINK training phase. The brand logos were from the UK market and were either fast moving consumer good brands (e.g. drinks or chocolates), or UK service brands (e.g. banks or newspapers). This mix and variety of brands was used to increase the likelihood of identifying a range of brand preferences within the specific experimental population. During the control condition the brand stimuli were removed, and selection was signified an increase of the number selected (See Experiment 3).

Measures

The first phase was a computer-based rating questionnaire where the participants were asked to rate their familiarity, preference, and loyalty to 40 different brand images. These were presented one at a time in a random (self-paced) order – each image was presented a total of four times, thus participants made 160 responses. Each image remained on-screen until a rating was indicated via a keypress, with possible ratings being: 1 = "very disloyal"; 2 = "disloyal"; 3 = "neutral"; 4 = "loyal"; 5 = "very loyal", with the same Likert-scale used for familiarity and preference (See Figure 10:Panel a). The measure of loyalty was used as the criteria for inclusion in the BLINK, with the preceding question used to ensure consistency of preferred brand.

Design

Each participant was randomly assigned into one of the three conditions. Due to the nature of the task (discovering a hidden rule), we decided to be conservative and had each of the participants only perform the BLINK once. Consequently a between subject design was necessary to answer the research hypotheses. For the second phase of the experiment (the IGT) the independent variable was the location of the brand image (or lack thereof, within the neutral "no logos" condition) on the decks, this was different in each condition (loyal good, loyal bad, neutral). The dependent variable in the second phase is the deck chosen: A,B,C,D further classified as "good" (decks C or D) or "bad" (decks A or B).

Procedure

The participants were run in groups of four to six. Initially the participants were given a broad outline of the study. The rooms were dimly lit and the participants sat on a chair approximately 60 cm away for the computer monitor, which was positioned at eye level. Dividers and headphones ensured that adjoining participants did not influence performance. The experiment itself consisted of three phases, which lasted approximately 30 minutes. Phase one consisted of the brand loyalty rating task (lasting 5-10 minutes, see measures for details). Phase two was a training phase of the experiment (lasting 2 minutes), during this phase participants were trained towards the brand identity of the four decks. This phase consisted of two stages: Firstly, participants were presented the four brands and their corresponding deck number; secondly, participants were presented with the brand on the screen and had to respond with the correct corresponding deck number. During this second stage participants were required to respond within 1000msec, as well as to get the correct corresponding deck number (see Figure 10:Panels b & c). After 10 correct trials in a row participants proceeded to Phase three (the BLINK).

Phase three followed the procedure developed for the BLINK in Experiment 3, with one main exception. This main exception was the presentation of brand stimuli during 'deck' selection. Meaning that as a participant selected a number the associated brand image appeared at the centre of the BLINK feedback display (see Figure 10:Panels d & e below). This procedure of enlarging the brand image on the screen post selection meant that the time to deliberate between the trials was increased as compared to Experiment 4. Specifically, the growing took 800msec and within this window participants were unable to respond in the task.

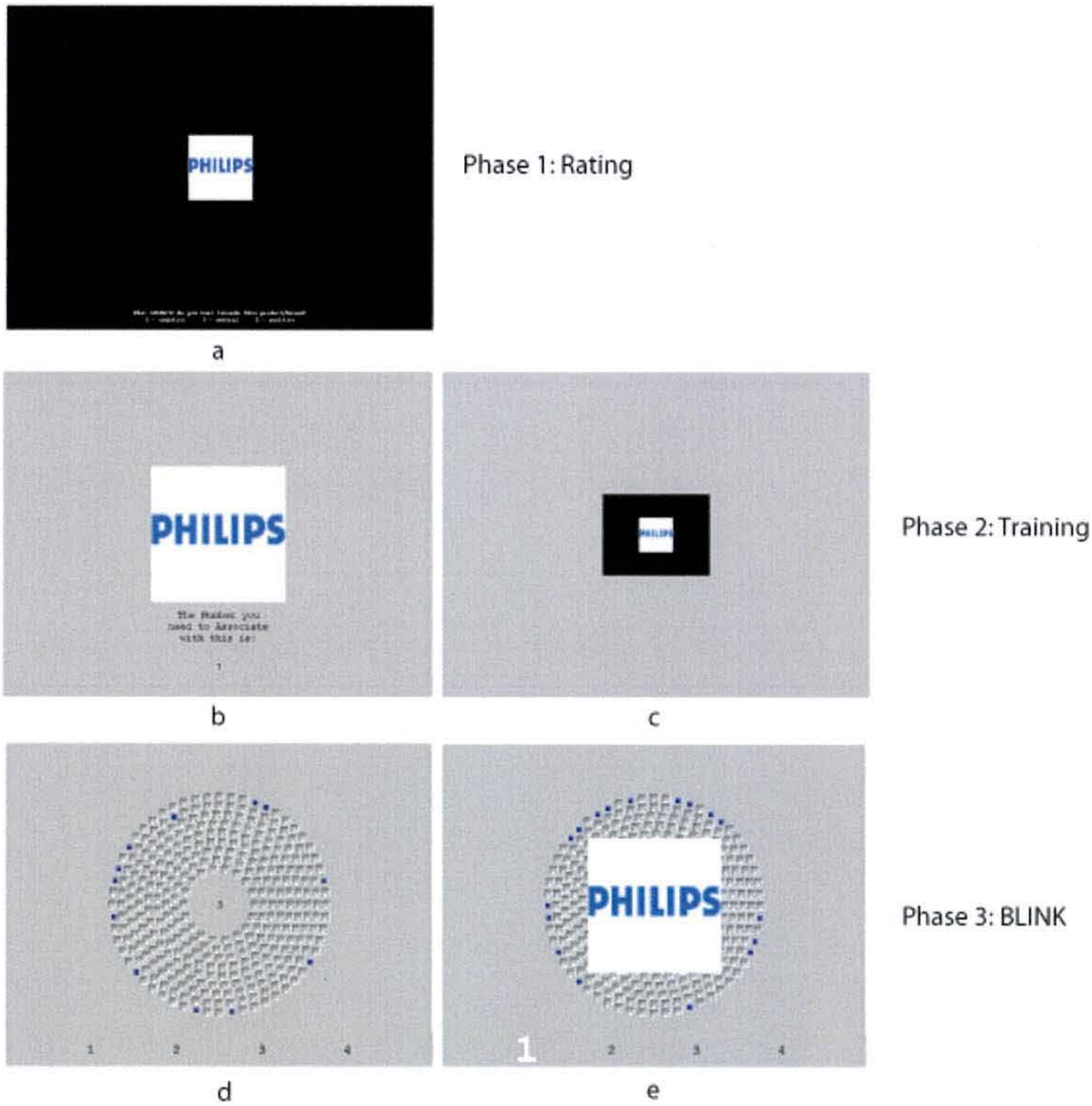

Figure 10: Experimental procedures. Each row represents a different phase of the task. Panel a: the brand-rating phase of the task. This information was then past to the training phase. Panel b & c: the training phase. In Panel b participants were explained the corresponding the

number, and in panel C they had to press the number in just the presence of the brand image. Panel d & e shows the BLINK phase, panel e shows the outcome a participant would observe after pressing the key 1, which was associated with the Philips brand.

Results

The 5 participants were excluded from "adverse-on-good" condition (N=19), and 4 participants were excluded from "loyal-on-good" condition (N=20). Exclusions were based on those previously stated in Experiment 3. The results section is split into two sections, the first looks at traditional BLINK block analysis, and the second discusses the results in relation to the EV model. Due to the deliberation time induced within the task, time taken to complete is not presented, as there were no discernable differences.

BLINK Block Analysis

For this analysis all ten blocks of fifty card selections will be used: 1-50, 51-100, 101, 150, 151-200, 201- 250, 251-300, 301-350, 351-400, 401 -450 and 451-500. The net score for each block was calculated in the traditional method, i.e. by subtracting the number of good selections from the number of bad selections ([C+D]-[A+B) to produce an IGT score. The maximum a participant could score if they chose advantageously was +50 (i.e. a score above 0) and the minimum if they chose disadvantageously was -50 (i.e. a score below 0).

A 10 (BLOCK) x 2 (CONDITION) mixed factor ANOVA revealed a main effect of Block, $F(9, 279) = 3.298$, $p = 0.001$, suggesting that if the brands are ignored participants did still learn to avoid the bad decks. There was a significant linear contrast to this main effect of BLOCK, therefore over time positive decks were selected more often than negative decks (see Figure 11). There was also a significant interaction between CONDITION and BLOCK, $F(9, 279)=1.935$, p=0.47. This suggests that deck choice was influenced by the condition i.e. which brands where placed on which deck.

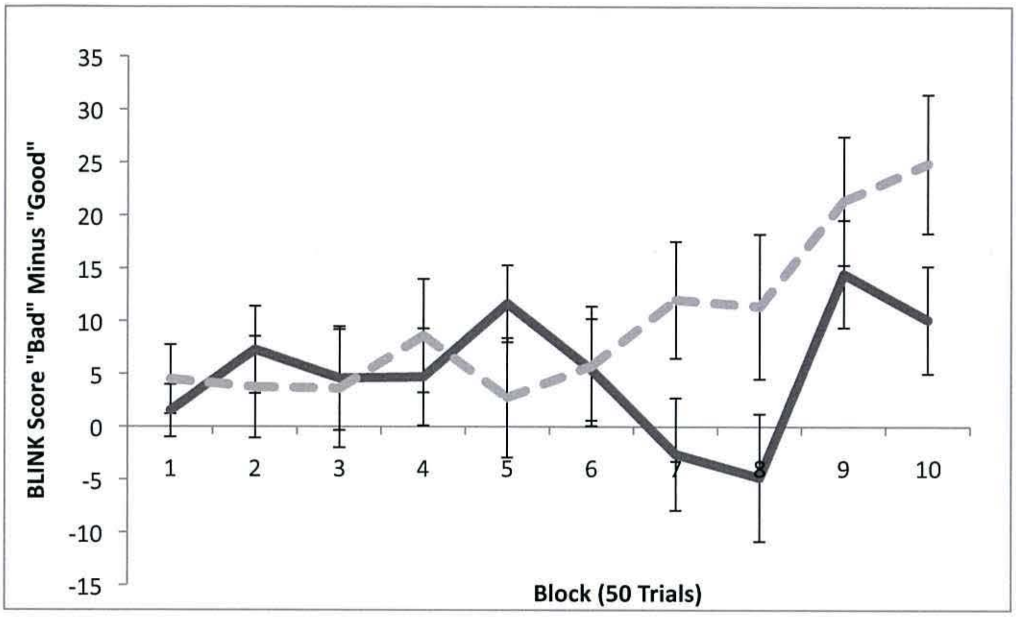

Fig. 11. Mean IGT Score per block for "adverse on bad"(Solid line) and "loyal on good"(Dashed Line). The error bars represent the Standard error for each block.

For further analysis a series of One-way ANOVAs were conducted on Deck run length (i.e. how long participants would continuously select from one deck) , time taken to return to deck (i.e. how many selections of other decks a participant would take to return to a deck once they discontinued selection from that deck), the time taken till end game point; in all cases no significance was found.

EV Model Analysis

To contrast the three conditions were compared within the EV model. The data were fitted to the EV model (Busemeyer and Stout, 2002). The G2 statistic revealed that the data only just fit to this model (*M*=2.27, *SE*=1.88), a one-way ANOVA revealed no between group significance, (ps = >.05). For the three other parameters, a one-way ANOVA showed a between-subject significance for the consistency parameter, F (2,85) = 3.570 p=.034 , with Tukey-HSD post-hoc comparison showing significant difference between Loyal-on-Good and Adverse-onBad (*MD*=+/-1.09, *SE*=0.48, p=. 028) with the value being higher in the Loyal-on-Good compared to the neutral face condition (*see Table 5*). Suggesting that they are more consistent in their deck selection during Loyal-on-Good than Adverse-on-Good. The two other parameters revealed no significance differences (ps = >.05).

Table 5

Expectancy Valence Model Value Means for Experiment 4 ---Means(SE)

	Control	Loyal-on-Good	Adverse-on-Good
Model Fit (G2)	13.20 (2.30)	1.30(3.69)	2.70(3.51)
Attention (a)	0.43 (.09)	.37(.07)	.46(.09)
Recency (w)	0.31 (.09)	.33(.07)	.36(.09)
Response Consistancy (c)	2.27 (0.42)	0.60(0.32)	-0.51(0.50)

Discussion

In this study we replicated the findings that we showed within Experiment 1. There was however a difference in terms of a longer time for the segregation between the decks to occur in their learning. What these data suggests is that the BLINK can be biased by the presentation of brands that are associated with the decks.

One of the main reasons we feel that the data takes longer to diverge in the performance patterns is due to the weaker associations felt with the brand and the deck. Even though we did have a training phase where they associated the two, unlike in Experiment 1 there was no presence of brands during the actual task. Interestingly this reduction in deliberation time did impact the way that we associated meaning with the images, which suggests that the integration of the win/loss information requires more time when there is a presence of an associated yet incidental image.

Theses findings put together make an important contribution towards the findings of the "hot" and "cold" decision-making processes that underlie the effects that we found within Experiment 1 and the present experiment. Specifically, the separations between the deck representations and the associated brand images in the initial stages show that to guide the 'hot' system quickly their needs to be the presentation of the images whilst making the choice. It is the attentional capture of the brands that are displayed that guides the decision-making process. In a sense this finding confirms that the selection of the decks in Experiment 1 was a biasing demand characteristic within the first few blocks. However, overtime participants learnt to associate the decks with the brand images, and as a result they learnt better within the 'congruent' condition in comparison to the 'incongruent' condition. What was driving this effect though?

If we take an Evaluative Conditioning (De Houwer, 2007) approach to understand this effect we can suggest that the latent value in the brands make the conditioning of the decks representation to be blunted. In a sense we are making an US-CS1-CS2 pairing within Experiment 4. With the US being the deck number, the CS1 being the trial feedback, and the CS2 being the brand image. If both of the CS are adding a value attribute to the deck (US) then the preference will form towards it. However this preference formation can only occur when the pairing comes into a propositional knowledge (Corneille, Yzerbyt, Pleyers, & Mussiler, 2009), and with the post-decision presentation there is perhaps a break down of this stimulus regularity.

Whereas within Experiment 1 the pairing order was more like CS2-US-CS1, where the regularity of the stimulus was more conducive to learn the pairings and those have a strong propositional knowledge of the US. Taken together this model of the learning process suggests that the "cold" or "cognitive" of the CS1 (trial feedback) drives decision-making more when it is the most clearest signal of regularity, however when the stimulus regularity of the "hot" or "emotive" CS2 (brand image) is held in knowledge this drives decision-making within Experiments 1 & 4. This concept will be explored further within the general discussion.

Chapter 3: An Introduction to Time Perception

All perception takes place in time. Thus, time is an essential component of any perceptual event. The perception of the passage of time has been studied at great depth. However, so far no singular "clock" has yet to be discovered (Mangels & Ivry, 2004; Posner, 2005). What is now known is that there are several ways in which time perception can alter – both in the long-term (e.g. across lifespan) and in the short-term (e.g. across a single day, or even hours, or seconds). Although time perception appears to alter with age for many reasons (e.g. proportional, complexity, and routine), we are not concerned with such long-term effects on time perception. The time perception that is of interest here is short-term, that is within the space of seconds. In the short-term, time perception can alter as a function of an event (Ursano et al., 1999). A commonly used example of this is the altered self-report of time perception during a car crash, where observers report what seems like a drastic elongation or slowing down of time (Ursano et al., 1999). There are a variety of explanations as to why this is the case (see Posner, 2005) for a review of this) for example the increased levels of arousal experienced when the event is happening as well as processes of attention that fluctuate as a response to the event. Within the context of this thesis we will be particularly interested in time perception in terms of this short-term phenomenon, and we will examine it as a function of attentional processes that might alter such perception of time.

The way in which we measure time perception will influence our estimates of it (Mangels & Ivry, 2004). This is in part due to the nature of time perception. It is a sense that does not have a clear and direct correspondence to physical input from the environment (e.g. visual perception is fairly directly related to photons and auditory perception is related to sound waves, but time perception is a meta-percept). As such, to measure a single event one must signal the event for it to be measured. That is, an onset and offset of the period to estimate must be defined for any estimate to take place. These various issues make the estimation of time perception a difficult challenge.

What is clear in the literature is that the perception of time can expand or contract dependent on the stimulus that is presented. One crucial factor is the processing required in the task, for example when a participant must focus on time duration only, an increased number of stimuli can increase the perceived duration of time (Thomas & Brown, 1974), whereas when a participant has a dual task an increased number of stimuli will decrease the perceived duration of time (Zakay, 1993). In Thomas & Brown's study (1974), the researchers looked at how participants perceived the duration of a window of time that was filled with either brief tones or silence. They showed that those windows "filled" with tones were perceived to last longer than those that were not, this illusion is know as the filled-duration illusion (Thomas & Brown, 1974). To look at an opposite effect, Zakay (1993) manipulated the nontemporal information-processing load during the time to estimate window. They showed that there was a positive relationship between the load of the secondary task and a decrease in the perceived duration of time. What these two studies highlight is that the perception of time subjectively alters. As such, one might wonder what processes create this alteration of times subjective experience?

<u>Times Subjective Expansion</u>

Research in neuropsychology has yet to show a specific time perception deficit, however what has been demonstrated is that lesions of certain regions can alter perception of time. For example, H.M. who underwent bilateral medial temporal lobe resection, suffered overestimation difficulties with time intervals greater than 20 seconds, but no issues with timing estimates less than 20 seconds. Eisler & Eisler (2001) concluded that this showed the importance of working memory in these short time estimates. Furthermore, patients with right MTL resection suffered problems with overestimating retrospective time intervals and have no deficits with prospective time estimation, whereas patients with left MTL resection show the converse effect (Drane, Lee, Loring, & Meador, 1999). These findings have suggested the dopermegeneric pathway plays a role in time perception, in particular research has highlighted that dopamine transmission levels in the striatum are effected within MTL deficits (Lipska, Jaskiw, Charpusta, Karoum, & Weinberger, 1992). And a deficit in the dopamine transmission is perhaps at the core of the deficits in correct replication of time perception estimation. Indeed pharmacological studies have been conducted to look at the role of neurotransmitters in the perception of time. One clear candidate is dopamine, and in particular Meck (1996) found that within rats heightened levels of dopamine led to an increased interval response (i.e. an underestimation of time) and a reduced levels of dopamine let to a decrease interval response (i.e. an overestimation of time). Meck (1996) concluded that dopamine levels aided an internal accumulator clock and the subsequent net transmission rate either increased or decreased the "ticking" speed of the clock. It would seem that neurotransmitter stimulants increase the "ticking" of this internal clock (e.g. nicotine, caffeine (Ague, 1974)).

Both neuropsychological and pharmacological studies on time perception have been somewhat confounded by the more global deficits that could have contributed to an altered perception of time. However, what seems apparent through the literature is that it is the apparent accumulation of processing from the onset to offset of the window of time that alters the subjective expansion of time. Moreover, recent literature highlights the pivotal role that attention plays in such temporal expansion (Tse, et al., 2004). Indeed research on people with attention deficit disorder also supports the notion that attention plays a crucial role in time perception (Levin et al., 1996). In fact, the link between attention and time perception has a long history, beginning in the recent era with William James and later championed by researchers such as Katz and Ulrich (James 1890/1950; Katz, 1906; Mattes & Ulrich, 1998).

