The Interactive Effect of Cognition, Emotion, And Motivation on Behavior

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Rajeshwari Muthukumaran

Supervisors:

Rashmi Gupta (IITB Supervisor)

Antonio Verdejo-García (Monash Supervisor)

Naomi Kakoschke (Monash Co-Supervisor)

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Abstract

Recent studies have shown that attention bias to affective distractors depends on a task's perceptual load (Morris, Yeomans, & Forster, 2020; Gupta et. al, 2016). Attention bias to affective stimuli also varies based on evaluative dimensions such as valence and predictability (Gupta et. al, 2016; Raymond & O'Brien, 2009). The current thesis incorporates three such affective stimuli: emotional, value-learnt (learnt motivation) and food cues (inherent motivation). The aims of the thesis were two-fold (a) to understand the specifics of the interaction between perceptual load and affective distractors; and, (b) to extend the findings of previous research in the context of conscious perception by using more direct measures of the impact of emotional/ value-learnt stimuli on perceptual accuracy. In the empirical studies discussed within this thesis, participants performed a letter-search task, in which they searched for a target (X or N) in either a low (circular non-target letters) or high (angular non-target letters) perceptual load condition, along with irrelevant (a) emotional faces (happy or angry); (b) value- learned stimuli (gain or loss; high or low predictable); (c) food cues (high- or low-caloric density). An independent study validated the food cues used in (c) to ensure cultural relevance. In addition to the letter-search task, in (a) and (b) in 25% of trials, a meaningless squiggle was presented in the periphery, and participants were required to detect the squiggle. Overall, the results of these experiments suggest that under high-load conditions, task performance was poorer in the presence of negative affective distractors (angry and loss-related faces), while performance was better in the presence of positive distractors (happy and gain-related stimuli). Furthermore, food distractors did not affect task performance in high-load conditions. These findings have implications for understanding the interactive effect of attention and affective stimuli in shaping perception and the concept of affect-driven attention.

Keywords: Attention, perceptual load, conscious perception, emotions, happy, angry, value-learning, loss, reward, food, caloric density, food-pics database

Declaration

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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Like every PhD scholar I too had my major period of disillusionment both professionally and personally. It would be appropriate to say that I faced more issues than your favourite magazine. I am grateful to everyone whose understanding, compassion and kindness helped me through it. Specifically, I would like to thank all the pets that have offered me immense support like no human ever can. Thank you for existing: every dog on campus, hostel cats; gerbils, hamsters and conures at home. A huge thank you to my doctoral cohort (JP, Shubham and Sham) for your input and spirited discussions. I would like to specially thank those who heard me when I most needed: Suraj, Dr NK, my therapists, Anees and Ren. Neh, Rohit, Indhu and Poori, I could never thank you enough; you are my well-wishers, a source of inspiration and motivation.

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Chapter I: General Introduction

Distraction by Meaningful Stimuli from a Load Theory Framework

The Introductory chapter gives an overview of the theories and concepts discussed in this thesis, which aimed to understand the interaction between various meaningful affective stimuli and perceptual load on task performance. The affective stimuli focused on in the current thesis were emotions (happy and angry) and motivation (value-learned gain and loss associated stimuli with high and low predictability; and, high- and low- caloric density food cues). This chapter discusses in brief selective attention, and attention bias to each of the meaningful stimuli and their implications under the load theory framework (Lavie & Tsal, 1994; Lavie, 1995).

The literature search was conducted in various electronic research databases such as Pubmed, Springer, APA PsycNET, Scopus, Science direct, Frontiers, and search engine 'Google Scholar' and was limited to relevant articles published in the English language. Few of the search terms and phrases used to find articles included attention bias, load theory of attention, perceptual load, inattentional blindness, emotion-induced blindness, load-induced blindness, emotion, angry faces, happy faces, emotion processing, motivation, value-learning, value-driven attention, reward learning, reward-driven attention, punishment/ loss, food, food databases, appetitive cues, eating behaviour, and food consumption.

Overview

A vast amount of sensory information is present in our environment, and not all of it is perceived. Selective attention involves differential processing of various sensory stimuli that results in filtering out relevant information to prevent information overload (Goldstien, 2011; Driver 2001; Theewus, 1993). For example, to selectively read and coherently understand this thesis, one should be able to easily filter and ignore irrelevant nearby chatter. Several theories have been proposed to explain selective attention and what makes information relevant. The earliest theories fall into early and/or late selection models. While the early selection model conceptualized that the selection of relevant information occurs *before* semantic or in-depth processing of the abstract stimuli at the sensory system level; the late selection model dictated that this selection happens *after* semantic or in-depth processing of the abstract stimuli (Cherry, 1953; Broadbent, 1958; Deutsch & Deutsch, 1963; Triesman, 1964; Kahneman, 1973).

Lavie's perceptual load theory supposedly resolved this age-old dispute of whether the information is selected/ignored at an earlier or later stage of information processing (Lavie & Tsal, 1994; Lavie, 1995). This theory attempts to explain the process of selection in terms of limited attention resources. It postulates that the extent to which distractor(s) get processed is determined by the perceptual load of the attended information (see Lavie, 2005, for a review). According to the theory, under high perceptual load (for example, high visual complexity) the distractor interferences on goal-directed behavior/ task would be evident in terms of poorer attended-task performances (Lavie & Tsal, 1994; Lavie, 1995). Similarly, under low perceptual load there would be comparatively lesser distractor interference. Consequently, one could infer that the operations of this attention economy is one of the main causes and consequences of goal-directed behaviours.

Attention Bias: Orienting to Relevant Information

Apart from limited attention resource availability, the process of orienting and selecting 'relevant' information has been traditionally dissected into goal-driven "top-down" and stimulus-driven "bottom-up" selection (Corbetta & Shulman, 2002; Koch & Tsuchiya, 2007). There have been many analogous dissections in attention literature (refer to Table 1), however, for the purpose of this thesis, we will operationally define goal- and stimulus-driven attention. During goal-driven selection, adaptive selective attention focuses on these ongoing goals

(Koch & Tsuchiya, 2006; Anderson 2013). For example, when doing a crossword, we selectively scan the puzzle for a particular word. This visual search is cognitively demanding (Anderson, 2013). In the case of stimulus-driven selection, attention allocation is driven by stimulus features such as when a novel or loud noise captures our attention (Koch & Tsuchiya, 2007; Anderson, 2013). Therefore, stimulus-driven selection allocation is involuntary, quicker, and less cognitively demanding than goal-driven selection (van Zoest, Donk, & Theeuwes, 2004; Anderson 2013; Anderson & Kim, 2019). This tendency to proritise certain information, whether it is based on current goals or stimuli salience, is referred to as an attention bias (Azriel & Bar-Haim, 2020). The perceptual load theory of attention and the underlying mechanisms that help select relevant information have shown that goal-driven attention capture (that is, task performance) will be poorer under high perceptual load conditions (see Lavie, 2004, for a review).

Table 1

The terms similar to goal- and stimulus- driven attention capture is evident throughout various theoretical models.

Two traditional dissections		Authors (year)
Salience- driven	Goal- driven	Anderson (2013)
Bottom-up processing	Top-down processing	Koch and Tsuchiya (2006)
Exogenous	Endogenous	Posner and Cohen (1984)
Reactive	Proactive	Dual mechanisms of control model (Braver, 2012)
Probability based (noise)	Strength based (surprise)	Hohwy (2012) (not in detail)
Early selection (high load)	Late selection (correct allocation- low load)	Lavie's theory (1995)

Furthermore, some novel, salient and meaningful distractors are able to break through this high-load-driven attentional capture barrier (Failing & Theeuwes, 2018; Lavie, Ro & Russell, 2003). For example, due to their salience and novelty (stimulus-driven), yellow-coloured taxis are easier to spot on a busy road (for example, Hu, De Rosa, & Anderson, 2019). Various reviews consider this traditional dichotomy of goal- and stimulus-driven attention as incomplete as there is a possible third mechanism based on affect-based meaningful stimuli (Munneke et al., 2015; Awh et al., 2012; Raymond, 2009). The current thesis includes experimental work on such affect-driven attention capture.

Affect-Driven Attention

In addition to the existing goal-driven and stimulus-driven attentional biases, recent studies have shown a novel affect-driven selective attention. This corresponds to an attentional bias to emotional and motivational stimuli (Vuilleumier, 2005; Vuilleumier & Huang, 2009; Anderson, Laurent, & Yantis, 2011; Gupta & Raymond, 2012; Hajcak, et al., 2013; Kennedy, Rawding, Most, & Hoffman, 2014; Preciado, Munneke & Theeuwes, 2017; Gupta et al., 2019; Gupta et al., 2014). The following sections first discuss emotional and learnt motivational stimuli, followed by inherently motivating food stimuli due to the similarities between the former two meaningful affect-related types of stimuli.

Attention Bias to Emotional Stimuli

Emotions, similar to attention, are complex phenomena difficult to operationalise. Classic models of emotion have tried to understand the interdependence and temporality of physiological experiences, neural activities and cognitive appraisal in order to define emotions (James, 1922; Plutchik, 1982; Schachter & Singer, 1962). There are primary emotions that are said to have universal facial expressions corresponding to each (such as happiness); and therefore, have an inherent meaning that led to the conclusion that emotions are innate (Matsumato & Ekman, 2008). In the current study, emotions are defined as innate physiological responses enabling appraisal of the environment, readiness to act, and affective experience (Moors, 2009).

Emotionally loaded stimuli, such as an image of a laughing baby or a spider, are central to our interaction with the world and hold evolutionary and social significance (Vaish, Grossmann, & Woodward, 2008; Moors, 2009; Oliveira et al., 2013). Quick and efficient processing of emotions influences and guides the processing of information and behaviours (Pourtois, Schettino, & Vuilleumier, 2012). Especially, the broaden-and-build theory postulates positive emotions expand an individual's ability to experience the inner and outer environments, in comparison to negative emotions which narrow down the experience (Fredrickson, 2004). The attention bias to emotional, when compared to neutral stimuli, can be affected by the two evaluative dimensions of emotional stimuli: valence (value associated with the emotion, expressed on a continuum from negative- neutral- positive) and arousal (perceived intensity of the emotion, expressed from calming to exciting) (Kensinger & Schacter, 2006). Rage is an example of a highly arousing negative emotion, while contentment is an example of a low arousing positive emotion (refer to Lundqvist, Flykt, & Öhman, 1998; for example, emotional face stimuli).

Valence

The studies on processing biases of positive and negative emotions reveal that they vary based on the nature of the stimuli and experimental paradigms (Kauschke, Bahn, Vesker, & Schwarzer, 2019). Empirical studies report a consistent anger-superiority effect, whereby angry faces were detected more quickly and efficiently than happy faces (Hensen & Hansan, 1988; Ceccerini & Caudek, 2013). A processing advantage was found for threatening/negative emotional stimuli as targets and distractors (for example, Maratos, Mogg, & Bradley, 2008; Yates, Ashwin, & Fox, 2010; Yao, Ding, Qi, & Yang, 2013). On the contrary, many studies have also reported a happiness-superiority effect (more efficient detection of happy faces; for example, Miyazawa & Iwasaki, 2010; Savage, Becker, & Lipp, 2016). Numerous studies have reported attentional prioritization to positive emotional distractors (Olivers & Nieuwenhuis, 2006; Most et. al., 2007; Gupta et. al., 2015; Gupta & Srinivasan, 2015; Gupta et al., 2016). As to whether irrelevant positive emotional stimuli facilitate or impair task-relevant information processing, the evidence is unclear (Most et. al., 2007; Gupta et al., 2015).

Possible explanations for the discrepancies in the reported emotion-related superiority effects could be that first, many of these studies incorporated either positive or negative stimuli rather than comparing responses to both types within a single study (for example, Yates et al., 2010). Second, most of the paradigms used simple attention capture paradigms and did not manipulate attentional resource availability, an important factor affecting attention allocation to information (for example, Gupta et al, 2015; Gupta et al., 2016). Third, some studies showed that attentional capture by happy or angry emotions could vary based on the perceptual stimulus characteristics where the anger superiority effect is likely to occur with dynamic rather than static images and the happiness superiority effect tends to occur when realistic images are used (Ceccarini & Caudek, 2013; Savage et al., 2016). As the above experiments used static images, Lundqvist et al. (2014) posit that the discrepancies in attention allocation could be attributed to the stimuli's emotional arousal.

Arousal

The historical debate of the anger- vs happiness superiority effect was settled based on evidence that high arousing images, irrespective of their valence, capture attention more quickly (Lundqvist et al., 2014). Studies have also confirmed that high-arousing stimuli (when compared to low- and neutral-arousing) require less attentional resources and facilitate target processing when attention is constrained temporally (Keil & Ihssen, 2004; Anderson 2005; Mather & Sutherland, 2011). Due to these established findings, most studies (reported in this review) have only manipulated valence or matched for arousal (Yates, Ashwin & Fox, 2010; Gupta et al., 2015).

Attention Bias to Value- learnt Motivational Stimuli

The current thesis considers two types of motivational stimuli: value- learnt (value is imbued to a neutral stimulus through repeated and consistent associations with positive /

negative feedback, experience and habits; Raymond & O'Brien, 2009; Jiang & Sisk, 2019) and inherently motivating stimuli (in this case, food cues, which are usually rewarding but can also hold negative connotations when associated with weight gain; Wilson et al., 2021). Motivation initiates, maintains and adapts behaviour to attain an outcome (Wilson & Keil, 1999; Staddon & Cerutti, 2003). Here we discuss the process through which neutral stimuli attain meaning and saliency: value-learning (Rajsic et al., 2017; Le Pelley et al., 2016; Dewey, 2011).

Unlike emotion which is largely considered innate and chronic, value-learning tends to last over a long period (7-9 months; Anderson & Yantis, 2013). This associative value- learning often occurs by selection and reward history. Selection history implies that attention allocation to a stimulus that was previously consistently selected and prioritised tends to eventually automatically capture attention (refer to Theeuwes, 2019; Failing & Theeuwes, 2018; Anderson, 2016; for a review). Reward history posits that a stimulus previously associated with rewards is more likely to automatically capture our attention (refer to Failing & Theeuwes, 2018; Anderson, 2016; for a review). Therefore, the success of learning and allocation of attention to the value-learnt stimuli can depend on either of these reinforcement histories based on several factors such as the attention demand of the task, demand for efficient task performance and task relevance (Theeuwes, 2019; Failing & Theeuwes, 2018; Anderson, 2016; MacLean & Giesbrecht, 2015).

Apart from reinforcement histories, the prioritization of attention can depend on the evaluative dimensions of stimuli. Similar to emotional stimuli, the strength of the stimuli can be defined in terms of dimensions of its valence (similar to emotional valence, expressed on a continuum from negative/ low value to positive/ high value) and predictability (the consistency with which a stimulus predicts an outcome, expressed from high to low) (Sutton, & Barto, 1990; Anderson, Laurent, Yantis, 2011; Dewey, 2011; Le Pelley et al., 2016; Gupta et al., 2016:

Experiment 3; Gupta et al., 2019; Gupta, 2022). For example, getting a gift every birthday from a parent would be an example of a predictive, positive association (refer to a commonly used associative learning task, Raymond & O'Brien, 2009).

Learned valence

Humans demonstrate a preference to approach reward-associated stimuli and avoid aversive information (Veenhovan, 2003). Studies have shown that we tend to optimize our behaviour to yield high-value relative to low-value rewards (Navalpakkam, Koch, & Perona, 2009; Navalpakkam, Koch, Rangel, & Perona, 2010; Anderson, 2013). Attentional prioritization to rewarding and punishing stimuli has been observed in the literature (Anderson, Laurent, and Yantis, 2011; Hickey et al., 2011; Schmidt, Belopolsky, & Theeuwes, 2015a; Anderson & Halpern, 2017). In contrast to positive and neutral stimuli, those associated with shock, aversive feedback and loss tend to capture our attention and in general, are associated with poorer information processing (shock being more potent; Yates et al., 2010; Schmidt et al., 2015a,b; Anderson, 2016a; Ballard, Sewell, Cosgrove, & Neal, 2019).

Numerous studies argue that the unique attention bias to rewarding stimuli is another selective attention mechanism (in addition to goal- and stimulus-driven); also known as reward-history driven attention (Theeuwes, 2019; Failing & Theeuwes, 2018; Marchner & Preuschhof, 2018; Anderson, 2016; Awh, Belopolsky, & Theeuwes, 2012). Here, studies observed a selection prioritization to stimuli repeatedly associated with reward (Anderson, Chiu, DiBartolo, & Leal, 2017). Reward learning appears to persist in complex stimulus-reward contingencies such as when a previously rewarding stimuli now yields punishments, which is associated with a reduced attentional bias (Anderson, 2013; Kim & Anderson, 2019; Pearson & Le Pelley, 2020). This shows that value-learning can undergo changes and modify its structure. Further, attention bias was not only shown in relation to the learned rewarding stimuli, but also to stimuli that share similar features (Anderson, Faulkner, Rilee, Yantis, & Marvel, 2013; Anderson, 2017). This shows that attention bias to rewarding stimuli, evidenced in many studies, appears to have complex learning contingencies such as generalisalibity of attention bias based on stimulus features.

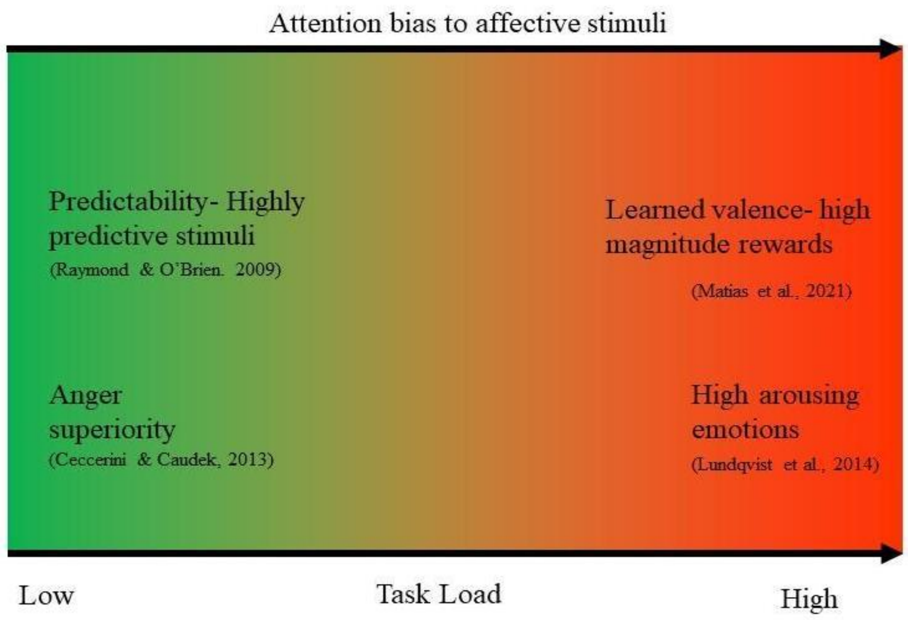
Parallel to attention capture by emotional stimuli, attentional capture to value-learnt stimuli appears to vary with attention resource availability. Studies have shown that under resource-constrained (high-load) situations reward associated neutral faces appear to be processed and affect relevant task performance as well (Gupta et al., 2016: see Experiment 3; Raymond & O'Brien, 2009). This complements an earlier study finding that showed that angry face distractors associated with learnt negative motivational valence did not interfere with task performance under high-load conditions (Yates et al., 2010).

Learned predictability

The repetitive associations between a stimulus and its outcome help predict future actions and guide decisions (Anderson, 2013). We are wired to reduce the errors in prediction by quickly learning complex stimulus-outcome contingencies (Hohwy, 2012). The most predictive rewards capture more attention, and the association is learned faster (Jahfari & Theeuwes, 2016). The latter shows how predictability directly affects the speed of stimulus-outcome learning (Gupta, Raymond, Vuilleumier, 2019). Nevertheless, some studies show that explicit awareness of predictability and contingency of the stimuli is not necessary for it to capture attention (Leganes-Fonteneau, Scott, & Duka, 2018). Many earlier studies reported using the value-learning paradigm used by Raymond and O'Brien (2009), whereby participants had no knowledge of the stimuli- outcome contingencies. Here, they found that when attention was not constrained (under low-load conditions), predictability drives the attention allocation. It is interesting to note that Raymond and O'Brien (2009) demonstrated that attention-constraint affected the attention capture by value-learnt stimuli based on valence or predictability.

Figure 1

Attention prioritization to affective stimuli based on attentional load and affective stimulus feature



Taken together, the literature suggests that affective (that is, both emotional and motivational) stimuli appear to have a competitive advantage in capturing attention when compared to neutral stimuli; even when attention is constrained (refer to Figure 1; Pessoa, 2008; Raymond & O'Brien, 2009; Gupta, Hur, & Lavie, 2015; Watson et al., 2019). Affect-driven attention thereby shares mechanisms similar to goal-driven or stimulus-driven attention (Mohanty & Sussman, 2013; Anderson & Kim, 2019). However, affective stimuli also modulate both automatic and voluntary attention capture (Raymond, 2009; Mohanty & Sussman, 2013; Le Pelley et al., 2016). Overall, this preliminary evidence assists in differentiating affect-driven attention from the traditional dichotomy of attention.

Affect-Driven Attention: Similarities and Differences

Emotional and motivational stimuli share similarities and differences in their processing. Although stimuli-outcome associations are learned and emotions are innate, recent studies have started exploring whether learned salience (value-learning) can override attention bias to innate salience (emotions). One study reported that the poor performance of the main task as a result of a highly arousing negative emotional distractor was reduced when it was imbued with a higher reward value (Padmala & Pessoa, 2014). Following this, Yokoyama, Padmala, and Pessoa (2015) also showed that highly predictable rewarding stimuli also reduced the interference of negative emotional stimuli on task performance. This shows that (a) learnt motivational value could counteract the effect of emotional stimuli and (b) emotional stimuli are not automatically processed and that their prioritization is susceptible to their relevance. Although strong conclusions on value-learning driving attention allocation cannot be made, these interesting findings nevertheless direct the focus on understanding value-learning and emotion as parallels. Previous studies (Padmala & Pessoa, 2014; Padmala & Pessoa, 2015) contribute to the evidence that value-learnt and emotional stimuli appear to be modulated by attention availability (Pessoa, 2002, 2008; Gupta et al., 2015). There is also opposing evidence that emotions are processed automatically due to their inherent meaning and are unaffected by resource availability (Vuilleumier, Armony, Driver, Dolan, 2001). Pessoa (2013) proposed the former as strong automaticity and the latter as weak automaticity of emotional processing. However, the current review provides evidence that attention bias to affective stimuli appears to depend on its evaluative dimensions as well as the attention resource availability.

The evidence on affect-driven attention capture has led to integration and study of emotion and motivation. Raymond (2009) attempted to show the interdependent interaction between emotion and value-learning driven attention capture at various stages of information processing, which consequently influence behaviour. According to this model, affect-driven evaluation of the sensory input occurs once the information is attended to. Interestingly, this model also indicates a direct and automatic influence of associative learning on selective attention. However, this model has considered goal setting as dependent on associative learning. It does not discuss how perceptual load, goal- and stimulus-driven attention capture fit into the picture; rather there is only a mention that both of these can be overridden by affect-driven attention capture. In addition, a recent study has suggested that emotion could be a fundamental feature of information processing, similar to stimulus features and goals (Todd, Miskovic, Chikazoe, & Anderson, 2020). With this, Oliveira and colleagues (2013) provided a model that suggested individual differences in the personal relevance of the emotional distractor and inherent motivation to perform the task modulate the relationship between perceptual load and attention bias to emotional stimuli. The latter could imply that affect-driven attention should be examined in conjunction with individual differences.

Implications of Affect-Driven Attention

The conceptualization of affect-driven attention broadens our knowledge in understanding information processing. Furthermore, there are practical and clinical implications of understanding affect-driven attention capture. Affective stimuli are all around us and are used in various fields such as artificial intelligence, and consumer research (marketing and advertisements). Understanding the consequences of affective stimuli on information processing and behaviour could help improve the decision-making algorithms in artificial intelligence research, influence consumers to choose healthy products over unhealthy and so on. At the clinical and subclinical levels, exploring the attention bias to negative faces can help understand the severity, treatment efficacy and treating individuals with depression and anxiety (Bar-Haim, 2010; Duque & Vázquez, 2015). Aberrations in reward learning can be especially observed in individuals with addiction, especially to substances (for example, Diekhof, Falkai, & Gruber, 2008; Anderson, 2016). Interestingly, similar to the modulation of affect driven-attention by the perceptual load in a healthy sample, studies have implicated that perceptual load plays a role in attention biases to affective stimuli such as threatening stimuli in clinical samples (Theodorou, Konstantinou, & Panayiotou, 2021). Hence, affect-driven attention and attention economy can interactively help critically evaluate attention allocation to omnipresent affective stimuli.

Distraction by Food Cues

Food is an example of an inherently rewarding, motivational stimuli that can automatically capture our attention (Hardman et al., 2021; Jansen, Houben, & Roefs, 2015). Few studies have studied emotion and value-learning together due to their similarities, as discussed previously (Gupta et al., 2016; Yokoyama et al., 2015). Motivation is not restricted to value-learning but has a broader definition that often subsumes needs, goals and experiences (Reeve, 2016; Raymond, 2009). Therefore, this thesis has incorporated naturally motivating food cues to understand its role in shaping perception.

Unhealthy food consumption is a major public health problem and continues to rise in prevalence (Luhar et al., 2020; Swain & Chowdhury, 2018). There are two commonly used models to explain and understand unhealthy eating behaviour. First, the incentive-sensitization model of obesity proposed that increased availability and exposure to energy-dense and highly-palatable food had led to these food stimuli attaining an incentive salience through repeated consumption (Robinson & Berridge, 2000). Consequently, salient foods and food-related stimuli tend to capture attention and lead to overconsumption as evident in obesity (Werle et al., 2021; Nijs & Franken, 2012; Robinson & Berridge, 2000. 2008). The second model, the dual-systems perspective, proposes that eating behaviour is elicited by parallel stimulus- and goal-driven processes (McClure & Bickel, 2015). Apart from the deliberate goal-oriented process, consumption also depends on uncontrolled and automatic attention bias (Pitchers, Sarter, & Robinson, 2018; Temple, 2016, McClure & Bickel, 2015).

Attention bias to food stimuli has been associated with eating behaviour, hunger, craving, obesity and weight gain (Field et al., 2016; Meule & Platte, 2016; Kakoschke, Kemps, & Tiggemann, 2015; Werthmann et al., 2011; Castellanos et al., 2009). Although, some studies have reported discrepant findings such as a lack of or small difference in attention biases to food between healthy and unhealthy weight groups or found a lack of association between attentional bias to food, food consumption and individual differences in body weight (Hardman, et al., 2021; Hagan et al., 2020; Field et al., 2016). These discrepancies show that there could be possible modulating factors that affect distraction by food. More recently, attention bias to food has been studied from a perceptual load framework in healthy samples (Morris, Yeomans, & Forster, 2020; Morris, Keith Ngai et al., 2020; Morris, Vi, et al., 2020). This research showed that the distractor interference caused by food cues (high-calorie sweets only) was eliminated during high-load conditions (Morris, Yeomans, & Forster, 2020). These studies shed light on the role of the attention economy on attention bias. However, further research needs to be conducted to replicate these novel findings with a variety of foods, such as low-calorie savoury foods.

In addition to obesity, patterns of disordered eating characterised by overconsumption and persistent selection of energy-dense but nutrient poor (that is, unhealthy) choices have led to the conceptualisation of ‘food addiction’ (Polivy, Herman, & Mills 2020; Gordon et al., 2018; Rogers, 2017; Gearhardt et al., 2016). Recent research has also demonstrated similarities between food and drug addictions in terms of aberrant functioning of the neural reward circuit, elevated impulsivity and bias to drug/food-related stimuli (Gordon et al., 2018; Rogers, 2017;

Temple, 2016). One study has shown that individuals with opioid addiction (receiving methadone maintenance treatments) have an attention bias to not only drug-related stimuli but also non-drug-related rewards (Anderson, Faulkner, Rilee, Yantis, & Marvel, 2013). This would indicate the pervasive nature of reward-driven aberrance in attention capture. Overall, the ability of rewarding food stimuli to capture, hold and delay disengagement from attention could be a possible cognitive marker for unhealthy food consumption, even in obesity (Deluchi, et al., 2017).

A Roadmap of the Thesis

This section attempts to briefly delineate the process that led to the 5 experiments included in this thesis. Based on previous research it is clear that (a) affective stimuli (emotional and value- learned) capture attention, and (b) two of the factors that affect this attention capture are the evaluative dimensions of affective stimuli and perceptual load. However, only a few studies have manipulated specific dimensions of emotion and perceptual load (for example, Gupta et. al, 2016; Raymond & O'Brien, 2009). To address this gap in the literature, the current set of experiments manipulated the evaluative dimensions of emotional (valence) and value-learnt stimuli (valence and predictability). Perceptual load was manipulated using the visual letter-search task. We used a direct measure of perception in the letter- search task by introducing a peripheral neutral meaningless stimulus following Macdonald and Lavie (2008). Participants recorded the presence or absence of the stimuli. The current experiments 1, 2 and 3 used the same direct measure of perception. Note that experiment 2 was a follow-up conducted to reiterate the findings in experiment 1. Therefore, experiments 1-3 aimed to:

1. Examine the interaction between attentional availability and emotion on conscious perception of target stimuli.

   a. We additionally aimed to identify how personality traits affect the allocation of attention to irrelevant angry and irrelevant happy emotional facial stimuli under different attention conditions, which may affect perception.

2. Examine the interaction between attentional availability and motivation on conscious perception of target stimuli.

Based on the results of these 3 experimental studies, we explored the distracting role of perceptual load and specific, omnipresent meaningful food stimuli on perception. An attentional bias to food stimuli, when compared to neutral stimuli, has been demonstrated by previous studies (Field et al., 2016; Meule, & Platte, 2016). The recent studies have shown that this attention bias to high calorie sweet food disappears during high-load conditions and is thus consistent with the perceptual load theory (Morris, Yeomans, & Forster, 2020; Morris, Keith Ngai et al., 2020; Morris, Vi, et al., 2020). Therefore, experiment 5 attempted to replicate these findings with food that are low-calorie and include a gustatory variety (sweet and savoury tasting foods). The aim of this experiment was to:

3. Understand the distractor interference of low- and high-calorie food in the low and high perceptual load conditions.

Experiment 4 was a nationwide validation study of a comprehensive food.pics food database in India. Previous studies have validated the database in European and American samples (Bonin et al., 2021; Prada et al., 2017; Blechert et al., 2019, 2014). This was primarily conducted to validate the norms in India, namely, a South Asian country, and to utilise the validated sample of images and subjective Indian ratings for experiment 5. We also conducted secondary analysis that would further describe the subjective Indian ratings and compare them to the database norms. Overall, experiment 4 aimed to:

4. Evaluate the food-pics_extended norms in an Indian sample by using a smaller subset 300 of food images.

    a. The secondary aim was to conduct an exploratory analysis on the Indian data to better describe and understand the current study's culture specific subjective ratings by evaluating the impact of cultural, individual (for example, gender) and state (for example, hunger) variables on the perception of food (images).

Summary

Overall, the review of the literature suggests taking into consideration emotional and motivational stimuli in parallel when examining traditional selective attention capture, i.e., goal- and stimulus-driven. The forthcoming chapters describe empirical work aimed at disentangling the specific role of positive and negative emotions, and, general and food rewards in combination with perceptual load on attentional measures.

Chapter II

Irrelevant Angry, But Not Happy, Faces Interfere with Conscious Perception Under High Perceptual Load: The Role of Trait Impulsivity

Introduction

Many stimuli compete for our attention in daily life. Moreover, there appears to be a preferential allocation of attentional resources to emotional over neutral stimuli (for a review see: Pessoa & Ungerleider, 2004; Yiend, 2010, Gupta, 2019,) as emotions play an essential role in providing meaningful social and environmental cues. For example, a frown or a smile can change the meaning of a verbal expression such as 'I am fine'. Given the saliency of emotional stimuli, it has been proposed that attention interacts with emotion (Fenske, & Raymond, 2006; Pessoa 2008 for a review). The popularity of this view regarding attentional prioritisation towards emotions has led to new conceptualisations such as (a) emotional attention, which is defined as a reflexive, automatic attentional capture and modulation by emotional stimuli (Vuilleumier & Huang, 2009); and (b) emotion-induced blindness, which is defined as an impairment in identifying a neutral target that immediately follows a threatening or fearful distractor (Singh & Sunny, 2017).

Emotion and Attention

Previous studies have indicated that positive and negative emotional stimuli impact our scope of attentional resources differently (Fredrickson, 2004; Fredrickson & Branigan, 2005; Gupta & Srinivasan, 2015; Srinivasan & Gupta, 2010, 2011; Gupta, Hur & Lavie, 2016). For example, many studies have reported that the processing of happy emotions expands the scope of attention, and this in turn can help reduce anger (Fredrickson & Branigan, 2005; Srinivasan & Gupta, 2010, 2011; Summerell et al., 2019). Moreover, it has been shown that the processing of happy faces requires fewer attentional resources, while the processing of angry faces requires more attentional resources (Srivastava & Srinivasan, 2010; Gupta et al., 2016, Experiment 2).

Happy and angry emotional distractors automatically capture attention and interfere with primary task performance even when irrelevant to the task (for a review see: Yiend, 2010). One factor that determines the processing of distractors is the perceptual load of the primary task. Perceptual load is one of the most critical aspects of attention processing. It is related to the complexity of the visual display that places processing demands on the perceptual system (Lavie, 2005, 2006, for a review). According to the perceptual load theory, engaging in a high attention-demanding task, relative to low attention-demanding task, they have fewer resource to process a distractor (Lavie, 1994; for a review see: Lavie, 2005, 2010). Thus, a distractor's interference is lower in high (relative to low) attention-demanding task conditions (Lavie & Tsal, 1994; Beck & Lavie, 2005).

Perceptual Load, Emotion and Perception

Empirical evidence suggests that perceptual load plays an important role in conscious perception. For example, using the inattentional blindness paradigm, a study observed reduced awareness of the distractor during high (relative to low) attention-demanding conditions (Cartwright-Finch & Lavie, 2006). The unexpected stimulus was non-emotional; therefore, the role of a distractor’s emotional content in awareness under different load conditions was unclear. To test this, Gupta and Srinivasan (2015) conducted a study in which an emotional face (happy, sad or neutral) was presented as a distractor at the centre of the screen in a low-load and high-load visual letter-search task. Participants searched for a target letter (X or N), among other non-target letters, in the letter-search task on each trial. At the end of the task, they were given a surprise face recognition subtask in which the face that was presented in the last trial of the letter-search task was presented along with a new face. They were required to recognise the face that was presented in the last trial of the letter-search task. The study found that the recognition accuracy of happy faces was unaffected by the load, whereas the recognition of sad faces was significantly worse in high-load conditions, which supports the hypothesis that awareness is confined to task-relevant information under high-load conditions (Lavie, Beck & Konstantinou, 2014). Similarly, Gupta et al. (2016, Experiment 2) found that happy face distractors captured attention when participants were engaged in highly demanding attention tasks. In contrast, angry face distractors did not capture attention in high perceptual load conditions. Together, these results indicate that positive and negative emotion differentially interact with perceptual load to determine distractor processing or conscious perception.

Furthermore, Gupta and Srinivasan (2015) demonstrated that the reduction of the processing of negative emotion during high-load conditions as a consequence of rapid forgetting (given that awareness of the distractor was measured, unexpectedly, after the primary letter-search task) (see Wolfe, 1999; Macdonald & Lavie, 2008). For example, a study (Macdonald & Lavie, 2008) argued that since an extra stimulus (the emotional face) was unexpected, it might have been perceived but generated a weak signal that might be difficult to retrieve from memory due to the delay between the responses to the primary task and the unexpected question (see Teichner & Krebs, 1974; Bashinski & Bacharach, 1980). Consequently, the results of inattentional blindness might be confounded by the surprise single-question method due to rapid forgetting.

To avoid the potential confounding effects of rapid forgetting, Macdonald and Lavie (2008) modified the inattentional blindness paradigm to include an expected 'critical' stimulus (CS) across multiple trials. This modified paradigm allowed the calculation of the effect of perceptual load on response bias and detection sensitivity. The detection sensitivity of CS is reduced more significantly under high- than low-load conditions, which indicates that high perceptual load influences conscious perception and reduces the ability to detect irrelevant stimuli. This phenomenon is known as ‘load-induced blindness’ (Macdonald & Lavie, 2008). However, their study did not include emotional information, which crucially modulates the conscious perception of irrelevant stimuli (Gupta & Srinivasan, 2015). Therefore, it is important to establish the manner in which irrelevant emotional information modulates load-induced blindness phenomena.

Personality Traits, Emotional Processing and Attention Capture

Trait Anxiety and Emotional Processing

There is also evidence that personality traits such as anxiety and impulsivity affect attention capture and emotion processing (Carver & Johnson, 2018; Kang, Kim, Kim & Lee, 2019; Yu et al., 2018). Trait anxiety encompasses a tendency to experience and attend to negative emotions such as fear in routine life (Gidron, 2013). Individuals with trait anxiety show higher brain activation of areas that are often implicated in fear-related emotional fluctuations and emotion processing (for example, the amygdala and the insula; Todd, Miskovic, Chikazoe, & Anderson, 2020; Brühl, Rufer, Delsignore, Kaffenberger, Jäncke, & Herwig, 2011; Stein, Simmons, Feinstein, & Paulus, 2007). Similarily, it has been suggested that individuals with a high level of anxiety recognise negative words more than positive words (Yu et al., 2018). Various studies also show that higher trait anxiety scores are associated with an increased attention bias to threatening stimuli (such as angry faces and shock) and misinterpretation of emotionally ambiguous stimuli as threatening (Mogg & Bradley, 2016; Bishop, 2007).

Impulsivity and Emotional Processing

Trait impulsivity refers to a wide range of behaviours or executive functions that are performed without foresight or are ill-conceived and, often, risky, which results in poor outcomes (Zisner & Beauchaine, 2015). Recent developments such as the five-factor model of impulsivity recognise that positive and negative emotions might promote impulsive behaviour (Pearlstein et al., 2019; Carver & Johnson, 2018; Whiteside & Lyman, 2001). Impulsivity also modulates attention bias to various socially meaningful stimuli such as faces, as well as food and addictive substances (van den Akker et al., 2014; Coskunpinar & Cyders, 2013). In support of this, evidence shows that individuals with high impulsivity have (a) poorer control over impulsive behaviour, but (b) are able to maintain attention better when emotional stimuli are present (Leshem & Yefet, 2019). It has been suggested that individuals with high impulsivity recognise angry faces more often than positive faces (d'Acremont & Van der Linden, 2007). Furthermore, a few clinical disorders (such as, attention-deficit hyperactivity disorder and binge-eating disorder) also indicate a possible interaction between attention and trait impulsivity (Steadman, & Knouse, 2016).

Overall, it appears that personality traits such as anxiety and impulsivity modulate attention and emotion. However, the manner in which these traits modulate attention capture of emotional stimuli under different attention-demanding conditions is unclear (Yu et al., 2018; d'Acremont & Van der Linden, 2007). Since individuals with trait anxiety and impulsivity process negative emotions more readily than positive emotions, it is important to determine whether these traits affect the allocation of attention to irrelevant angry and happy emotional face stimuli under different attention conditions, which may in turn affect perception.

The Current Study

Existing literature shows that perceptual load affects awareness of distractors and processing of emotional stimuli, but the extent to which attentional load and emotions interact in predicting conscious perception remains unclear. The current study adds to the body of work on the impact of perceptual load and emotional distractors on conscious awareness of expected stimuli (critical stimulus: CS). In addition, we were interested in the difference between angry and happy faces. It has been found that when emotional distractors are presented with high probability (i.e., in 100% of trials), emotional distractors do not interact with perceptual load to modulate the primary letter-search task. Nevertheless, attention and perceptual load interact in determining performance on the secondary task (i.e., recognition of emotional distractors; see Srinivasan & Gupta, 2010; Gupta & Srinivasan, 2015). In the present study, there were two tasks: the primary 'letter-search task' and the secondary 'squiggle-detection task'. The attentional requirements are higher when there are two tasks. It has been suggested that under a divided-attention condition, negative emotion interferes with task performance more than positive emotion (see Srinivasan & Gupta, 2010: Experiment 2). Moreover, we presented face distractors in 100% of the trials; therefore, we predicted that emotional-distractor faces would not interact with perceptual load to modulate performance on the primary letter-search task. However, we predicted that attention and perceptual load would interact to modulate the secondary squiggle-detection task, which would be mediated by trait impulsivity.

Experiment 1

Based on the findings of Macdonald and Lavie (2008) and Gupta et al. (2016), we hypothesised that during high-load conditions, participants would be less accurate in detecting the squiggle in the presence of angry (relative to happy) face distractors. Gupta et al. (2016) suggested that the majority of attention resources are required to process angry faces; hence, most of the attention resources will be consumed by processing angry faces in the high-load condition, which would leave little attention resources to detect the secondary task (squiggle-detection). In contrast, in the low-load condition, we expected no difference between the positive and negative conditions in the accuracy of CS detection as enough resources would be available to detect the squiggle. Previous studies have highlighted (but not extensively considered) a possible role of personality variables in the attentional capture of emotional stimuli (Carver & Johnson, 2018; Kang, Kim, Kim & Lee, 2019). Therefore, the current study studied the possible moderating role of trait impulsivity and anxiety in the interaction between attention and emotion. Since individuals with high impulsivity process negative emotions more than positive emotions, we predicted that highly impulsive individuals would allocate more attention to processing the angry face distractors in the high-load condition, which may interfere with the detection of the secondary task (squiggle-detection). In the first experiment, we conducted one main and one control task to test these hypotheses. In the main task, the participants searched for the target letter and CS. In the control task, the participants only searched for the CS. Furthermore, to clarify the results of the first experimental findings, we conducted a brief follow-up experiment: Experiment 2.

Methodology

Participants

A total of N = 69 (18–38 years of age; *M* = 25.45 years, *SD* = 4.87 years; 25 females) right-handed participants who reported normal or corrected-to-normal vision participated in this experiment after their informed consent was given to the researchers. The rationale behind selecting this age group was that older individuals tend to experience the positivity effect, that is, they are more biased toward positive stimuli than negative stimuli (Reed & Carstensen, 2012). We estimated (using G-Power; Erdfelder, Faul, & Buchner, 1996) a necessary sample size of 45 to detect a medium-size effect of 0.25 (Gupta & Singh, 2021) and to obtain a power level of 0.95. However, since we aimed to examine the role of personality traits in the interaction between cognition and emotion, we included more participants to examine individual differences.

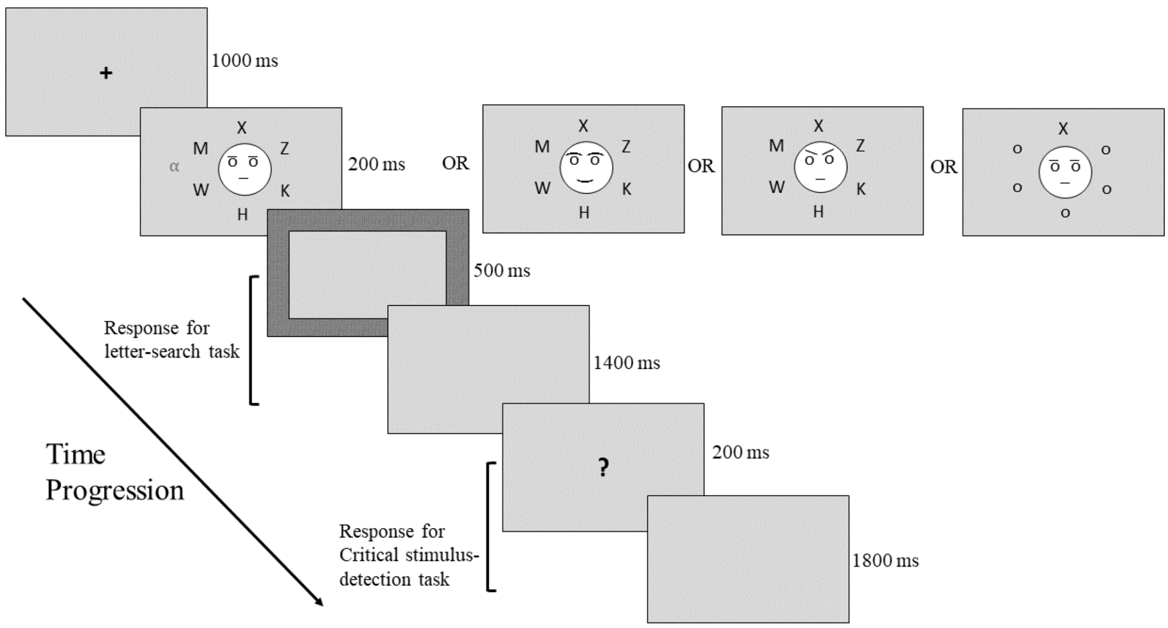
Apparatus and Stimuli

Stimuli were displayed on a 24-inch colour monitor (60 Hz, resolution 1,920 × 1,080 pixels) that was viewed binocularly from a distance of 60 cm. E-Prime software (Version 3.0), which operated on a computer with a B360 Gaming HD, Intell CoITM) i7 CPU @3.20 GHz system processor generated stimuli and recorded responses acquired through a number pad. A total of 12 static grey-scale photographs of young adults (six male and six female identities with three emotions) were selected from the Karolinska Directed Emotional Faces (Lundqvist, Flykt, & Öhman, 1998). Each face displayed all three emotions (happy, angry and neutral) without ears and hair and was subtended at a visual angle of 3.3º × 4.9º. The backgrounds in these experiments were grey (Red/Green/Blue values 150,150,150) with black text.

The current study used an amalgam of the IB paradigm that was used by Macdonald and Lavie (2008) and the emotional distractor trials that were used by Gupta et al. (2016). This approach enabled us to combine the three key manipulations into a single task: (a) perceptual load, (b) an emotional stimulus (happy, angry and neutral faces) in the middle of the letter ring, and (c) the CS (the squiggle) in the periphery in 6 different positions. Further, the positions and the visual fields for the CS, target letter, and distractors were counterbalanced (see Figure 2); For example, the CS was presented either in the same visual field as the letter or in the opposite visual fields and the CS was presented closest to farthest from the target across trials.

Figure 2

An example of progression of a high-load trial with a neural (with a squiggle) trial. Stimulus display examples of high-load trial with a happy or angry face distractor and a low-load trial with a neutral face distractor is added. Real pictures of faces were used in the experiments.



Six letters were presented in the letter-search subtask in a circle that had a radius of 3.0º, along with the target letters, ‘X’ or ‘N’ (0.6º × 0.6º). Each of the letters appeared in half of the trials. The other five positions were occupied by ‘O’s (0.4º × 0.5º) in the low perceptual load condition, and the letters H, K, M, W, and Z (0.6º × 0.6º) in the high perceptual load trial. The stimulus display was present for 200 ms after the fixation display, and the participants had to respond to the letter-search subtask by pressing the ‘0’ key when target ‘X’ was spotted, and the ‘2’ key when ‘N’ was spotted. A meaningless grey shape, CS (0.3° × 0.3°), which was obtained from Macdonald and Lavie (2008), was presented at one of six equally spaced locations outside the letter ring at an 8.5° radius. Since the distances between the target and CS are counterbalanced, the closest distance between the target and the CS was 3.7° and the farthest was 6.9°. A black mesh pattern mask was used after the stimulus presentation. This mask covered the entire screen except for a small square area (9.5° × 9.5°) in the centre in order to not cover the space previously occupied by the letters; this was similar to the process that was used by Macdonald and Lavie (2008). The participants were then asked to press the key ‘a’ or ‘s’ after presenting the question mark display as a response to ‘absence of squiggle’ and ‘presence of squiggle’, respectively. Participants performed two subtasks in the experiment: letter-search and CS-detection. Unlike the previous study (MacDonald & Lavie, 2008), we presented emotional faces as distractors in the present study, which captured attention. Therefore, we wanted to ensure that participants understood the task before performing the main trials. Hence, 36 practice trials were given for each load condition. Each load condition comprised 144 main experimental trials in. Finally, there were control blocks for each load condition with trials, during which the participants performed only the CS-detection subtask and were asked to ignore the circle of letters. In the control block, participants were required to respond to squiggle only. In this simple block, a poor CS detection in the control blocks would imply an inability to spot the CS effectively. Therefore, we predicted that there will not be any difference in the sensitivity score between the low and high-load conditions as participants were instructed to respond to squiggle (not the letter) only as whole attention was directed to squiggle detection. D’ score of the control block was also used to test whether participants were paying attention to the task/experiment. A low d’ score (< 75%) in the control block may suggest that, in general, participants were not paying attention to the experiment (see MacDonald & Lavie, 2008, for discussion). Therefore, this cut-off (< 75%) was used to screen participants. Participants whose d’ score was <75% in the control block, were removed for the final analysis (see MacDonald & Lavie, 2008, for similar criteria).

Personality Trait Measures

Trait impulsivity. The short version of the UPPS-P Impulsive Behaviour scale (SUPPS; Cyders et al., 2014) was used to measure trait impulsivity. The questionnaire was based on Whiteside and Lyman's (2001) proposal that impulsive behaviour has five facets or pathways: (a) urgency, which refers to the tendency to act rashly when under extreme negative (negative urgency) or positive (positive urgency) emotions; (b) lack of premeditation, which implies a tendency to act with no or less thinking and planning; (c) lack of perseverance, which connotes the lack of ability to sustain focus on the current task; and (d) sensation-seeking, which is the tendency to seek activities that are novel or thrilling. The SUPPS-P consists of 20 questions (four items per subscale), which were rated on a four-point Likert scale that ranged from 'strongly disagree' (1) to 'strongly agree' (4). A higher total score indicated higher impulsivity. It has been reported that SUPPS-P has good construct validity (the comparative fit index for the 5-factor model is 0.98), and some studies have reported that the five factors can be summarised by one overall factor (the CFI = .91 for the one overall factor; Zhu et al., 2016). Therefore, the composite trait impulsivity score was used in this study. Internal consistency between the facets is varied between 0.74 and 0.88 across subscales (Cyders et al., 2014; Dugré et al., 2019).