Tse and collegues (2004) probed the question of attention and its subjective expansion of time in a number of experiments based around an oddball paradigm. The basic premise of the experiments was to study the perception of time towards low-frequency stimuli (the oddball) within a run of high-frequency stimuli (the standards). Within this paradigm the standards' time duration would remain constant (e.g. 800 msec), whereas the oddball's duration would vary across trials. Participants were required to state (two-alternative forced choice question) whether the oddball duration was longer or shorter than the standards. With the critical point of perception being the point at which participants estimated the perception of time of the oddball being the same as that of the standard (i.e. the Point of Subjective Equality (PSE). This PSE was derived from a psychrometric function (this will be explained further in the method/results section below). In a series of seven experiments Tse et al. (2004) supported the notion that time perception fluctuates around the veridical duration based on: 1) The amount of information judged in the interval (i.e. the amount of standards); 2) The complexity of the stimuli. And they also demonstrated that the attentional processes that are tracked by the observer drive this effect. Indeed, in their conclusion they remark that the oddball heightens the cost of the spatial or temporal resolution and that this cost is made due to the interest or importance of the oddball. That is:

> "By making novel or important events run in *slow motion* they may be processed in greater depth per unit of objective time than are *normal* events." (Tse et al., 2004)

As such, if meaningful images are more important than other images then they should be allocated attentional priority, and as such the perceived duration of them should alter as a function of their meaning. Indeed, heightened attention has been shown towards emotional stimuli before; as such we will now review some of the literature discussing that.

Meaning and Attention

In the decision-making section of this thesis we highlighted the way that meaningful images can impact upon the way that we make decision and learn new information about these decisions. One of the possible explanations we posited relates to the way that meaningful images capture our attention within a task. A variety of ways as to how this attentional capture occurs has been studied at great depth. However, one area that little research has focused on is the way that a range of different meaningful images may capture attention. There are numerous tasks that we could have chosen to look at this. However, we will use a time perception task to assess this question. There are multiple reasons for this; the main one is that we wanted to push the lower temporal and perceptual thresholds of the attentional impact of meaningful images. In a sense to discover how low level the effects of meaning can go. In the next few paragraphs I will describe the current literature on emotion and attention and how that relates to this chapter.

Emotion has been shown to impact attention in a variety of ways. To discuss how emotional stimuli impact upon attention I will point out variety of task that have been conducted on the topic. And explain the current understanding on why and in what way these emotional stimuli impact upon attention. The effects of emotion on attention can be broken down in terms of both 'stimulus-driven' and 'state-dependent' impacts (Pessoa, 2009). Simply put, a 'stimulus-driven' effect derives from sensory input from the outside world (e.g. a delicious looking cake), whereas the 'state-dependent' effect derives from an input from mind (e.g. I feel hungry). Within this chapter we will primarily focus on the 'stimulus-driven' effects literature, and in subsequent chapters we will examine the effects of state dependence.

Visual perception is the classical area where 'stimulus-driven' effects of emotion have been examined in relation to attention. Previous research has examined numerous ways in which emotion may impact attention. Researchers have used a range of tasks to investigate such effects including visual search, filtering, and cuing (for a review, see Yiend, 2009). For an example let us consider the visual search paradigm. Within this paradigm researchers present an array of stimuli to the observer and try and assess the speed of reactions towards the presence or absence of a target stimulus (Treisman & Galade, 1980). The critical dependence within the task is the reaction time of confirmation, which can be altered as a function of array size and/or range of distracters. As the number of distracters present in the array increases, so does the time for the observers to find the target stimuli. As a result, researchers can ascertain how the level of target "pop out" alters over range of array sizes. Using a variety of stimuli they are then able to determine the overall capture of attention between stimuli used in both the distracter array and as the target.

Classical uses of the visual search paradigm within emotion research have used facial expressions as stimuli. Typically there are two approaches to looking at visual search (Yiend, 2009). One where the array consists of a crowd of faces with one expression, and a target face with either the same or a different expression (Horstmann, 2009). The second commonly used approach is where the array consists of neutral stimuli with a target face or a neutral target and an array of faces (Frischen, Eastwood & Smilek, 2008). These two designs differ in that the former measures both the distraction effect of facial expressions in the array, as well as the attraction effect of the target. Whereas the later looks at the attraction effect of the facial expression separately, when it is either the array or the target. The later approach is often regarded as easier to interpret (Frischen, Eastwood & Smilek, 2008; Yiend, 2009), due to the single direction of the distraction (i.e. you measure only the distraction effect or the attraction effect to the target). A consistent finding with this approach is that negative (fear or anger) and valenced (happy or sad) evoke either a distraction effect when they are in the array, or an increased speed of processing when they are the target (see for examples: Eastwood, Smilek, & Merikle, 2001; Frischen et al., 2008; Ohman, Flykt, & Esteves, 2001).

The dot-probe task (MacLeod, Matthews, and Tata, 1986) is one of the main paradigms used to look at the effect of emotions in attentional cueing. The dot-probe runs as follows: Two stimuli are displayed side by side, they disappear and after a short break a target appears in one of the two locations where the previous stimuli were presented; the participants task is to respond towards a categorical decision on the target (e.g. press "T" if it's a horizontal dot, or press "B" if it's a vertical dot). The critical measure is the ability of the two stimuli that are displayed before the target to cue the target. These two stimuli often differ on their emotionality (e.g. one could be a angry face, the other a neutral face). Using this paradigm, one classic finding is that anxious participants have their attention captured by an angry face and this results in speeded detection of the cued target (MacLeod, Matthews, and Tata, 1986).

Another paradigm that has been adapted to look at the role of emotion in attention is the Stroop task (Stroop, 1935), a task which primarily looks at a participant's ability to focus attention and filter out distracting information. The task has been adapted from the normal word-colour naming vs. colour-of-word naming by looking at the ability of participants to name the colour of the word when it is emotionally charged. For example, researchers have shown an increased latency of naming of undesirable traits (Pratto & John, 1991).

One study that directly posed the question of emotions role within time perception was Angrilli and colleagues (1997). They presented IAPS images to participants for 2,4, and 6 seconds, and required reproduction of the time duration via an analog scale or button push. They found that the levels of arousal and valence affected reproduction. In particularly, for negative images of high arousal there was an over-estimate of time, whereas for negative images of low arousal there was an under-estimate of time. The findings were clear, however as the task required a specific action to replicate the time (i.e. button press, or rotation of analog scale) it was unclear if the altered estimation was a perceptual or action driven effect.

From these paradigms, and many others, it is clear that emotion and attention interact and that emotion can impact upon the performance of participants towards an attentional task. One paradigm that has been used recently to measure the impact of attention on time-perception is the oddball tasks (Tse et al, 2004) discussed above. Given that this paradigm appears to offer a way to carefully quantify the impact of visual images on time perception, it seems to be a good paradigm within which to examine the impact of meaningful images on attention and time perception.

Aims of the Studies

What is clear from the evidence above is that meaningful images, and in particular facial expressions, capture attention. Using the TSE paradigm as outlined by Tse et al. (2004) we wanted to asses how meaningful images impact upon the subjective expansion of time (TSE), which is a proxy measure of attentional capture. Two questions were of interest within the experiment: 1) Does the perception of time alter as a function of stimulus meaning; 2) Does this impact upon the duration of the perceptual event as perceived by the observer, or is it more of a function of the accuracy of estimating the duration of the perceptual event. Both questions can be addressed by using a variety of meaningful images in the oddball paradigm. And, specifically, the first question can be answered by examining the point of subjective equality (PSE) of the duration of the meaningful images, and the second question can be addressed by examining the just noticeable difference (JND) of responses to meaningful images . To this end, we conducted a series of experiments to probe these questions.

Experiment 5A took the original Tse et al. (2004) procedure and adapted it to incorporate IAPS images. Experiment 5B looked at the role of motivational state in time estimations. Experiment 6 was a pilot study where we created a new adaptive procedure and tried to replicate the findings from a recent study using this procedure (Seigfried & Ulrich, 2008). Experiment 7A&B used this new procedure to tackle some of the possible limitations of Experiment 5 and also expanded the stimulus set to look at both valance and arousal. Experiment 6 looked at how consumer-related meaningful images (brands) impacted upon time perception.

Experiment 5A: Does valence alter temporal expansion ?

In Experiment 5A, we look at the whether temporal expansion is altered as a function of the valence of the images presented. To do this we used a group of IAPS images that covered a range of valences. We selected a range of IAPS images that differed on their scale of valance. Specifically, the images were chosen so that only the dimension of valence (i.e. high, low, and neutral) differed between the images while the two other dimensions (arousal and dominance) stayed the same. During the task the standard image was the same across conditions, and was neutral on all three dimensions of valence, arousal, and dominance. For this study we used the method of constant stimuli to estimate the PSE and JND for each of the oddball images.

Method

Participants

12 Bangor University undergraduates with normal or corrected to normal vision participated. They received course and printer credits as compensation.

Stimuli & Apparatus

All the stimuli within the experiment were photos of animals. With the standard being a group of buffalos (IAPS No. 1675). When an oddball stimulus appeared (approximately every 8 images) it would be either a negative, positive, or neutral image (selected randomly from a set of 9 such images). The negative IAPS images used were images 1250, 1275, and 1965. The positive IAPS images used were images 1255, 1270, and 1995. And the three-baseline/neutral IAPS images used were images 1262, 1271, and 1985 (see Figure x below). . The task was presented on a 17" CRT Windows machine running EPrime 1.2. Stimuli were 400 x 400 pixel dimensions. Responses were recorded via keyboard presses "z" and "/".

Procedure

The experiment was run in a batch-testing set-up, and a maximum of six participants would be run at the same time. After a demonstration of the task, participants were given an information sheet and consent form, which they completed before continuing. The testing rooms were dimly lit, with three identical computer set-ups in both rooms. The chairs were placed so the participant was approximately 60 cms away from the monitor. Dividers and headphones ensured that outside noise and other participants did not influence performance. The experiment took approximately 54 mins and was split into three blocks that were approximately 18 minutes each with a 1 minute break between blocks.

After giving informed consent, the participant was seated at the computer and the experiment ran itself. Standard stimuli would be presented for 1,050msec ± 50msec, and would have an ISI that would be chosen randomly between 940 and 1,040 msec. Every 6 -11 trials an oddball would be presented instead of the standard. During the task, participants were asked to fixate on the centre of the screen and pay attention to the durations of the oddball stimuli in comparison the standard stimuli. When the oddball appeared they had to respond whether they felt it's duration was longer or shorter than that of the standard (forced choice). They had to respond before the next oddball appeared, otherwise the trial would be counted as a no-response trial and it would be presented again later in the trial sequence.

The duration of the oddball would be either 600, 800, or 1000 msec. And each one of these durations had four ratings for each of the nine oddball stimuli. The order of the durations was pseudo-randomized to ensure that during each of the four blocks the time response was taken once for each stimuli and presentation time. This resulted in a block lasting between 180 to 240 trials, resulting in duration of between approximately 6 – 8 minutes with a one-minute break between blocks. Each block contained 27 oddballs. This resulted in a total time of approximately 54 minutes, during which the participants judged the durations of 108 oddballs, with 12 of these judgments being for each of the nine stimuli. Due to certain random elements (e.g. ISI, standard: oddball ratio, and oddball response) the length of the experiment could vary by ± 5 mins. Upon completion of the time perception task participants were thanked and then debriefed about the study.

Results

The critical dependent variable was the PSE, and this is taken to be the point where participants responded that half of the oddball trials were longer in duration than the standard.

This PSE was derived from a Weibull fitted curve, and was calculated as a whole and for each image separately. The average PSE was 797 msec (30.28 SD), which is similar to previous findings (Tse et al., 2004). An one-way (Valence: High vs. Neutral vs. Low) ANOVA reveled no significant differences between image type, $F(2, 30) = .01$, $p>.05$. When doing an image by image analysis, no significant differences were found $F(2, 30) = .08$, $p > .05$. Qualitatively, however, there seemed to be differences by image type (see Figure 10 below).

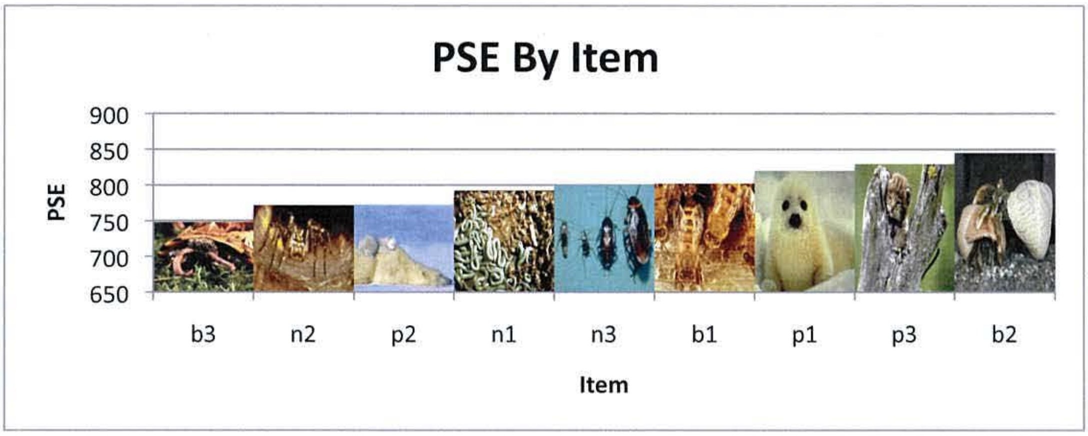

Figure 10: A bar chart showing the PSE of the different valenced stimuli as derived from Weibull fitted psychometric functions.. For the items b = Baseline; p = Positive; and n = Negative.

Experiment 5B: Do motivationally relevant stimuli alter time distortion?

In Experiment 5A we found that image valence did not alter time distortion. However, valence is only one aspect of an image. Next we wanted to see if motivationally relevant stimuli might capture attention differently and thus create greater time distortion. To this end we selected the motivational state of hunger. The stimulus for the standard was an item of furniture (e.g. a chair) and the stimulus used for the oddball would either be non-motivationally relevant (animals) or would be motivationally relevant (food). For this study once again we used a method of constant stimuli.

Method

Participants

19 Bangor University undergraduates with normal or corrected to normal vision participated. They received course and printer credits as compensation.

Stimuli & Apparatus

The apparatus was the same as in Experiment 1a. The standard image was that of a chair. The oddball was either an image of food or an animal. Three images of food were used (burger, pizza, and pasta), and three images of animals were used (koala, dog, and elephant). All image dimensions were the same (400x400 pixels).

Procedure

This was the same as in Experiment 5A. With the two differences being the stimuli and the motivational state. Participants were assigned to either the hungry (N = 9) or the not hungry group (N = 10) based on prior consumption. That is, participants were asked if they had eaten in the last three hours, if they had they were assigned to the not hungry group. If they had not eaten then they were assigned to the hungry group. To further induce the motivational state (hunger) in the hungry group, participants first rated 30 food images in terms of how delicious they were. As a control, the non-hungry group rated 30 furniture images on how stylish they were. A 5-point Likert scale was used in this induction phase, with 1 being either not stylish or not delicious, and 5 being very stylish or very delicious, and with 3 being neutral. Each image was rated once and the induction phase lasted 5 mins prior to the time perception task. The results from this induction task were not analyzed, and none of the stimuli in this rating phase were used in the time perception task.

Results

PSE were calculated the same as in Experiment 5A. The average PSE was 863 msec (SD = 93.83). A two (hungry vs. not) by two (animal vs. food) ANOVA was conducted revealing no interaction $F(1,34)=.01, p = 0.91$. And there were no main effects of group (hungry vs. not) $p = 0.58$, or image type $p= 0.32$. This demonstrated that there was no effect of either the state or the image type on the PSE. These results suggest that the subjective expansion of time does not vary as a function of the motivational relevance of the stimuli.

Discussion

Within Experiment 1A & 1B we found that time was equally distorted by all unexpected stimuli. Whether the oddballs were extreme on a valence dimension (Experiment 1A) or motivationally relevant (Experiment 1B) the amount of time distortion remained constant. This finding is indeed interesting given that previous research had suggested that time perception can alter as a function of emotion (Angrilli et al., 1997). We found consistent levels of temporal distortion (in terms of the PSE) between the various groups and we showed that the magnitude of the oddball effect (as measured in Tse et al., 2004) holds constant for a variety of stimulus types.

There are a number of possible explanations as to why we did not find any impact of the various stimuli on time distortion. Firstly, the procedure was long, and the number of responses each individual had to make to oddball stimuli was very low; this may have led to a burn-out effect whereby participants were not fully engaged with (and attending to) the stimuli. Secondly, although the normative data suggests otherwise, the levels of arousal differed qualitatively between the various stimuli, and this could have led to high variance between the stimuli.

To further address the first point of critique we decided to change the procedure from a method of constant stimuli to an adaptive weighted-up-down procedure (Seigfried & Ulrich, 2008). To examine the second point, we used the new procedure to systematically go through each of the dimensions of the IAPS, and include the stimuli within the same study. To further ensure that the stimuli (IAPS images) have the proper connotations with our participants, we have also included a rating phase of the images before and after the time perception procedure.

Experiment 6: Using an adaptive staircase procedure to measure times subjective expansion

With the results from the experiments above we decided that we needed a better measure of the subjective expansion of time to better understand if meaningful images impact upon time perception. To this end we developed a version based on the adaptive procedure outlined by Seigfried & Ulrich (2008). As a point of pilot testing we looked at this with more simple stimuli, with the standard being a grey disc and the oddball being a red disc. Due to the precise nature of the stimuli and the measurement technique only a few observers were required.

Method

Participants

4 Bangor University undergraduates with normal or corrected to normal vision participated. They received course and printer credits as compensation.

Stimuli & Apparatus

The standard image was a grey circle on a black background. The oddball was a red circle on a black background. The apparatus and response was the same as in Experiment 5.

Procedure

The same set up (testing rooms, computer configurations, etc) was used as in Experiment 1. And, the stimulus parameters for the standards were also the same. The only difference in this experiment was the timings for the oddball (red) stimuli. Specifically, the duration of the oddball would be from one of the two staircases. One of the staircases was trying to estimate the 25% point and the other was trying to estimate the 75% point. This was achieved with a weighted up-down procedure (Kearnbach, 1991). The resultant durations would depend on participants' responses, with the 25% starting at 327 msec below 835 msec (835 msec being the average point of TSE) and the 75% started 327 msec above 835 msec. During the 25% staircase, if the participant responded as shorter then the staircase would increase by 80 msec, whereas when they said longer then the staircase would decrease by 240 msec. For the 75% staircase, the rules were reversed, meaning that a "shorter" response would increase the oddball duration by 240 msec whilst a "longer" response would decrease it by 80 msec. For each staircase 25 responses were required towards that oddball per block, meaning that a participant would see at least 50 oddballs, 25 from the 25% staircase and 25 from the 75% staircase. After the required number of response was achieved, the task ended. Due to certain random elements (e.g. ISI, standard: oddball ratio, and oddball responses) the length of the experiment could vary by ± 2 mins. Upon completion of the time perception task participants were thanked and then debriefed about the study.

Results

Due to the new adaptive nature of the procedure we changed the analysis and wrote a procedure within IGOR Pro 6.01 software (Wavemetrics, Inc, 2009) to analyse the data (see Appendix II for script). We fit a square root weighted Sigmoidal curve to the response data.

Using this curve we derived two measures: the PSE which was the same as in Experiment 1 (i.e. where participants respond “longer” 50 % of the time), and a just noticeable difference (jnd). The jnd was easier to obtain within this procedure, and this was calculated by taking the difference between where a participant responded “longer” 75% and 25 % of the time (see Figure 11 for example data).