Trait anxiety. A subscale of the state-trait anxiety inventory (STAI; Spielberger et al., 1983) was used to measure trait anxiety. The STAI- trait (STAI-T) subscale consisted of 20 questions that were rated on a four-point scale, from 'almost never' (1), 'sometimes' and 'often' to 'almost always' (4). The scale has been widely used and has good test-retest reliability (0.71 to 0.75, Spielberger et al., 1983) and Cronbach's alpha of > 0.83. The STAI-T has also shown good convergent validity with other anxiety measures (Elwood, Wolitzky-Taylor & Olatunji, 2011; Julian, 2011). The psychometric properties of the scale range from good to excellent across various clinical and non-clinical samples (Elwood et al., 2011; Julian, 2011). Trait rather than state anxiety was measured because individuals with trait anxiety are more likely to be predisposed to bias towards threatening information such as angry faces. The current study was conducted in a calm and comfortable set-up; therefore, state-anxiety, which is more sensitive to acute manipulations of mood or stress, was not the preferred measure (Elwood et al., 2011).

Procedure

The participants were recruited via advertisements on the email portal of the Indian Institute of Technology Bombay (IITB). Participants were first provided with an information sheet in which the experimental procedure was outlined, which included the risks, benefits and other relevant study details. The participants then provided informed consent before completing questions relating to demographics. Once all questions were clarified and consent was provided, the participants completed practise trials to familiarise themselves with the experimental set-up. The experiment occurred in a dimly lit room, and the participants underwent the practice block, which was followed by the experimental block. The order of high-load and low-load blocks were counterbalanced among the participants (refer to Figure 2 for example trials).

The participants completed the letter-search subtask, which was followed by the CS-detection subtask. Finally, they underwent the control block in which half of the low- and high-load trials were presented in the same order in which the load blocks were presented initially. The control block served to understand the baseline performance of participants and screen for poor data in the CS-detection subtask. Here, the participants only respond to the CS-detection subtask, although the trial progression is the same as that of the main experimental blocks. There were sufficient breaks during and between each block. After the control blocks, participants completed the SUPPS-P and STAI trait anxiety questionnaires; data for the latter was collected using Google forms. The participants were finally debriefed about the purpose of the study and compensated for their time and effort monetarily. The ethics committee of IITB approved the study.

Statistical Analysis

The following performance indices were derived from the primary task: letter-search reaction times (RTs) and accuracy. The CS-detection sensitivity (*d'*) was derived from the secondary task (squiggle detection task). The detection sensitivity was calculated from the hit rates and the false alarm rates for the CS-detection subtask. A mixed analysis of variance (ANOVA) was performed using 2 × (Impulsivity: high versus low) as a between-group factor; and 3 × (Emotions: angry, happy and neutral) and 2 (loads: high versus low) as within-group factors for the *d'* and β scores separately. Similar to previous studies, the high-impulsivity (N=29) and low- impulsivity (N=29) groups were created based on the median of the overall score (Doran, & Tully, 2018; Grisetto, Delevoye-Turrell, & Roger, 2021). In the current study, those with overall impulsivity scores above 43 were in the high impulsivity group. Anxiety was not controlled or randomized in the experiment, hence a better way to understand the role of anxiety is by statistically controlling for it. Since the current sample is slightly skewed towards higher trait anxiety, we performed an analysis of covariance (ANCOVA) using 2 load (high versus low) × and 3 emotions (happy, angry and neutral) as within-group factors by using the d' score, in which the anxiety score was used as a covariate. Paired sample t-tests were performed to compare angry and happy emotions conditions, whether or not an interaction effect between load and emotion existed. The sample had anxiety levels within the moderate-to-high range (M = 44.4, SD = 9.5). Since individuals with anxiety tend to overestimate threats with neutral faces (Peschard & Philippot, 2017), the current study focused mainly on the presence or absence of the differences between happy and angry emotional conditions.

Data Cleaning

In the RT analysis, trials were excluded in which the letter-search response was incorrect or the letter-search RT was less than 200 ms or greater than 2000 ms. On average, participants did not respond in 4% of the letter-search trials and 9% of the CS-detection task trials in high-load. In the same manner, they did not respond in 2% of the letter-search task trials and 6% of the CS-detection task trials. Furthermore, In the CS-detection subtask analysis, trials in which the search response was incorrect and trials on which participants had not responded to the CS subtask were excluded (see Macdonald & Lavie, 2008). The data of 12 participants was removed from further analysis due to poor data quality (CS accuracy of <75 % in the control block or letter-search accuracy of <65 % (Gupta et al., 2016) in the experiment, which was the process that was followed in similar previous studies (Macdonald & Lavie, 2008; Gupta et al., 2016). These criteria ensured that participants paid attention to the task. There was a total of 58 participants (*M* = 25.76 years, *SD* = 4.96 years; 19 females) in the final analysis.

Results

Critical Stimulus-Detection Task

Main task.

Sensitivity. The results of the 2 × 3 × 2 ANOVA revealed a main effect of load such that the *d'* value was significantly lower in the high-load (*M* = 3.51, *SD* = 1.25) than the low-load condition, (*M* = 3.86, *SD* = 0.86), $F(1, 56) = 5.14$, $MSE = 2.062$, $p = .027$, $\eta_p^2 = .08$, which confirms that our perceptual load manipulation was effective. Nevertheless, the three-way interaction between impulsivity, emotion and load showed only weak significance: $F(2, 112) = 1.32$, $MSE = .45$, $p = .058$, $\eta_p^2 = .05$. It is important to note that without the inclusion of impulsivity, the two-way interaction between load and emotion is not significant, $p = .19$.

Therefore, to further clarify the role of impulsivity we performed a two-way repeated-measures ANOVA using 2 (Load: high versus low) × 3 (Emotion: happy, angry and neutral) as within-group factors for both the high and low impulsive groups separately. Interestingly, an interaction effect between load and emotion was significant in the high impulsive group (F(2, 56) = 4.11, MSE = .42, p = .022, η_p^2 = .13), but not in the low impulsive group, (F(2, 56) <1).

The paired sample t-tests were conducted for the high impulsive group accordingly. The *d'* sensitivity measure for the high perceptual load condition revealed that irrelevant angry faces (M = 3.31, SD = 1.12) significantly reduced the squiggle's detection sensitivity compared to irrelevant happy faces (M = 3.86, SD = 1.06), (t(28) = 2.96, p = .01, d = .55). In addition, irrelevant angry faces significantly reduced the squiggle's detection sensitivity compared to neutral faces (M = 3.71, SD = 1.02), (t(28) = 2.61, p = .03, d = .48). There was no significant difference in the *d'* value between happy and neutral face distractor conditions (p = .85). None of the pairwise comparisons were significant (p > .40, for all) in the high impulsive group under the low-load condition. Notably, Cohen's d value comparing angry and happy (d = .55), and angry and neutral (d = .48) conditions in the high-load condition in the high impulsive group was moderate to high, which may show a strong effect. It may indicate that individuals with high impulsivity are more distracted by angry face distractors when compared to happy and neutral face distractors in the high perceptual load condition; which consequently may interfere with the conscious perception of target stimuli (the squiggle). The rest of the main effect and interaction effects were not significant (p > .11, for all).

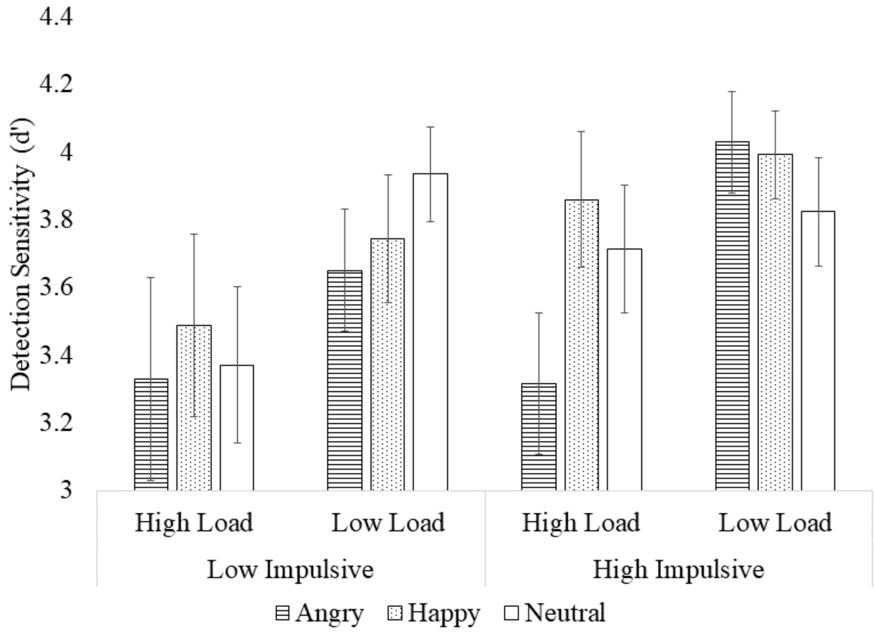
Table 2

The mean percentage hit rate, the false alarm rate and the mean d' for CS- detection as a function of perceptual load and emotion in high and low impulsive groups in Experiment 1 (main task).

	Conditions	Hit rate (%)	False alarm rate (%)	d'
Low impulsive	High-load angry	83.14	.04	3.33
	High-load happy	84.28	.04	3.49
	High-load neutral	83.46	.02	3.37
	Low-load angry	88.72	.02	3.65
	Low-load happy	92.14	.03	3.74
	Low-load neutral	93.49	.02	3.93
High impulsive	High-load angry	83.58	.02	3.32
	High-load happy	90.23	.02	3.86
	High-load neutral	88.87	.02	3.71
	Low-load angry	94.95	.02	4.03
	Low-load happy	95.89	.02	3.99
	Low-load neutral	95.04	.03	3.82

Figure 3

The d' values as a function of perceptual load and emotions in a high- and low-impulsivity groups with standard error bars for experiment 1 main task are shown.



The RmANCOVA after controlling for anxiety scores revealed a significant main effect of emotion, ($F(2, 112) = 3.07$, $MSE = 0.4$, $p = .05$, $\eta_p^2 = .05$). Further paired sample comparisons showed that irrelevant angry faces ($M = 3.58$, $SD = .92$) significantly reduced the squiggle's detection sensitivity compared to irrelevant happy faces ($M = 3.77$, $SD = .82$), ($t(57) = 2.33$, $p = .05$, $d = .31$). The rest of the main effect and interaction effects were not significant ($p > .11$, for all). Note that there were no interactions with anxiety, however, the unique distracting ability of irrelevant angry faces, compared to happy faces, persisted even when perceptual load was removed from the equation.

Criterion. The results of the 2 × 3 × 2 ANOVA revealed that the response criterion (β) was significantly more stringent in the high-load ($M = .26$, $SD = .48$) than in the low-load condition ($M = .11$, $SD = .35$), $F(1, 56) = 8.34$, $MSE = .089$, $p = .005$, $\eta_p^2 = .13$. The main effect of emotion was significant, ($F(2, 112) = 3.32$, $MSE = 0.4$, $p = .04$, $\eta_p^2 = .06$). Further paired sample comparisons showed that the response criterion was significantly more stringent when irrelevant angry faces (*M* = .23, *SD* = .35) were present when compared to irrelevant happy faces (*M* = .13, *SD* = .32), ($t(57) = 2.47$, $p = .03$, $d = .32$).The rest of the main and interaction effects were not significant ($p > .13$, for all).

When controlling for anxiety, none of the main effects nor the interaction effect was significant ($p > 0.35$, for all).

Control Task.

Sensitivity. In the control task, the 2 × 3 × 2 yielded a two-way interaction between load and emotion, $F(2, 112) = 4.06$, $MSE = .25$, $p = .02$, $\eta_p^2 = .07$. Further paired sample t-tests revealed a that in high perceptual load condition the irrelevant angry faces (*M* = 4.24, *SD* = .84) significantly reduced the squiggle's detection sensitivity compared to irrelevant happy faces (*M* = 4.51, *SD* = .38), ($t(57) = 2.40$, $p = .04$, $d = -.32$). In addition, irrelevant angry faces significantly reduced the squiggle's detection sensitivity compared to neutral faces (*M* = 4.53, *SD* = .36), ($t(57) = 2.51$, $p = .03$, $d = -.33$). These results are in line with the previous main task findings. There was no significant difference in the *d'* value between happy and neutral face distractor conditions ($p = 1.33$). The t-tests yielded no significant effect found in the low-load condition ($p > .10$, for all). The rest of the main effect and interaction effects were not significant ($p > .86$, for all). Since there was no significant three-way interaction between load, emotion and impulsivity, further analysis with high and low impulsivity groups was not required.

Table 3

The mean percentage hit rate, the false alarm rate and the mean d' for CS- detection as a function of perceptual load and emotion in high and low impulsive groups in Experiment 1 (control task).

	Conditions	Hit rate (%)	False alarm rate (%)	d'
Low impulsive	High-load angry	92.99	.01	4.10
	High-load happy	98.28	.00	4.46
	High-load neutral	99.42	.00	4.56
	Low-load angry	98.85	.00	4.53
	Low-load happy	97.70	.00	4.41
	Low-load neutral	100	.01	4.47
High impulsive	High-load angry	70.70	.01	4.38
	High-load happy	99.42	.00	4.56
	High-load neutral	98.85	.00	4.51
	Low-load angry	97.70	.01	4.37
	Low-load happy	95.40	.00	4.35
	Low-load neutral	98.16	.01	4.40

The RmANCOVA controlled for anxiety scores yielded main effect of load, $F(1, 56) = 5.72$, $MSE = .313$, $p = .02$, $\eta_p^2 = .09$. The interaction between load and anxiety was also present, $F(1, 56) = 6.05$, $MSE = .313$, $p = .02$, $\eta_p^2 = .10$. The difference between high-load ($M = 4.43$, $SD = .53$) and low-load ($M = 4.42$, $SD = .52$) conditions are negligible. The main effect of emotion was also present, $F(2, 112) = 4.08$, $MSE = .24$, $p = .02$, $\eta_p^2 = .07$. The interaction between emotion and anxiety showed a weak significance, $F(2, 112) = 3.01$, $MSE = .24$, $p = .053$, $\eta_p^2 = .051$. However, the consequent paired sample t-tests based on emotion conditions yielded no significant effects ($p > 0.08$, for all). The rest of the main effect and interaction effects were not significant ($p > .86$, for all).

It is crucial to note that perceptual load was not manipulated during the control task. However, there appears to be a two-way interaction between load and emotion (when impulsivity is accounted for) and the main effect of load (when controlling for trait anxiety). The former could imply that even when participants were instructed not to respond to the letter search task, they mentally did so out of habit and practice. In the latter case, the difference between high and low-load was negligible, hence the effect could be due to other individual factors that were not controlled in the current study.

Criterion. The results of the 2 × 3 × 2 ANOVA revealed a significant main effect of emotion, $F(2, 112) = 3.70$, $MSE = 0.52$, $p = .03$, $\eta_p^2 = .06$). Further paired sample comparisons showed no significant difference between the response criterion of happy, angry and neutral conditions ($p > .07$, for all). The rest of the main and interaction effects were not significant ($p > .07$, for all).

When controlling for anxiety, none of the main effects nor the interaction effect was significant ($p > 0.07$, for all).

Letter-search detection task

Reaction Time. The letter-search RTs were significantly slower in the high-load condition (M = 790 ms, SD = 112 ms) than in the low-load condition ($M = 675$ ms, $SD = 133$ ms), $F(1, 57) = 45.70$, $MSE = 25066$, $p < .001$, $\eta_p^2 = .44$, which confirms that the perceptual load manipulation was effective in the visual-search subtask. The other main and interaction effects were non-significant ($p > 0.13$, for all).

Accuracy. The letter-search accuracies were significantly lower in the high perceptual load condition ($M = 73\%$, $SD = 9\%$) than in the low perceptual load condition ($M = 94\%$, $SD = 4\%$), $F(1, 57)= 390.376$, $MSE = 0.009$, $p < .001$, $\eta_p^2 = .87$, which confirms that the perceptual load manipulation was effective in the visual-search subtask and in line with the previous findings in letter search RT. The other main and interaction effects were non-significant ($p > 0.19$, for all).

Experiment 2

In Experiment 1, the average CS detection sensitivity (d') is higher than in the study by Macdonald and Lavie (2008). Of note, there has been a consistent ceiling effect of detection sensitivity in each of the distractor and load conditions. This general ceiling effect of d' scores irrespective of conditions could be due to the higher number of practice trials in Experiment 1 (36 trials in each load condition). In Experiment 2, to test this, we conducted a follow-up study with the same methodology as Experiment 1 except with lesser practice trials (12 trials in each load condition). The aim of this experiment was to check if the ceiling effect persisted with fewer practice trials.

Methodology

Participants

A total of N = 14 (18–38 years of age; *M* = 27.4 years, *SD* = 4.1 years; 7 females) right-handed participants who reported normal or corrected-to-normal vision participated in this experiment after giving their informed consent. Four participants' data were discarded as their letter search task was lower than 65% (Gupta et al., 2016). The 10 participants' data were included for further analysis (*M* = 27.5 years, *SD* = 3.6 years; 4 females).

Stimuli and Procedure

The apparatus, stimuli, and procedure were the same as in Experiment 1 except that the participants were given fewer practice trials. Here, following the study by Macdonald and Lavie (2008), before starting the main experimental block participants were shown 6 example trials with no CS and 6 example trials with CS. The participant then verbally confirmed the presence or absence of the CS. The trials were repeated if the participants failed to spot the CS at least 3 times. In the current study, all participants required only one set of practice trials and there were no repetitions.

Results and Discussion

The aim of this experiment was to check if the ceiling effect of load persisted with less practice trial in Experiment 2. We compared the d’ value of both experiments (Experiment 1: more practice; Experiment 2: less practice). There was no significant difference in the d’ value between the two experiments, $t(1, 66) = .767$, $p = .446$, $d = .26$, which may indicate that the ceiling effect observed in Experiment 1 was not due to the higher number of practice trials.

General Discussion

The current study aimed to examine the interaction between attentional availability and valence of emotional distractors on conscious perception of expected stimuli. More specifically, we examined whether trait anxiety or impulsivity modulated the interaction between emotion and perceptual load in detecting a squiggle. The main results showed that only in high impulsive participants during high-load conditions did the irrelevant angry faces (compared to happy and neutral faces) significantly reduce their sensitivity to detecting the squiggle. These results could indicate that trait impulsivity modulates the interaction between emotion and load. These results have theoretical implications in the understanding of the role of personality traits in the interaction between attention and emotions when conscious perception is being shaped.

Robustness of Perceptual Load Theory

Overall, CS-detection sensitivity was higher in the low- relative to high-load condition. This finding is in line with the perceptual load theory, which suggests that even a simple cognitive detection task is affected by the capacity limitations of attention. However, the differences in awareness of the CS (in terms of detection sensitivity) can be explained as a trade-off between top-down and bottom-up processing. Tsuchiya and Koch (2008) demonstrated that top-down attentional processing is required for conscious awareness, namely, full reportability of information. Both top-down and bottom-up processing require attention. Since attention is limited, in this case, bottom-up processing has taken precedence due to the presence of a meaningful salient stimulus (emotional distractor) over the top-down processing of a goal-oriented stimulus (evidenced by the drop-in detection sensitivity of CS). The findings further reiterate the importance of understanding the emerging concepts of emotional attention (Vuilleumier and Huang, 2009) and emotion-induced blindness (Singh & Sunny, 2017) and the need to extend the perceptual load theory of attention to such stimuli.

Although the attentional load theory aligns well with our findings, alternative frameworks, such as the search mode theory (Bacon & Egeth, 1994), may offer another interpretation for the main effect of load on squiggle-detection performance. According to the search mode theory, during singleton detection, other salient elements capture attention, which facilitates the detection of the peripheral onset. The search mode theory explains the current findings without reference to attentional resources by focusing on differences in search strategies. For example, when participants searched for a target stimulus (i.e., X or N) amongst the distractor stimuli (i.e., O's) in the low-load condition, they performed singleton detection, which is not the case in the high-load condition where participants deployed a feature-based search (angular feature, here) and searched for an X or N among other angular letters. This could explain why detection sensitivity was higher in the low- relative to high-load condition in the present study. However, it does not entirely account for the interaction between the perceptual load and emotional distractors in squiggle detection. During a high-load condition, when a feature-based search was deployed, angry face distractors interfered with squiggle detection, although they do not share common features. The latter finding is better explained by the perceptual load theory and the corresponding limited attentional resources in a high-load condition (Biggs & Gibson, 2010).

The Modulating Role of Impulsivity

The current study demonstrated that trait impulsivity modulated the interaction between load and emotion in the CS-detection task. Specifically, detection sensitivity was lower in the presence of angry than happy or neutral distractor conditions, but only for the high impulsive group under the high-load condition. Previous studies have reported that higher trait impulsivity is associated with poorer emotion regulation, attention deficits and disorders linked to the psychopathology of emotion, behaviour and cognition (for example, attention-deficit hyperactivity disorder, addiction, personality disorders, and mania; Gupta et al., 2006; Mitchell et al., 2012; Nigg, 2016). Similarly, a recent study reported that individuals with high trait impulsivity performed poorer than those with low impulsivity on cognitively demanding tasks (Leshem & Yefet, 2019). Moreover, it has been suggested that individuals with high impulsivity (relative to individuals with low impulsivity) process and remember angry faces more than happy faces (d'Acremont & Van der Linden, 2007). It is essential to note that the initial three-way interaction between load, emotion and impulsivity is weak, however, the pairwise comparisons in individuals with relatively high impulsivity indicate moderate to strong ($d > .4$) effects. Therefore, the interaction of load with emotion and impulsivity should be interpreted cautiously and further explored before a strong claim can be made.

Attention Processing of Irrelevant Angry Stimuli

Under the high perceptual load condition, more attention was captured by angry face distractors than by happy face distractors in individuals with high impulsivity. It has been suggested that more attention resources are required to process angry faces than happy faces (Gupta et al., 2016). Consequently, during the high-load condition, irrelevant angry faces might use the attention resources in our divided attention paradigm, leaving fewer resources for squiggle detection in individuals with high impulsivity. It has also been suggested that angry faces capture and hold attention more than happy faces (Fox et al., 2000; Srivastava & Srinivasan, 2010). Consequently, angry stimuli relative to happy stimuli are more difficult to disengage from, which can interfere with task performance (Belopolsky, Devue, & Theeuwes, 2011; Becker et al., 2019). In line with this view, a meta-analysis concluded that positive stimuli are processed more automatically and at earlier stages of attention processing than are negative stimuli (Pool et al., 2016). In the current study, although attention prioritisation to positive stimuli might have occurred, happy faces might not have interfered with the task performance because they require fewer attentional resources. This finding supports the emotionality hypothesis, which posits that stimuli with affective content draw more attention than neutral stimuli (Nummenmaa et al., 2006). The current study also suggests that positive stimuli do not adversely affect concurrent task performance.

Previous research has revealed that the interaction between load and emotion could be modulated by individual differences such as the motivation to engage in the main target task and the personal relevance of the emotional stimuli (Oliveira et al., 2013). The inclusion of personality trait variables (for example, impulsivity) in the present study has provided further evidence for the modulation of the interaction between perceptual load and emotions. In addition, previous studies have shown that individuals with high anxiety levels tend to have a bias towards processing threatening angry faces (Mogg, Garner & Bradley, 2007). The current sample was skewed towards the higher end of the trait anxiety level with only five participants in the low-anxious group (i.e., a score of below 32). It is important to note that studies have suggested that anxiety scales use increased cut-off scores (Julian, 2011) and it is possible that our study population has a higher average than the norms of STAI. Overall, there is a possibility that anxiety scores influenced attentional capture and interference from angry faces, as has been previously reported (Peschard & Philippot, 2017).

It is also important to consider the current results in the context of previous work using similar letter-search paradigms. Specifically, Gupta et al. (2016, Experiment 2) found that participants were slower to detect targets in the presence of happy face distractors in the high-load condition. Although we did not find a similar effect on RTs in the current study, we did not intend to replicate the results of Gupta et al. (2016) as our aim and methodology differed somewhat. Unlike Gupta et al. (2016) the current study aimed to use a direct measure of conscious perception: detection sensitivity. First, Gupta et al. (2016) examined the role of irrelevant emotional stimuli in the primary letter-search task using only a single primary letter-search task. In contrast, the present study included two tasks: the primary '*letter-search task*' and the secondary '*squiggle detection task*'. A significant effect of the load is reflected in letter search and CS detection tasks in experiment 1. Furthermore, it has been suggested that under divided attention conditions, negative emotions interfere with the task more than positive emotions do (see Srinivasan & Gupta, 2010: Experiment 2); which compares to the results found in the current study. It could be inferred that (a) under low-load conditions, possibly due to the availability of attentional resources, irrelevant emotional distractors do not affect task processing, (b) during high-load conditions positive emotions interfere with task performance, and, (c) while performing dual tasks, due to its ability to hold attention, during high-perceptual load negative emotions interfere only with the secondary task. The current study design could be closely associated with divided attention or multitasking/ dual tasks. Previous studies have shown the effect of dual-tasks on cognition, such as performance costs in one or more task(s) and observable lapses in attention (Mickley Steinmetz, Waring, & Kensinger, 2014; Madore, et al., 2020). A handful of studies also show that while multitasking, emotional processing of negative and positive stimuli may vary, and, distraction by emotional stimuli persists even while multitasking (Kern, Libkuman, Otani, & Holmes, 2005; Keefe, Sy, Tong, & Zald, 2019).