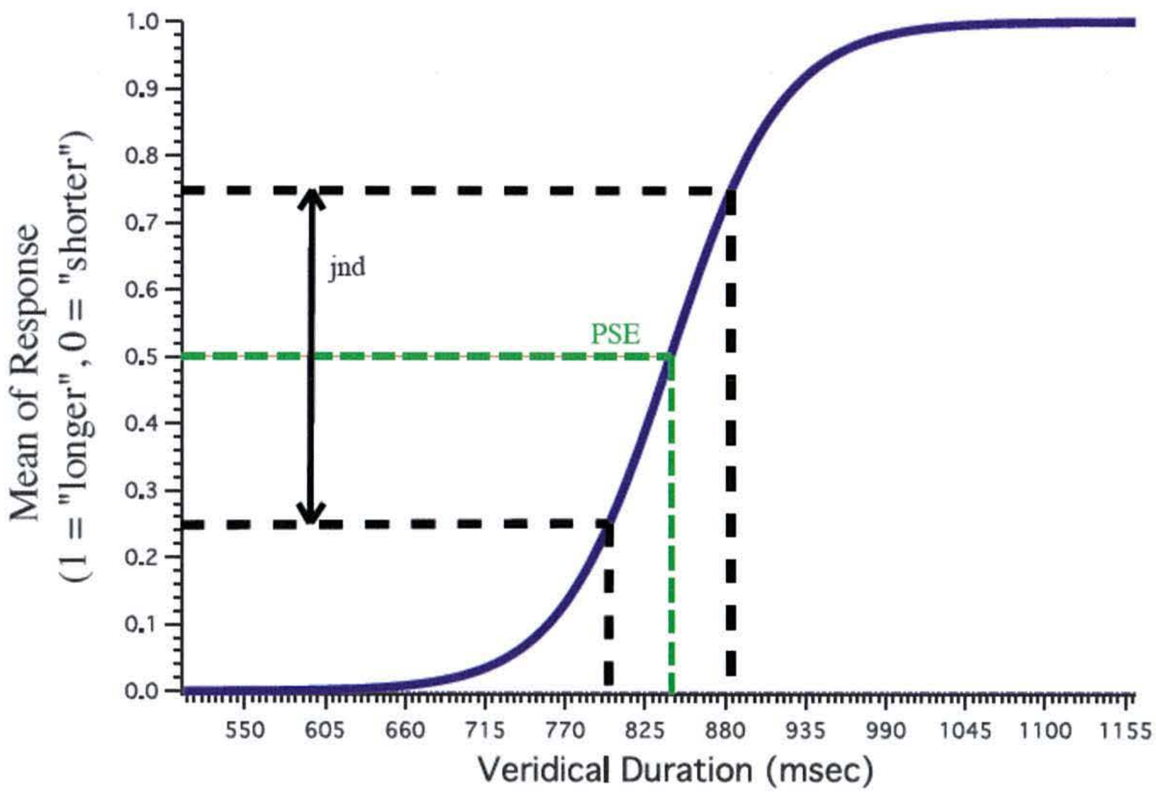

Figure 11: The derived psychometric function from the time subjective expansion paradigm. The x axis corresponds to the veridical duration (oddball presentation time). The y-axis corresponds to the participants response. The green dashed line highlights the PSE and the black dotted lines correspond to the two points from which the jnd is derived.

In addition to the PSE and the jnd, we also calculated the ratio of temporal expansion (Temporal Expansion Factor). This is obtained by dividing the PSE of the oddball by the veridical duration of the standard image. As such a TEF value > 1 indicates temporal expansion, and a TEF value < 1 indicates temporal contraction.

The PSE for the oddball was 850 msec (SD 120 msec), the jnd was 180 msec (SD 80 msec). With an average TEF value of 1.3 across participants. These results indicate that the adaptive procedure gives comparable results to the method of constant stimuli procedure. And as such we decided to proceed with experiments that looked once again at the impact of meaningful stimuli on times' subjective expansion.

Experiment 7A: Temporal expansion and arousal and valance: One oddball picture per block

As in Experiment 5A in this experiment we used IAPS images to look at the role that valence may have on temporal expansion. Additionally we added another condition whereby we looked at the role of arousal within temporal expansion. To combat one possible issue with Experiment 1A we also decided to have the participants pre-rate the stimulii so that we selected images that participants rated as having high/low valance or high/low arousal. Due to the length of administration required we had to separate the two groups of VALANCE and AROUSAL. Thus, each participant was assigned to one or the other group.

Method

Participants

24 (12 in VALANCE, 12 in AROUSAL) Bangor University undergraduates with normal or corrected to normal vision participated. They received course and printer credits as compensation.

Stimuli & Apparatus

The apparatus and response was the same as in Experiment 1. For the VALANCE group the oddballs could be from these IAPS pictures: High valence (mean valance/arousal = 7.0 / 5.3)

2208, 2250, 2260, 2501, 2560, 2650; neutral (5.0/5.5) 2020, 2190 2200, 2210, 2214, 2215; low valance (2.3 / 5.5) 2120, 2205, 2590, 2730, 2750, 2800. All theses pictures were scenes involving humans and the standard was a neutral image of a man. For the AROUSAL group the oddballs could be from these IAPS pictures: High arousal (mean arousal/valance = 7.0 / 4.3) 1020, 1111, 1120, 1201, 1300, 1321; neutral (5.0 / 5.5) 1030, 1121, 1205, 1303, 1945; low arousal (2.3 / 6.2) 1419, 1450, 1604, 1946. All these pictures were scenes involving animals and the standard was a neutral picture of a snake. (See Figure 12 for examples).

Figure 12: Examples of the stimuli used within Experiment 7A.

Procedure

This experiment had two phases: A pre-test rating phase, followed by the staircase version of the temporal expansion paradigm. The first phase was the pre-test rating, and here participants were required to categories the images as being high, low, or neutral on the two dimensions of arousal and valance. As a result of the participants selections three oddball images were selected to be taken into the main phase of the task. So that, for example, in the VALANCE group one image that was selected as high valance and neutral arousal, one image that was low valance and neutral arousal, and finally one image that was neutral for both categories.

In the main phase of the task the experiment followed the same procedure as Experiment 6, with the use of an adaptive procedure. This time, however, what was the entire task in Experiment 6 was seen as a block for this experiment. Each block used one of the three images as the oddball, and as a result each image had 50 duration responses.

The ordering of the within subject conditions was counter-balanced. The three blocks would have either a neutral, high value, or low value stimulus as the oddball, with the standard stimulus being the same neutral stimuli throughout. Thus, in total there would be 150 responses that participants made towards the oddball. Due to certain random elements (e.g. ISI, standard: oddball ratio, and oddball response) the length of the experiment could vary by ± 5 mins. Upon completion of the time perception task participants were thanked and then debriefed about the study.

Results

Analysis followed the same approach as employed in Experiment 6, thus we once again fitted a square root weighted Sigmoidal curve to the participant response data to derived three measures: PSE, jnd and TEF. We broke down the analysis for the two (valence and arousal) groups.

Valance Group

There was an overall temporal expansion effect (Standard Duration =1050 msec, Oddball M = 781 msec, SE = 41 msec). However this time dilation was not modulated by valance, all p's > .05. The jnds were also unaffected by valance, all p's > .05. See Table 8.

Measure	level	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
pse	Negative Valance	786.667	49.441	677.847	895.486
	Neutral	785.750	40.673	696.229	875.271
	Positive Valance	771.333	44.856	672.605	870.061
jnd	Negative Valance	189.583	31.371	120.537	258.630
	Neutral	187.083	26.285	129.230	244.936
	Positive Valance	161.500	24.205	108.224	214.776

Table 8: Showing the two derived measures for the Valance group.

Arousal Group

There was an overall temporal expansion effect (Standard Duration =1050 msec, Oddball M = 827 msec, SE = 33 msec). Again, time dilation was not modulated by valance all p's > .05. The jnds were also unaffected by valance, all p's > .05. See Table 9.

Measure	level	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
pse	High Arousal	808.667	47.052	705.105	912.228
	Neutral	826.667	45.255	727.060	926.273
	Low Arousal	845.583	23.940	792.892	898.274
jnd	High Arousal	193.583	26.389	135.503	251.664
	Neutral	141.750	23.210	90.666	192.834
	Low Arousal	216.667	31.460	147.424	285.910

Table 9: Showing the two derived measures for the Valance group.

There were no significant differences between the groups.

Experiment 7B: Temporal expansion and arousal and valance: Multiple oddball picture per block

As in Experiments 5A and 6 we were unable to show that temporal experience was influenced by the valence of a stimulus. Expanding on Experiment 5A, we also examined arousal and once again showed no differences by stimulus type. This is, once again, somewhat counter-intuitive to the findings of the attentional impact of emotional stimuli. One possible explanation of the lack of effect could be due to some "wear-out" of the value of the stimuli during the long exposure to one type of picture. That is, with the blocked design perhaps on the initial experience of the oddball the value is evoked in the participant, but in subsequent exposures this is not the case due to some form of habituation. As a result we decided to conduct one more experiment using the same stimuli. However this time there would be multiple oddball types for each of the three categories of stimuli. As an initial test we decided to only look at the Valance group.

Method

Participants

14 Bangor University undergraduates with normal or corrected to normal vision participated. They received course and printer credits as compensation.

Stimuli & Apparatus

Identical to Experiment 7A

Procedure

Followed the same main phase procedure as in Experiment 3A. But only within the VALANCE group. However this time there was no pre-rating phase and the whole range of stimuli were used, with the levels broken up by block. The ratings were recorded within category rather than within image. This meant that for example, in the block with high valance 50 responses were recorded for the six stimuli that were predetermined to be high valance and neutral in both dominance and arousal. That is, the staircase tracked the oddball within the block irrelevant of the difference in pictures.

Results

Analysis followed Experiment 3A in that once again we fit a square root weighted Sigmoidal curve to participant response data to derived three measures: PSE, jnd and TEF. Due to prior reasons (see above) only the Valance Group was present within Experiment 3B.

Valance Group

There was an overall temporal expansion effect (Standard Duration = =1050 msec, Oddball M = 781 msec, SE = 41 msec). As before, the time dilation was not modulated by valance, with all p's > .05. The jnds were also unaffected by valance, all p's > .05. See Table 10.

				95% Confidence Interval	
Measure	level	Mean	Std. Error	Lower Bound	Upper Bound
pse	Negative Valance	786.667	49.441	677.847	895.486
	Neutral	785.750	40.673	696.229	875.271
	Positive Valance	771.333	44.856	672.605	870.061
jnd	Negative Valance	189.583	31.371	120.537	258.630
	Neutral	187.083	26.285	129.230	244.936
	Positive Valance	161.500	24.205	108.224	214.776

Table 10: Showing the two derived measures for the Valance group.

Looking at the jnd and the PSE differences between this group in Experiment 3B and Experiment 3A we decided to compare the two experiments. So a between-subject factor was added to the repeated-measures ANOVA we used for analysis. Resultant tests revealed no significant difference of the interaction for either the PSE, (F=.68), or the jnd measures. As well as obviously still no main effects of PSE or jnd by Valance level, all p's > .05.

Experiment 8: Brand logos and temporal expansion

Throughout the thesis we have looked at the way different meaningful images impact upon performance. As a result we felt that we needed to extend the research on time perception into a different type of meaningful stimuli. Once again we used brand logos as a stimulus set. As in the decision-making experiments, here again we decided to use a range of brand logos and have participants subjectively rate them, and then subsequently use them in the task. Following the procedure used in Experiments 3A we used three stimuli as the oddball within the task. One which the participant rated as being highly liked; highly disliked, and neutral. As a standard, a neutral brand logo was used.

Method

Participants

18 Bangor University undergraduates with normal or corrected to normal vision participated. They received course and printer credits as compensation.

Stimuli & Apparatus

The main phase (temporal expansion paradigm) used the same apparatus and responses as before. Brand logos were presented as 24-bit bitmap files with dimensions of 400x400 pixels throughout the rating and the main phase. The brand logos were from the UK market and were either fast moving consumer good brands (e.g. drinks or chocolates), or UK service brands (e.g. banks or newspapers). This mix and variety of brands was used to increase the likelihood of identifying a range of brand preferences within the specific experimental population. The rating phase was a computer-based rating questionnaire where the participants were asked to rate their familiarity, preference, and loyalty to 40 different brand images. These were presented one at a time in a random (self-paced) order – each image was presented a total of four times, thus participants made 160 responses. Each image remained on-screen until a rating was indicated via a keypress, with possible ratings being: 1 = "very disliked"; 2 = "dislike"; 3 = "neutral"; 4 = "liked"; 5 = "very liked", with the same Likert-scale used for familiarity and loyalty. The measure of liking was used as the criteria for inclusion in the main phase, with the preceding question used to ensure consistency of preferred brand.

Procedure

The experiment consisted of two phases: The pre-rating phase and the temporal expansion phase. Participants initially sat through a brief presentation outlining the dimensions to be used within the pre-rating phase to ensure consistent dimension anchoring throughout. The pre-rating phase then began, and participants took 5 minutes to complete the task rating each brand logo being rated once per dimension. Participants' highest, lowest and two most neutral brand logos were then taken into the main phase.

During the main phase a blocked design was used, meaning that each level of image was used once during individual blocks. The ordering of the blocks was counterbalanced to a latin-square between-subject design. The main time subjective expansion phase ran the same as in Experiments 3A. Ensuring that for each of the three brand logos used as oddballs there were 50 duration responses.

Results

Analysis followed Experiment 3A in that once again we fit a square root weighted Sigmoidal curve to the participants response data to derived three measures: PSE, jnd and TEF.

There was an overall time expansion effect (Standard Duration 1050 msec, Oddball M = 823 msec, SE = 4 msec). However this was not modulated by brand rating, all p's >.5. We observered a significant main effects of brand rating on the jnd's, F (2,32) = 3.408, p = .0446. Post hoc tests revealed the difference lay within the "hated" condition, t (16) = 4.804, p = .02 See table 11 for means.

				95% Confidence Interval	
Measure	level	Mean	Std. Error	Lower Bound	Upper Bound
pse	"Hated"	835.412	46.174	737.527	933.296
	"Neutral"	826.412	49.943	720.536	932.287
	"Loved"	809.706	43.920	716.600	902.812
jnd	"Hated"	137.235 *	21.205	92.283	182.187
	"Neutral"	219.706	40.477	133.899	305.513
	"Loved"	226.059	37.696	146.148	305.970

Table 11: Showing the two derived measures by brand level. The asterix denotes significance difference p = .02.

Discussion

Of all the four experiments this experiment was the only one to show significant effects of the derived measures by level of value towards the oddball. And, this was only observed within the jnd measure. This measure is seen as an acuity measure towards the perceptual event rather than a difference of the perceived perceptual event. That is, participants did not see the oddball as being different in terms of its duration; rather they responses were more consistent between the 25% and 75% points. This effect could be driven by multiple reasons and will be discussed in the general discussion below.

General Discussion

In a series of four experiments we examined temporal expansion as a phenomenon which could serve as a possible index of attentional engagement. Throughout the studies we showed that the effect of subjective expansion of time towards an oddball is consistent as shown in previous studies (Tse et al, 2004; Seigfried & Ulrich, 2008). We expanded the literature by using stimuli that differed on dimensions of value towards them, using a variety of meaningful images. However, the value of the stimuli did not effect the perceived expansion of time within all of the experiments presented. Only one significant effect of value was found using brand logos in Experiment 4. Within this experiment there was a difference with the perceptual acuity towards the perceptual event, as highlighted in differences in jnd. Taken together, these results suggests that the temporal expansion phenomenon is related to attention and the novelty of the attention grabbing stimulus regardless of the emotionality of the oddball. We hypothesise that novelty in and of itself creates an orienting pulse that distorts time perception. The fact that this orienting pulse is insensitive to the content of the orienting stimulus suggests that this phenomenon may either originate very early in visual processing, and/or orginate in a stream that does not carry details of the specifics of visual stimuli (e.g. sub-cortical or tectal pathway). The impact of this orienting pulse on time perception is likely different than the effect observed by others with longer durations (e.g. Angrilli, et al, 1997). Given sufficient time to process the visual information, the emotional content of the stimulus may impact time perception in higher cortical areas (through the geniculocalcarine pathway).

Previous studies on emotion and attention highlight the impact that varying levels of emotion can have within attentional paradigms (Yiend, 2009). What is different to the majority of these studies in comparison to these experiments is the information processing required and the subsequent response required by the participant. For example, within the visual search paradigm there is a stimulus bound response, in that participants are required to report the face within an array of faces. It is perhaps this local processing of the stimuli that effects attention, rather the global processing of the perceptual event that is required within the temporal expansion paradigm employed here. Firstly, it has been suggested that global feature processing is more of a dominate force than local processing (Kimchi, 1992). This effects attention in that it bias it towards the local processing more than the global processing within the task (Clore, Gasper, & Garvin, 2001). Within the visual search paradigm the local feature processing is boosted by the affective value of the stimuli, and that in turn leads to performance differences based upon conditions. However, within the temporal expansion tasks reported here the visual presentation and the duration to which the participants respond to are closely tied. That is, participants are not required to process any local features for them to correctly report the time just the global feature of time. This is one possible explanation of the null effects found in these experiments. However this explanation does not hold up fully when examining the previous literature using this task, for example when local features of the stimuli were altered (for example, when using an expanding oddball disc within stationary disc standards, see Experiment 3 in Tse et al., (2004)) a stronger effect of times subjective expansion was found.

If we suggest that local processing can occur within this paradigm, then what other explanations are there for the lack of an effect. One other explanation, as mentioned previously, is that the stream of processing required within the task is too low-level to incorporate the meaningfulness of the stimuli into the perceptual event. In the extreme case we could suggest that the timing information required for the correct replication of time duration estimates is as low-level as the tectal pathway, which supplies information directly towards attention networks within the parietal cortex rather than the information requiring the geniculocalcarine pathway where the information flows into the ventral and dorsal streams. However, one less extreme explanation is that the networks that process the emotional information and the attention information are disassociable within the prefrontal cortex. To make this claim, however, we must look at previous literature on the networks of emotion and attention.

So firstly, let us look at literature that has examined the dissociable networks of emotion and attention in higher-cortical regions, namely the prefrontal cortex. Indeed Yamasaki, LeBar & McCarthy (2002) tried to do such using an oddball paradigm and using IAPS images as distracters in an attention task. Their results highlighted that attention and emotion differ in their neural representation in the prefrontal cortex (with the attention information residing in a dorsal stream, and the emotional information residing in the ventral stream), and that the information between the two is integrated within the anterior cingulated cortex (ACC) (Yamasaki, et al., 2002). Furthermore research on the oddball paradigm highlights the heightened activation of the ACC during the presentation of the oddball, an orienting affect classically seen as the P300 (Potts et al., 1996). Taken together, the suggested role of the ACC in the oddball task coupled with the possible integration of emotional and attention in the ACC (Yamasaki et al., 2002) suggests if the time perception effect is occurring in higher cortical areas then there should be some form of modulation of the effect based on the emotionality of the stimulus. Without this effect, as demonstrated in the above experiments, we can make the claim that the time subjective expansion task is fundermentally controlled by low-level processes. Obviously there are limitations to this explanation, which will be discussed later on.

One finding that we must not ignore is the jnd difference found within Experiment 4. To reiterate we found that "hated" brands had a smaller jnd than either "loved" or "neutral" brands. So firstly, what does a difference in jnd mean, and secondly what does this difference mean within this task.

The derived measure of jnd comes from the slope between the 25 and 75 percentile, and is classically seen as an observer's minimum amount by which a change in stimulus value alters a difference in the perception. For example within the current set of experiments the average jnd was 190 msec, as such the duration of the oddball would have to differ by 190 msec for an observer to tell the difference between two oddballs (NB: This is directly related to the oddball effect, meaning that the step-size would be different if comparing two durations without the standard interval used in the task). So when we compare the stimuli within Experiment 4 "hated" brands have the lowest jnd of all the experiments, that of 137 msec, Meaning that there is a heightened sensitivity to perceptual shifts within this condition. So what are the possible reasons for this? Well one possibility is that it is a sign of an attentional capture of the "hated" brands. Take for example Roesch, Sander, Mumenthaler, Kerzel, & Scherer (2010) study on the psychophysics of emotion, within this study they looked at the time required to make a categorical judgment towards facial expressions. They found that there were no differences in the thresholds (PSE) required to make the judgments, but indeed found a difference in the jnd's for both fearful and happy faces. This led them to the conclusion that there is a difference between the perceptual systems processing information, and the processing priority of the stimuli. And when the priority of the stimuli is high (i.e. more attentional capture) a more informative and less variable response is given (Roesch, et al., 2010). However, why do we only show this effect within one condition over a number of studies used to assess this effect?

The most simple of explanations is that the stimuli did not evoke another affect in the participants to elicit attentional capture. And it was only during the most evocative condition, "hated" brands, that any attentional effect occurred. In the future, we could to address this question directly by looking at skin conductance response (SCR) towards the oddball, however there are some fundamental issues which makes this task difficult to use within this experiment design, especially in terms of the signal to noise ratio being too low due to high task variance (e.g. the variance in duration of the oddball could lead to variance in SCR, coupled with possible habituation effects and high stimuli variance). One other explanation is that the task what not sensitive enough towards perceptual variance to clearly demonstrate jnd differences. In the Roesch et al., (2010) they used a Bayesian adaptive staircase known as QUEST (Watson & Pelli, 1983), in future studies we could consider using this design to possible ascertain a better measure of variance of the jnd. Indeed currently a study is using this within the time subjective expansion paradigm as well as using a similar paradigm to Roesch et al. (2010) to further probe the effect of meaningfulness on time, specifically targeting possible differences between the perceptual event and the variance towards that perceptual event.

Conclusion

Meaningful images led to no difference in the perceived subjective experience in an oddball paradigm looking into times subjective expansion, however in one of the conditions the just-noticeable difference differed as a function of stimulus value. As such, we suggest that within the present task, attention is the dominate driver in the effect, and meanings role is limited and often seemingly non-existent. Meaningfulness can impact upon performance, but at the low-level the effect is minimal and does not alter what the observer perceives.

Chapter 4: Meaningful Images and Inhibitory Control

In the following chapter we will discuss two studies that have looked at the role of meaningful images in inhibitory control. The first experiment discusses a subjectively rated stimulus-specific effects of meaningful images on inhibition, and the second experiment looks at both stimulus and state specific effects of meaningful images. Inhibition is an essential cognitive process and the way in which we are able to filter out information is especially important in how we relate and act towards meaningful images. In this chapter we look at these performance effect, and in Experiment 10 of the chapter we look at both the performance effects and their possible neuronal representations.

Experiment 9: Brands and Inhibition: A Go/No-Go Task Reveals the Power of Brand Influence

Within the consumer environment there is an abundance of products, and a large amount of brands for the consumer to select from. When faced with the option of selecting a new TV, do you choose a Plasma or and LCD, and subsequently will that be a Sony or a Samsung or any of numerous other brands. During each stage of the consumer decision-making process there are options to choose from, and as a result when choosing one option we must inhibit others. This process has been studied in relation to the process of inhibitory effects in memory; for example, for brand recall (Alba & Chattopadhyay 1985,1986; Miniard, Unnava, & Bhatla, 1991; Lindsey & Krishnan, 2007) and memory for advertisements (Burke & Srull, 1988). However the process this study is concerned with is action-based (response) inhibitory control. More specifically, we are interested in understanding the way in which brand logos can evoke differential effects on inhibitory control dependent on brand familiarity and "liking". Research on familiarity and liking has often focused on the concept of a mere exposure effect that is well documented, and will be discussed, however in this research we will focus on the effect of incidental stimulus (brands) on inhibitory control.

Inhibitory Control

One of the dominant ways to understand inhibitory control is by building up a mandatory response to a stimulus and then requiring the participant to withhold this response on cue. This approach is present within the Go/No-Go (GNG) paradigm (see Think/No-Think for another example (Anderson & Green, 2001)). In the GNG paradigm, a pre-potent tendency to respond is created in the participants by presenting them with trials that require a response a high proportion of the time. For example, around 90% of trials might require the participant to perform an action (e.g. press the space bar) when a stimulus is presented. However, on the No-Go trials (e.g. 10% of trials), the stimulus is immediately repeated and the participant is required to withhold responding whenever this happens. As the participant becomes accustomed to responding to a stimulus, the act of inhibiting a response becomes unnatural and as such the task taps into the processes involved in inhibitory control.

Over the past few years researchers have used the Go/No-Go task to examine a variety of questions, from clinical populations, to motivationally relevant stimuli. For example, Roberts et al., (2008) examined influences menstrual cycles, Garavan and Stout (2005) looked at populations of substance abusers, and Schulz et al. (2007) looked into affective disorders. We present a brief overview of these findings in the following paragraphs.

In regard to menstrual cycle, Roberts et al. (2008) examined the ability of women to inhibit responding to photographs of attractive males. They used such photographs in a simple Go/No-Go paradigm and obtained both behavioural and fMRI data. They found participant's performance varied as a function of menstrual cycle phase. Specifically, in the *f*MRI when participants were in the midlueal phase of their cycle, when they were most likely to conceive, there was a decreased activity in right ventral Inferior Frotal Gyrus during the trials of males faces in the follicular phase in comparison to female faces. This finding highlighted the role of motivation within the GNG, in particular the evolutionary relevance of the stimuli impacting upon the ability of inhibition. That is, the ability to be able to filter the information about male faces during peak chances of conception is crucial to maximize the changes of selecting the right male, which Roberts et al. (2008) discussed in relation to parental investment theory (Trivers, Willard, 1973).

In regard to affect the Go/No-Go has had widespread use in testing the emotional processing capability of healthy adults and patients with affective disorders (Schulz et al., 2007, 2009). For example, Murphy and colleagues (1991) found that manic patients are faster to respond to happy stimuli and similarly, depressed patients are quicker to respond to unhappy stimuli, similar results were found with errors during the task with depressed patients (Erickson et al., 2004). In addition, a GNG study using affective facial expressions found participants responded more slowly to frightened faces and found it difficult to appropriately inhibit responses to happy faces (Hare, Tottenham, Davidson, Glover, & Casey, 2005).

Liking and Familiarity

It is generally agreed within the marketing domain that there is a relationship between how familiar one is with a brand, and how in turn this affects liking (Rindfleisch & Inman, 1998). However this relationship between familiarity and liking is indeed bi-directional. With views held that familiarity leads to liking often explained through the increased perceptual fluency of the stimuli after repeated exposure (Reber et al., 2004) resulting in an increased liking of that stimuli. Whereas heuristic and prototypical effects providing the underpinnings of the opposite effect, when liking leads to familiarity (Monin, 2003). However, Rindfleisch & Inman (1998) suggested that within brands this relationship is somewhat different, and instead of being based on mere exposure it is indeed the social desirability that drives the familiarity-liking relationship. To this end it is important for us to constrain our brand set to more privately-consumed products, with this controlled for we can examine not the underpinnings of the relationship, but how these two effects impact separately on inhibitory control.

Aims of present study

Previous research has used the GNG paradigm to understand inhibitory control. More recently, studies have investigated the effects of motivationally relevant stimuli on participant performance within the task (Roberts et al., 2008). Previous research has also been conducted with affective stimuli (Schulz et al., 2007). However, brand logos are stimuli, which may have both motivational and affective relevance. To separate recognition from affect, and more specifically familiarity from liking, we choose to use two sets of brands: one set comprised of familiar brands and the other of unfamiliar brands. Due to individual differences in brand familiarity and liking, we expect to find a distribution of liking and familiarity towards the brands. With the previous literature in mind, we predict that there will be an overall effect of familiarity, which will be shown by a faster response to familiar brands than unfamiliar brands during the no-go (NG) trials. Furthermore, we predict that there will be an effect of subjective liking towards the brands, this will be more elusive and will be present as a biased response towards the liked brands.

Method

Participants

Twenty-Eight undergraduate psychology students (15 Female, Mean age 20.1) from Bangor University volunteered to participate through an online experimentation booking system. The entire procedure took approximately 30 minutes and participants received course and printer credits for their participation. The research was approved by the School of Psychology ethics committee.

Apparatus

The E-Prime experimentation software (PST, 2002) was used to conduct both parts of the experiment. The software ran on Pentuim 4 (3.06 GHz) computers running the Windows XP operating system platform. The experiment was displayed on 17" CRT monitors (800x600, 85Hz, 32bit). Participants sat in front of the monitor at an approximate distance of between 40 – 60cm; and, during the GNG task they placed their dominant hand on the space bar.

Stimuli

120 brands were used throughout the tasks; there selection was based on previous results obtained at the lab and also our intuition to which brands would be unfamiliar to UK students. 60 of the brands were familiar and ranges of brand categories were used. The dimensions of the brand stimuli was 320 x 320 pixels. Each image was a NoGo trial once.

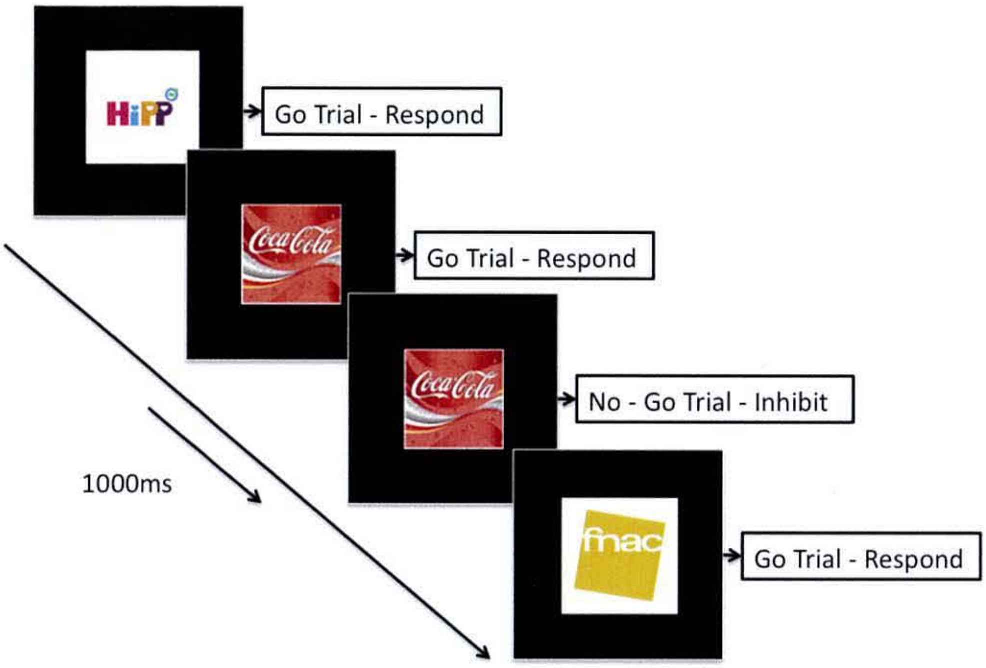

Figure 12: Schematic of the GO/NO-GO trials. Each trial lasted 1000ms, with stimulus presentation lasting for 600ms and an ISI of 400ms. During go trials participants were required to make the response during the trial time 1000ms (not just when the image was on the screen), during the no-go trials participants were required not to make a response in the 1000ms trial window.

Measures

During the rating phase of the experiment participants were asked two questions about the brand logos: "How familiar are you with this brand?" and, "How much do you like this brand?" They responded to these questions on a likert scale. The scale was five points ranging from one being negative, three being neutral, and five being positive responses.

Procedure

The experiment was run in a batch-testing set-up, meaning that a maximum of 6 participants could be run at the same time. After a brief presentation on the requirements of the participants during experimentation, the participants were given an information sheet and consent form, which they were asked to complete before continuing. The experiment took approximately 25 minutes with the Go/No-Go task lasting 18 minutes and the rating task lasting approximately five minutes. Participants sat in one of two rooms, which each had three computers in. The rooms were dimly lit and participants sat at a chair with there eyes approximately 60cms away from the screen. Dividers and headphones ensured that adjoining participants did not influence performance.

After signing the consent form the experiment proper began. Participants were informed that they needed to respond as quickly as possible when the brand logos were presented onto the screen during the Go trials, and not to respond to the brand logo during the No-Go trials. The ease of the task meant that no practice block was necessary, as an example was shown to them during the pre-experiment briefing. The required response to the Go trials was the spacebar, and participants were asked to place both index fingers on it. The Go/No-Go trial frequency was 1 Hz meaning that each trial lasted for 1000msec and was preceded and succeeded by trials of the same duration (see Figure 1). Within the 1000msec trial window the brand logo was presented for the first 600msec, and the remaining 400msec was a blank screen. Thus resulting in an inter-stimuli-interval (ISI) of 400msec. During the ISI the screen was black, during the logo presentation the logo took up the centre 320x320 pixels of the screen and the rest was the same black as in the ISI. The Go/No-Go experiment consisted of 1080 trials broken into four blocks of 270 trials; during the end of block participants had a self-timed break (minimum of 30 sec). In each block there were 30 NoGo trials, meaning in total there were 120 NoGO trials.

After completing the Go/No-Go experiment participants then started the rating task, at which point they were told the dimensions on which they would be rating the brands. Participants were also informed that the familiarity and liking should be unrelated to there performance within the task, that is, not to rate the brands that were unfamiliar to them previously to the Go/No-go task as now being familiar. The order of presentation of dimensions was always familiarity followed by liking, so that any effect carry-over was kept the same between participants. Each trial presented the brand image in the centre of the screen with text prompt displayed at the bottom of the screen showing the scale and the required response. Upon completion of the rating task participants were thanked and then debriefed about the study.

Results

Familiarity

Each participant's ratings were used to divide the stimuli into two sets: one set consisted of brands that had the rating 1 (most unfamiliar), and the other where the rating was 5 (most familiar). Stimuli having these extreme ratings of either 1 or 5 accounted for 82.28% of the stimuli across participants (SD = 12.33%). A set of paired-sample t-tests was used to compare GNG performance for familiar and unfamiliar brands. Differences omission errors were significant $t(27)=2.039$, $p=0.05$, MD=0.714, SE=0.350. (Figure 13, panel a). Average reaction times for the GO trials showed no significant difference as a function of familiarity, $t(27)=0.783$, $p=0.44$, MD=1.66, SE=2.76, (Figure 13, panel c). Performance on NOGO trials (where participants were required to inhibit their response) revealed no significant difference in accuracy between conditions, $t(27)=-1.33$, $p=0.194$, MD=-2.31, SE=2.14, (Figure 13, panel b). However, the reaction times for errors of commission (mistakenly pressing a key when a response should have been inhibited) revealed a significant difference between the stimulus sets, $t(27)=4.699$, $p<.001$, MD= 21.70, SE=4.619 (See Figure 13, panel d). Specifically, participants made more rapid errors to familiar stimuli.

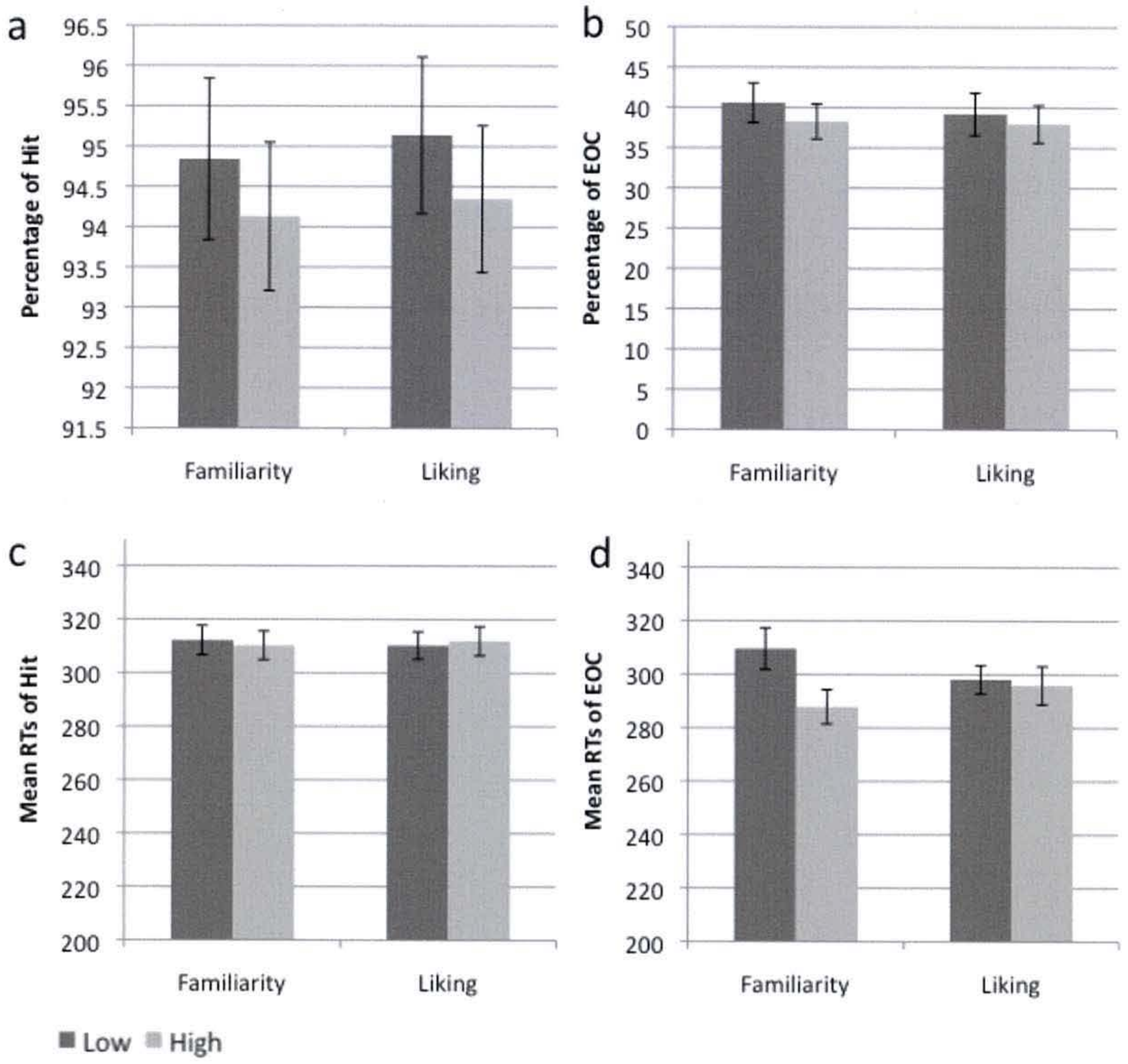

Figure 13: Performance of participants for the different measures, and different subjective-ratings. (a) Percentage of Hit for GO trials. I.e. pressing the space bar when required to do so. (b) Percentage of errors of commission. I.e. pressing the space bar when it was not required to do so. (c) Mean RT for GO trials, (d) Mean RT for errors of commission. Error bars indicate standard error.

Because performance on this task will be influenced by both sensitivity and criterion shifts, we next used a signal detection analysis on the accuracy data. We calculated measures of sensitivity (d') and response bias criterion (c) (Macmillan & Creelman, 1991). These values were calculated by taking into account "hits" (responding on a GO trial) and "false alarms" (errors of commissions, i.e. incorrectly responding on a NOGO trial). We found significant differences on the measure of sensitivity (d') as a function of stimulus familiarity, $t(27) = 2.523$, $p = 0.016$, $\eta 2 = 0.84$. Specifically, participants had worse perceptual sensitivity towards the *familiar* stimuli. The criterion (c) showed no significant difference between stimulus sets, $t(27) = 1.080$, $p = 0.290$, $\eta 2 = 0.50$.