The current study supports and attempts to understand the persisting role of emotional distractors even when attention resources are scarce.

Second, in the Gupta et al. (2016) study, irrelevant emotional stimuli were presented with low probability (i.e., on only 25% of trials; the distractor was absent in the remainder), which allowed the establishment of an attentional capture measure that was not moderated by habituation (see Forster & Lavie, 2008). It was found that when emotional distractors were presented with higher probability (for example, in 100% of the trials), the emotional distractors did not interact with the perceptual load to modulate the primary letter-search task. However, both interacted to modulate the secondary task (recognising emotional distractors (see Srinivasan & Gupta, 2010; Gupta & Srinivasan, 2015). For this reason, we presented emotional distractors in 100% of trials; due to habituation in the current paradigm, the effect of emotion could be diluted, as predicted and evidenced in the primary *letter-search task*. However, we expected both attention and emotion would interact to modulate the secondary '*squiggle-detection task*', which might be mediated by high impulsivity, which is what we identified in the present study.

Theoretical and Practical Implications

The findings of the current study suggest that emotion and perceptual load interact in contributing to our conscious perception of relevant information. The findings of the present study also shed light on the mediating role of impulsivity in the interaction between emotion and attention. In addition, these findings expand upon our understanding of the role of emotions in cognition. The theoretical models of attention (such as the perceptual load theory of selective attention) focus on top-down and bottom-up processing but have not yet incorporated the emotion-driven attentional aspect. The current study advocates further research and inclusion of emotional attention in such models, which were previously studied in relevance to psychopathology in aspects such as risky behaviour, addiction, and depression (Gladwin, Figner, Crone & Wiers, 2011; Roiser, & Sahakian, 2013). The findings of the present study also have practical implications. For example, on a busy road, a car driver who processes angry emotional stimuli (for example, yelling, angrily conversing over the phone) of a passenger may miss critical information about the road ahead (for example, a pedestrian walking in front of the car;(see Grissinger, 2012). The study findings imply that reducing perceptual clutter (load) and negative emotional information from the environment might facilitate information processing and in the case of the driver, prevent an accident from occurring.

Limitations and Future Directions

This study also contains certain limitations. First, the sample consists of many individuals with moderate-to-high levels of trait anxiety. Although trait anxiety was statistically controlled for, further work could experimentally control this factor by specifically recruiting high and low anxiety groups or by incorporating sub-clinical and clinical samples, especially when using threatening stimuli. Similarly, extensive research into the direction of the influence of impulsivity in the interaction between perceptual load and attention is required. In the present study, interaction effects that were mediated by impulsivity were weak (p = .058); therefore, future studies are required to incorporate these variables using a larger sample size. Future work could explore the roles of adjunct variables of impulsivity and anxiety by using other measures to reach a methodological triangulation, such as the use of behavioural impulsivity measures. Only one experiment was conducted. Hence, further studies are required to increase confidence in the findings.

Second, the cognitive paradigm used here incorporated multiple factors such as attention, emotion and personality; however, simpler designs would enable robust conclusions, because complicated tasks take time to complete, for example, the using of positive and negative emotional stimuli in different experimental blocks could be temporally well-spaced. Similarly, the current study used a neutral emotional distractor condition; future studies could use no distractor conditions or manipulate arousal to ascertain the attenuation of load and emotions and clarify our findings. Further, Hay et al. (2006), have suggested using no distractor conditions to help understand ceiling effect. In the present study, participants were required first to detect letters then the squiggle. Therefore, the memory process may have played an important role in this process. Further studies are required to test these possibilities explicitly in the context of emotional distractors. Motivational stimuli such as substance-related stimuli (for example, alcohol, food) have been tested along a path similar to emotional stimuli. Therefore, the role of motivational distractors could be an interesting variable to replace emotional distractors in the current paradigm. This work reiterates the role of potent emotional distractions in information processing.

Conclusion

The current study demonstrated that when attentional demands increase, angry emotional distractors reduce the ability to perceive target stimuli consciously in a sample of healthy adults. This interaction was evident in individuals with high impulsivity, but further research is required to strengthen and clarify the modulating role of impulsivity. Preliminary evidence suggests that emotional distractors do not interfere with task performance when attention resources are available, however, the findings indicate that when attention resources are scarce, angry emotional distractors can limit our ability to perceive the environment.

Experiment 3: Chapter III

Loss Associated Faces Deter Conscious Perception Under High Perceptual Load

Introduction

We selectively attend to a small amount of the visual information in our environment. This selective attention prevents us from overloading and enables us to efficiently process information (Lu, 2008). The efficiency of selective attention is influenced by several cognitive and behavioural factors. Two such factors are value-learning (for example stimuli associated with gain and loss) and perceptual load (high and low processing demands on the perceptual system). The current study attempted to demonstrate the role of perceptual load and value-learned distractors on conscious perception of expected stimuli.

Attention and Value-learning

Value-learning is a process through which neutral stimuli attain meaning and saliency (Rajsic et al., 2017; Dewey, 2011). The learning occurs with repeated and consistent associations between a neutral stimulus and motivational values (gains and losses). For example, people often carry a 'lucky' pen or wear a 'lucky' colour during examinations as they associate the neutral object with the previous success (gain/reward).

Selective attention to value-learned stimuli helps us rapidly predict, learn, modify, and adapt our behaviour (Le Pelley et al., 2016; Kovach et al., 2014; Kim, 2013; Yechiam & Hochman, 2013; Hohwy, 2012; Staddon & Cerutti, 2003). Research has shown that positive emotional stimuli (erotic images, happy faces, neutral faces imbued with high reward) tend to automatically capture attention and interfere with primary task performance even when irrelevant to the task (Gupta et al., 2016). This could imply that gain-related stimuli might capture attention in a similar fashion as positive emotional stimuli do. Thus, our attentional allocation is biased toward such value-learned stimuli, as it is toward emotionally meaningful stimuli (Theeuwes & Belopolsky, 2012; Arnell et al., 2007; Öhman et al., 2001). Attentional bias to value-learned stimuli (also called value-driven attention; Anderson, 2013, 2014) appears to vary based on two key evaluative dimensions, namely, learned valence and predictiveness (Le Pelley et al., 2016; Raymond, 2009).

Learned valence

The idea that allocation of attention is based on the positive (gain/reward) or negative (loss/punishment) valence of the stimuli is referred to as ‘learned valence’ (Le Pelley et al., 2016; Anderson, 2013; Anderson et al., 2011a,b; Raymond, 2009). A preference for attending to gain-associated stimuli and avoiding aversive information has been reported (Veenhovan, 2003; Ikemoto & Panksepp, 1999). Loss associated stimuli have been shown to predict slowed task processing due to prioritising and holding attention (Schmidt et al., 2015a,b; Notebaert et al., 2011). Gain-associated stimuli not only capture visual attention quicker, but hold and guide visual spatial attention (Rajsic et al., 2017; Preciado & Theeuwes, 2014; Hickey et al., 2014; Theeuwes & Belopolsky 2012). More recent studies have also shown value-learned stimuli easily engage our attention irrespective of their valence, and only rewarding stimuli are supposedly difficult to disengage (Sun et al., 2017; Müller et al., 2016). Research has also shown that when the reward association is subliminal and not consciously perceived, it can still capture and guide attention (Bourgeois et al., 2016). However, Failing and Theeuwes (2017) noted reaction times were slower for high-predictable reward distractors than low-predictable reward distractors, but only when the participants were aware of the stimulus-reward relationship. Hence, the awareness of the learned motivational contingency and the effect of value-driven attention capture in the larger perceptual processing needs to be delineated. Overall, it is evident that learned valence can modulate attention capture and thereby, interference with task performance.

Learned predictiveness

Learned predictiveness proposes that the attention allocation to value-learned stimuli is based on how reliably (high or low) the stimuli predicts the consequences (Griffiths & Thorwart, 2017; Le Pelley et al., 2016; Raymond, 2009). Predictable, compared to unpredictable, stimuli are processed earlier and detected more readily (Alink et al., 2010). Studies have shown that if a stimulus is consistently associated with gain, it (a) does not yield a reward during the experimental phase and/ or (b) would now be a distractor and affect ongoing relevant task processing, the value-learned stimuli might still capture attention (Anderson, 2016a; Le Pelley et al., 2016). Overall, there appears to be a greater focus on reward-related processing (possibly due to its clinical relevance in disorders such as addiction and compulsivity; Anderson, 2021). Only a handful of studies have studied attention allocation to learned valence and predictiveness (Gupta et al., 2016; Gupta et al., 2019; Gupta, 2022; Schmidt et al., 2015a,b; Raymond & O'Brien, 2009).

Value-learning and perceptual load

Perceptual load is related to the complexity of the visual display that places processing demands on the perceptual system (see Lavie, 2005, 2006, for a review). According to the perceptual load theory of selective attention, when individuals are engaged in a high attention-demanding task, they have fewer resources to process a distractor, relative to engagement in a low attention-demanding task (Lavie, 1994; for a review see: Lavie, 2005, 2010). Thus, a distractor's interference is lower in high (relative to low) attention-demanding task conditions (Lavie & Tsal, 1994; Beck & Lavie, 2005). Macdonald and Lavie (2008) showed that perceptual load plays a key role in the conscious perception of information. They found that the detection sensitivity of a neutral, peripheral target (critical stimulus) was significantly reduced under high-load compared to low-load conditions, a phenomenon known as "load-induced blindness" (Macdonald & Lavie, 2008). However, various meaningful distractors such as emotion and motivation tend to capture our attention (Yiend, 2010; Gupta et al., 2016; Gupta et al., 2019).

The limited availability of attention resources and value-learned stimuli interactively affect selective attention. A study in value learning constrained attention availability temporally in a rapid serial visual presentation (Raymond & O'Brien, 2009). The authors found that when attention was available, highly predictive face stimuli recognition was better irrespective of their valence. When attention was constrained, the recognition was poorer only for neutral and loss-associated faces. This is in line with the more recent study by Gupta et al. (2016: see Experiment 3) where a similar effect was found when attention was constrained by manipulating perceptual load. In their study, during a low-load visual letter-search task, the centrally present irrelevant value-learned stimuli captured attention, but only the high gain stimuli captured attention during high-load conditions. It is important to note that this study did not report any differences in the predictability of value-learned stimuli. So, learned predictiveness and not reward by itself shapes attention allocation (Sali et al., 2014); a significant claim that valence overrides predictability could not be made.

The Current Study

Previous studies measured the role of attention allocation and value-learning using indirect measures that infer perception, such as reaction time (Gupta et al., 2016; Gupta et al., 2019; Raymond & O'Brien, 2009). The current study attempted to demonstrate the role of perceptual load and value-learned stimuli in predicting perception using a more direct measure of perceptual awareness, namely, detection sensitivity (Macdonald & Lavie, 2008).

In addition, few studies have examined both valence and predictability (Raymond, 2009), and fewer have incorporated them while manipulating the attentional load (Gupta et al., 2016). Therefore, we were interested in (a) whether the valence or predictability of the value-learned stimuli affected the perception of the critical stimulus, (b) the difference between negative and positive distractors (that is, learned valence), and (c) the difference between high and low predictable distractors. Based on previous research (Experiment 3 of Gupta et al., 2016); Raymond & O'Brien, 2009); Macdonald & Lavie, 2008), we proposed the *attention-constraint hypothesis* of value-learning. Specifically, we expected that in high-load conditions, participants would be more accurate in detecting CS in the presence of gain than loss-associated face distractors. As gain, rather than loss-associated faces, would take less attentional resources to process, leaving more attentional resources to detect squiggle under high perceptual load condition. At the same time, we expected no such difference would be present in the low-load condition because enough attentional resources would be available to process both gain and loss associated faces that would not modulate squiggle detection under the low perceptual load condition. In contrast, we expected that in the low-load condition, participants would be more accurate in detecting CS in high- when compared to low-predictable conditions, while no such difference would be found in the high-load condition because it has been suggested that when enough attentional resources are available, predictability (high vs low), but not valence, modulates visual perception (see Raymond & O'Brien, 2009).

Methodology

Participants

A total of N=55 (18–39 years of age; *M* = 24.04 years, *SD* = 4.32 years; 18 females) right-handed participants who reported normal or corrected-to-normal vision participated in this experiment after giving their informed consent to the researchers. We included only young-middle aged adults as older adults tend to experience the positivity effect, namely, a bias towards positive stimuli (Reed & Carstensen, 2012). We estimated (using G-Power; Erdfelder et al., 1996) a necessary sample size of 50 to detect a medium-size effect of 0.5 (Gupta & Singh, 2021) and to obtain a power level of 0.95.

Design

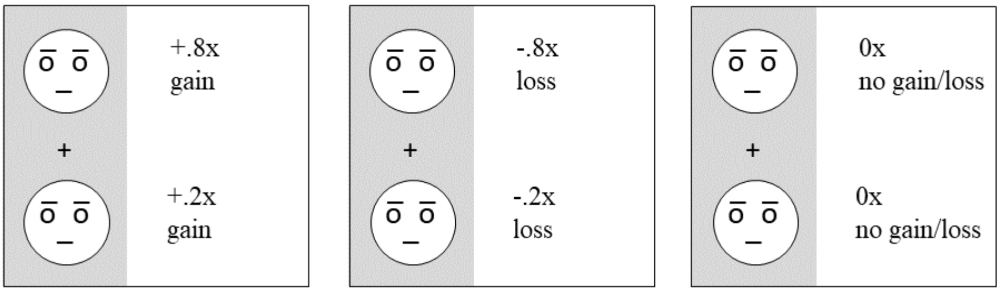
The study used a 2 × 5 design, corresponding to the two levels of load (high and low), and learned motivational values (high gain, low gain, high loss, low loss, and neutral). From here on, learned motivational value refers to the five levels, and valence or predictability will be used to refer to the individual gain/loss or high/low predictable groups, respectively.

Apparatus and Stimuli

Stimuli were displayed on a 24-inch colour monitor (60 Hz, resolution 1,920 × 1,080 pixels) that was viewed binocularly from a distance of 60 cm. E-Prime software (Version 3.0), which operated on a computer with a B360 Gaming HD, IntelI CoITM) i7 CPU @3.20 GHz system processor generated stimuli and recorded responses acquired through a number pad. A total of 6 static grey-scale photographs of young adult males with neutral expressions were obtained from the Karolinska Directed Emotional Faces (KDEF) database (Lundqvist et al., 1998). Each face subtended a 3.3º × 4.9º visual angle in greyscale and was used without ears or hair. All backgrounds in these experiments were in grey (Red/Green/Blue values 150,150,150) and text in black. The current study used facial stimuli due to their socio-biological relevance to humans, which inadvertently captures attention (Lavie et al., 2014; Devue et al., 2009). Hence, if a distractor captures more attention than another, it would imply it was because of the value and not the face identity. Examples of neutral faces can be observed in Figure 4.

Figure 4

Example of the 3 face pairs in the value learning task: gain, loss, and neutral. The actual experiment used actual face stimuli and not schematic ones.



Measures

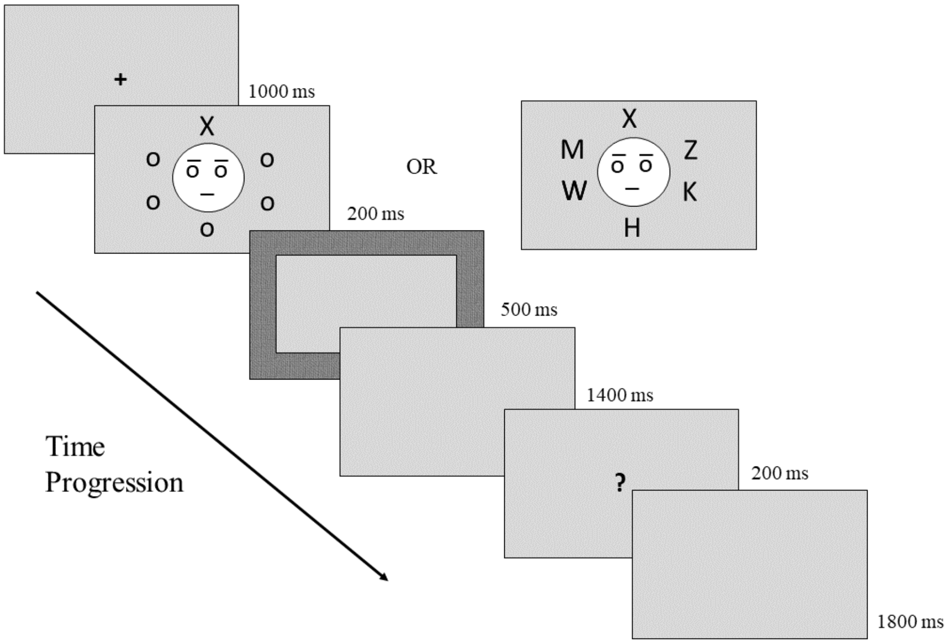
Value-learning task. Following the value-learning tasks used by Raymond and O'Brien (2009), a pair of faces were presented on each trial: one below and the other above the fixation cross, which was presented in the centre of the computer screen. Participants had to select one of the faces using the keyboard keys 'T' (for the top) and 'B' (for the bottom). Following this, the participants saw either (a) the message 'win' accompanied by a beep sound; (b) 'loss' accompanied by a lower beep sound or (c) 'nothing' accompanied by no sound. Below the message, the points earned in the trial appeared: +10 (gain), -10 (loss), or 0 (no gain/loss). There were six variations of the value-learned task where the faces and the value imbued by them were counterbalanced. The trials were self-paced. There were three pairs in total: gain, loss, and neutral (refer to Figure 4). In each gain and loss pair, one of the faces was more predictive of the outcome (80% of the time of 0.8x) than the other (20% of the time or 0.2x). Each pair was presented 100 times randomly. In total, there were 300 trials.

Motivational Attentional Blindness (MAB) task. The current study used an amalgam of the paradigm used by Macdonald and Lavie (2008) and the value-learned distractor trials that were used by Gupta et al. (2016) (refer to parent paper for examples). This approach enabled us to combine the three key manipulations into a single task: (a) perceptual load, (b) a value- learned distractor stimulus (high gain, low gain, high loss, low loss, and neutral) in the middle of the letter ring, and (c) the CS (the squiggle) in the periphery in 6 different positions.

Six letters were presented in the letter-search task in a circle of radius 3.0º with the target letters, ‘X’ or ‘N’ (0.6º × 0.6º). Each of the letters appears in half of the trials, and the other five positions are occupied with ‘O’s (0.4º × 0.5º) in the low perceptual load condition and the letters H, K, M, W, and Z (0.6º × 0.6º) in the high perceptual load trial. The stimulus display was present for 200 ms after the fixation display, and the participants had to respond to the letter-search task by pressing the ‘0’ when spotting target ‘X’ and ‘2’ when spotting ‘N’. A meaningless grey shape, CS (0.3° × 0.3°), obtained from Macdonald and Lavie (2008), was presented at one of six equally spaced locations outside the letter ring at an 8.5° radius. Since the distances between target and CS is counterbalanced, the closest distance between the target and the CS was 3.7° and the farthest was 6.9°. A black mesh pattern mask was used after the stimulus presentation. This mask covered the entire screen except for a small square area (9.5° × 9.5°) in the centre in order to not cover the space previously occupied by the letters; this was similar to the process that was used by Macdonald and Lavie (2008). The participants were then asked to press the key ‘a’ or ‘s’ after presenting the question mark display as a response to ‘absence of squiggle’ and ‘presence of squiggle’, respectively.

Figure 5

Example of the progression of an experimental trial. low-load, neutral trial with no squiggle in the stimulus display. (b) high-load, neutral trial with a squiggle in the stimulus display.



The participants, therefore, performed two tasks in the experiment: letter-search and CS-detection. The task consisted of 72 practice trials for each high and low-load. Similarly, 240 main experimental trials per load were present. Finally, there were control blocks for each load condition with 120 trials during which the participants only performed the CS-detection task and were asked to ignore the circle of letters. In this simple block, a poor CS-detection in the control blocks would imply an inability to spot the CS effectively (see MacDonald & Lavie, 2008, for discussion).

Additional Measures

The study also incorporated additional measures of individual differences based on previous studies (Perri, 2020; Anderson, Kim, Britton & Kim, 2019; Padmala & Pessoa, 2010; Hickey, Chelazzi, & Theeuwes, 2010a,b; Poy, del Carmen Eixarch, & Avila, 2004) The measures include trait impulsivity (UPPS-P Impulsive Behaviour scale, Lynam, Smith, Whiteside, & Cyders, 2009), value- driven attention questionnaire (Anderson, Kim, Britton, & Kim, 2019) and sensitivity to punishment and reward questionnaire **(**Torrubia, Avila, Moltó & Cesaras, 2001). There were no meaningful associations among the overall detection sensitivities (*d'*) in high- and low-load conditions, and the additional measures. Hence, more details on these measures are incorporated in the supplementary section.

Procedure

The participants were recruited via advertisements on the email portal of the Indian Institute of Technology Bombay (IITB). Participants were first provided with an information sheet in which the experimental procedure was outlined, which included the risks, benefits and other relevant study details. The participants then provided informed consent before completing questions relating to demographics. Once all questions were clarified and consent was provided, the participants completed practice trials to familiarise themselves with the experimental set-up. The experiment occurred in a dimly lit room. First, the participants completed the value-learning task. Then the participants started the MAB task with the practice block, followed by the experimental block. The order of high-load and low-load blocks were counterbalanced amongst the participants (refer to Figure 5 for example trials). The participants completed the letter-search subtask, which was followed by the CS-detection subtask. Finally, they underwent the control block in which half of the low- and high-load trials were presented in the same order in which the load blocks were presented initially. The control block served to understand the baseline performance of participants and screen for poor data in the CS-detection subtask. Here, the participants only respond to the CS-detection subtask, although the trial progression is the same as that of the main experimental blocks. There were sufficient breaks during and between each block. After the control blocks, participants completed the questionnaires via Google forms. The participants were finally debriefed about the purpose of the study and compensated for their time and effort monetarily. The ethics committee of IITB approved the study.

Data Preparation

The data from n=6 participants with poor value-learning task performance (<330 points) were removed (Gupta et al., 2016). The resulting n=49 participants (18–39 years of age; *M*= 24.18 years, *SD* = 4.5 years; 16 females) were included in the analyses. Based on previous value-learning research (Gupta et al., 2016, Experiment 3; Raymond & O'Brien, 2009) we adopted the exclusion criteria of 65% of correct choices on the gain and loss pairs on the last 30 trials of the value-learning task. The 49 participants satisfying this criterion were included for further analysis. From the MAB task the following performance indices were derived: CS detection sensitivity (*d'*) and response bias scores (β) calculated from the hit and false alarm rates for the CS-detection subtask; and, letter-search RT and letter-search accuracy from the letter- search subtask. In the RT analysis, trials were excluded in which the letter-search response was incorrect or the letter-search RT was less than 200 ms or greater than 2000 ms. Further, in the CS-detection task analysis, trials in which the search response was incorrect or participants had not responded were excluded (see Macdonald & Lavie, 2008).

Data Analysis

A two-tailed 2 × 5 repeated measures analysis of variance (RmANOVA) was conducted using perceptual load (high and low) and learned motivational value (high gain, low gain, high loss, low loss, and neutral) for the performance indices separately. In addition, to obtain clarity on the evaluative dimensions of value learned stimuli (learned valence and predictability), another 2 × 2 × 2 RmANOVA was conducted to examine the interaction between load (high and low), valence (gain and loss), and predictability (high and low). As in previous studies, valence and predictability were calculated by taking the average and neutral conditions are thus not incorporated in this analysis (Gupta et al., 2019). For example, the total *d'* for gain was the average of high and low gain. Based on the RmANOVA results, pairwise mean comparisons using two-tailed t-tests were conducted. Pearson correlations were conducted to test the relationship between VDAQ scores, overall UPPS-P scores, and SPSRQ scores, with overall high-load *d'* and overall low-load *d'*. Alpha levels were set to 0.05 for all analyses.

Results

Value-learning task

There was a significant difference in learning performance between gain and loss pairs (t(1, 48)= 2.76, p = .008, d = .394); where the gain pairs, the high-probability win face (0.8x) was chosen more often (M= 97.8%, SD= 7.3%) and in the loss pairs, the low-probability loss face (-0.2x) was chosen more often (M= 93.1%, SD= 1.5%). In the neutral no-outcome control pair, an arbitrarily selected face in each pair was chosen on 44.5% (SD = 4.3%) of trials.

Critical stimuli subtask

Experimental block.

Sensitivity. Sensitivity scores are presented as a function of the perceptual load and value-learned stimuli in Table 4. There were no significant main effects or interaction effects in the 2 × 5 RmANOVA analysis (all *p's* > .106).

In the 2 × 2 × 2 RmANOVA, the main effect of valence was significant, F(1, 49) = 5.61, MSE = .74, p = .022, η_p^2 = .105. Follow-up paired samples t-tests indicated that the CS detection was significantly higher in gain (M = 3.22, SD = 1.34) than loss conditions (M = 3.02, SD = 1.53), t(48) = 2.37, p = .022. The other main and interaction effects were non-significant (p > .14, for all).