We conducted further analysis to assess any effects that might have developed over time. To do this, we analyzed GO trial accuracy and EOC percentage between the 1st half and the 2nd half of the experiment. We conducted separate repeated measure ANOVAs with factors of FAMILIARITY (two levels) by HALF (two levels). For GO trial accuracy there was still the main effect of FAMILIARITY [$F(27,1) = 14.357$, $p = 0.001$] however, there was no significant difference across BLOCK [$F(27,1) = .702$, $p = 0.409$], and there was no interaction [$F(27,1) = 2.844$, $p = 0.103$]. For EOC there was an effect of HALF [$F(27,1) = 21.656$, $p = 0.000$], meaning that as time went on participants made more EOC (See Figure 14). There was no main effect of FAMILIARITY [$F(27,1) = .192$, $p = 0.665$] or an interaction [$F(27,1) = 3.027$, $p = 0.093$],

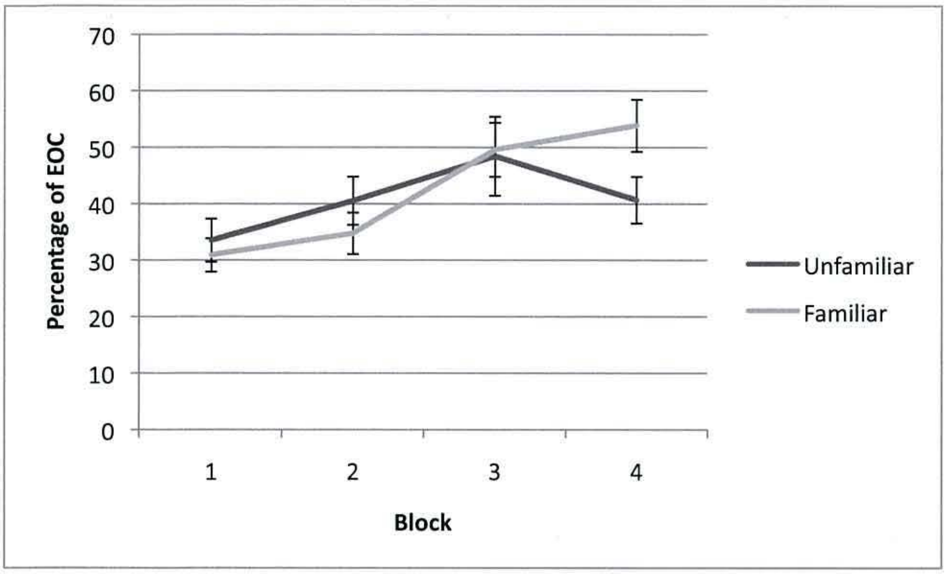

Figure 14: Errors of commission (i,e, responding when not required) over the four blocks. Error bars indicate standard error.

<u>Correlation and Brand Analysis</u>

A Spearman's correlation was conducted between familiarity and liking which showed a strong significant positive correlation, $r = 0.71$, $p = 0.000$. That is, the greater the rating of familiarity the greater the rating in liking, and vice versa. After conducting analysis separately for liking the results yielded uninformative differences. As such a targeted analysis was conducted to try and tease apart the two effects. With this in mind we now chose items that were rated as familiar by a participant (rating of 4 and above) and split these stimuli into liked (rating of 4 and above) or disliked (rating of 2 and below). Due to this more stringent selection criteria five participants were removed from the data set due to insufficient trials for reliability. After conducted repeated measures ANOVAs for measures of Go and EOC percentage and reaction times no significance was found (all ps >0.5).

For each brand image we plotted a number of scatter graphs to examine the mean EOC percentage (Figure 15), familiarity (Figure 16), and liking (Figure 17), and finally familiarity vs.

liking (Figure 18). Added to this we conducted analysis on the two rating dimensions (Table S1).

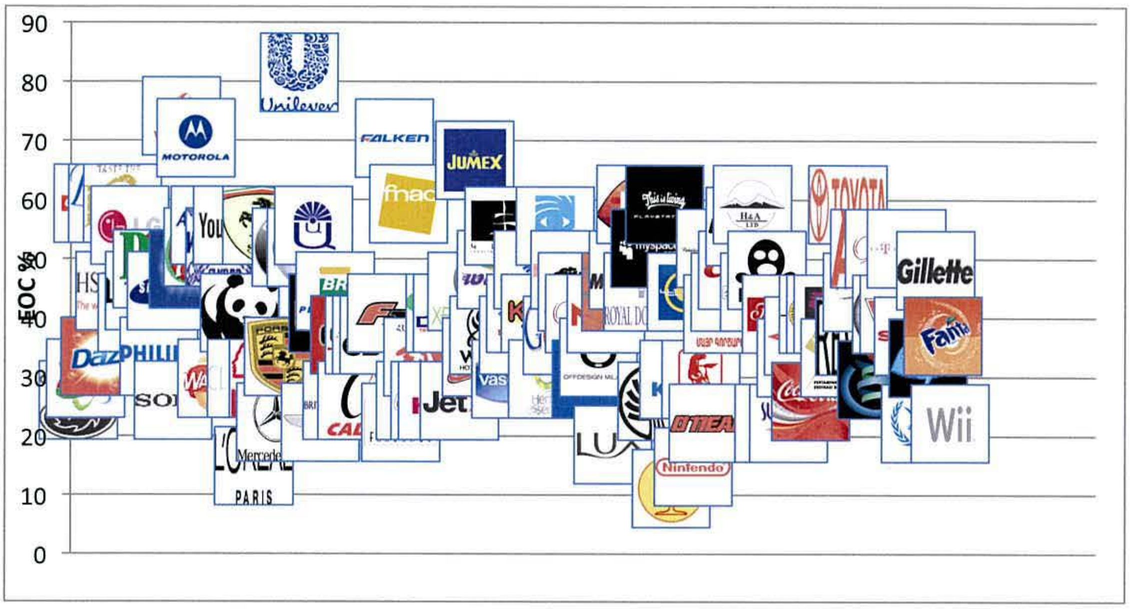

Figure 15: The EOC percentage by brand, the horizontal axis is arbitrary.

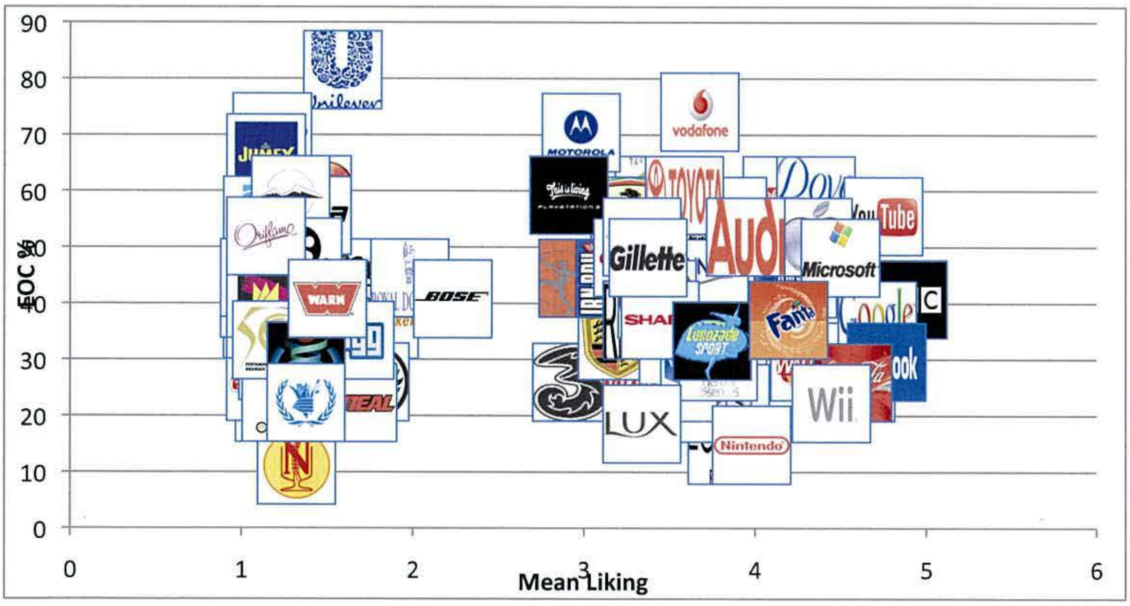

Figure 16: Scatter plot showing EOC percentage on the vertical and mean liking on the horizontal axis.

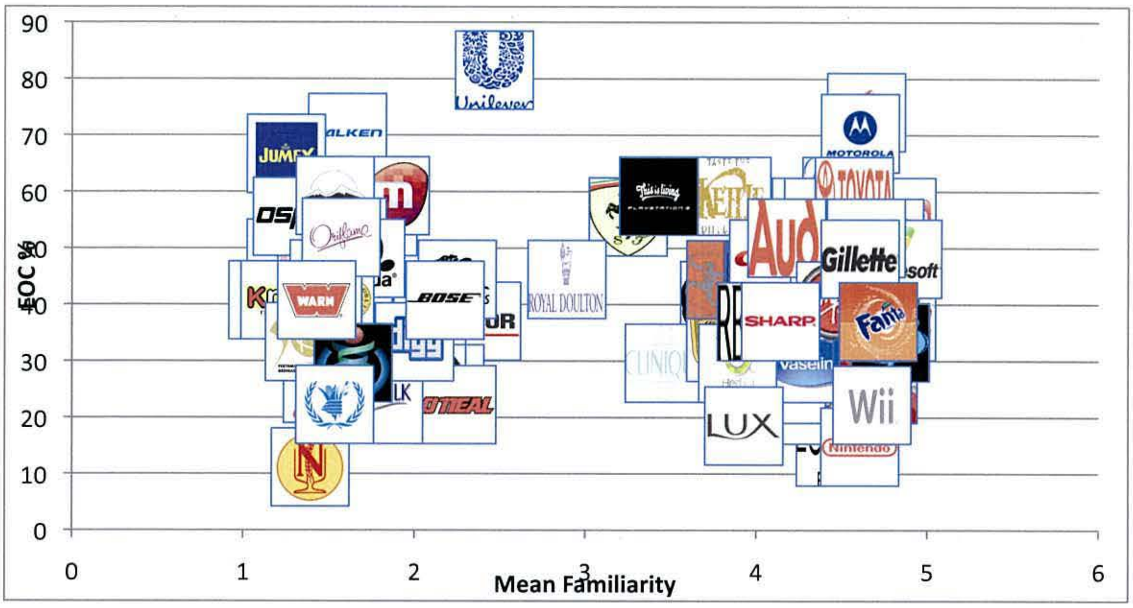

Figure 17: Scatter plot showing EOC percentage on the vertical axis and mean familiarity on the horizontal axis.

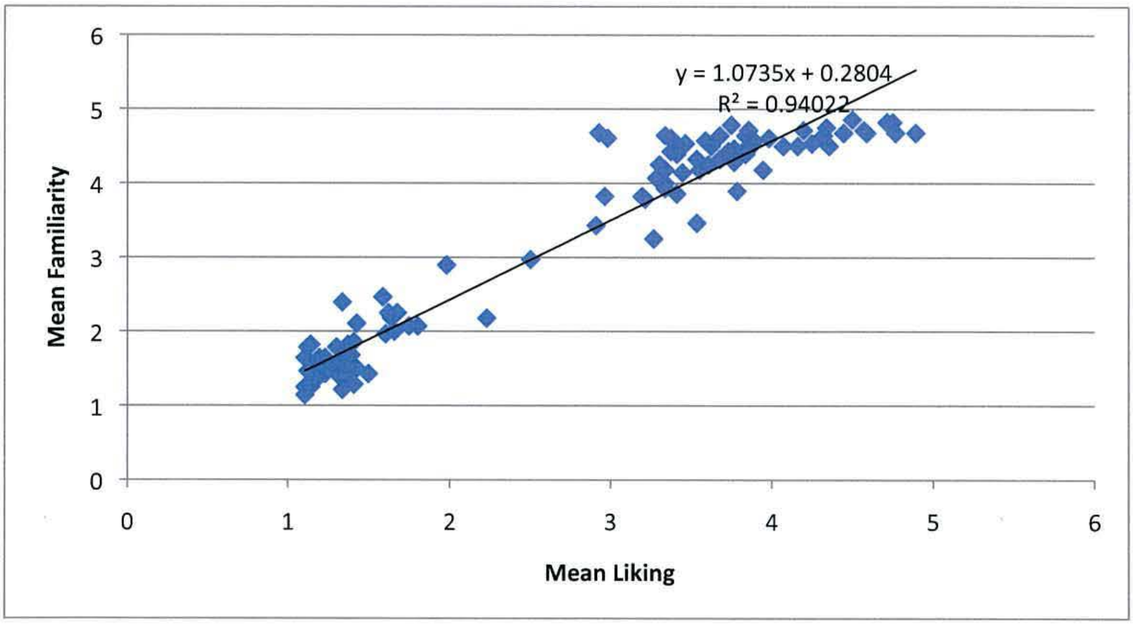

Figure 18: Scatter plot showing mean familiarity against mean liking. A linear trendline is also been appended to the scatter with the correlation coefficient and equation displayed.

Discussion

We found that familiarity produced significant and distinct effects on inhibitory control for brand stimuli. To our knowledge this is the first use of brand stimuli in an inhibitory control task, and the novel findings have both theoretical and applied implications for stimulus processing and brand-related inhibitory control. We found that participants were more likely to make more omission errors to highly familiar stimuli. We also found an overall greater sensitivity towards unfamiliar stimuli. Could these results be explained in relation to predominate models of inhibitory control?

First we consider Logan & Cowan's (1984) horse-race model of response inhibition. Their model (Logan & Cowan, 1984) was initially developed to explain results from the stop-signal paradigm (a conceptually similar paradigm to Go No/Go) and stipulates two processes (respond/inhibit) that compete for dominance on each trial. In this "winner takes all" model, the final behavioural outcome (respond/inhibit) will depend on whichever process passes its' threshold first.

How might familiar impact the horse-race model processes? Previous research suggests a tendency towards approach-related (respond) behavior with positive stimuli and a tendency towards withdrawal-related (inhibit) behavior with negative stimuli (e.g, Cacioppo & Gardner, 1999). In the context of the horse-race model, this suggests a faster "respond" signal in the presence of a familiar stimulus. However, this is not what we found. In terms of error rates, we saw a decreased approach-related (respond) behavior to the *familiar* stimuli. We found evidence for this counter-intuitive effect in both the lower GO accuracy for familiar stimuli. Recall that we observed faster reaction times for EOC when the stimulus was highly familiar. In terms of the horse-race model, this seems to suggest that the respond process was sped up. However, if this were the case, this same speeding should have also manifested itself as a difference in the GO RTs, and accuracy – a result demonstrated by several previous studies using GNG and emotional stimuli (Albert, Lopex-Martin, & Carretie, 2010) but a result that we did not observe.

Another possible explanation is that the effects could be due to the task demands and context effects present in the task. Specifically, in the GNG task participants are likely to be looking for a “signal to withhold responding”. They know that the (explicit) signal to withhold is the repetition of a stimulus. In other words, they must be constantly monitoring for a “repeat”. Although this may sound like a fairly straightforward task (“was this a repeat?”) it does place certain demands on the participant’s cognitive and attentional resources. Although this decision is achievable via reliance on traditional memory processes, perhaps within the context of the experiment, another (perhaps even easier) way to render this judgment is based on how familiar the stimulus seems. If a stimulus was *just* seen moments before, then it should be highly familiar. It might be this mechanism that leads to failures with the highly familiar stimuli. Specifically, when a highly familiar stimulus appears, the participant mistakenly attributes the immediate sense of familiarity engendered by the stimulus to a mis-remembered prior presentation of the stimulus, and thus they fail to respond.

Our original hypothesis was that highly familiar brand logos would have a greater “draw” and would thus make it more difficult for participants to inhibit their responding when required (i.e. more errors of commission). However, the story turned out to be more complex. While participants *were* equally able to withhold responding to both types of stimulus, we found that when they *did* make an error of commission, they made it far faster to the highly familiar stimuli. Taken together, these results suggest that whilst the “draw” of familiar/liked stimuli can be inhibited, such inhibition requires greater suppression of the highly-familiar stimuli and that when this inhibition fails, the greater draw of the highly-familiar stimuli is revealed via quicker errors.

Research into the déjà-vu effect (Jacoby & Whitehouse, 1989) may provide insight into the findings of the current study. An illusion of memory can be formed by the previous unconscious processing of stimuli (Whittlesea, 1993). Within this task one of the main findings was that high familiarity created poorer performance in the GO trials, something unintuitive at first. However, considering the task requirements (i.e. to recall if the previous stimulus is repeated), the illusion of memory towards familiar brands could directly interfere with this primary task. That is, if a participant sees a highly familiar brand then their response (or lack thereof) might be influenced by their illusory memory rather than task-relevant working memory.

Finally, a further explanation could be the understood using the dual competition framework as outlined by Pessoa (2009). In this model Pessoa proposes that the three components (inhibition, shifting, and updating) in executive control share resources and as a result the perceptual processing boost towards a stimuli can affect the behavioral outcome based on task demands. Within our task one could propose that the greater perceptual processing of the familiar stimuli led to an increased gathering of information, however due to the none threatening nature of the stimuli this effect was modest, or 'soft' prioritization occurs (Pessoa, 2009). As a result the overall effect on performance is weak, however due to the sensitivity of omission errors we capture the effect in this dependent measure rather than the inhibitory dependent measure. Indeed, the exogenous arousing quality of familiar brands may actually boost attention and resulting in better performance in terms of inhibition.

There are broader applied and theoretical implications of this study. Firstly, discovering the role of inhibitory control in consumer behaviour is essential, particularly given the prevalence of compulsive shopping (Dittmar, 2005), and the potential clinical implications compulsive shopping has. Understanding if inhibitory mechanisms are destabilized by the presentation of brands is crucial if there is to be future development of attentional modulation intervention tasks similar to those developed by researchers in addiction (e.g. Fadardi, Cox, 2009). For psychological research in general this study once again highlights the necessity to control for familiarity and liking, as the former may affect the accuracy of mnemonic judgments, whilst the latter may bias performance on the basis of valence. As such, a greater level of control should be placed on these stimulus characteristics, being treated both as independent and significant factors on experimental design and findings.

To conclude, brand familiarity and brand liking both contribute to a participant's inhibitory performance. A déjà-vu like effect appears to influence behaviour when a participant is very familiar with a brand. That is, one could suggest that participants knew they needed to enact inhibitory control, however they over compensated for brands with which they were very familiar. When this mechanism failed, however, their desire to respond quickly was evident. Taken as a whole, the results demonstrate that preexisting affect (liking) and familiarity can dramatically alter ones ability to exert inhibitory control. Future research may help unravel the relationship between these phenomena and such important real-world behaviours as brand-loyalty, compulsive shopping, and overeating.

Experiment2: The Neural Representations of Meaning

Throughout the thesis we have explored the role of meaningful images in performance and learning. There have been frequent discussions of the possible neural representations of these meaningful stimuli. Within this experiment we will explore these representations via the use of fMRI. Using the Go/No-Go paradigm once again we studied the role of both the motivational state of the participants (food manipulation) and its' influence on task performance to stimuli of altering motivational relevance (food vs. furniture). Food stimuli was used due to the well defined regions of interest present in neuroscience literature, and unlike other meaningful images food is innately salient and as such less subjective variability is present.

The use of food stimuli in neuroscience research has been broad (van der Laan, de Ridder, Viergever, & Smets, 2011). A stimulus that has intrinsic salient value, though whose value can change dynamically as a result of changes in motivational state (i.e. hunger) (Hinton, Parkinson, Holland, Arana, Roberts, & Owen, 2004), food and its impact on behaviour is crucial facet of human nature. As a mere stimulus its intrinsic salient value can be evoked by visual (Linné, Barkeling, Rossner, & Rooth, 2002), olfaction (O'Doherty et al., 2000), and/or semantic (Arana, et al. 2003) stimulation. In terms of state fluctuation a variety of motivational states have been experimentally induced, including hunger, satiety and craving. For example, numerous papers have looked at the influence of the state of hunger on task performance (van der Laan et al., 2011) consistently inferring a direct influence of hunger on both relevant (Leland & Pineda, 2006; Peich, Pastorino, & Zald, 2010) and irrelevant stimuli (Piech, Hampshire, Owen, & Parkinson, 2009).

<u>Neural Correlates of Food Processing</u>

Previous studies can be divided into studies that have looked at the neural circuitry involved in either the processing of food stimuli, or the consumption/ ingestion of food. These studies have been conducted using both human and non-human neuroscience techniques. The main purely perceptual taste centre is referred to as the gustatory cortex and comprises as the anterior insular and the frontal operculum (Kobayashi, 2006). However the key areas of interest to us are those involved in both the visual perception and cognition related to food stimuli. Within this literature what is clear throughout is the importance of the orbital frontal cortex (OFC) and sub-cortical regions, in particularly the amygdala and striatum.

A recent meta-analysis of human fMRI studies by van de Laan et al. (2011) looked at the neural correlates cohesions between studies looking into the visual processing of food. Dividing their analysis into three commonly assigned experimental manipulations (1 – Food vs. Non-Food; 2 – Hungry vs. Sated; 3 – High Energy Foods vs. Low Energy Foods) five key regions of interest were defined: Lateral OFC; Lateral occipital complex (LOC); Middle insular cortex; Amydala; and Striatum (van de Laan et al., 2011). In particular the lateral OFC is concerned with the processing of the visual presentation of the food stimuli when directly in contrast to non-food, and the variance of attributes of the food stimulus (i.e. aesthetical judgements). LOC is traditionally seen as a region sensitive to object categories (Grill-Spector et al., 2001), and as such during the food vs. non-food contrast this also shows a pervasive activation amongst studies. Another element of the LOC is the higher attentional capture of food stimuli vs. the contrast stimuli and its resultant impact on LOC activation (Peelen & Downing, 2005). Middle insular cortex is has been related to the actual representation of the taste and the craving therein (de Araujo & Rolls, 2004), and the memory associated with prior consumption of a food (Pelchat et al., 2004)

The subcortical straitum body in particular the ventral straitum has been a prelevent region of activity in food studies (van de Laan, et al., 2011). It is postulated that its pivotal position within the limbic system, and as such connectional association with amgdala and prefrontal cortex, underlies its role in anticipatory affect (Knutson & Greer, 2008). And in particular the nucleus accumbens encodes the response towards reward prediction, for example when decided to purchase desirable products (Knutson & Greer, 2008). With food stimuli this is highlighted through its increased activation towards high vs. low energy food (van de Laan, et al., 2011). Similarly the amygdala, has been implicated in the rewards processing as seen once again in high versus low-calorie food processing (Killgore, Young, Femia, Bogoroddzki, Rogowska, & Todd, 2003).

In relation to other meaningful images, there is strong cross correlation between the processing of the emotional information within brands, faces, and IAPS and the neural correlates discovered within the food stimuli focused studies. For example, McLure et al. (2004) clearly demonstrated the role of OFC and amygdala in the processing of brand information. This is often referred to as a universal centre for currency, where the brain represents the future reward in a scalar internal currency (Montague & Berns, 2002). In particular the obitofrontal and striatal circuty that computes an ongoing valuation of the potential payoffs of a stimuli irrelevant of the actual stimuli itself (O'Doherty et al., 2001).

Decision making and food

Throughout the thesis we have discussed the role of meaningful stimuli on performance and learning. There has been some research to date that has looked at this in correspondence with food stimuli. For example, Piech et al. (2009) looked at the role hunger had on the ability of participants to shift their attention sets using a well-defined set-shifting task (Hampshire & Owen, 2006). In this study it was demonstrated that our cognitive flexibility could be altered negatively if we were in heighted motivational states. In particular large effects were shown during "stimulus-induced desire", this procedure involved a 4-min presentation of food stimuli vs. a 4-min presentation of flower stimuli before participants performed the attentional set-shifting task.

Another relevant paper looked at the neural activation elicited by restaurant menu presentation (Piech et al., 2010). In this study participants choose between three items on a menu, and the trial would ask for this decision based on which item they thought easiest to cook or, which item they would like to eat. This manipulation was selected so to evoke either an affective response (i.e. like to eat) of the choice, or a more cognitive response (i.e. ease to cook). In a sense these two decisions fell either into the "fast and frugal" system one decision or the "slow deliberate" system two decisions (this was discussed extensively in chapter 2). A further hunger state manipulation was present in the study (i.e. hungry or sated). Critically this study highlighted the role of the medial prefrontal cortex in the affective choice as opposed to the OFC, this was suggested as role of value prediction during the affective choice and the role of suppression in the cognitive task (Piech et al., 2010). Indeed this study highlights how the neural representations of the food stimuli can differ on the meaning evoked by the decision of question, that is the intrinsic value can alter as a function of task demands.

Further afield from the research on food, researchers have looked at motivational state and the neural response to stimuli that is specific to the state. For example, Roberts et al. (2009) was discussed earlier on in the thesis and once again this paper is of important relevance to the present study. In particular the study itself used an identical behavioural paradigm (i.e. the Go/No-Go task with pictures), and furthermore it looked how meaning of stimuli modulated BOLD response. Specifically this study showed modulation of the neural circuitry based on sexual desire (motivational state) towards relevant meaningful images (attractive men), highlighting that the level of meaning can be both state and stimulus driven.

Willpower

In Experiment 9 we briefly discussed the role of will-power on the ability to in act inhibitory control towards meaningful stimuli in a task. In particular we demonstrated that during the task depletion of the inhibitory control systems occurs. As such one of the ways in which this could be experimental induced is either to create a stimulus-induced desire intervention (see for example Experiment 6, or Piech et al., (2009)). Or an alternative way to measure the depletion of inhibitory control willpower is to boost or reduce it via the administration of sugar. Previous studies have demonstrated that giving either a sugary or non-sugary drink can influence willpower (Masicampo & Baumeister, 2009). Masicampo and Baumeister (2009) looked at how participants were able to inhibit a “decoy” option within the selection of three items within a commonly demonstrated effect of attraction on decision making. Participants were divided into two groups, one where they received lemonade with added sugar (glucose) and one where they received lemonade with added artificial sweetener (non-glucose). After this they then performed a self-control task which was either depletive or not. The critical dependent variable was a decision making task administered at the end of the experimental session, this was in the form of a three alternatives decision where two of the alternatives were closely matched and one was not. This type of task creates an attraction effect towards the two that are matched, effect is seen as a system one decision error. It is hypothesised that these system one errors become more frequent when cognitive resources have been depleted, and it was this hypothesis that held true for the Masicampo and Baumeister (2009) study.

Further research on willpower and perception has been conducted within the neuroscience literature. For example (Chambers, Bridge, & Jones, 2009) looked at the perception of effort in high and low glucose manipulated states on exercise performance. One apparent problem with the administration of a drink (as seen in Masicampo and Baumeister (2009)) is the possible impact the increase of glucose levels would have on the physiology of the participants. As a result Chambers et al. (2009) required only a mouthwash of the drinks (i.e. no ingestion) to be administered to the participants. With this in mind in our present study we would only administer mouthwashes as a form of state manipulation.

Aims

In the present experiment, we sought to combine previous findings on the neural circuitry involved in the visual presentation of food and that of inhibitory control. Furthermore to elicit differential levels of motivational relevance of the meaningful stimuli we made two state manipulations. The first state manipulation being the hunger of the participant, and the second being the levels of willpower. Added to this the paradigm that will be used will look at the inhibitory systems involved. More specifically, it will be the interaction between the state dependent and stimulus specific effects that allow us to explore how we represent meaningful images within an inhibitory control task. In terms of the neural circuitry involved in the task, we expect that during the state of hunger participants will encode the anticipatory response towards food items as being more rewarding, and as a result the required response for their ability to enact inhibitory control will be subsequently increased. In particular circuitry in the obitofrontal straital circuity, and inhbititory networks will modulate as a function of these experimental manipulations, in both stimulus and state driven effects.

Method

Participants

14 healthy volunteers participated in the study (three females; two left-handed; group average age was 25.6, SD=3.2). Each participant came to three sessions apart from one who came to four during which one of the sessions recording anomalies required him to be withdrawn from that session and return later. All participants were either staff or students at Bangor University, and they were paid £40 in total for the three sessions. No participants indicated any dietary conditions specific to the present study. The study gained ethical approval via the Bangor University School of Psychology Ethics Committee.

Design

Participants were allocated into one of three sessions before they came for the fMRI recording, and this order was counterbalanced. The three sessions were HUNGRY SUGAR; HUNGRY WATER; SATED SUGAR. Each participate came to the study at roughly the same time (within an hour window) for each one of the sessions. All sessions took place during the morning, and as such the main difference between sessions was whether they had consumed breakfast or not. Participants in the two HUNGRY conditions were instructed to not eat after 8pm on the evening before the sessions and not to consume breakfast. They were also instructed to only drink water. In the SATED condition participants were told to eat normally and have breakfast before they came to the session. At the beginning and end of each session levels of hunger were recorded via a visual analogue scale, which ran from 0 (not hungry) to 100 (extremely hungry). To measure the willpower effect a mouthwash was administered 12 minutes before the fMRI recording commenced. The mouthwash could be either tap water, or a sugary drink. With HUNGRY SUGAR and SATED SUGAR sessions participants had the sugary drink, and HUGRY WATER session participants had the water. Each session lasted approximately 1 hour with another research study ran concurrently. The tasks scanning time began at the beginning of the recording session and lasted 26 minutes.

Procedure

After a pre-screening interview where an information sheet and consent form participants were allocated to one of the sessions and given instructions via email as per their condition. Participants arrived at the Bangor Imaging Unit at roughly the same time of the day each time and the procedure was as follows. They were given forms to fill out (consent; MRI safety questionnaire; visual analogue scale for hunger; basic information; last meal dietary information) whilst they used the condition specific mouthwash. The mouthwash was 200ml and participants were informed to use it whilst filling out the forms, which would on average take 2 minutes. After this phase participants blood glucose levels were taken via a commonly used thumb accumeter. After the blood sample was provided the participant was placed in the scanner and the experimental task requirements for the Go/No-Go were outlined. The presentation was via a rear projection screen, which was viewed through a mirror, placed on the head coil. For the task they were told to respond as quickly as possible the instant the item was presented on the screen (Go trial), and not to respond if the item was repeated (No-Go Trials). Responses were made via a button box, which was placed on the participant's abdomen, and for go trials a single press of a button was required using the participants index fingers. The GNG trial frequency was 1 Hz (see Figure 1). Within the 1000 msec trial window the image was presented for the first 800 msec, and the remaining 200 msec was a blank screen grey screen. During the presentation period the image took up the centre 320x320 pixels of the screen and the rest was the same black as in the ISI. The Go/No-Go experiment consisted of 1080 trials broken into four blocks of 270 trials. At the end of each block participants had a self-timed break (minimum of 30 sec). Resulting in each stimuli being a NoGo trial once and a Go trial eight times. Following the GNG task participants were ran in another study, and after conclusion of this they were then removed from the scanner and a further blood sample was taken. Participants were debriefed, and paid at the conclusion of the third scanning session.

fMRI Acquisition and Analysis

For fMRI recording a Phillips Intera Acieva 3.0T MR system was used. An intial reference scan was conducted for participant slice alignment and to resolve sensitivity variations. All scans used the SENSE parallel approach (Pruessmann et al., 1999). For the anatomical scan a T1-weighted high resolution parameters were used (FOV 288 288 , 130 continuous axial slice, voxel size 1x1x1) taking 8 minutes. For the T2* weighted echo-planar imaging sequence thirty-four 3 mm thick continuous slices axial slices were collected, (FOV 230 230, 2.4x2.4x3mm, TR: 2000 msec, TE: 58 msec, 96 x 96 matrix size in Fourier space).

The fMRI data was analysed in Branvoyager QX 2.2 (BrainInnovations Inc., 2001). The time-series data was motion-corrected using trilinear interpolation with the first time-series data from session one as reference volume. A cubic spline slice time correction was conducted on the ascending intereleaved time-series data, as well as a high-pass 0.006Hz Fourier temporal filtering. All time-series data was fitted to a Talairach space (Talairach & Tournoux, 1988), and no spatial smoothing took place.

The time-series data was modeled as follows: All GO responses were collapsed and used as baseline response, four predictors were modeled from onset to offset: Incorrectly responding to Food when participants are required to withhold the response (i.e. Errors of commission; EOCFood); Incorrectly responding to Furniture when participants are required to withhold the response (i.e. Errors of commission; EOCFurn); Correctly not responding to food when participants are required to withhold the response (i.e. Correct Reject, CRFood); Correctly not responding to furniture when participants are required to withhold the response (i.e. Correct Reject, CRFood). Trials when participants missed were discarded due to infrequence (1%). A variable of session was also included as a predictor. Added to the six motion predictors a total of 10 predictors were regressed against the baseline to form a hemodynamic response function.

The main analysis was an unconstrained whole-brain random effects procedure. We used a threshold of clusters containing 25 or more voxels, and an uncorrected propability value of .005. Bonferroni correction was not used due to its over stringent nature, however when possible these corrected scores will be reported. For the interaction a 2 (NoGo) x 2 (Stimulus) x 3 (State) Three-Factors ANOVA With Repeated Measures was conducted, using the ANCOVA analysis tool in Brainvoyager QX with % change volume of interest analysis conducted after voxels pass threshold.

Results

Results will be broken down into three sections; first we will describe the state questionnaires that looked at the hunger levels between participants. Secondly, we will describe the behavioural results, and finally we will outline the fMRI results.

State Manipulation Results

An 3 level repeated measures ANOVA was conducted on the participants levels of state for the three sessions. There was an overall significant difference between levels of state, $F(2,26) = 46.017$, $p = .0001$, post-hoc t-test revealed significant differences between both Hungry Sugar vs. SatedSugar , $t(13) = 7.161$, $p = .000$, and HungryWater vs. Sated Sugar, $t(13) = 7.962$, $p = .000$, with higher levels of hunger in both the HungryWater ($M = 51\%$ $SE = 4\%$), and HungrySugar ($M = 49\%$ $SE = 6\%$) as compared to SatedSugar ($M = 7\%$ $SE = 1\ \%$). This reveals that the state manipulation of hunger worked in terms of the subjective feeling of hunger as measured by a visual analogue scale.

Behavioural Results

A 3 (State: HungryWater vs. HungrySugar vs. SatedSugar) × 2 (Stimulus: Food vs. Furniture) ANOVAs on the error of commission (EOC) revealed a significant main effects of stimulus, $F\ (1,22) = 10.453$, $p = .008$, but no main effect of State or interaction (all $ps > 0.05$). That is participants made more errors to Food stimuli vs. Furniture stimuli.

fMRI Results

When participants failed to correctly withhold their response during the NoGo trials (EOC) we saw overall main effect activation in right Superior Frontal Gyrus, right anterior cingulated, and bilateral posterior cingulated (see Table x) these are regions that often are highlighted within this task (Roberts et al., 2008). There was one area that showed an interaction with stimulus type the rightSFG, $F(1,25) = 8.622$, $p = .008$, with Food stimulus showing greater activation than Furniture (see Figure 18). No state effects were shown on the original analysis, so we removed one of the Hungry conditions and so now had a 2 levels of state, showed a large effect of caudate activity, $F(1,25)=26.69$, $p = .000049$, with heightened activity in the Hungry state as compared to the Sated state. Added to this there was no interaction between state and stimulus.

When participants correctly withheld their response during the NoGo trials (STOPS) activity was present within commonly assumed structures in inhibitions (Garavan et al., 2002; Garavan et al., 2003; Li et al., 2006; Roberts et al., 2008) see Table 11. However, there was no main effects of stimulus type or phase, and no stimulus by phase interaction.

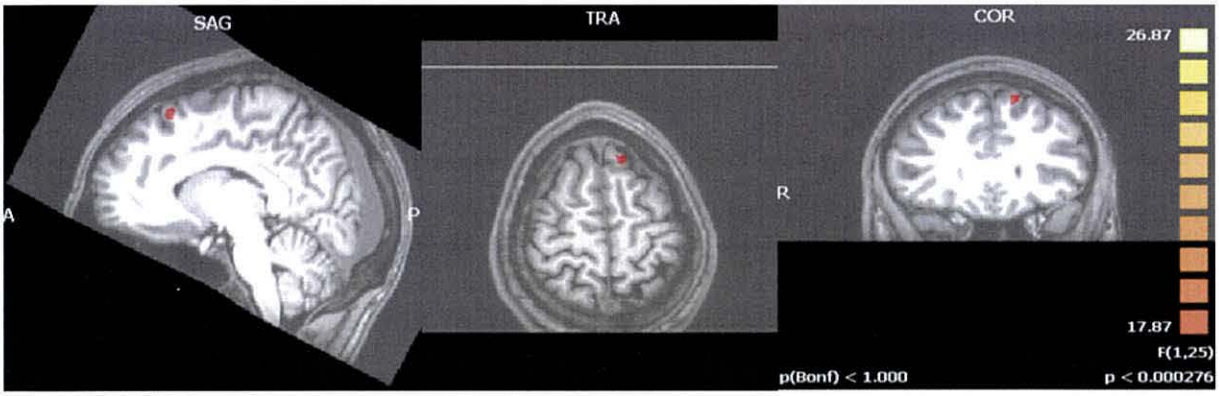

Figure 18: A volume of interest map for the right SFG (radiological convention). This region showed heightened BOLD signal change to Food vs. Furniture during EOC trials.

ROI	BA	x	y	z	NrofVoxels	t
EOC						
rSFG+	8	21	47	43	97	5.97
rACC	32	10	25	36	49	6.451
PCC	23	0	-26	25	94	6.312
Caudate*						
STOPS						
rSFG	8	20	48	42	36	5.313
lMFG	9	-35	29	33	42	5.692
lMFG	32	-5	11	46	122	-6.182
lMFG	6	-2	2	54	240	-6.144
rSTG	22	54	-10	5	73	6.29
rTTG	41	56	-21	11	82	6.2
Cuneas (1)	18	-4	-76	8	220	6.818
Cuneus (2)	17	2	-84	11	306	6.964

Table 11: The foci of brain activation, all areas pass Bonferonni correction. + Indicates Stimulus main effect, * Indicates state effect (NB: Caudate only showed significant activations during state main effects and did not show a main effect of activation during EOC vs STOPS).

Discussion

Our study tried to look at how motivation state coupled with meaningful images could modulate brain activations in regions implicated in inhibitory control as well as value processing. There was an altered state of neuronal activity that was of stimulus-specific and state-specific; however we were at this point unable to find neuronal activity that represented a state-specific by stimulus-specific interaction. However the results once again highlight brain regions that are involved in inhibition. Indeed our behavioral results indicate that there was observable differences for the state, so the brain is encoding and acting differently we just at this point have been unable to decode the signal from the neuronal noise.

In terms of the main effects there are some interesting activations and I will discuss the interpretations of these activations. In the STOPS contrast there were two strong activations in the Cuneus (Visual Cortex) and these fell within V1 & V2 regions of the visual cortex. These activations are presumed to stem from a reciprocal feedback effect of attention from posterior parietal or inferior temporal cortex (Deco & Rolls, 2004). In that during trials when participants correctly withheld their response their attention was more focused and as a result they were able to perform the task correctly. This maybe one of the root causes why there was no stimulus by state interactions within the EOC condition, as the mistakes may have been driven by lapses in attention, and as a result the full processing of the stimuli could not occur. However this is not fully supported as a stimulus effect was indeed found within this contrast, in particular the right SFG showed stronger activation for Food vs. Furniture. The reason that there was stronger activation can stem from roll that prefrontal cortex has within to error monitoring (Garavan, Ross, Murphy, Roche, & Stein, 2002) and during EOC participants encoded the fact that they had made an error. Due to the higher value of the food, the error was in a sense "greater" in that it is more important for the brain to register the error towards something that has value than something, which has less. The posterior cingulated activation is also of interest, in particular in previous studies of the Go/No-Go this region has been implicated as a valance dependent activation (Schulz, Clerkin, Halperin, Newcorn, Tang & Fan, 2009), indeed when shifting the threshold of the activation maps higher there is a strong level of activation of this region that is stimulus dependent in the EOCs. With further more rigorous analysis we hope to be able to get a better measure of this PCC activation.

Caudate activation as an overall main effect of state may indeed play a role in this heightened activation. Research has suggested that caudate as part of the dorsal straitum is key in the dopagemenc pathway involved in goal-directed behavior (Knutson & Greer, 2008), and that during the state of hunger one's ability to correctly select the right stimulus is more highly encoded as a state driven goal (van de Laan, et al., 2011). Indeed we hope to have found a stimulus by state interaction, however perhaps with the lack of encoding of the visual information in these sub-cortical regions it may have been purely a state driven effect that lead towards caudate increased BOLD. Furthermore the ACC activation in the same trial type suggests that heighted error related monitoring occurs within this EOC trial in comparison to the STOPS trials, and that this is perhaps the core of the affective and attentional integration found within neocortex (see the discussion on this in Chapter 3 on time perception).