The 2 × 2 × 2 RmANOVA also showed a significant two-way interaction between load and valence, F(1, 49) = 6.6, MSE = .378, p = .014, η_p^2 = .120. This may indicate that load and valence together modulate the detection of CS. As expected the paired sample t-test revealed significantly higher detection sensitivity to CS in high-load gain distractor conditions (M =

3.15, *SD* = 1.56) than loss conditions (*M* = 2.79, *SD* = 1.78), $t(48) = 3.26$, $p = .004$, $d = .466$. No significant difference between gain and loss conditions were found in the low- load condition, $p = .645$. This shows that only during high-load conditions the valence of the distractor affected CS detection.

Despite no interaction between predictability and perceptual load, as a-priori, we proceeded with the t-test to understand the differences between high and low predictability in high and low-load conditions to test for the attention-constraint hypothesis. During low-load conditions high-predictability distractor conditions yielded significantly higher detection sensitivity (*M* = 3.36, *SD* = 1.49) than low-predictability (*M* = 3.17, *SD* = 1.6), $t(48) = 2.09$, $p = .04$, $d = .299$ (refer Table 4). No significant difference between high and low conditions were found in the high-load condition, $p = .780$. This shows that only during low-load conditions the predictability of the distractor affected CS detection. The rest of the main and interaction effects were not significant, $p > .149$, for all.

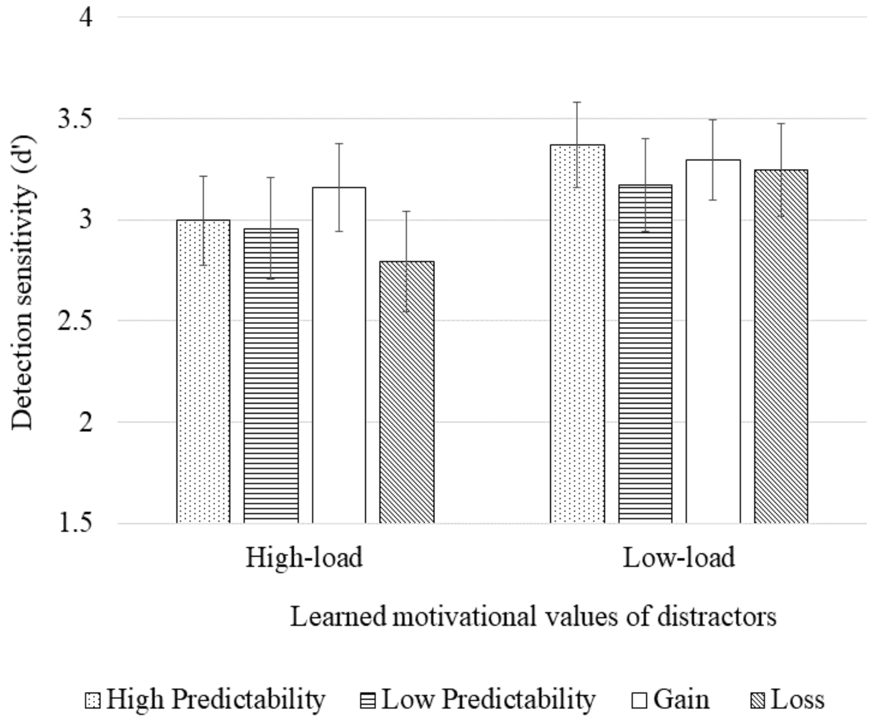
Table 4

The mean percentage hit rate, the false alarm rate, and the mean d' for CS-detection as a function of perceptual load and learned motivational value in experimental conditions.

Conditions	Hit rate (%)	False alarm rate (%)	d'
High-load high gain	80.7	6.2	3.15
High-load low gain	82.1	7.9	3.17
High-load high loss	79.3	10.4	2.85
High-load low loss	75.2	8.9	2.74
High-load neutral	80.4	10.3	2.89
Low-load high gain	86.5	0.2	3.42
Low-load low gain	84.2	7.7	3.17
Low-load high loss	85.1	7.6	3.32
Low-load low loss	82.3	7.7	3.18
Low-load neutral	82.1	8.5	3.1

Figure 6

The d' values as a function of perceptual load and learned motivational value with standard error bars are given.



Response criterion (β). There were no significant main or interaction effects for the response criterion (β) in the 2 × 5 RmANOVA (p > .07, for all). The 2 × 2 × 2 analysis for response criterion revealed a three-way interaction between load, valence and predictability, $F(1, 49) = 4.33$, $MSE = .12$, $p = .042$, $\eta_p^2 = .083$. This suggests that the response bias in the detection of CS (a willingness to report 'present') could be modulated by distractor's valence and predictability, and, perceptual load, but the paired sample t-tests of criterion in valence and predictability conditions across high and low-load were not significant, p >.058 for all. The other main and interaction effects were non-significant, p > .17 for all.

Control block.

Sensitivity. In the 2 × 5 control blocks, there was an interaction effect between load and value, $F(1, 49) = 3.74$, $MSE = .304$, $p = .006$, $\eta_p^2 = .072$. This suggests perceptual load and distractor's learned value modulate the detection of CS. However, it is important to note that in the control lock participants only performed the critical stimuli subtask where load was not actively manipulated (load was manipulated by the letter search task). The paired sample t-test showed that only in low-load conditions, the detection sensitivity to CS was significantly higher during low gain distractor conditions (M = 4.31, SD = .89), when compared to neutral (M = 3.91, SD = 1.20), $t(48) = 3.37$, p = .024, d= .481. The other paired sample t-tests reveal no significant differences in detection of CS based on the learned motivational value of the distractor across high- and low- load were, p >.156 for all.

Table 5

The mean percentage hit rate, the false alarm rate, and the mean d' for CS-detection as a function of perceptual load and motivation in control conditions.

Conditions	Hit rate (%)	False alarm rate (%)	d'
High-load high gain	95.6	1.1	4.26
High-load low gain	95.9	1.7	4.21
High-load high loss	97.1	2.4	4.15
High-load low loss	98.2	1.1	4.41
High-load neutral	95.6	0.9	4.26
Low-load high gain	94.4	2.4	4.15
Low-load low gain	94.6	0.7	4.31
Low-load high loss	91.0	1.9	4.01
Low-load low loss	90.7	2.2	3.96
Low-load neutral	89.7	1.9	3.91

The 2 × 2 × 2 analysis revealed a significant main effect of predictability, $F(1, 49)$ = 5.414, MSE = .119, p = .024, η_p^2 = .101. Here the detection sensitivity during high predictable distractor trials (M = 4.23, SD = .942) were slightly higher than that in low predictable distractor trials (M = 4.21, SD = .911). This implies predictability could modulate the detection of CS. Since the participants did not perform the letter search task, they would have additional attention resources. Therefore, when more resources are present, it is possible that predictability of the stimuli guides attention capture by distractor stimuli. However, it is important to note that the difference in detection sensitivity between high and low predictable distractor trials is small but significant. There was also a three-way interaction between load, valence, and predictability, $F(1, 49) = 8.746$, $MSE = .195$, $p = .005$, $\eta_p^2 = .154$. This would suggest that the distractor's valence and predictability along with perceptual load influences the detection of CS. The paired sample t-tests on *d'* sensitivity revealed that in low-load gain distractor conditions yielded significantly higher detection sensitivity (M = 4.22, SD = .833) than loss (M = 3.98, SD = 1.27), $t(48) = 2.08$, $p = .043$, $d = .297$); however no such difference was found in the high-load condition, $p = .568$. The other paired sample t-tests of valence and predictability conditions in high and low-load were not significant, $p > .1$ for all. The other main and interaction effects were not significant, $p > .057$ for all. It is crucial to note that perceptual load was not manipulated during the control task. There still appears to be a two-way interaction between load and value and a three-way interaction between load, valence and predictability. This could imply that even when participants were instructed not to respond for the letter search task, they mentally did so out of habit and practice. However, there was no main effect of load found and the pairwise comparisons have not yielded meaningful results; hence the interaction effects with load could be due to other individual factors that were not controlled in the current study.

Response criterion (β). There were no significant main or interaction effects for the response criterion in the 2 × 5 RmANOVA, $p > .09$ and $p > .06$ for all respectively. There were significant no main or interaction effects for the response criterion in the 2 × 2 × 2 RmANOVA either, $p > .06$ for all. This suggests that there was no response bias in detecting CS.

Letter-search task

Accuracy. The main effect of load was significant in both the 2 × 5 and the 2 × 2 × 2 RmANOVAs, $F(1, 49) = 113.2$, $MSE = .031$, $p < .001$, $\eta_p^2 = .702$ and $F(1, 49) = 110.53$, $MSE = .037$, $p < .001$, $\eta_p^2 = .697$, respectively. That is, for both the analysis, there was better target letter detection during low- ($M = .89$, $SD = .06$ and $M = .9$, $SD = .06$) than high- load ($M = .71$, $SD = .10$ for both with and without neutral conditions) conditions. This shows that load modulated the detection of target letters irrespective of value-learned distractor present (with or without neutral conditions as well). The other main and interaction effects were non-significant, $p > .06$ for all.

Reaction Time. The main effect of load was significant in 2 × 5 and 2 × 2 × 2 RmANOVAs, $F(1, 49) = 23.14$, $MSE = 50345$, $p < .001$, $\eta_p^2 = .325$ and $F(1, 49) = 23.65$, $MSE = 39712$, $p < .001$, $\eta_p^2 = .330$, respectively. That is, for both the analysis, that there was better target letter detection during low- ($M = 715$ ms, $SD = 156$ms and $M =714$ms, $SD = 156$ms) than high- load ($M = 812$ms, $SD = 131$ms and $M = 812$ms, $SD = 132$ms) conditions. This shows that load modulated the reaction time to target letter irrespective of the presence of value-learned distractor (with or without neutral conditions as well). In addition, there was also a two-way interaction between load and valence in the 2 × 2 × 2 RmANOVA, $F(1, 49) = 4.22$, $MSE = 1140.3$, $p = .045$, $\eta_p^2 = .081$. The paired sample t-test showed that participants were faster to detect target letter in the presence of distractor face associated with gain ($M = 711$ ms, $SD = 154$ ms) compared to distractor face associated with loss ($M = 717$ ms, $SD = 155$ ms) condition, $t(48) = 2.76$, $p = .008$, $d = .395$; there was no difference in the high-load gain and loss conditions, $p = .134$. The other main and interaction effects were non-significant, $p > .12$ for all. These results confirm that the perceptual load manipulation was effective in the visual-search task.

Discussion

The aim of the experiment was to examine the interactive role of valence, motivational salience, and attentional resources in conscious perception. The main results showed that the distractors' learned valence (gain or loss) and perceptual load interactively influenced target perception, as hypothesised. Specifically, as predicted in, during the attention-demanding high perceptual load condition, detection sensitivity to the target was better when positively valence (gain), than negatively (loss) valence, distractor stimuli were present, which supports our attention-constraint hypothesis. Further, the main effect of perceptual load was present only in letter-search and not in critical stimuli (target) task performance. This implies that perceptual load alone modulated letter-search task performance.

Effect of learned valence on perception

The current study showed a main effect of valence, that is, the perception of target stimuli was better during gain (when compared to loss) distractor trials. This is in line with previous studies showing prioritised attention capture by value-learned stimuli (Le Pelley et al., 2019; Libera & Chelazzi, 2009). The current study also shows an interaction between valence and perceptual load. Specifically, poorer perception of target stimuli in high-load loss compared to gain conditions, as hypothesised. However, many studies have shown that reward stimuli interfere with task performance (Leganes-Fonteneau et al., 2019; Gupta et al., 2015; Anderson, 2016b). Possible reasons for this contradictory finding are discussed below.

First, differences in experimental paradigms, variable stimulus presentation, and response times are probable factors influencing value learning (Pessoa, 2015). Specifically, in comparison to the current study, previous studies have (a) used simple attention manipulation paradigms such as attentional blink and colour-singletons and (b) to test the effect of either rewards or losses by manipulating their magnitude or predictability (Watson et al., 2020; Chelazzi et al., 2013; Anderson et al., 2011). So, a plausible reason for the poorer task performance during loss, and not gain, distractor conditions could be due to the higher task demands in the current study.

Second, previous studies that manipulated reward have demonstrated high rewarding stimuli capture attention and are difficult to disengage (Chelazzi, et al., 2013; Anderson et al., 2011b). A study that used both the polarities of valence showed that negative stimuli are relatively more difficult to disengage or utilise more attention resources (consequently leaving less for the CS task processing) (Gupta, et al., 2015). Further, many previous studies used simple value-learned stimuli such as colour or shape singletons (Watson, et al., 2020; Hickey et al., 2014), whereas the current study used relatively complex (neutral) face stimuli. The latter could also imply that our experimental paradigm might have better ecological validity than the ones used in the previously mentioned studies. The mechanisms underlying moment- to moment reward processing are still being studied extensively, and studies do show that under some conditions, rewards can enhance task performance (Failing & Theeuwes, 2017; Rajsic, et al., 2017). In summary, the current findings extend on previous work and show that loss, not gain, deters CS task performance.

Effect of perceptual load on perception

The current findings show that perceptual load, not value-learning, influenced performance in the letter-search task. The response time and detection accuracy during the letter-search task were quicker and better in low-load conditions, respectively. This finding aligns with Macdonald and Lavie (2008) and is consistent with the perceptual load theory of attention (Lavie, 1995, 2005). Nevertheless, in the neutral shape target detection task, value-learned stimuli (and not perceptual load) influenced the detection sensitivity. One plausible reason could be that its effect was stronger since the perceptual load was manipulated in the letter-search task. In the neutral shape target detection task, value-driven attention could influence the attention bias and overcome goal-driven attention (target detection). This phenomenon of overcoming goal-driven attention was also found in other studies (Preciado et al., 2017). This further adds strength to the claim that value-driven attention is distinguishable from traditional goal-driven attention in the sense that it can modulate both automatic and voluntary attention capture (Le Pelley et al., 2016).

Theoretical Implications of the Study

The theoretical implications of the findings also include the extended support for the perceptual load theory (Lavie, 1995, 2005) and the hypothesis on value-learning. The findings support those distinguishable mechanisms underlie value-driven attention (Preciado, Munneke, & Theeuwes, 2017; Le Pelley et al., 2016). Moreover, the study findings support the computational neuroscientific circuit models that show cognitive and behavioural actions to value-learned stimuli are learnt using predictability and valence-based information (Kim, 2013; Frank, 2011).

Implications for the attention-constraint hypothesis. Further, this study has theoretical implications for the attention-constraint hypothesis, in terms of processing of value-learned stimuli. Research has shown that value-learning affects selection of information at an early stage and does so differentially based on its evaluative dimensions (Gupta et al., 2016; Raymond & O'Brien, 2009). The preliminary finding that perception is influenced by valence when attention resources are lesser is in line with the findings of Raymond and O'Brien (2009). When constrained temporally or by visual complexity (perceptual load), attention availability appears to have similar interaction with value-learned stimuli. During low-load conditions, the detection sensitivity was better during highly predictive distractor trials (highly predictive of gain/loss) than poorly predictive distractor trials. This also aligns with the attention-constraint hypothesis, but a stronger claim for the impact of predictability could not be made. In support of this reasoning, valence by itself modulated the perception of target stimuli, but predictability did not. Overall, these findings are in line with studies that show that predictive stimuli enhance processing abilities (Wiesera et al., 2016; Alink et al., 2010). The current study gives a possible directionality to the interactive influence of predictability and perceptual load on task-relevant information processing.

Practical Implications of the Study

The findings also have practical and clinical implications. For example, in real world situations such as when an individual is crossing the road, they may see multiple advertisements containing learned motivational value loaded information such as alcohol and money. According to our findings, there is a higher chance that the individual may not notice important information (for example, traffic signal or oncoming traffic) if the banner had negative (say, high petrol prices) when compared to positive (say, discounts at a mall) information. This might lead to jaywalking and accidents consequently. Based on a healthy sample, the current study shows that positively valence value-learned stimuli appear to facilitate perception. Recently a study has attempted to incorporate drivers of attention in instructional designs to capture a learner's attention (Stalbert, 2022). Rewards and punishments have been used in learning for a long time, however there is potential to drive a learner's attention in the desired manner by using such value-learnt stimuli as well.

From a clinical perspective, aberrant reward processing is mainly observed in substance and behavioural addictions (Verdejo-Garcia et al., 2019; Anderson, 2016b; Field et al., 2016; Kakoschke, et al., 2015 Garcia-Garcia et al., 2014). In addition, attention bias to non-drug-related positive stimuli appears to be similar to drug-related attentional biases; in specific, individuals with addiction were found to have more significant attention biases to non-drug-related positive stimuli (Anderson, 2016b, Anderson et al., 2013). Therefore, the current study paradigm, which uses non-drug-related positive stimuli, could be extended and validated to a subclinical and clinical population with higher reward-seeking behaviour or aberrance in reward-related information processing.

Limitations and Future Directions

The results obtained in this study are subject to some limitations. First, the study recruited a healthy sample of young adults. Future studies could recruit samples with high/low trait impulsivity, attention to reward, or sensitivity to reward/punishment to determine whether they mediate the relationship between attention and value-learning. The current study attempted to understand the impact of value-learning at an early level of information processing. Thus, future studies could incorporate higher cognitive processes such as decision making to understand the journey of value-driven stimuli. Finally, the current study used visual stimuli. It would be interesting to explore if the current study findings generalise across sensory systems since inattentional blindness appears to affect the auditory senses (inattentional deafness; Causse et al., 2016).

Conclusion

The current study demonstrated that when attentional demands increase, loss related distractors reduce the ability to perceive target stimuli consciously in a sample of healthy adults. We propose an attention-constraint hypothesis of value-learning where information processing is influenced by the valence of a distractor when attention resources are scarce and predictability when attention resources are readily available. The current study has demonstrated the role of valence in target perception. However, further evidence is required to strengthen support for the role of predictability. The preliminary evidence showed that highly predictable distractors can enhance our ability to perceive targets in an environment.

Experiment 4: Chapter IV

Cultural evaluation of the food.pics_extended database on an Indian sample

Introduction

In the last few decades, our food environment has changed dramatically in terms of the types of food, increased availability and portrayal of unhealthy food in advertisements and social media (Juul et al., 2018). The increased consumption of unhealthy food has been attributed to lifestyle diseases such as chronic obesity and poor health outcomes such as cardiovascular, liver and lung problems, diabetes, hypertension and certain kinds of cancers (Center for Disease Control and Prevention, 2019; World Health Organization, 2016).

Apart from the environmental factors, the cognitive underpinnings of food-related decisions and consumption is another area of research that is thriving in an attempt to better understand the current obesity epidemic (Charbonnier et al., 2016). The evidence suggests that food, especially high-caloric density foods, tends to capture our attention quicker and distract us more than non-food stimuli (de Vries et al., 2020; Morris et al., 2020; van Dillen, & van Steenbergen, 2018; Sawada et al., 2017; Meule, & Platte, 2016). In addition, foods that capture our attention can influence our consumption patterns, such as impulse buying (Zhang & Seo, 2015). It is important to note that such food related research often uses visual exposure to static food images as a substitute for real food. Although food images have been found to elicit simulations of consuming actual food, there are multiple characteristics of the images itself that can affect the reliability and generalizability of the outcomes thus found (Dai et al., 2020; Simmons et al., 2005). Consequently, the need for standardized food stimuli databases arises.

Food.Pics Database

Databases containing a wide variety of standardised stimuli facilitates uniformity and ease of access to variations of the stimuli. Such databases include the Karolinska directed emotional faces database for faces and emotion (KDEF; Lundqvist et al., 1998), which are constantly evolving to strengthen their validity and reliability. Similarly, for food images there are a number of existing databases such as the FoodCast research image database (FRIDa; Foroni et al., 2013), cross-cultural food image database (CROCUFID; Toet et al., 2019) and open library of affective foods (OLAF; Miccoli et al. 2014). The largest and most comprehensive food image database, by far, with 896 food images is the food.pics_extended database (Blechert et al., 2019). The latter database was extended to provide extensive normative data and add more variety, especially cultural diversity (Blechert et al., 2019).

Cultural Differences in Food Evaluation

Bringing back the focus on the need for standardized and adequate databases, studies have shown that the perception of food by all our senses and its evaluation contributes to our food consumption (Blechert et al., 2014). Specifically, food image related visual characteristics such as perceptual salience modify our food preferences (Dai et al., 2020; Milosavljevic et al., 2012). For example, a study showed that people chose perceptually salient/ colourful food irrespective of the healthiness and taste of food (Dai et al., 2020). Overall, it is evident that the food images often used in food related research are variable, which hinders comparability across studies (Charbonnier et al., 2016). Therefore, the use of standardised, reliable and valid food images is critical to facilitate generalizability of results and comparison across studies.

Beyond cognitive factors, the potential differences in food valuation across different cultures also affects our usage of food cues in research, generalisation of findings and consequently the understanding of food consumption (Mangalassary, 2016). For example, previous work on cultural differences in food cue evaluation found that a Portuguese sample rated whole foods and low-calorie foods more positively than the German and German-speaking sample in the study by Blechert et al., 2014 (Prada et al., 2017). More recently, (Bonin et al., 2021) found that French participants rated high- caloric and processed foods as more desirable and positive than the Portuguese and German participants. Thus, as cultural differences in food preferences are evident, it is crucial to explore the cultural validity of such standardised food images.

The Current Study

To date, studies providing cultural comparisons of the food.pics database have focused on samples from European countries, but it is not clear whether these findings extend to other cultural groups. For example, in India, the average food basket and dietary pattern have become more diversified and preferences for dietary value and quality have increased over time, especially in those households with higher income (Kumar & Dey, 2007). Further, the perception of food in India is primarily shaped by various socio-cultural and class factors (Natrajan & Jacob, 2018). Most Indian households consume a carbohydrate-rich diet that falls short of the recommended average daily calorie and nutrient consumption (Sharma et al., 2020). Since there are no existing culturally valid subjective ratings for food images for an Indian sample, we intend to explore any cultural differences in the extended food-pics image database (Blechert et al., 2019). The primary purpose of the current study was to evaluate the food-pics_extended norms in an Indian sample by using a smaller subset of food images.

Similar to the initial validation of the food.pics database (Blechert et al., 2014), we attempt to better describe and understand the current study's culture specific subjective ratings by evaluating the impact of cultural, individual (such as gender) and state (such as hunger) variables on the perception of food (images). For example, studies have shown that (a) women were less aroused by food, rated the foods to be more familiar and had lower desire to eat than men; however, some reported no differences in palatability and desire to eat (Blechert et al., 2014; Miccoli et al. 2014; Prada et al., 2017) (b) hunger was associated with desire to eat and liking of food (Blechert et al., 2014; Bonin et al., 2021) (c) sweet foods were rated as more arousing and palatable than salty/ savory foods (Blechert et al., 2014; Miccoli et al. 2014; Bonin et al., 2021). Age and BMI were also observed to have minor influence on evaluation of food, and differences in eating habits and gustatory quality have been reported in the food.pics database study (Blechert et al., 2014). The current study, explored these variables to establish the reliability of the above-mentioned findings in Indian culture.

Further, it is essential to understand the relationship between the evaluative dimensions in order to effectively match images on their most important evaluative dimension(s) rather than all; and consequently, reducing the confounding effects of the evaluative dimensions itself. A study used regression modelling to understand the relationship between arousal and valence while evaluating affective images (Lohani et al., 2013). With respect to food image valence, arousal and palatability are often used to match images (Morris et al., 2020; Meule & Platte, 2016). Based on previous studies and our correlation analysis, regression modelling was performed. In addition to establishing food perception related trends in an Indian sample this would facilitate comparison between subjective ratings of other cultures as it contains data on individual differences that might influence food evaluation (Toet et al., 2019).

Methodology

Participants

The sample included 200 participants (N = 123 females, 61.5%) who volunteered to participate in an online survey conducted using Pavlovia, Psychopy (Pierce et al., 2019). Participants were aged 18-65 years (*M* = 25.01 years; *SD* = 5.24 years). Inclusion criteria were as follows: Indians currently residing in India, able to read and understand English, neurotypical, and normal or corrected-to-normal vision/hearing. Most of them self-reported consuming an omnivorous diet (68%), and most of the sample were not currently dieting

(88.5%). Body Mass Index (BMI= kg/m^2) values ranged from underweight to obese range, but the majority were in the normal range (that is, BMI: 18.50 - 24.99) (56.5%; overall M = 24.18, SD = 4.49, max = 45.5, min = 13.7).

Table 6

Participant descriptive statistics.

Sample characteristic	n(%)	Mean (SD)	Range
Age (years)		25.01 (5.2)	47 (65-18)
Gender			
Male	76 (38%)		
Female	124 (62%)		
Eating Style			
Omnivore	136 (68%)		
Vegetarian	62 (31%)		
Vegan	2 (1%)		
Current dieting behaviour			
Dieting	23 (11.5%)		
Not-dieting	177 (88.5%)		
Education			
Post-graduate	107 (53.5%)		
Undergraduate	93 (46.5%)		
BMI (kg/m2)		24.2 (4.49)	31.81 (45.49-13.68)
Underweight (BMI<18.5)	15 (7.5%)	17.03 (1.33)	(4.74 (18.42-12.68)
Normal weight (BMI 18.5–24.9)	113 (56.5%)	22.27 (1.72)	6.38 (29.41-25.08)
Overweight (BMI 25–29.9)	57 (28.5%)	27.07 (1.32)	4.33 (29.41-25.08)
Obesity (BMI >= 30)	15 (7.5%)	34.75 (3.96)	15.01 (45.49-30.48)

Note: N=200

Stimuli

We selected 300 images based on two calorie categories with 148 images in low-caloric density and 153 in high-caloric density categories. The calorie categories were based on kilocalories per 100grams (kCal/100g; as given in the food.pics database; Blechert et al., 2019) as low (below the median) and high (above the median). For details of the images please see appendix A. The independent sample *t*-test revealed that the high- and low- caloric density groups were significantly different across the dimensions of kCal/100g (as intended) and image characteristics green and red, but not for image characteristics blue and complexity (see Table 7).

Table 7

Descriptive data for the selected sample food images and the independent sample t-test statistics of the sample groups for calorie and image characteristics.

	Low caloric density (N=148)		High caloric density (N=152)		t-test between low- and high- caloric density groups
	Mean (SD)	Range (max-min)	Mean (SD)	Range (max-min)	
kilocalories per 100g of food	67.92 (47.6)	158 (162-4)	341.25 (131.75)	575.55 (741-165.45)	$t(298)= 23.772$, $p < .001$, $d= 2.745$
Image characteristics					
Red	.45 (.08)	0.41 (0.67-0.26)	.48 (.06)	0.38 (0.73-0.34)	$t(298)= 3.42$, $p= 0.001$, $d= 0.395$
Green	.35 (.06)	0.32 (0.51-0.19)	.33 (.04)	0.26 (0.43-0.17)	$t(298)= 3.523$, $p< .001$, $d= 0.407$
Blue	.21 (.06)	0.29 (0.37-0.09)	.2 (.05)	0.24 (0.32-0.08)	$t(298)= 1.281$, $p= 0.201$, $d= 0.148$
Complexity	.10 (.05)	0.24 (0.26-0.02)	.11 (.05)	0.25 (0.27-0.02)	$t(298)= 1.135$, $p= 0.257$, $d= 0.131$
Processed nature of food (n(%))					
Whole food	83 (56.08)		9 (5.92)		
Processed food	65 (49.91)		143 (94.07)		
Taste of food (n(%))					
Sweet	36 (24.32)		79 (51.97)		
Tasty	81 (54.73)		55 (36.18)		
Neither	31 (20.94)		18 (11.84)		

Food Evaluation Task

Participants rated a random selection of 50 out of the 300 food images, as rating 300 images could not be reliably done by the participants. Previous studies on food database rating have asked participants to each rate ~5 to ~100 images (Foroni et al., 2013; Lang et al., 2008). Since they were only required to rate a subset of the 300 images, the significance or lack thereof in image characteristics were not considered a deterrent. Here each image was rated by 18-50 participants. Participants rated each image based on the seven dimensions as in the initial validation of the food.pics database (see Table. 3). A single image was displayed on the computer screen at a time. Participants rated the food image across each of the dimensions on a visual analogue scale (VAS; solid horizontal bars with no value gradations, approximately 8 cm long) with anchors on either end. Participants responded with mouse clicks on the VAS which ranged from 0 (extreme left) to 100 (extreme right) (see Table 8). The participants received one sample food image (#835, avocado) for their practice trial ratings. The task was self-paced; however, participants took 20 minutes on average to complete the task.

Table 8

The seven scales on which participants rated each image along with their description and anchors.

Normative scale	Description	Scale anchors
Familiarity	Defined as whether the participant recognised seven the object or not.	Dichotomous: yes/no
Recognizability	Defined as whether the object was easy or difficult to identify	Dichotomous: yes/no
Complexity	It was characterised by "many components or details," and "many colours/edges/pieces."	"very little" to "very high"
Valence	It was characterised by how negatively or positively the participant viewed the object; that is, whether they found it was repulsive or attractive.	"very negative" to "very positive"
Arousal	It was characterised by how much the object aroused an emotional reaction in the participant.	"not at all" to "extremely"
Palatability/ tastiness	It was characterised by how delicious the participant found the depicted food in general, regardless of whether they wanted to eat it at the moment or not.	"not at all" to "extremely"
Desire to eat/ craving	It was characterised by how much the participant would like to eat the depicted food if it were available at that moment.	"not at all" to "extremely"

Demographics, Food habits, and Hunger

Demographics (age, height, weight, gender, education, location) and food habits (weight, diet) were also assessed. Hunger was measured using Grand's (1968) 4-item hunger scale. Participants reported time elapsed since their last meal and time until their next anticipated meal (estimated to the nearest 15 minutes). They also rated subjective hunger (1 = "not hungry at all"; 7 = "extremely hungry") and craving for their favourite food (1 = "none at all"; 6 = "as much as I could get") on Likert scales. Although the scale has not undergone formal validation, it has been widely used in appetite research (Tappar & Pothos, 2010; Kakoschke et al., 2015).

Procedure

The information sheet outlining the experimental procedure, which included the risks, benefits, and other relevant study details were provided to the participants. Once all questions were clarified, participants provided informed consent before completing questions relating to demographics, food habits and hunger. They then completed a practice trial of the food evaluation task to familiarise themselves with the experimental set-up and the rating scales. The study was conducted online using Pavlovia, Psychopy (v.2020.1.3, Pierce et al., 2019). Various validation and experimental studies using food images have been successfully conducted online, hence the online survey mode was adopted (Toet et al., 2019; Blechert et al., 2014; Zampollo et al., 2012). The survey was available between February 2021 and April 2021. Recruitment of participants happened through social media platforms and university mailing lists. Since data collection was done during the COVID-19 pandemic, such recruitment platforms and the online survey mode was efficient and most feasible. Once the task was completed, any further questions were clarified and they were compensated for their time and effort monetarily.

Data analysis

SPSS version 28 was used for analysis. The primary analysis aimed to examine cultural differences in food ratings for the 300 images used in this study relative to the original validation study reported by Blechert et al. (2019) across the seven evaluative dimensions by using a 2 (Sample: Indian versus original) × 2 (Caloric density: low, high) ANOVA. Similar to the previous studies, we divided the images based on their caloric density (Bonin et al., 2021; Blechert et al., 2019; Prada et al. 2017). Bonferroni correction was applied for the *p* values to control multiple comparisons. The alpha levels for all reported analyses are .05.

The secondary exploratory analysis included correlation between the evaluative dimensions. Based on the correlations and previous studies (Morris et al., 2020; Meule & Platte, 2016) regression was conducted to determine whether the evaluative dimensions of palatability, valence and arousal predict desire to eat to establish a potentially predictive relationship between the evaluative dimensions (similar to Lohani et al., 2013). We tested for multicollinearity, which implied redundancy in independent variables in the regression model. The dependent variable (or criterion) is desire to eat (or craving) in the current study. The independent variables (or predictors) are valence, arousal and palatability (or tastiness). Collinearity diagnostics showed a further need for enquiry (all *VIFs* > 6.9; refer to Table 9). Using condition index (42.35) and variance proportions, the subsequent diagnosis showed collinearity between valence and palatability. Therefore, we proceeded with a 2-way regression model after removing valence as a predictor.

Table 9

Collinearity statistics for the 3-way regression model with the desire to eat as the criterion.

Predictor	Tolerance	VIF
Valence	0.136	7.353
Arousal	0.144	6.939
Palatability	0.083	12.071

Further exploratory analysis was conducted to study the variables that could potentially influence subjective ratings, similar to previous studies using the food.pics database (Bonin et al., 2021; Blechert et al., 2019; Prada et al. 2017). We conducted correlations between the rating dimensions and individual variables such as hunger (Grand hunger scale, 1968), BMI, and age. A similar analysis was extended to group ratings based on gender, diet (dieting versus not-dieting), eating habits (omnivore versus vegetarian), and food types (savoury versus sweet; processed versus whole food). Note that some foods are assigned neither savoury nor sweet (for example rice) and some foods are assigned neither processed or whole-food (for example tomatoes with mozzarella cheese) in the food.pics_extended database (Blechert et al., 2019). For example, tomatoes with mozzarella cheese have been assigned under processed food. The gustatory quality comparison was only done for those rated sweet or savoury, however, based on previous studies the foods were assigned their level of processing (Bonin et al. 2021, Prada et al. 2017).

Results

Comparison with food.pics_extended database: Univariate ANOVA 2 (study sample: Indian versus original) x 2 (caloric density)

Familiarity. The main effect of study sample was present in such a way that the Indian participants (M= 84.4 %, SD= 18.6 %) were less familiar with the food items than the original study sample (Blechert et al., 2019) (M= 92.2 %, SD= 14.2 %), $F(1, 596) = 26.1$, $MSE = 266.62$, $p < .001$, $\eta p^2 = .042$. The interaction between study sample and caloric density and the main effect of caloric density were not significant, all *ps*> .29.

Recognizability. Similar to familiarity, the main effect of study sample was present indicating that the Indian sample (M= 81.6 %, SD= 21.2 %) was less able to recognize the food than the original study sample (M= 89.5 %, SD= 20.5%), $F(1, 596) = 21.6$, $MSE = 433.51$, $p < .001$, $\eta p^2 = .035$. The interaction between study sample and caloric density and the main effect of caloric density were not significant, all *ps*> .08.

Complexity. A significant, but weak, interaction between study sample and caloric density was present, $F(1, 596) = 6.77$, $MSE = 150.87$, $p = .010$, $\eta p^2 = .01$). The main effect of study sample was present where, the Indian sample (M= 47.9, SD= 13.7) reported a higher number of components (i.e., details/colors/edges/pieces) in the food images than those in the food.pics_extended study (M = 34.2, SD = 10.7), $F(1, 596) = 188.2$, $MSE = 150.87$, $p < .001$, $\eta p^2 = .238$. The main effect of caloric density was not significant ($p = .43$). Further, the independent sample *t*-tests revealed no significant difference between the calorie groups ($p = 0.06$). However, a significant difference between the high- (M = 32.5, SD = 9.3) and low- (M = 35.9, SD = 11.8) calorie groups in the original study sample, $t(298) = 2.771$, $p = 0.002$, $d = 0.32$ was found.

Valence. A significant interaction between study sample and caloric density was present, $F(1, 596) = 56.13$, $MSE = 94.65$, $p < .001$, $\eta p^2 = .086$). The main effect of study sample was present whereby Indian participants rated the foods more positively ($M = 63.1$, $SD = 10.4$) than the original study participants ($M = 53.2$, $SD = 9.9$), $F(1, 596) = 152.8$, $MSE = 94.65$, $p < .001$, $\eta p^2 = .204$. The main effect of caloric density was not significant, $p = .08$. Furthermore, the independent sample *t*-tests revealed that the Indian as well as the original study sample rated high- calorie images more positively ($M = 65.3$, $SD = 9.6$; $M = 49.5$, $SD = 8.1$) than low-calorie ($M = 60.7$, $SD = 10.7$; $M = 56.9$, $SD = 10.2$), $t(298) = 3.898$, $p < .001$, $d = 0.45$; $t(298) = 6.852$, $p < .001$, $d = 0.791$, respectively).

Arousal. The interaction between study and caloric density was found, $F(1, 596) = 33.33$, $MSE = 102.86$, $p < .001$, $\eta p^2 = .053$). We found a main effect of study sample where Indian participants ($M = 51.8$, $SD = 12.3$) appeared to be more emotionally aroused by the food than those in the original study ($M = 31.8$, $SD = 8.3$), $F(1, 596) = 582.7$, $MSE = 102.86$, $p < .001$, $\eta p^2 = .494$. The main effect of caloric density was found, where emotional arousal for low- calorie food ($M = 40.2$, $SD = 12.9$) was significantly lower than those for high- calorie food ($M = 43.4$, $SD = 15.8$), $F(1, 596) = 14.51$, $MSE = 102.86$, $p < .001$, $\eta p^2 = .024$. Furthermore, the independent sample *t*-tests revealed that in the original study sample found low- calorie group ($M = 32.6$, $SD = 9.2$) to be more arousing than high ($M = 30.9$, $SD = 7.2$), $t(298) = 1.709$, $p = 0.022$, $d = 0.197$, however the Indian sample found high- calorie foods more arousing ($M = 55.8$, $SD = 11.9$) than low- calorie foods ($M = 47.8$, $SD = 11.5$), $t(298) = 5.853$, $p < .001$, $d = 0.676$.

Palatability. The interaction between study and caloric density was found, $F(1,596) = 34.08$, $MSE = 157.04$, $p < .001$, $\eta p^2 = .054$). The main effect of study groups was present where, the Indian sample ($M = 57.9$, $SD = 13.9$) found the food more palatable than the original study sample ($M = 54.9$, $SD = 11.7$), $F(1, 596) = 8.3$, $MSE = 157.04$, $p = .004$, $\eta p^2 = .014$. The main effect of caloric density was not significant, $p = .08$. Further, the independent sample *t*-tests reveal that Indian sample found high- calorie food as tastier ($M = 61.8$, $SD = 12.8$) than low-calorie food ($M = 54$, $SD = 13.9$), $t(298) = 5.019$, $p = 0$, $p < .001$, $d = 0.58$. However, the original study sample rated low-calorie food as tastier ($M = 57.1$, $SD = 12.4$) than high- calorie groups ($M = 52.9$, $SD = 12.8$), $t(298) = 3.124$, $p = .002$, $d = 0.361$).

Desire to eat (craving). The interaction between study and caloric density was found, $F(1, 596) = 21.24$, $MSE = 150.57$, $p < .001$, $\eta p^2 = .034$. The main effect of study groups was present where, craving for food is significantly higher in the Indian sample ($M = 47.5$, $SD = 13.4$) than the original study sample ($M = 31.4$, $SD = 11.5$), $F(1, 596) = 256.4$, $MSE = 150.57$, $p < .001$, $\eta p^2 = .301$. The main effect of caloric density was not significant, $p = .06$. Further, the independent sample *t*-tests reveal that the Indian sample found high- calorie food as more desirable ($M = 50.7$, $SD = 12.6$) than low-calorie groups ($M = 44.2$, $SD = 13.6$), $t(298) = 4.319$, $p < .001$, $d = 0.499$. However, the original study sample reported low-calorie food as more desirable ($M = 32.8$, $SD = 12.9$) than high- calorie groups ($M = 30.1$, $SD = 9.7$), $t(298) = 2.06$, $p = .04$, $d = 0.238$.

Table 10

Mean ratings and t-test statistics for comparison between low- and high-caloric densities of the seven dimensions.

Evaluative dimensions	Low- caloric density (n=148)	High- caloric density (n=152)	*t*-test between high- and low- caloric densities
	Mean (SD)		
Familiarity	84.39 (18.57)	86.29 (17.83)	$t(298)= 0.905$, $p= 0.092$, $d= 0.104$
Recognizability	80.22 (21.89)	82.99 (20.43)	$t(298)= 1.134$, $p= 0.065$, $d= 0.131$
Complexity	46.99 (13.9)	48.82 (13.60)	$t(298)= 1.148$, $p= 0.063$, $d= 0.133$
Valence	60.77 (10.74)	65.36 (9.61)	$t(298)= 3.898$, $p < .001$, $d= 0.450$
Arousal	47.82 (11.49)	55.76 (11.97)	$t(298)= 5.853$, $p < .001$, $d= 0.676$
Palatability	54.03 (13.98)	61.79 (12.77)	$t(298)= 5.019$, $p < .001$, $d= 0.580$
Desire to eat	44.23 (13.58)	50.75 (12.57)	$t(298)= 4.319$, $p < .001$, $d= 0.499$

Relationship Between Evaluative Dimensions

Correlations. The one-way random-effects model of intra class correlation (ICC) indicates that overall, the measures used show moderate inter-rater reliability (r = .647) (Koo & Li, 2016). As expected, familiarity and recognition were highly correlated (r = .965, p < .001). Familiarity and recognition are correlated with all other evaluative dimensions, except complexity. The interesting cluster of correlations are those between arousal, valence, palatability and desire to eat; that is, the more positively a food is rated, the higher it arouses an emotional reaction, the more palatable it appears to be and more it is craved (all rs > .87, *ps* < .001). Note that only moderate to substantial (r > .4) and significant correlation coefficients are discussed.

Table 11

*Inter item Pearson correlation. **p < .001*

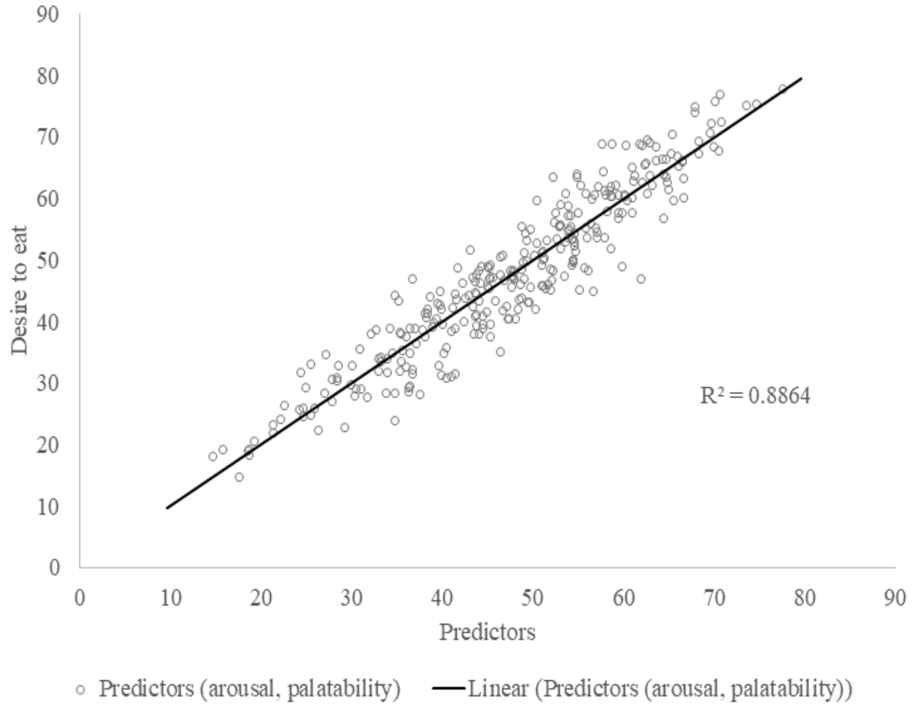
	1	2	3	4	5	6	7
1. Familiarity	1						
2. Recognition	.965**	1					
3. Complexity	0.089	0.058	1				
	(*p*=.126)	(*p*=.320)					
4. Valence	.614**	.608**	.397**	1			
5. Arousal	.514**	.518**	.436**	.872**	1		
6. Palatability	.586**	.572**	.413**	.929**	.924**	1	
7. Desire to eat	.502**	.495**	.393**	.883**	.896**	.939**	1

The regression model indicated the two predictors, arousal and palatability, explained 88.6% of the variance (adjusted R^2 =.886, $F(2,297) = 1159.19$, $p < .001$). As desire to eat increases by one unit, arousal increases by .212 units and palatability by .733. The resulting multiple regression equation was:

Predicted desire to eat = .212 (arousal) + .733 (palatability) - 5.963

Figure 7

Regression scatter plot of desire to eat as the criterion.



Exploratory analysis: Role of Individual Variables on Evaluative Dimensions

The hunger ratings show associations with the evaluative dimensions however age and BMI did not show interesting trends. Grand's hunger scale ratings were significantly, positively (but weak) correlated with arousal (r = .26, p < 001) and palatability (r = .25, p < .001), and moderately with craving (desire to eat) (r = .51, p <. 001). Craving for favourite food subscale scores showed moderate, positive associated with desire to eat rating (r = .49, p < .001). There was also weak, positive correlation between craving subscale and complexity (r = .14, p<001), arousal (r = .34, p < .001) and palatability (r = .21, p <. 001) ratings. Age shows weak, negative (but significant) correlations with valence (r = -.22, p = .002), arousal (r = -.19, p = .007), palatability (r = -.23, p = .001) and desire to eat ratings (r = -.16, p = .02). BMI does not appear to be correlated with any of the seven evaluative scales (for all, *ps* > .09).

Gender differences. Females were significantly more familiar with the food than men, $t(598) = 2.20$, $p = .028$, $d = .18$ (see Table 12). Men gave significantly higher complexity, $t(598) = 2.1$, $p = .035$, $d = .17$), arousal, $t(598) = 5.27$, $p < .001$, $d = .43$), palatability, $t(598) = 2.99$, $p = .003$, $d = .24$) and desire to eat (craving), $t(598) = 5.4$, $p < .001$, $d = .44$) ratings than women. No significant difference was observed between the genders across the other dimensions (for all, *ps* > .079).

Table 12

Mean ratings and t-test statistics for comparison between males and females of the seven dimensions.

Evaluative dimensions	Total (n=200)	Female (n=124)	Male (n=76)	*t*-test between male and female
		Mean (SD)		
Familiarity	85.35 (18.19)	86.75 (18.28)	83.31 (19.98)	$t(598)= 2.20$, $p= .028$, $d=.18$
Recognizability	81.62 (21.17)	82.41 (21.78)	80.41 (22.16)	$t(598)= 1.12$, $p= .265$, $d=.09$
Complexity	47.92 (13.75)	46.91 (14.80)	49.44 (14.59)	$t(598)= 2.1$, $p= .035$, $d=.17$
Valence	63.10 (10.42)	62.58 (11.12)	64.26 (12.29)	$t(598)= 1.76$, $p= .079$, $d=.14$
Arousal	51.84 (12.37)	49.66 (12.82)	55.51 (14.32)	$t(598)= 5.27$, $p< .001$, $d=.43$
Palatability	57.95 (13.91)	56.67 (14.36)	60.33 (15.58)	$t(598)= 2.99$, $p= .003$, $d=.24$
Desire to eat (craving)	47.53 (13.45)	45.06 (13.80)	51.70 (16.08)	$t(598)= 5.4$, $p< .001$, $d=.44$

Eating habits. Comparison between dieters and non-dieters could not be performed as there were very few dieters in the current study. However, omnivores rated the food to be more familiar, $t(598) = 2.558$, $p = 0.011$, $d = 0.209$, but less complex $t(598) = 2.702$, $p = 0.007$, $d = 0.221$, than vegans and vegetarians (see Table 13). No significant difference was observed between the two groups across the other dimensions (for all, *ps* > .06).

Table 13

Mean ratings and t-test statistics for comparison between omnivores and vegans/vegetarians of the seven dimensions.

Evaluative dimensions	Omnivores (n=136)	Vegans/ vegetarians (n=64)	*t*-test between omnivores and vegans/vegetarians
	Mean (SD)		
Familiarity	86.61 (18.27)	82.40 (21.91)	$t(598)= 2.558, p= 0.011, d= 0.209$
Recognizability	82.57 (21.55)	79.38 (24.49)	$t(598)= 1.691, p= 0.091, d= 0.138$
Complexity	46.77 (13.45)	50.11 (16.68)	$t(598)= 2.702, p= 0.007, d= 0.221$
Valence	62.63 (10.51)	63.92(14.61)	$t(598)= 1.24, p= 0.216, d= 0.101$
Arousal	51.04 (12.80)	53.23 (15.99)	$t(598)= 1.856, p= 0.064, d= 0.152$
Palatability	57.76 (14.14)	58.06 (18.10)	$t(598)= 0.225, p= 0.822, d= 0.018$
Desire	47.26 (13.84)	47.86 (18.13)	$t(598)= 0.458, p= 0.647, d= 0.037$

Differences in ratings: Food variables

Gustatory quality. Participants rated sweet foods significantly more familiar, $t(249) = 3.333$, $p = 0.001$, $d = 0.422$, recognisable, $t(249) = 3.755$, $p < .001$, $d = 0.476$, positive, $t(249) = 4.994$, $p < .001$, $d = 0.633$, arousing, $t(249) = 4.526$, $p < .001$, $d = 0.573$, palatable, $t(249) = 5.344$, $p < .001$, $d = 0.677$, and desirable, $t(249) = 5.661$, $p < .001$, $d = 0.71$ than savoury foods. No significant difference was observed in the complexity dimension ($p = .285$) (see Table 14).

Table 14

Mean ratings and t-test statistics for comparison between sweet and savoury foods on the seven dimensions.

Evaluative dimensions	Sweet (n=115)	Savoury (n=136)	*t*-test between sweet and savoury
	Mean (SD)		
Familiarity	89.11 (15.16)	81.56 (19.88)	$t(249) = 3.333$, $p = 0.001$, $d = 0.422$
Recognizability	86.61 (17.56)	76.69 (23.25)	$t(249) = 3.755$, $p < .001$, $d = 0.476$
Complexity	48.41 (12.26)	50.30 (15.15)	$t(249) = 1.072$, $p = 0.285$, $d = 0.136$
Valence	66.96 (9.91)	60.63 (10.08)	$t(249) = 4.994$, $p < .001$, $d = 0.633$
Arousal	56.51 (11.57)	49.72 (12.06)	$t(249) = 4.526$, $p < .001$, $d = 0.573$
Palatability	63.65 (12.23)	54.90 (13.49)	$t(249) = 5.344$, $p < .001$, $d = 0.677$
Desire	53.35 (12.45)	44.33 (12.69)	$t(249) = 5.661$, $p < .001$, $d = 0.717$

Degree of processing. Participants rated processed foods more complex, $t(298) = 4.843$, $p < .001$, $d = 0.606$, positive, $t(298) = 2.248$, $p = 0.025$, $d = 0.281$, emotionally arousing, $t(298) = 5.369$, $p < .001$, $\underline{d} = 0.672$, palatable, $t(298) = 4.498$, $p < .001$, $d = 0.563$, and desirable, $t(298) = 3.577$, $p < .001$, $d = 0.448$ than less processed foods (see Table 15).