The only stimulus driven effect was for the right Superior Frontal Gyrus (rSFG). The rSFG has been implicated to play a role in inhibition (Garavan, et al., 2002) as well as working memory (Boisgueheneuc et al., 2006). If we firstly assume that it is the inhibitory mechanism that are diving the effect, what possible reason is there for this increased activation for food? One reasons could be that during trials where food are repeated it is harder for participants to withhold their response, and that a strengthen activation stems from an increased level of cognitive torque used to try and prevent the action. If we take the working memory explanation then we could suggest that the food items representation is held more strongly in working memory, and even though this should result in better performance the increased activity may suggest that working memory has to work "harder" during this task to recall the last item.

There are a number of limitations to this study in its present state, and further analysis must be conducted to understand the mechanisms at work. One of the problems with using a event-related design within fMRI is that one needs a good measure of the baseline, added to this you need to be able to convolve the latent BOLD response. As a result we were unable to decode the stimulus information towards the Go trials. In future designs using a rapid-event related analysis multivariate technique we hope to better tease the impact of the food vs. non-food in the

GO trials. With this information we will be better able to define the regions of interest for this contrast, and then hopefully get a true stimulus by state interaction effect.

In sum, we found activation of inhibition in the typical regions involved in this type of task (Roberts, et al., 2008). We found a phase effect in dorsal striatum (Caudate), and a stimulus effect in rSFG. However, we showed no interaction between stimulus and state, further analysis and possible covariate analysis needs to be performed to fully understand the effects. What is clear though is that food stimuli evoke larger errors when in a depleted state and this results in an altered representation of the neural networks involved in this.

Chapter 5: General Discussion

This thesis examined the effects of a variety of meaningful images on a series of cognitive tasks that probed three areas of research: decision-making, time perception, and inhibitory control. Throughout, we examined how these images impacted upon participants' performance and in some cases their ability to learn. During this chapter I will summaries the main findings of these experiments, discuss their applied and theoretical implications, and provide some discussion on possible directions for future research

Decision-Making

In a series of four experiments we demonstrated a number of findings related to the impact of meaningful images on decision making. The main finding was that decision-making is influenced by meaningful images, even if these images have no primary relationship with the actual outcomes of the trials. For example, in Experiments 1 and 4 we showed that brand logos to which one has an affinity can bias your selection towards the decks on which they appear. And that this biasing will subsequently either help or hinder learning during the task. Within Experiment 2 we demonstrated how meaningful images with strong intrinsic value (faces?) have a less flexible representation, and this results in an inability to shift preferences towards the deck selections in a positive way. Furthermore, within this same chapter we also discovered that the time taken to make a decision is often fundamentally constrained by the ability to integrate the information into a construct, and when using more visceral feedback techniques (the BLINK paradigm) one can shape the representations towards decks far faster, but importantly with the same number of trials required.

Applied & Theoretical Implications

This chapter had some important applied and theoretical implications. Marketing is one of the applied areas to which these results are relevant . Marketing is, to a great extent, all about biasing consumer decision making. (Heide & John, 1992). Indeed, marketers often use brand representations to differentiate their products and even to extent their brands into new product categories (Aaker & Keller, 1990). It is perhaps somewhat surprising that brands often help inform (or bias) decisions when one realizes how unrelated the brands are to the real-world outcomes of consumer decisions. Within the marketing literature there is a common belief that brand extensions can only work if they are a "good" fit with the previous representation of the brand (Aaker & Keller, 1990). However, what we have demonstrated is that this fit does not have to be related to consumer products at all. That is, if you have a strong brand then any object to which you attach the brand will have some incremental benefit in terms of consumers decisional biasing towards it. Of course, it must be noted that this biasing may not influence the satisfaction of the consumer. The brand will merely serve to bias initial selection and the results of the selection (e.g. satisfaction or disgust) will likely lead to later (perhaps more cognitive) influences on subsequent decisions.

Furthermore, the research outlined in Experiment 2 also suggests that information surrounding or somehow spatially connected to a choice will alter decision-making. Again this has applied relevance within the consumer domain. If, for example, a consumer chooses a product that they like but which is surrounded by sad faces, or they consume a product surrounded by sad faces, they may not be able to encode the real level of satisfaction correctly. This has interesting ramifications for companies, because it suggests that it is not just important that people like your product, but also that the context in which they make the choice and the consumption could be of paramount importance as well.

In addition, there are a number of theoretical implications of these studies. In particular Experiment 1, 2, & 3 probed the role of meaning within decision-making. These three experiments contribute to our understanding of the somatic marker hypothesis (Damasio, 1994; as discussed in Chapter 2: Experiment 1). Firstly, the "afferent feedback" required to integrate the information about wins and losses may be influenced by the stimuli associated with that feedback. For example, in Experiments 1 & 3 the tag of representation towards the brand may have either reduced or increased the anxiety with the selection, and with this heightened affective response the ability to integrate the wins and losses may have become either boosted or reduced. The results of Experiment 2 suggest that the SMH is susceptible to a repressed signal when processed within an environment with negative or neutrally valenced stimuli. Experiment 3 either goes directly against the idea of the SMH or suggests that the afferent feedback can occur at very fast speeds, and the integration of the information is not based on time, but indeed based on the number of samples (information) received.

In addition when comparing all of the experiments together we can also suggest ways that the 'hot' and 'cold' systems are working together to intergrate information into a decision process. Experiments 1 & 4 contrasted in the amount of samples required for the emotional brand information to bias the decision-process, this could be based on the BLINK driving more of the "hot" system initially purely from the trial feedback. As a result the trial feedback drove the decision-making predominately during the initial trials, and it wasn't until the participant conceptualized the brand stimulus regalities that the brand information biased the decision. This further supported the notion that the BLINK taps more into the "hot" processes whereas the IGT taps more into the "cold" processes.

Future Research & Limitations

Some of the limitations of these studies stem from the transient nature of motivation during the tasks and the subsequent variety in participants choices. Throughout these experiments it was very difficult to get enough power within the general linear model, this stems from many assumptions that the model makes about the data. For example, most models of IGT performance assume that during the first block of trials (e.g. the first 10 or 20 selections), participants should choose more from the negative decks. However, because it is the beginning of the task, there is no prior information about which deck to select and hence variance is higher within this block, as the trials go on participants are more likely to select more similar decks and as a result the variance decreases. This is one of the primary reasons why IGT data often violate sphericity. Another difficulty with standard approaches towards analyzing IGT data is that they tend to presume that all participants are at the same level. We tried to combat these issues with the cognitive modeling analysis. However, due to the nature of this analysis, it looses a great deal of information on the progression (e.g. learning) across the trials, and thus it is the best-fit parameter of the overall trial sequence that tends to be used to quantify performance. There are ways to combat this issue, which utilizes a blocked approach to using the cognitive model, however this does not get around the issues that are present within the general linear model. One way to try and gauge a better understanding of the how the initial trials impact performance levels would be with a step-wise multiple regression analysis (Dymond, Cella, Cooper, & Turnbull, 2010). However, this approach seems more applicable when one uses it to predict performance following a change in the task (e.g. after a contingency switch of the decks

(Dymond et al., 2010). It is unclear what such an analysis would add in a block-wise analysis of IGT data.

Another possible limitation of the studies presented here is related to the idea of a "demand characteristic" -- a point that is discussed at length in Experiment 1. This limitation directly applies to several of the experiments (Experiments 1,2, and 4). And, in a sense, Experiment 2 directly probes this question. In that, during Experiment 2 we did not "guide" selections via positive and negative images on different decks, we merely displayed the same valenced images on all of the decks. Thus, the images gave no information to the participants, and as a result any effect they had in the task was not due to demand characteristics. Indeed, this was one of the reasons we felt using varying levels of faces on the backs of decks could have led to less interpretable results, as participants responses would be very much guided towards the salient face for selection.

In terms of future research, there are three main avenues that could be explored. The first of these would be to further the stimulus sets and behavioral manipulations used to understand the relationship between meaning and decision making. Specifically, using sets of stimuli that have even more robust meaning to participants (for example, photos of family or friends) could help maximize the effects. A second avenue for future research would be to look at special populations. For example, it would be interesting to see whether patients with damage to the VMPFC would also have their decisions biased by meaningful images. In addition, from a more applied perspective it would also be interesting to examine similar effects in depressive patients or those who are compulsive shoppers.

One interesting variable that could be further investigated would be to look again if there was any subsequent switch in preferences post-test phase. Although we did try to address this issue in the faces experiment (Experiment 2), as mentioned in that chapter, faces may have been a poor choice of stimulus with which to examine this issue. For example, it might have been better examined using neutrally branded stimuli (or even unknown products or shapes).

As was suggested above the BLINK and IGT may tap into slightly different processes of the dual-system processing (i.e. "hot" and "cold". One study by Figner and colleagues (2009) looked at two types of the Columbia Card Task (CCT), one version of the CCT was meant to tap into the "hot" system and the other the "cold" system. Unlike in these present studies however Figner and collegues (2009) directly measured how the two tapped into these systems via self-report and electrodermal activity. In future studies in would prove prudent to try and measure the BLINK and IGT with these self-report and electrodemal activity, to gauge better the ways in which the two tap into the different dual-system processes.

From a clinical perspective, our results suggest that it might be interesting to explore if people's underlaying reward structures can be changed by introducing relevant stimuli within the IGT. For example, it might be possible to set up a for of IGT whereby participants are forced to choose certain items (by having them on the good decks) and this may lead to the development of a greater affinity towards them. Likewise, perhaps drug dependent users could be exposed to a version of IGT whereby the substances you wish them not to choose could be placed on a bad deck and through performance of the IGT it may be possible to retrain them (see for example Stroop retraining; Fadardi & Cox, 2009)).

Finally, research using transcranial magnetic stimulation techniques has shown that rTMS can blunt performance in the IGT (Knoch et al., 2006). This result, coupled with an understanding of the role of prefrontal cortex within meaning, suggests that it would be interesting to see if we could remove the effect of the IGT biasing by selectively suppressing these regions with rTMS. For example, we may find that participants are less biased by brand information if the "temporary" lesion is applied to OFC than when applied to STS.

While the use of some form of functional imaging (e.g. fMRI) would be interesting, the suitability of such techiques for the present studies seems unlikely at this time. Specifically, due to the speed of the decision-making process and the latent BOLD response conducting such experiments within an fMRI experiment would pose a variety of obstacles, and although the IGT has been used within fMRI (see the review by Lin et al., 2008) we would have to modify the experiment to be time locked. While this is possible, Experiment 3 suggests that the decision-making elements within the IGT are very fast. And, introducing an elongation of the process may end up tapping into elements of the decision-making process that are different to those occurring within the paradigms described in this thesis.

Time-Perception

In a series of experiments we showed that image meaning did not impact the time distortion effect previously reported in the literature (Angrilli et al., 1997). We varied the stimulus (e.g. brands, scary spiders, etc) and state (e.g. hunger) and were unable to find any significant modulation of the size of the time distortion effect. The only slight exception to this was when pre-rated brand images were used in the oddball paradigm. In this case, it was not the size of the distortion that was found to vary, instead it was the reliability (in terms of jnd) that varied. In other words, in this one condition it was not the perceptual event that fluctuated, it was only the acuity towards the perceptual event.

Applied & Theoretical Implications

The most important theoretical implication of this study is that it suggests that the time-distortion effect takes place at a very early stage in processing. In other words, it is a phenomenon that is driven simply by the pure sensory novelty of a stimulus and not by any meaning or relevance that the stimulus may have.

Future Research & Limitations

The nature of the paradigm used to elicit the time distortion phenomenon is quite similar to those used to elicit the P300 event-related component. Thus, it might be interesting to further investigate this using either an ERP study looking at the P300 and/or an fMRI using an event-related design. Given the likely "deep" structural origin of this phenomenon, I believe that an fMRI study would be very beneficial to the understandings of the effects that we have observed. In particular, such a study would allow us to localize the regions of the brain that are locked to the varying levels of stimulus meaning. However, there are some adjustments to the paradigm that would need to be done, in particularly teasing the effect of the visual perception of the meaningful image from the time perception modulation. One way to tackle this would be to use a temporal expansion localizer in one of the runs (i.e. to get the regions of the brain that specifically encode for the perceptual event of time perception), and to follow this up with a variety of oddballs.

One limitation of these sets of experiments comes from the nature of the IAPS images. These images have become somewhat dated in their appearance and even when participants categorise them into different levels of valence this is always done towards an anchor.

Inhibitory Control

In the two studies on inhibitory control we found that meaningful images consistently impact participant's ability to withhold responses. This was demonstrated behaviourally in Experiments 9 and 10. While others have previously demonstrated such effects using faces and

IAPS images, this is the first time such a paradigm has been used with brands and with the stimulus-specific design used in Experiment 10.

Applied & Theoretical Implications

The clearest applied and theoretical implication of these experiments is related to the role of inhibitory control in consumer behaviour. This is a particularly important issue given the prevalence of compulsive shopping (Dittmar, 2005), and the potential clinical implications compulsive shopping has.

In addition to this applied relevance, this research once again highlights the necessity to control for familiarity and liking when using stimuli within various paradigms. This is important because familiarity may affect the accuracy of mnemonic judgments, whilst the liking may bias performance on the basis of valence. As such, a greater level of control should be placed on these stimulus characteristics, being treated both as independent and significant factors on experimental design and findings.

We conducted Experiment 10 in an attempt to further understand the neuroanatomical underpinnings of inhibitory control and meaningful images. The results of this study suggested that inhibitory control in the presence of meaningful images relies on well-known networks involving the frontal cortex. In particular, we found that striatum and rSFG play a role in the integration of error monitoring, and encode based on state and stimulus-specific trats.

Future Research & Limitations

One of the hardest tasks to do within meaningful images is to separate out the liking and familiarity aspects of the image. They are clearly interleaved as constructs, which was clearly demonstrated in Experiment 9. In future studies we aim to separate these constructs further, by fine-tuning the brand data set to include brands that diverge on these two dimensions. Within

Experiment 10 further analysis needs to be done on the data to fully understand the effects that are present.

Meaningful Images

At its core, this thesis aimed to understand the role of meaningful images in performance and learning. In no way have we tackled all of the questions that are involved with this area, however there have been multiple contributions to its general understanding. One of the most important contributions is our demonstration that meaning, within the context of emotion, can alter the way in which stimuli impact performance. For example, the only meaningful image to truly impact upon the temporal expansion paradigm was brands. This indeed highlights one of the problems with research into emotion: often participants are merely subjected to images that have a basic emotional valence, but fundamentally lack an individualized meaning. It is this subjective personal relevance that incorporates familiarity, emotion, and personal experience that can help us better understand how our representations of objects may influence our behaviour. With this in mind, future research should try and better understand how the meaning of objects differ between individuals, and not just on some preordained construct of emotion. In other words, it is not only emotion that is important, but instead it is emotion *that has meaning for the observer*. Further studies must be conducted to understand how, for example, emotion towards your loved ones can impact on the way that you interact and integrate the information towards that meaning.

Conclusion

In our approach to understanding meaning and its impact upon performance and learning we have tackled three core areas: decision making, time perception, and inhibitory control. The different paradigms used deal with three primary regions of the brain: Emotional decision-making is deemed to centre around ventral medial prefrontal cortex and associations with sub-cortical regions (e.g. amgdala); Time-perception within this thesis evolves around more low-level (possible tectal) pathways; and finally, inhibitory control deals with the more superolateral prefrontal cortex and associations with sub-cortical regions. For each one of these regions meaning seems to matter to a certain extent. Thus, it appears that the internal representation of the meaning of an image can exert a powerful force on many aspects of human behaviour.

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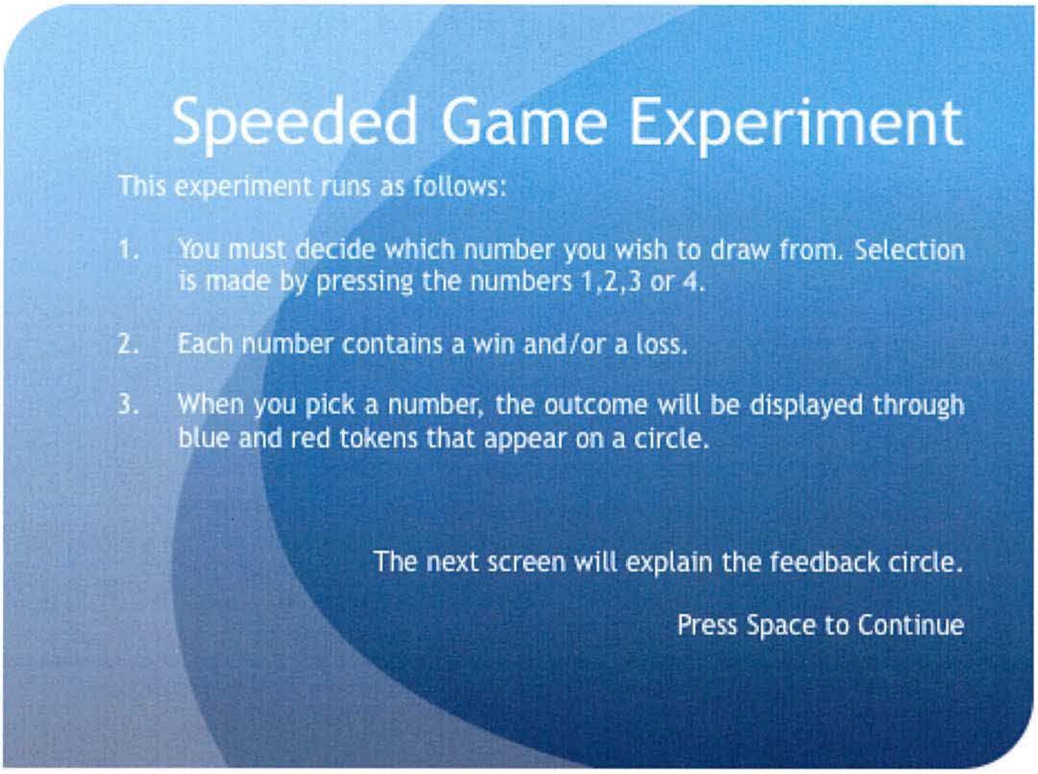
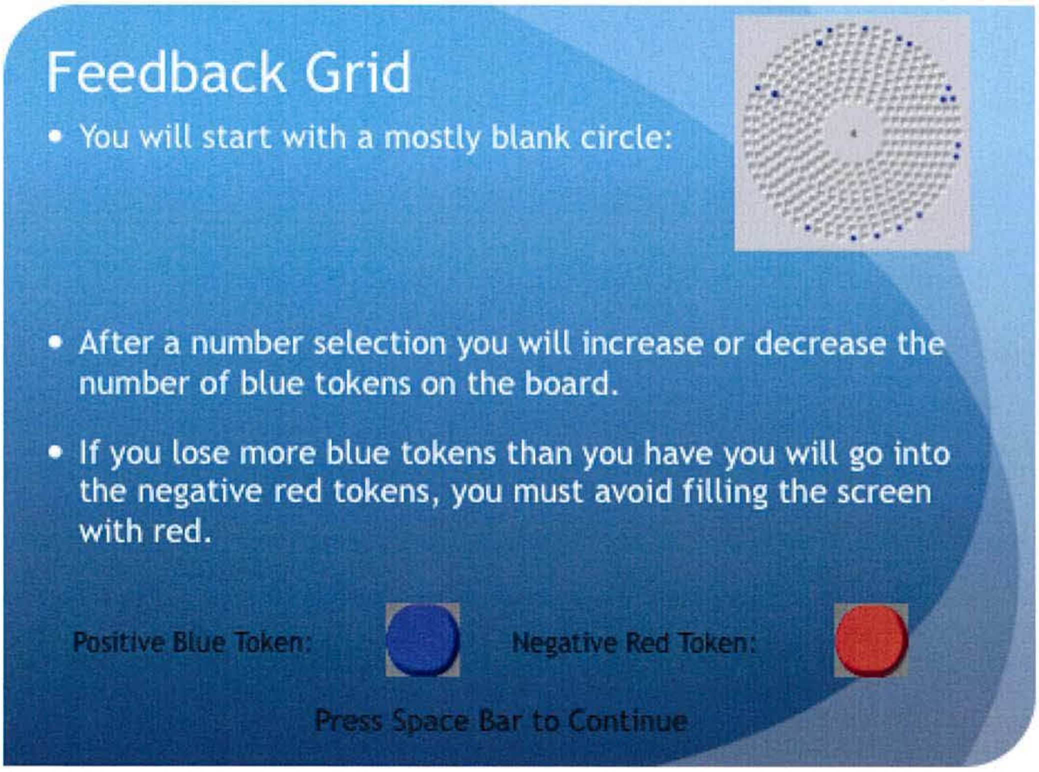
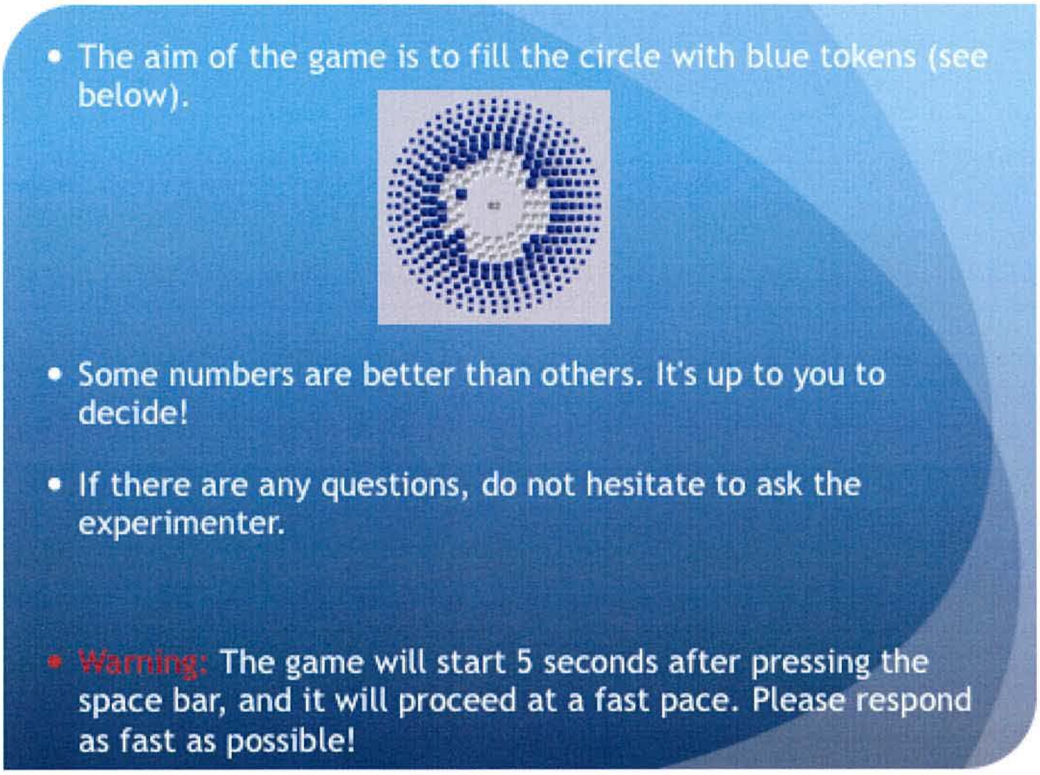
Appendices