Table 15

Mean ratings and t-test statistics for comparison between whole and processed food of the 7 dimensions.

Evaluative dimensions	Whole (n=92)	Processed (n=208)	the *t*-test between whole and processed
	Mean (SD)		
Familiarity	87.47 (18.29)	84.42 (18.12)	$t(298)= 1.338$, $p= 0.182$, $d= 0.168$
Recognizability	84.95 (20.64)	80.15 (21.29)	$t(298)= 1.816$, $p= 0.07$, $d= 0.227$
Complexity	42.34 (12.74)	50.39 (13.49)	$t(298)= 4.843$, $p< .001$, $d= 0.606$
Valence	61.08 (10.99)	63.99 (10.06)	$t(298)= 2.248$, $p= 0.025$, $d= 0.281$
Arousal	46.33 (11.64)	54.29 (11.92)	$t(298)= 5.369$, $p< .001$, $d= 0.672$
Palatability	52.69 (14.85)	60.29 (12.84)	$t(298)= 4.498$, $p< .001$, $d= 0.563$
Desire	43.43 (14.63)	49.34 (12.51)	$t(298)= 3.577$, $p< .001$, $d= 0.448$

Discussion

The current study primarily aimed to extend the validity of the existing most comprehensive food database, food-pics, norms to an Indian sample. The study was conducted with an Indian adult sample using 300 images from the food.pics_extended database on seven evaluative dimensions: familiarity, recognition, complexity, valence, arousal, palatability (tastiness), and desire to eat (craving). The study showed that the Indian sample was less familiar and less able to recognise the food images relative to the database norms.

Comparison with Food.Pics_Extended Database

The current study shows that in general, our results were not consistent with those evidenced in the food database evaluation study (Blechert et al., 2019). Cultural differences between subjective ratings of all the evaluative dimensions was found. The results show that the participants in our study are significantly less familiar and less able to recognise foods in the images when compared to the database norms, which included a predominantly German-speaking sample (Blechert et al., 2019). Although the globalisation of the food market has rendered access to various foreign cuisines, the findings reveal that familiarity could be a major factor to consider while selecting food stimuli to use in studies with Indian samples (further discussed below; Boivin et al., 2014; Wu, & Cheung, 2002). Despite being less familiar, Indian participants rated the food images to be more complex, positive, emotionally arousing, palatable and desirable when compared to the food.pics_extended database norms. Congruent with these findings, research shows that familiarity with food from other cultures affects their desire to consume a particular food (Jang, & Kim, 2015; Seo et al., 2013). It was found that when the food is unfamiliar or difficult to recognise, individuals tend to use supplementary information to evaluate the food (Blechert et al., 2014; Seo et al., 2013; Aldridge et al., 2009). Therefore, in the current study, it is possible that for unfamiliar images participants relied only on visual information such as complexity and attractiveness.

Further, the Indian sample has rated high-calorie food as more palatable, desirable and arousing than low-calorie food; whereas, the database norms show that low-calorie food is more arousing, palatable and desirable. One possible reason for the incongruent findings could be that the German food consumption patterns are more natural and healthier in Europe (Moser, 2016). Specifically, an increase in the consumption of organic fruits and vegetables in Western and European nations was observed, especially the United States of America and Germany (Moser, 2016). However, various studies have also reported increased consumption of meat, unhealthy soft drinks and cheap foods regardless or the health consequences in the German sample (Seubelt et al., 2022; Heuer et al., 2015). Furthermore, even though Indian cuisine has typically been considered ‘healthy’, there has been a steady decline in traditional food consumption and an increase in consumption of high-caloric and unhealthy fast foods (Anand, 2011). This could have led to poor and unhealthy food consumption that does not meet the dietary requirement standards (Anand, 2011; Sharma et al., 2020). Taken together, both cultures appear to have recent unhealthy consumption trends however the cultural differences evidenced could be relative. Further research into Indian and Asian cultures along with other European cultures is required to explore potential individual differences, other than culture and food consumption trends, that could contribute to these discrepant findings.

Relationship Between the Evaluative Dimensions

The correlation results show a high association between familiarity and recognizability, which is expected. The other evaluative dimensions also showed moderate but significant positive correlations with familiarity and recognizability. This shows that the more familiar or recognisable the food is, the more positive, arousing, palatable and desirable we find the food to be. Further, the four evaluative dimensions of valence, arousal, palatability and desire to eat were highly correlated with each other. This finding is consistent with previous results demonstrated in the study by Bonin et al. (2021). Establishing subsets of closely related evaluative dimensions would help in structuring norms as well as matching food images for further research (Bonin et al., 2021; Morris et al., 2020; Meule & Platte, 2016).

In addition, the regression model performed using the Indian sample showed that arousal and palatability together are highly predictive of craving or desire to eat the food. Craving is usually measured using Individual variables such as reactivity to food cues and cognitive-emotional or neural responses (Meule, 2020; Taylor, 2009). However, in agreement with the current study, craving for food is also based on the characterises or evaluation of the foods themselves, such as high-calorie or palatable food (Massicotte et al., 2019; Roefs et al., 2006). Additionally, the state measure of hunger (Grand, 1968) correlated with the evaluative dimensions of arousal, palatability and desire to eat. This is This is congruent with previous research that have also observed that increased hunger is related to increased craving as well as valuation of high- calorie foods and perceived attractiveness of most food (Yeomans et al., 2004; Piech et al., 2009; Siep et al., 2009; Frank et al., 2010). Moreover, studies have also shown increased consumption of palatable foods even when not hungry (this has also been associated with overeating and obesity) (Yeomans et al., 2004; Lowe & Butryn, 2007). The implications of predictive relationships of craving are vast and essential to further understand food consumption.

Role of Individual and Food Variables on the Evaluative Dimensions

The present study found that a number of individual differences also predicted food ratings. Specifically, omnivores were more familiar with the food images and vegans/ vegetarians found the food more complex. This complements the findings by Prada et al., 2017. We also found that males rated the food as more complex, arousing, palatable and desirable than females, and females found the food to be more familiar. These results contrast those of Bonin et al. (2021). They did not report significant differences in terms of eating habits or gender, which could be due to a homogenous sample with only a small number of males (12%) and vegan/vegetarians (9%) in their study; in comparison the current study has a better representation of males (38%) and vegan/vegetarians (32%). Nevertheless, previous studies have shown gender differences in terms of food consumption, where women tend to make healthier choices and beliefs, greater weight control, and consume less meat (Wardle et al., 2004; Beardsworth et al., 2002). A study has also shown that there might be gender differences in satiation based on caloric values (Frank et al., 2010).

Current study findings indicate that foods with high-caloric densities are rated more positive, arousing, palatable and desirable than low-calorie foods. We also found that processed foods are rated more complex, positive, arousing, palatable and desirable than whole foods, while whole foods are easier to recognise than processed foods. In congruence with our findings, Bonin et al. (2021) noted that the trends in differences between processed and whole foods were similar to those found for high- and low-caloric density foods, respectively. This is plausible as the high-caloric density foods in this study, and in general, are likely processed, and the low-caloric density foods are likely natural, whole foods (Vergeer et al., 2019). Further, sweet foods were rated more familiar, positive, arousing, palatable, desirable and easier to recognise than savoury foods. These results are in congruence with previous literature, which show that high-calorie, tasty foods are often shown behavioural and cognitive preference and consumed more frequently than low-calorie/ bland foods (Bonin et al. 2021, Mason et al., 2019; Racine, 2018; Meule & Platte, 2016; Graham et al.,, 2011). However, various factors such as weight status and personality traits might modulate these healthy eating habits and food-related cognition (Kakoschke et al., 2019; Bongers at al., 2015).

Limitations and Future directions

The current study is subject to certain limitations. First, the results for the multi-cultural comparisons should be taken with caution as they were derived from a small sample of images from the food.pics_extended database. Furthermore, the studies using Portuguese and French samples reported ratings on a 10-point scale while the current study, similar to Blechert and colleagues (2019), used a 100-point scale. Future studies should attempt to validate a larger sample of images, such as the same 300 images used in the present study, to establish cultural reliability of standardised food image norms rigorously. Second, the current study asked participants to rate a subset of the total 300 images. Hence, the inter-rater validity could only be performed using the one-way random-effects model of ICC. Future studies could ask participants to rate the same set of images so that other ICC models can be used to test the interrater reliability across the individual evaluative dimension. As an extension, each image was also rated by a varying number of participants in the current study. It could be possible that those rated by fewer participants had more variance.

Further, the study sample comprised mostly young female adults who were omnivores and non-dieters, which could limit the generalizability of the current study norms. Finally, the data collection for the present study happened during the COVID-19 pandemic. Research has shown that there were changes in food consumption and weight gain during this pandemic (Bennett, Young, Butler & Coe, 2021; Sato et al., 2021). An Indian study reported both increases in consumption of healthy home-cooked meals and binge eating coupled with a drop in physical activity (Madan et al., 2021). These possible changes to lifestyle and other related factors could have affected the way participants rated the images. Extensive research could be done to understand the effect of such demographic variables on ratings of food images. In addition, future studies could also explore the validity of other food databases such as the foodcast research image database (Foroni et al., 2013) to expand the pool of culturally validated standardised images. The study findings show that future research in building food databases should consistently evolve to (a) incorporate food images from various cultures; and (b) standardise food images across not only image characteristics but also across cultures, especially those that have unique and global cuisines.

Conclusion

The current study provided norms for 300 food images from the food.pics_extended database using a large sample of healthy Indian adults. The main finding was that there are cultural differences in existing food image norms. The subjective ratings derived from this study can be further validated and used for food-related research in India. Preliminary findings indicate the desire to eat food can be predicted using evaluative dimensions: arousal and palatability. Further, the study showed that sweet, processed, high-caloric density foods are rated more arousing, palatable, desirable than savoury, whole, low-caloric density foods. These findings further reiterate the need for (a) culturally testing the reliability of existing norms for standardised food images; (b) matching food images on multiple evaluative dimensions and types of food while using in food cognition research.

Experiment 5: Chapter V

Food Cues Captures Attention Under Low-Perceptual Load Irrespective of Caloric Density

Introduction

There has been a global increase in the prevalence of overweight and obesity, that is, a body mass index (BMI) over 25 kg/m^2 (WHO, 2021; Swain & Chowdhury, 2018). In a developing country like India, the prevalence of overweight and obesity is predicted to reach 29% and 12%, respectively, by 2040 (Luhar et al., 2020). A notable driver of obesity is the increased availability of food cues and in turn, increased consumption (Swinburn et al., 2011; Herrera & Lindgren, 2010). Consider an example of a food delivery service that targeted midnight-cravings advertising on websites that are often visited late at night (Gupta, 2015). Such widespread presence of highly palatable (and high-calorie) food cues creates an obesogenic- environment (Boylend et al., 2016).

In addition to the environmental and lifestyle factors, current food habits are also influenced by human evolution (Crittenden, & Schnorr, 2017). In order to survive, humans have fostered effective foraging behaviours that enable them to seek and gather food effectively. Our taste preferences have evolved alongside gathering food that is highly palatable (tasty), fatty, sugary and has a high-caloric density (Crittenden & Schnorr, 2017; Breslin, 2013). Furthermore, diet quality of food consumption is often measured by nutrients present in food (Gicevic et al., 2021; Krebs-Smith et al., 2018). In general, unhealthy food is often high in calories, highly or ultra-processed and low in nutrients (Juul et al., 2018; Deluchi et al., 2017; Keshari & Mishra, 2016). Evolutionary taste preferences for energy-dense food and the current obesogenic- environment can be observed as a key driver of obesity and its consequential health risks (Deluchi et al., 2017; Boylend et al., 2016).

Attention Bias to Food Cues

Beyond the evolutionary and environmental influences on food consumption, cognitive processes, such as attention bias to food stimuli, play a role in the development and maintenance of unhealthy food consumption (Hardman et al., 2021). Studies have shown that food stimuli often automatically capture and hold our attention over other neutral cues in the environment and this attention bias has been associated with craving, obesity, weight gain and overconsumption of high-calorie food (Field et al., 2016; Meule & Platte, 2016; Kakoschke, Kemps, & Tiggemann, 2015; Werthmann, Roefs, Nederkoorn et al., 2011; Castellanos et al., 2009). However, some studies have reported a lack of (or smaller than initially thought) difference in attention biases to food between normal and overweight/obese weight groups or found a lack of association between attentional bias to food, food consumption and individual differences in body weight or BMI (Hardman et al., 2021; Hagan et al., 2020; Field et al., 2016). To further understand these discrepant findings, it is vital to explore the measures used to assess attention bias to food.

Measures of attention bias to food cues

Most previous studies on attention bias to food stimuli have used computerised cognitive paradigms including the visual probe task and modified Stroop task. In the visual dot-probe task, participants respond to target stimuli occurring at the location previously occupied by the stimulus of interest (in this case, food stimulus; congruent trials) or by a control stimulus (usually a neutral stimulus; incongruent trials). The attention bias scores are calculated generally by subtracting mean incongruent trial reaction times followed by congruent trial reaction times; larger positive bias scores indicate a stronger attention bias to food (for example refer Castellanos et al., 2009). Although obtained reaction time bias indices have been scrutinized for their reliability, modifications that allow strengthening the reliability of these indices are encouraged (Vervoort et al., 2021; van Ens et al., 2019).

In the case of modified colour-naming food Stroop tasks, the reaction time to naming the colour of food and non-food words serve as a measure of attention bias; a slower reaction time to colour-naming food word would indicate higher attention bias to food stimuli (for example refer, Nijs, Franken, & Muris, 2010). In a Stroop task, similar to the dot-probe task, the underlying attentional processes responsible for such a slow reaction time are unclear. Here, it is unclear whether the colour-naming is delayed due to increased attention to the semantics of the word (name of the food in this case) or avoidance of processing of the word (and focusing on the colour) (Algom, Chajut, & Lev, 2004).

Altogether, studies examining the attention capture abilities of food stimuli and their association with other food-related cognitions and behaviours have shown mixed results. Furthermore, clarification of unhealthy weight and consideration of finer gradations in body mass index, the inclusion of moderating factors, and improving psychometric properties of attention bias measures are recommended to delineate the underlying mechanisms of food stimuli processing (Field et al., 2016; Hagan et al., 2020; Hardman et al., 2021). Moreover, the role of available attentional resources in attention capture by food related distractors is unclear. Therefore, an update or modification of paradigms used to understand food stimulus appears to be a necessity.

Perceptual Load and Food Cognition

Food consumption has been previously understood from various frameworks such as the incentive-sensitization and dual-processing models. The incentive-sensitization model focuses on the strong motivation and hedonic pleasure derived from food as drivers of overconsumption (Robinson & Berridge, 2000). The dual-processing model posits that the underlying cognitive operations that might have a causal influence on cognitive biases and eating behaviour can be conscious and controlled or automatic and uncontrolled (McClure & Bickel, 2015). More recently, attention bias to food has been studied from a perceptual load framework in healthy samples (Morris, Yeomans, & Forster, 2020; Morris, Keith Ngai, Yeomans, & Forster, 2020; Morris, Vi, Obrist, Forster, & Yeomans, 2020).

Perceptual load is related to the complexity of incoming sensory information. The incoming information places processing demands on the perceptual system and determines distraction by task-irrelevant information (Lavie, 2005, 2006, for a review). According to the perceptual load theory of selective attention, when individuals are engaged in a high attention-demanding task, they have fewer resources to process a distractor, relative to engagement in a low attention-demanding task (Lavie, 1994; see Lavie, 2005, 2010 for a review). The significant difference between the mean response to the distractor of interest and control distractor (neutral or no- distractor) conditions would be indicative of the distractor's interference (for example, refer Forster & Lavie, 2007). The interference could facilitate or hamper task performance. Another measure of attention bias is the distractor's interference score, which is calculated by subtracting the mean response to distractor- absent from distractor- present trials (for example refer Gupta, Hur & Lavie, 2016). Unlike attention bias scores derived from Stroop and dot-probe tasks, interference calculated from tasks that manipulate perceptual load can be attributed to the effect of distractor salience and perceptual load. Therefore, according to the perceptual load theory, interference is lower in high relative to low attention-demanding task conditions (Lavie & Tsal, 1994; Beck & Lavie, 2005).

The recent studies that have applied a novel perceptual load framework show that during a visual letter search paradigm that manipulated load conditions, the distractor interference caused by food (sweets only) distractors was eliminated during high-load conditions (Morris, Yeomans, & Forster, 2020). This indicates that attention bias to food stimuli is reduced during high- attention-demanding tasks. Following this, participants were given a forced-choice memory test where stimuli presented in the letter-search task were presented along with the new stimuli. Interestingly, participants were able to recognise food more than non-food stimuli. They also found a lack of association between food memory and attention bias to food. This might imply that information regarding food is differently processed by attention and memory. Further studies have shown that during high-load conditions there was a reduction in food-related intrusive thoughts (chocolate) (Morris, Keith Ngai et al., 2020) In addition, those who performed high-load tasks reported a reduced sense of satiety (after consuming high-calorie food) and consumed more unhealthy food after the task (Morris, Vi et al., 2020). These studies shed light on the role of the attention economy on attention bias by using interference scores. However, these studies (Morris, Yeomans, & Forster, 2020; Morris, Keith Ngai et al., 2020) only used sweet, high-calorie food. It remains to be determined whether these findings can be generalised to other types of food (for example, savoury or low-calorie). Therefore, the current study utilized foods with high and low caloric density and different gustatory qualities (sweet and savoury).

The Current Study

Load theory appears to provide an alternative framework to study attention bias to food. Based on recent studies, we predict the elimination of interference of food stimuli during high-load conditions and not low-load conditions (Morris, Keith Ngai et al., 2020; Morris, Yeomans, & Forster, 2020). Therefore, the current study included a larger variety of food cues (low-caloric density and savoury) and attempted to replicate the previous findings (Morris, Yeomans, & Forster, 2020). We aimed to understand the distractor interference of low- and high-caloric food in the low- and high- perceptual conditions. In general, to strengthen the claim and robustness of using attention bias measures from a perceptual load framework, we expected to replicate the previous findings in the current experimental design. Based on previous studies, we hypothesised a larger attentional bias for food cues when compared to no distractor conditions (Hardman et al., 2021; Morris, Yeomans, & Forster, 2020). As previously discussed, studies exploring the relationship between attention bias to food and BMI have yielded conflicting results (for example, Hagan et al., 2020; Field et al., 2016). Hence, we decided to understand the role of BMI in the previously hypothesised relationship between perceptual load and food stimuli, even though we did not formulate a priori hypotheses about this relationship.

Methodology

Participants

The sample included 64 participants (70% female; N = 45) who volunteered to participate in an online survey. Participants were aged 18-36 years (M = 23.91 years; SD = 3.59 years). Inclusion criteria were as follows: Residents of India, able to read and understand English, no current diagnosis of psychiatric or neurological conditions, and normal or corrected-to-normal vision/hearing. Most participants indicated following an omnivorous diet (58%). Self-reported BMI values ranged from 15.41 kg/m^2 to 34.53 kg/m^2 (M = 23.08, SD = 4.28). The necessary sample size was calculated using G-Power (Erdfelder, Faul, & Buchner, 1996). It was estimated that $N = 155$ was required to obtain a power level of 0.80. The calculation was based on an effect size of 0.25 ($\eta p2 = 0.06$), for the critical interaction of load (low, high) by distractors (food, non-food and no distractor; Morris, et al., 2021). The current study has recruited 64 participants due to time constraints. Additionally, other studies using visual letter-search paradigms for emotional and motivational stimuli have included a relatively smaller sample size (<52, Lunn et al., 2019; Gupta et al., 2016). Further, Morris and colleagues evidenced unique attention capture abilities of food in low-load conditions. The current study uses distractor versus no distractor condition, therefore the effects observed might be stronger even with a sample size lower than the one estimated in the power analysis.

Stimuli

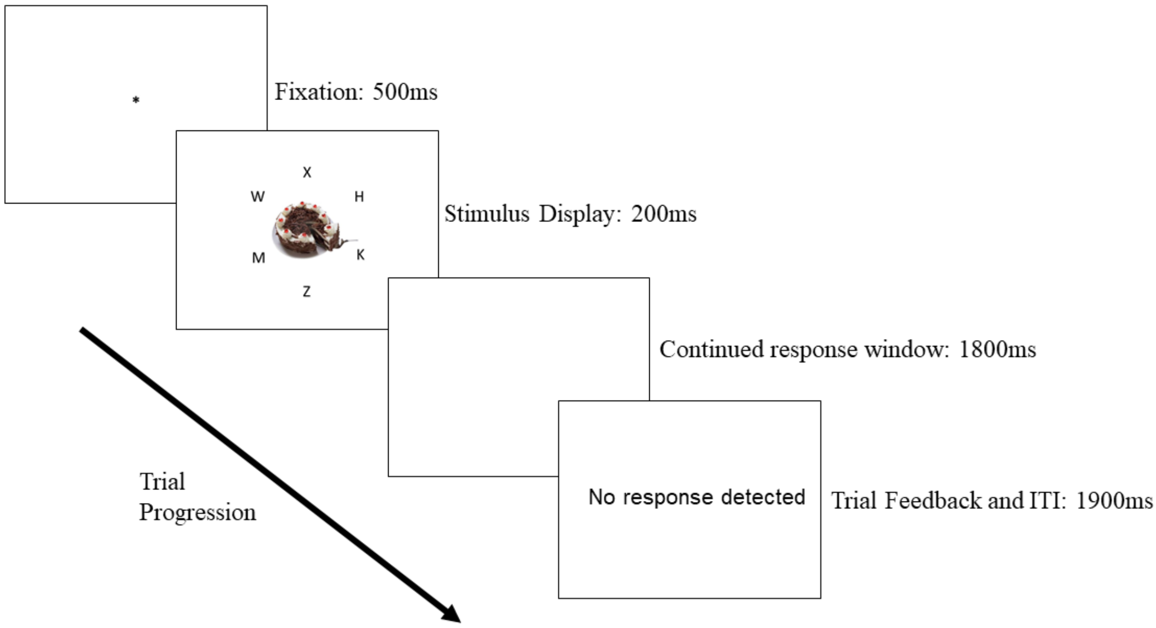
Based on our cultural validation study conducted with an Indian sample (Experiment 4; chapter IV), we selected a total of 24 static food images from the food.pics extended database (Blechert, Lender, Polk, Busch, & Ohla, 2019). These images included 12 high-calorie (M = 372.5 kcal, SD = 123.6 kcal) and 12 low-calorie (M = 84.3 kcal, SD = 41.9 kcal) foods. The high-calorie images were significantly higher in kilocalories per 100g than the low-calorie images ($t(22) = 7.65$, $p = .004$, $d = 3.12$), but did not differ in image complexity, colour characteristics, valence or arousal (all *p*s > 0.20).

Perceptual Load Task

The letter-search task was based on previous versions which used meaningful stimuli such as food and emotionally laden images (Morris et al., 2021; Gupta et al., 2016). Each trial began with a centrally presented fixation point for 500 ms, followed by a 200 ms presentation of the stimulus display (refer to Figure 8). The stimulus display included the target and distractor letters along with a centrally placed distractor (5.2º × 3.6º). There were six letters presented in the letter search within a circle that had a radius of 3.0º. Each of the target letters, ‘X’ or ‘N’ (0.6º × 0.6º), appeared in half of the trials. The other five positions were occupied by distractor letters: ‘O’s (0.4º × 0.5º) in the low-load condition, and the letters H, K, M, W, and Z (0.6º × 0.6º) in the high-load trial. The participants had to respond to the letter-search subtask by clicking on the ‘left arrow’ key when target ‘X’ was spotted, and the ‘right arrow’ key when ‘N’ was spotted. The participants had a response window of 2000ms on each trial. The response time window was followed by an inter-trial interval of 1900 msec. When participants did not give a response during this window, they received a ‘no response detected’ message. They received an error tone (beep) if they made any errors while responding.

Figure 8

Trial progression of a high-calorie (image #0074), high-load condition.



There was one low-load and one high-load block each comprising 96 trials. Each block contained 75% of distractor-absent trials (in which no distractor was presented) and 25% of distractor-present (12.5% low-calorie, 12.5% high-calorie) trials. Similar to Gupta et al., (2016), we presented distractors on low probability trials to avoid moderation by habituation. The block orders, target positions and distractor conditions were counterbalanced across all participants before any exclusion. The order of trials within each block was pseudo-randomised. Each participant received 12 practice trials to familiarise themselves with the task.

Self-Report Measures

The current study also incorporated other state and trait variables that are recommended as core psychosocial measures from the affect, stress and non-homeostatic domains and the motivation domain in the ADOPT initiative (Accumulating Data to Optimally Predict Obesity Treatment) for understanding eating behaviour and obesity (Sutin et al., 2018). In addition, we included one of the core behavioural measures to assess overall diet quality as recommended by ADOPT (Lytle et al., 2018). Thus, the secondary aim of the study was to examine whether state (diet quality, craving) and trait variables (craving, reward-based eating drive) modulate the association between distractor interferences, error scores and reaction time to food stimuli. Based on this the following measures were used in the current study: Grand's Hunger Scale (Grand, 1988), Food Cravings Questionnaire- Trait (FCQ-T; Meule et al., 2014), Reward-Based Eating Drive (RED) Scale (Mason et al., 2017) and the Prime Diet Quality Score 30-day measure (PDQS-30D; Gicevic et al., 2021). However, there were no meaningful associations between the questionnaire measures and distractor interferences. Therefore, the associations between measures alone are added in the supplementary section.