Appendix I: Experiment 3 Instructions


Speeded Game Experiment
This experiment runs as follows:
1. You must decide which number you wish to draw from. Selection is made by pressing the numbers 1,2,3 or 4.
2. Each number contains a win and/or a loss.
3. When you pick a number, the outcome will be displayed through blue and red tokens that appear on a circle.
The next screen will explain the feedback circle.
Press Space to Continue


Feedback Grid
• You will start with a mostly blank circle:
• After a number selection you will increase or decrease the number of blue tokens on the board.
• If you lose more blue tokens than you have you will go into the negative red tokens, you must avoid filling the screen with red.
Positive Blue Token:
Negative Red Token:
Press Space Bar to Continue



Appendix II: Time Perception Igor Script

```
#pragma rtGlobals=1          // Use modern global access method.


Function CreateUniqueSubjectsList()
        wave Subject

        Duplicate/O Subject,SubjectUniques
        Duplicate/O Subject,SubjectIncludes

        Variable totalrows = DimSize(Subject,0)      //65
        Variable RowNow, TotalUniques,PossibleUnique
        Variable/G TotalSubjects

        SubjectUniques[] = Subject[0]
        TotalUniques = 1        //totalrows
        for(RowNow=1;RowNow<(totalrows);RowNow=RowNow+1)        // Initialize
variables;continue test
                PossibleUnique = Subject[RowNow]

                FindValue/V=(PossibleUnique) SubjectUniques
```

```
            //print PossibleUnique," ,", V_value
            if (V_value>-1) //Found it - so, we already have that value

            else // it is new
                    SubjectUniques[TotalUniques] = PossibleUnique
                    TotalUniques = TotalUniques + 1
                    print PossibleUnique
            endif
        endFor
        Redimension/N=(TotalUniques) SubjectUniques
        Redimension/N=(TotalUniques) SubjectIncludes
        SubjectIncludes[] = 1
        TotalSubjects=TotalUniques

End

function GetASubject(whichSubject)
        Variable whichSubject
        Variable, RowNow, BrandCode1, BrandCode2, BrandCode3
        Variable totalrows = DimSize(Subject,0)
        Variable/G MidPoint, WorstBlock, BestBlock, NeutralBlock, Bad25Per,
Bad75Per, Neutral25Per, Neutral75Per, Good25Per, Good75Per, BadJND, NeutralJND,
GoodJND
        wave Subject, Procedure_Block, MeanScore, SrtNumber, OnTime
        wave Condition, BrandCode, Number
        FindValue/V=(whichSubject) Subject
        //FindLevel/


        if (V_value>-1)

                Make/O/N=(2000)/D SubjectMeanScore1
                Make/O/N=(2000)/D SubjectMeanScore2
                Make/O/N=(2000)/D SubjectMeanScore3
                Make/O/N=(2000)/D SubjectOnTime1
                Make/O/N=(2000)/D SubjectOnTime2
                Make/O/N=(2000)/D SubjectOnTime3
                Make/O/N=(2000)/D Srt1
                Make/O/N=(2000)/D Srt2
                Make/O/N=(2000)/D Srt3

                Make/O/N=(4)/D GoodBrandCoef
                Make/O/N=(4)/D NeutralBrandCoef
                Make/O/N=(4)/D BadBrandCoef
                Make/O/N=(5)/D GoodBrandConfid
                Make/O/N=(5)/D NeutralBrandConfid
```

```
Make/O/N=(5)/D BadBrandConfid

BrandCode1 = 0
BrandCode2 = 0
BrandCode3 = 0

for(RowNow=(V_value);RowNow<(totalrows);RowNow=RowNow+1)  //
Initialize variables;continue test
if (Subject[RowNow] == whichSubject)

if ( Number[RowNow] >= 1)
if (
BrandCode[RowNow] == 1)
///need to put
some where now variable

SubjectMeanScore1[BrandCode1] = MeanScore[RowNow]

SubjectOnTime1[BrandCode1] = OnTime[RowNow]

Srt1[BrandCode1] = SrtNumber[RowNow]
WorstBlock =
Procedure_Block[RowNow]
//This is a
counter for the wave
BrandCode1 =
BrandCode1 + 1
endif
if (
BrandCode[RowNow] == 2)
///need to put
some where now variable

SubjectMeanScore2[BrandCode2] = MeanScore[RowNow]

SubjectOnTime2[BrandCode2] = OnTime[RowNow]

Srt2[BrandCode2] = SrtNumber[RowNow]
NeutralBlock
= Procedure_Block[RowNow]
//This is a
counter for the wave
BrandCode2 =
BrandCode2 + 1
endif
```

```
                                                        if (
BrandCode[RowNow] == 3)
                                                             ///need to put
some where now variable
     SubjectMeanScore3[BrandCode3] = MeanScore[RowNow]
     SubjectOnTime3[BrandCode3] = OnTime[RowNow]
     Srt3[BrandCode3] = SrtNumber[RowNow]
                                                             WorstBlock =
Procedure_Block[RowNow]
                                                             //This is a
counter for the wave
                                                             BrandCode3 =
BrandCode3 + 1
                                                        endif
                                              endif
                                   endif

                    endfor
               Redimension/N=(BrandCode1), SubjectMeanScore1
               Redimension/N=(BrandCode2), SubjectMeanScore2
               Redimension/N=(BrandCode3), SubjectMeanScore3

               Redimension/N=(BrandCode1), SubjectOnTime1
               Redimension/N=(BrandCode2), SubjectOnTime2
               Redimension/N=(BrandCode3), SubjectOnTime3

               Redimension/N=(BrandCode1), Srt1
               Redimension/N=(BrandCode2), Srt2
               Redimension/N=(BrandCode3), Srt3


               //need to make it hold here until the info is complete
               K0 = 0;K1 = 1;

     CurveFit/Q/H="1100"/X=1/NTHR=0/TBOX=768 Sigmoid  SubjectMeanScore1
/X=SubjectOnTime1 /W=Srt1 /I=0 /D /F={0.950000, 5}
               wave W_coef
               wave W_ParamConfidenceInterval
               BadBrandCoef = W_coef
               BadBrandConfid = W_ParamConfidenceInterval
               findlevel/Q fit_SubjectMeanScore1,.25
               Bad25Per =  V_LevelX
               findlevel/Q fit_SubjectMeanScore1,.75
```

```
			Bad75Per =  V_LevelX
			BadJND = (Bad75Per)-(Bad25Per)

		K0 = 0;K1 = 1;
		CurveFit/Q/H="1100"/X=1/NTHR=0/TBOX=768 Sigmoid  SubjectMeanScore2 
/X=SubjectOnTime2 /W=Srt2 /I=0 /D /F={0.950000, 5}
			wave W_coef
			wave W_ParamConfidenceInterval
			NeutralBrandCoef = W_coef
			NeutralBrandConfid = W_ParamConfidenceInterval
			findlevel/Q fit_SubjectMeanScore2,.25
			Neutral25Per =  V_LevelX
			findlevel/Q fit_SubjectMeanScore2,.75
			Neutral75Per =  V_LevelX
			NeutralJND = (Neutral75Per)-(Neutral25Per)
		K0 = 0;K1 = 1;
		CurveFit/Q/H="1100"/X=1/NTHR=0/TBOX=768 Sigmoid  SubjectMeanScore3 
/X=SubjectOnTime3 /W=Srt3 /I=0 /D /F={0.950000, 5}
			wave W_coef
			wave W_ParamConfidenceInterval
			GoodBrandCoef = W_coef
			GoodBrandConfid = W_ParamConfidenceInterval
			findlevel/Q fit_SubjectMeanScore3,.25
			Good25Per =  V_LevelX
			findlevel/Q fit_SubjectMeanScore3,.75
			Good75Per =  V_LevelX
			GoodJND = (Good75Per)-(Good25Per)

			// now i need to plot the SrTNumber against the other thing

		endif


		End

		Function SetVarProc(sva) : SetVariableControl
			STRUCT WMSetVariableAction &sva
			Variable/G TheSubjectNow,TheSubjectNowCode,S_ThisSubjectIncluded
			wave SubjectUniques
			wave SubjectIncludes

			switch( sva.eventCode )
				case 1: // mouse up
				case 2: // Enter key
				case 3: // Live update
					Variable dval = sva.dval
```

```
                    String sval = sva.sval
                    break
        endswitch
        TheSubjectNowCode = dval
        TheSubjectNow = SubjectUniques[TheSubjectNowCode]
        GetASubject(TheSubjectNow)


End

Window PanelSubjectView() : Panel
        PauseUpdate; Silent 1           // building window...
        NewPanel /W=(74,61,788,559)
        ShowTools/A
        SetDrawLayer UserBack
        SetVariable setvar0,pos={1,2},size={100,15},proc=SetVarProc,title="Subject"
        SetVariable setvar0,value= V_Flag

        Display/W=(10,40,400,200)/HOST=#  fit_SubjectMeanScore1
        AppendToGraph SubjectMeanScore1 vs SubjectOnTime1
        ModifyGraph mode(SubjectMeanScore1)=2, lsize(SubjectMeanScore1)=5
        Label left "Bad Brand"
        SetActiveSubwindow ##


        Display/W=(10,200,400,360)/HOST=#   fit_SubjectMeanScore2
        AppendToGraph SubjectMeanScore2 vs SubjectOnTime2
        ModifyGraph mode(SubjectMeanScore2)=2, lsize(SubjectMeanScore2)=5
        RenameWindow #,G4
        Label left "Neutral Brand"
        SetActiveSubwindow ##

        Display/W=(10,360,400,560)/HOST=#   fit_SubjectMeanScore3
        AppendToGraph SubjectMeanScore3 vs SubjectOnTime3
        ModifyGraph mode(SubjectMeanScore3)=2, lsize(SubjectMeanScore3)=5
        RenameWindow #,G5
        Label left "Good Brand"
        SetActiveSubwindow ##

        //BAD COEF
        ValDisplay BadBrandPSE title="Bad Brand
PSE",size={150,20},format="";DelayUpdate
        ValDisplay BadBrandPSE value=BadBrandCoef(2)
        ValDisplay BadBrandRate title="Bad Brand
Rate",size={150,20},format="";DelayUpdate
        ValDisplay BadBrandRate value=BadBrandCoef(3)
```

```
//BAD CONFID
ValDisplay BadBrandCONFIDPSE title="Bad Brand PSE
Con",size={150,20},format="";DelayUpdate
ValDisplay BadBrandCONFIDPSE value=BadBrandConfid(2)

ValDisplay BadBrandCONFIDRate title="Bad Brand Rate
Con",size={150,20},format="";DelayUpdate
ValDisplay BadBrandCONFIDRate value=BadBrandConfid(3)

//Neutral COEF
ValDisplay NeutralBrandPSE title="Neutral Brand
PSE",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandPSE value=NeutralBrandCoef(2)
ValDisplay NeutralBrandBASE title="Neutral Brand
Base",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandBASE value=NeutralBrandCoef(0)
ValDisplay NeutralBrandMax title="Neutral Brand
Max",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandMax value=NeutralBrandCoef(1)
ValDisplay NeutralBrandRate title="Neutral Brand
Rate",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandRate value=NeutralBrandCoef(3)
//Neutral CONFID
ValDisplay NeutralBrandCONFIDPSE title="Neutral Brand PSE
Con",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandCONFIDPSE value=NeutralBrandConfid(2)
ValDisplay NeutralBrandCONFIDBASE title="Neutral Brand Base
Con",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandCONFIDBASE value=NeutralBrandConfid(0)
ValDisplay NeutralBrandCONFIDMax title="Neutral Brand Max
Con",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandCONFIDMax value=NeutralBrandConfid(1)
ValDisplay NeutralBrandCONFIDRate title="Neutral Brand Rate
Con",size={150,20},format="";DelayUpdate
ValDisplay NeutralBrandCONFIDRate value=NeutralBrandConfid(3)

//Good COEF
ValDisplay GoodBrandPSE title="Good Brand
PSE",size={150,20},format="";DelayUpdate
ValDisplay GoodBrandPSE value=GoodBrandCoef(2)
ValDisplay GoodBrandBASE title="Good Brand
Base",size={150,20},format="";DelayUpdate
ValDisplay GoodBrandBASE value=GoodBrandCoef(0)
ValDisplay GoodBrandMax title="Good Brand
Max",size={150,20},format="";DelayUpdate
ValDisplay GoodBrandMax value=GoodBrandCoef(1)
```

```
		ValDisplay GoodBrandRate title="Good Brand Rate",size={150,20},format="";DelayUpdate
		ValDisplay GoodBrandRate value=GoodBrandCoef(3)
		//Good CONFID
		ValDisplay GoodBrandCONFIDPSE title="Good Brand PSE Con",size={150,20},format="";DelayUpdate
		ValDisplay GoodBrandCONFIDPSE value=GoodBrandConfid(2)
		ValDisplay GoodBrandCONFIDBASE title="Good Brand Base Con",size={150,20},format="";DelayUpdate
		ValDisplay GoodBrandCONFIDBASE value=GoodBrandConfid(0)
		ValDisplay GoodBrandCONFIDMax title="Good Brand Max Con",size={150,20},format="";DelayUpdate
		ValDisplay GoodBrandCONFIDMax value=GoodBrandConfid(1)
		ValDisplay GoodBrandCONFIDRate title="Good Brand Rate Con",size={150,20},format="";DelayUpdate
		ValDisplay GoodBrandCONFIDRate value=GoodBrandConfid(3)



	EndMacro

	Function ButtonProcSPSSData(ba) : ButtonControl
		STRUCT WMButtonAction &ba

		wave BadBrandCoef, BadBrandConfid, NeutralBrandCoef,NeutralBrandConfid, GoodBrandCoef, GoodBrandConfid
		wave SubjectIncludes
		wave SubjectUniques
		wave SubjectDeckRunLengthHist,SubjectDeckReturnLengthHist
		String cmd
		variable/G  TheSubjectNow
		variable SubjectNow
		Variable/G TotalSubjects, Bad25Per, Bad75Per, Neutral25Per, Neutral75Per, Good25Per, Good75Per, BadJND, NeutralJND, GoodJND

		//TotalSubjects = 2
		switch( ba.eventCode )
			case 2: // mouse up
				// click code here
				printf "***** SPSS DATA *****\r"

	for(SubjectNow=0;SubjectNow<(TotalSubjects);SubjectNow=SubjectNow+1)	// Initialize variables;continue test


			//print "Condition is ", ConditionNow, "  Subject is ", SubjectNow, " ..."
```

```
                                GetASubject(SubjectUniques[SubjectNow])
                                if (SubjectIncludes[SubjectNow]==1)          //this
guy SHOULD be included
                                        GetASubject(SubjectUniques[SubjectNow])
                                        printf "%d\t%d\t",
SubjectNow+1,SubjectUniques[SubjectNow]

                                        //Bad

                                        printf "%d\t", BadBrandCoef(2)       // xhalf
                                        printf "%d\t", BadBrandCoef(3)       // rate

                                        printf "%d\t", BadBrandConfid(2)     // xhalf
                                        printf "%d\t", BadBrandConfid(3)     // rate
                                        printf "%d\t",  BadJND
                                        //Neutral

                                        printf "%d\t", NeutralBrandCoef(2)  // xhalf
                                        printf "%d\t", NeutralBrandCoef(3)  // rate

                                        printf "%d\t", NeutralBrandConfid(2)
        // xhalf
                                        printf "%d\t", NeutralBrandConfid(3)
        // rate
                                        printf "%d\t",  NeutralJND    // rate
                                        //Good

                                        printf "%d\t", GoodBrandCoef(2)      // xhalf
                                        printf "%d\t", GoodBrandCoef(3)      // rate

                                        printf "%d\t", GoodBrandConfid(2)  // xhalf
                                        printf "%d\t", GoodBrandConfid(3)  // rate
                                        printf "%d\t", GoodJND        // rate


                                printf "\r"       // Next subject
                                endif   //Subject Included
                        endFor // go through subjects
                        printf "\r"
                printf "***** END SPSS DATA *****\r"
                break
        endswitch

        return 0
End
```

```
Function ButtonProc(ba) : ButtonControl
	STRUCT WMButtonAction &ba

	switch( ba.eventCode )
		case 2: // mouse up
			// click code here
			CreateUniqueSubjectsList()
			break
	endswitch

	return 0
End

Function ButtonProcIncExc(ba) : ButtonControl
	STRUCT WMButtonAction &ba
	Variable/G TheSubjectNow,TheSubjectNowCode,S_ThisSubjectIncluded
	wave SubjectUniques
	wave SubjectIncludes

	switch( ba.eventCode )
		case 2: // mouse up
			// click code here
				if (SubjectIncludes[TheSubjectNowCode]==1)
					SubjectIncludes[TheSubjectNowCode]=0

				else

					SubjectIncludes[TheSubjectNowCode]=1

				endif
			break
	endswitch



End
```