Procedure

Participants were first provided with an information sheet in which the experimental procedure was outlined, which included the risks, benefits and other relevant study details. Once all questions were clarified and consent was provided, participants completed questions relating to demographics. They then completed practice trials to familiarise themselves with the experimental set-up of the Letter Search Task before completing the task, which was administered online using Pavlovia, Psychopy (v.2020.1.3, Pierce et. al., 2019). Hunger was measured before and after the completion of the letter-search task using Grand's hunger scale (1998). They were then automatically directed to questionnaires containing measures of FCQ-T, RED and PDQS-30D, which was administered via Google Forms.

Data Cleaning

The data of two participants were removed from further analysis due to poor data quality (letter-search accuracy of <60%) suggesting suboptimal performance in the experiment, which was the process that was followed in similar previous studies (Gupta et al., 2016). These criteria ensured that participants paid attention to the task. In addition, a participant was removed due to their ongoing psychiatric diagnosis, which was reported post-participation. There were a total of 61 participants included in the final analysis (refer to table 16).

Data analysis

The following performance indices were derived from the perceptual load task: letter-search reaction times (RTs), error rates, and distractor interferences. The error rates include the percentage of missed and incorrect letter search responses (Morris, Yeomans, & Forster, 2020). Distractor interferences were calculated by subtracting the index for no distractor present from the index for which the distractor was present (as in Forster & Lavie, 2008; Gupta et al., 2016). To test our primary aim, we performed analysis of variance (ANOVA) using 3 (Distractor conditions: high- caloric density, low- caloric density and blank) × 2 (Loads: high versus low) as within-group factors for the RT and error rate, separately. An additional ANOVA was performed using 2 (Distractor interferences: high- caloric density, low- caloric density) × 2 (Loads: high versus low) as within-group factors for the distractor interferences of RT and error rate separately. Paired sample t-tests were conducted based on the significant results from the ANOVAs. To test the secondary aim with BMI, analysis of covariance (ANCOVA) was conducted using 3 (Distractor conditions: high- caloric density, low- caloric density and blank) × 2 (Loads: high versus low) as within-group factors and BMI as the covariate for the RT and error rate, separately. Similar to the analysis of variances performed earlier, an additional ANCOVA was performed using 2 (Distractor interferences: high- caloric density, low- caloric density) × 2 (Loads: high versus low) as within-group factors and BMI as the covariate for the distractor interferences of RT and error rate separately. In an attempt to streamline the results, only relevant paired sample t-tests are reported. The alpha levels for all reported analyses are .05. All analyses were conducted using IBM SPSS Statistics 28.

Table 16

Descriptive statistics of the sample after data cleaning.

	n(%)	Mean (SD)	Range
Age (years)		23.91 (3.60)	18 (36-18)
Gender			
Male	17 (28%)		
Female	44 (72%)		
Eating Style			
Omnivore	35 (57%)		
Eggetarians (vegetarians who consume eggs)	10 (16%)		
Vegetarian	15 (25%)		
Vegan	1 (2%)		
Dieting			
Dieting	4 (7%)		
Not dieting	57 (93%)		
Education			
Post-graduate	25 (41%)		
Undergraduate	36 (59%)		
BMI (kg/m2)		23.03 (4.35)	19.12 (34.53-15.41)
Underweight (BMI<18.5)	6 (9%)	17.08 (1.12)	2.95 (18.36-15.41)
Normal weight (BMI 18.5–24.9)	41 (67%)	21.67 (1.82)	6.30 (24.89-18.59)
Overweight (BMI 25–29.9)	8 (13%)	27.34 (1.39)	4.08 (29.39-25.31)
Obesity (BMI >= 30)	6 (11%)	32.47 (1.65)	4.39 (34.53-30.14)

N= 61

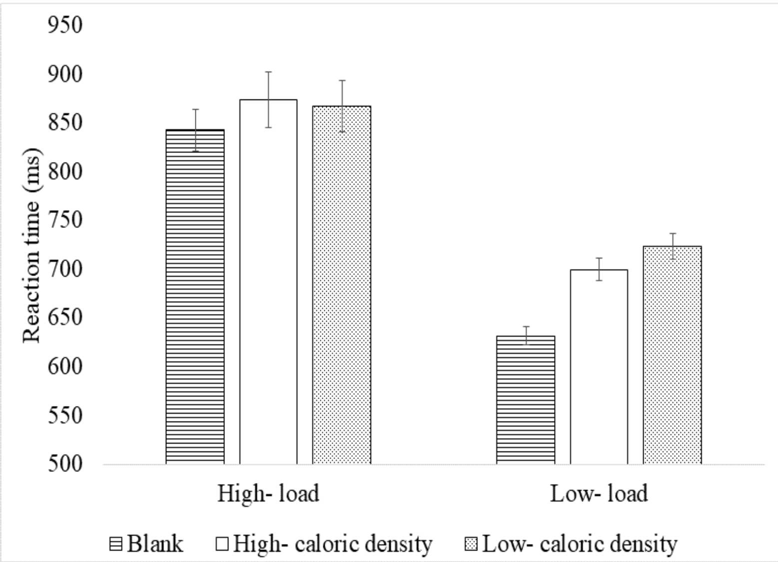
Results

Attention Bias to Food Stimuli

Reaction Times. The results of the 3 × 2 ANOVA revealed an interaction between load and distractor condition, $F(2, 120) = 10.00$, $MSE = 3432.03$, $p < .001$, $\eta p^2 = .143$. Following this, the paired sample t-test revealed a significant difference only in the low- load conditions: (a) between the RT of blank (no distractor) (*M* = 842.55 ms, *SD* = 164.79 ms) and high- caloric density food distractor (*M* = 873.75 ms, *SD* = 224.10 ms) conditions, t(60) = 9.15, $p < .001$, $d = 1.172$; (b) between blank and low- caloric density (*M* = 866.99 ms, *SD* = 202.21 ms) conditions, t(60) = 10.74, $p < .001$, $d = 1.375$; and (c) between high- and low- caloric density conditions, t(60) = 2.47, *p* .032, $d = .316$. Note the large effect sizes on the significant effects. Other effects were not significant (all *p*'s > .07).

Figure 9

The reaction time (ms) as a function of perceptual load and caloric density with standard error bars.

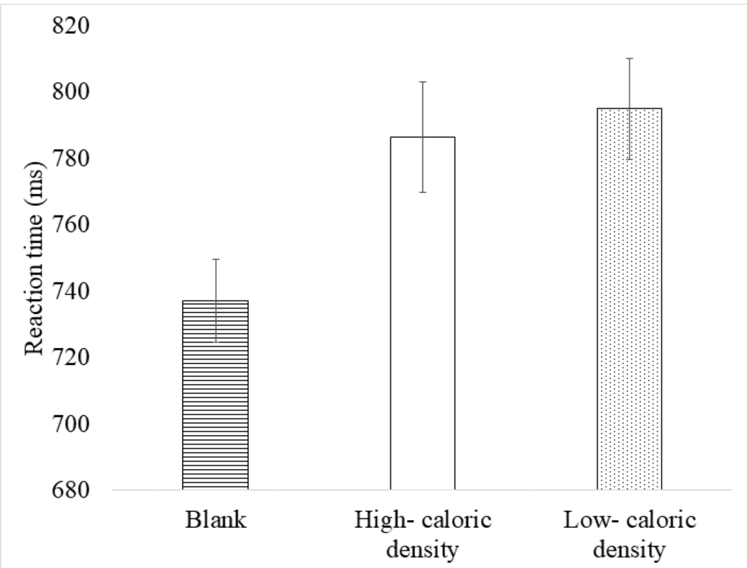


A main effect of load was present such that the RT was significantly higher in the high-load (M = 861.10 ms, SD = 197.03 ms) than the low-load condition, (M = 684.72 ms, SD = 88.23 ms), $F(1, 60) = 52.92$, $MSE = 53789.82$, $p < .001$, $\eta p^2 = .469$, which confirms that our perceptual load manipulation was effective.

The main effect of distractor conditions was also present, $F(2, 120) = 24.71$, MSE = 4837.55, $p < .001$, $\eta p^2 = .292$. Following this, the paired sample t-test revealed a significant difference between: (a) the RT of blank (no distractor) (M = 737.06 ms, SD = 98.04 ms) and high- caloric density (M = 786.62 ms, SD = 130.03 ms) conditions, t(60) = 5.84, $p < .001$, d = .748; and (b) the blank and low- caloric density (M = 795.04 ms, SD = 15.26 ms) conditions, t(60) = 7.20, $p < .001$, d = .922. There was no significant difference between high- and low-caloric density conditions (p = .812).

Figure 10

The reaction time (ms) as a function of caloric density with standard error bars.



The 2 × 2 ANOVA revealed a main effect of load as well, where the distractor interference was significantly lower in the high-load (M = 27.82, SD = 103.78) than the low-load condition, (*M* = 79.71, *SD* = 63.26), *F*(1, 60) = 18.61, *MSE* = 8828.07, $p < .001$, ηp^2 = .237. Other main and interaction effects were not significant (all *p*'s > .06).

Error Rates. The 3 × 2 ANOVA revealed a main effect of load, where the error rates were significantly higher in the high-load (*M* = 36 %, *SD* = 15 %) than the low-load (*M* = 6 %, *SD* = 7 %) conditions, *F*(1, 60) = 406.12, *MSE* = 209.72, $p < .001$, ηp^2 = .871. Other main effects and interaction effects were not significant (all *p's* > .36). The 2 × 2 ANOVA on distractor interference showed no significant main or interaction effects (all *F's* < 1).

Attention Bias to Food Stimuli: The Role of BMI

Reaction Times. The results of the 3 × 2 ANCOVA revealed a main effect of load where the reaction time was significantly higher in the high-load (*M* = 861.10, *SD* = 197.03) than the low-load condition, (*M* = 684.72, *SD* = 88.23), *F*(1, 59) = 12.689, *MSE* = 50498.82, $p < .001$, ηp^2 = .177. The main effect of distractor conditions was also present, *F*(2, 118) = 3.39, *MSE* = 4846.69, *p* = .0371, ηp^2 = .054. The interaction effect was not significant (*p* = .811).

The 2 × 2 ANCOVA revealed no significant main or interaction effects (all *F's* < 1).

Error Rates. The 3 × 2 ANCOVA revealed a main effect of load, where the error rates were significantly higher in the high-load (*M* = 36 %, *SD* = 15 %) than the low-load (*M* = 6 %, *SD* = 7 %) conditions, *F*(1, 59) = 6.40, *MSE* = 208.00, *p* =.014, ηp^2 = .098. Other main effects and interaction effects were not significant (all *p's* > .097). The 2 × 2 ANOVA on distractor interference showed no significant main or interaction effects (all *p's* > .064).

It is important to note that inclusion of BMI as a covariate has led to weakening of main and interaction effects. Especially, the interactive effect of perceptual load and food cues on reaction disappears in the covariate analysis. This notable weakening is also expressed in the effect size measure, partial eta squared. For example, the effect size of the main effect of load on reaction time without the BMI covariate is .469; and, with BMI covariate the effect size reduces to .177. This indicates that the model is better without the inclusion of BMI.

Discussion

The current study aimed to understand the interaction between attention availability and caloric density of food stimuli. The main results showed that perceptual load and caloric density interactively affected task performance. First, under low-load conditions, participants performed poorly (slower reaction time) on the task in the presence of food distractors relative to no distractor trials. More specifically, low-load conditions, participants took significantly longer to respond when low-, in relation to high-, caloric density images were present. Interestingly, no such difference was found in high-load conditions. Furthermore, irrespective of load, participants performed poorly on the task in the presence of food distractors than in no distractor trials. These results could indicate that the caloric- density of food affects task performance only under low-load conditions. These results have theoretical and practical implications in understanding attention bias to food stimuli in a healthy sample.

Robustness of load theory

As predicted, we demonstrated that perceptual load and caloric density interactively affected task performance. In line with perceptual load theory, the participants overall performed significantly poorer in high, in relation to low, load conditions irrespective of the presence or absence of food distractors (Lavie & Tsal, 1994; Lavie, 1995). The current results add to the existing literature on perceptual load theory by showing that the food distractors affected task performance only in low-load conditions and was eliminated during high-load conditions (Morris, Yeomans, & Forster, 2020; Morris, Keith Ngai et al., 2020; Morris Vi et al., 2020c).

There are various stimuli that tend to persistently capture attention even during high-load conditions, such as, novel, salient or intense emotional stimuli (Gupta et al., 2016; De Fockert, 2013). Food is a naturally rewarding and thereby salient stimulus (Jansen, Houben, & Roefs, 2015). However, food has not captured attention during high-load conditions unlike other motivationally rewarding stimuli (Gupta et al., 2016). Therefore, it can be said that the early information-processing mechanisms that underlie food cue perception are unlike other salient and motivational stimuli. A possible reason could be that food is naturally rewarding unlike the motivational stimuli used in Gupta and colleagues' study (2016) which was learned in a laboratory using a computerised choice task. Further, food has many complex evaluative dimensions when compared to the face stimuli used in their study (refer Blechert et al., 2014; Lang, Bradley, & Cuthbert, 2008; for a review). Therefore, the processing of food stimuli could be different from other motivationally rewarding stimuli. Last, although the findings of the study are in line with a previous study conducted by Morris et al., (2020), it is possible that food stimuli capture attention during high-load conditions, but the current study was not able to demonstrate the effect. This possibility exists because the study is underpowered as per the power analysis. Overall, it is evident that food stimuli, although rewarding, are affected by load similar to neutral or no distractor conditions under high-load.

Attention capture by food distractors

The current results show that irrespective of load, the low- and high- caloric density food distractors similarly deterred task performance when compared to no distractor conditions. This is in line with previous studies that have shown preferential attention allocation to food stimuli (van Ens et al., 2019; Werthmann, Roefs, Nederkoorn, Mogg et al., 2013; Werthmann, Roefs, Nederkoorn et al., 2011). This could be because food cues tend to rapidly capture and hold attention (Field et al., 2016; Nijs et al., 2010) and the current study has demonstrated that it specifically does so only under low-load conditions.

Current findings further show that under low-load conditions, participants took significantly longer to respond in low-, in relation to high-, caloric density distractor trials. This builds on previous research that showed that distraction from food cues vanishes in high-load conditions (Morris, Yeomans, & Forster, 2020). Previous studies have demonstrated an increased bias to high- caloric density in those with aberrant food consumption and eating disorders (Werthmann, Renner et al., 2014; Faunce, 2002). In particular, some studies have shown that even in subclinical populations, restrained eaters and those with subclinical signs of eating disorders, have a higher attentional bias to high- caloric density foods (for example, Polivy & Herman, 2017; Forestell et al., 2012, Placanica et al., 2002). In such cases, a higher incentive value and higher reward sensitivity is often associated with high- caloric density (Field et al., 2016; Forestell et al., 2012). The current study sample did not include such clinical populations. This could be a possible reason for the increased attention allocation to low-caloric density stimuli, compared to high-caloric density stimuli, which was observed in the current study. Moreover, many previous studies have compared high-caloric density foods with neutral or no distractor conditions rather than low-caloric density foods therefore the current study paradigm might have enhanced the salience to caloric density relatively (Dondzilo et al., 2022). Therefore, caloric density and load could be a factor that influences attention allocation to food stimuli, in addition to various other modulating and moderating factors such as impulsivity/ inhibition, and cognitive restraint (Love, Bhullar, & Schutte, 2020; Meule & Platte, 2016; Forestell et al., 2012).

Further, we examined the role of BMI in the interaction between perceptual load and food distractors using analysis of covariance. The ANCOVA results show that including BMI weakens the existing main and interaction effects of perceptual load and food distractors. The association between high BMI and attention bias has also shown mixed findings (refer Hagan et al., 2020; Hendriske et al., 2015; for reviews). The previous study that modulated perceptual load in a visual letter search paradigm also did not show an association between BMI and distractor interferences by food stimuli, similar to the current study (Morris, Yeomans, & Forster, 2020). In line with this, the current study shows that BMI does not affect the interaction between load and food distractors; however, more evidence is required to delineate the ambiguous role of BMI.

Theoretical and Practical Implications

The current study findings add to the existing body of research on load theory and its role in attention capture by meaningful stimuli such as emotion and motivation. The current study also iterates the importance of including low-caloric density food while including a healthy or control sample. This ensures that the task is sensitive to differences in caloric densities. The current study also has practical implications for research in unhealthy eating behaviour. The obesogenic environment that is characterised by increased availability and accessibility to unhealthy food has become a major factor influencing unhealthy eating behaviour and obesity (Kirk, Penney, & McHugh, 2010). The current findings provide preliminary evidence that in an environment whereby individuals are not engaging in high attention-demanding tasks, their attention is likely to be captured by low-caloric density foods which could result in healthy eating. This is in line with research that shows that mindful eating can help change unhealthy eating behaviours (Warren, Smith, & Ashwell, 2017). However, such behaviour often occurs when individuals are engaged in other tasks (such as watching television) or engage in inattentive eating which leads to a higher quantity of food or energy consumption (for example, Braude & Stevenson 2014). The current and previous research implies that distracted eating combined with the current obesogenic environment could be a factor contributing to the maintenance of unhealthy eating behaviour. The predictive role of interference by food distractors under load in food consumption needs further investigation in future studies.

Limitations and future directions

The results obtained in this study are subject to some limitations. First, the current study took place during the COVID-19 pandemic. Studies have shown lifestyle and food consumption changes such as an increase in physical activity, binge eating and consumption of home-cooked meals during this period (Bennett et al., 2021; Madan et al., 2021; Sato et al., 2021). All of these factors could have affected the attention allocation to food stimuli. Future studies could triangulate the current study results during the post-pandemic era. Second, the study utilized self-reported data regarding BMI and psychiatric diagnosis. A review suggests using Bioelectric impedance analysis and waist circumferences as some alternatives to traditional BMI percentiles (Daniels, 2009). Furthermore, in-person studies should aim to obtain objective rather than self-reported estimates of BMI..

Undiagnosed maladaptive eating behaviours may have also affected the current results. Therefore, future studies could use clinical diagnostic measures of maladaptive eating behaviours such as the eating disorder inventory-3 (Garner, 2004). Aberrant reward processing is observed in obesity and food addiction (Campana et al., 2019; Garcia-Garcia et al., 2014; Volkow et al., 2011). The current study paradigm can be extended to and validated in a clinical sample or a subclinical sample with problematic reward-related processing. Finally, the current study used food stimuli that varied only on caloric density, however, there are other evaluative dimensions that play a major role in attention biases and food consumption such as palatability or tastiness (Blechert et al., 2014). As the current study did not assess these dimensions, future studies could attempt to do so to provide a more comprehensive evaluation of food stimuli characteristics.

Conclusion

The current study demonstrated that when attentional demands increase, the distraction by food stimuli vanishes. The findings suggest that caloric density and perceptual load interactively influence task performance. Preliminary evidence indicates that task performance is significantly poorer in the presence of food distractors, especially low-caloric density food. Interestingly, when independent of perceptual load, task performance was significantly poorer in the presence of both low and high- caloric density food, alike, when compared to the absence of distractors. Overall, the current findings imply that distracted eating combined with the current obesogenic environment could be a factor contributing to the maintenance of unhealthy eating behaviour.

Chapter VI: General Discussion

The overall aim of this thesis was to understand the interaction between various affective stimuli (emotional faces, faces associated with high-low gain and loss, and food stimuli) and perceptual load on task performance (in this case target perception). Specifically, four empirical studies were conducted to explore the role of evaluative affect dimensions (such as valence), personality traits and various relevant variables (such as hunger, sensitivity to rewards and punishments) in this interaction. The aims and key findings from each of these empirical studies is summarised below.

The first study aimed to examine the interaction between the availability of attentional resources and valence of emotional face distractors on conscious perception of expected stimuli. More specifically, we examined whether trait anxiety or impulsivity modulated the interaction between emotion and perceptual load in detecting a squiggle. The main results showed that only in participants with high impulsive traits the irrelevant angry faces (compared to happy and neutral faces) significantly reduced their sensitivity to detecting the squiggle during high-load conditions. These results may indicate that trait impulsivity modulates the interaction between emotion and load.

The aim of the second study was to examine the interaction between the availability of attentional resources and value on conscious perception of expected stimuli. The main results showed that distractor' learned valence (gain or loss) and perceptual load interactively influenced the perception of the target. Specifically, as predicted based on our attention-constraint hypothesis, during the attention-demanding high perceptual load condition, detection sensitivity to the target was better when positively valenced (gain), than negatively (loss) valanced distractor stimuli were present. Further, the main effect of perceptual load was present only in the letter-search task and not in the critical stimuli (target) task performance. This implies that perceptual load alone modulated letter-search task performance.

The third study was performed to obtain subjective ratings for food images from the food.pics database in an Indian sample to improve the selection of stimuli set for the subsequent experimental study. The study aimed to extend the validity of the existing most comprehensive food database norms to an Indian sample. Note that the previous validation studies have been conducted in European samples (Bonin et al., 2021; Prada et al., 2017), which makes the third study the first of its kind to obtain subjective ratings in an Asian population. The study was conducted with an Indian adult sample who rated 300 images from the food.pics_extended database on seven evaluative dimensions: familiarity, recognition, complexity, valence, arousal, palatability (tastiness), and desire to eat (craving). The study showed that the Indian sample was less familiar and less able to recognise the food images relative to the European and US samples represented in the database norms. Therefore, the subjective ratings obtained by our study can be further validated and used for food-related research in India involving food cues.

The fourth study aimed to understand the interaction between the availability of attentional resources, BMI, and caloric density of food stimuli. The main results showed that perceptual load and caloric density interactively affected task performance. More specifically, under low- load conditions, participants performed poorly on the task in the presence of food distractors than no distractor trials. Under low- load, participants took significantly longer to respond when low-, in relation to high-, caloric density images were present. Interestingly, no such difference was found in high- load conditions. Furthermore, irrespective of load, participants performed poorly on the task in the presence of food distractors than no distractor trials. These results could indicate that the caloric- density of food affects task performance only under low-load conditions. Moreover, we examined the role of BMI in the interaction between perceptual load and food distractors. In line with a recent study (Morris, Yeomans, & Forster, 2020), which the fourth study aimed to extend, we found that BMI does not affect the interaction between load and food distractors. However, more evidence is required to delineate the ambiguous role of BMI. These results have theoretical and practical implications in understanding attention bias to food stimuli and food consumption in a healthy sample.

Overall, these findings suggest that under high- load conditions, task performance was poorer in the presence of negative affective distractors (angry and loss related faces), while performance was better in the presence of positive distractors (happy and gain related faces). Furthermore, it is interesting to note that although both value-learned stimuli and food stimuli have motivational value, food distractors did not affect task performance in high-load conditions, unlike the value-learned stimuli. The findings have implications in understanding (a) the interactive effect of attention and affective stimuli is shaping perception, (b) differential and unique attention prioritizing abilities of affective stimuli that are based on stimuli dimensions (such as valence, predictability), (c) processing of affective stimuli, and, (d) the differences and similarities between distraction by affective stimuli on task performance. We also found a possible modulating role for other factors in the interaction between attention and affective stimuli such as personality traits. For example, the interaction between load and emotion was evident only in those with high impulsivity. The latter finding implies that studies examining the processing of affective stimuli needs to incorporate related factors such as individual differences.

Updating the Load Theory of Attention

The load theory of attention has typically been used to understand the role of perceptual load in attention and perception using neutral stimuli (Lavie & Tsal, 1994; Lavie, 1995, 2005;

Macdonald & Lavie, 2008). Recent research has incorporated meaningful affective stimuli such as emotion, value- learning and food cues. These studies have demonstrated high variability in attention capture by affective stimuli under high and low-load conditions (Morris, Yeomans, & Forster, 2020; Gupta et. al, 2016; Raymond & O'Brien, 2009). The current thesis (experiments 1, 2, 3 and 5) has shown that the evaluative affect dimensions are crucial in determining attention capture and interference by affective stimuli. For example, in experiment 5 (chapter V), distraction by food cues disappears under high- load conditions for both high- and low- caloric density food cues. Nevertheless, the negative valence of emotional and value learnt stimuli persisted to interfere with task performance even under high-load conditions. Affective stimuli are all around us and affect our perception at any given moment.

In conclusion, affect- driven attention includes both emotional and motivational stimuli as attention capture abilities of emotional and motivational are similar and this mechanism can be differentiated from the traditional goal- and stimulus- driven attention capture (Gupta et al., 2016; Munneke et al., 2015; Awh et al., 2012; Raymond, 2009). The current study supports this as we found that negatively valenced emotional (angry faces) and value- learned (loss-associated faces) stimuli deter task performance (experiment 1, chapter II; experiment 3, chapter III). Interestingly, perceptual load affects the attention capture by these affective stimuli depending on their evaluative dimensions. Therefore, it is evident that the load theory framework needs to be updated to incorporate affective and other meaningful stimuli in the context of modulating attention than only focusing on perceptual load and neutral stimuli.

Affect-Driven Attention as a Unique and Standalone Concept

The need to update and restructure the load theory framework to incorporate affect-driven attention comes from various evidence suggests that affect-driven attention is a unique concept. To begin with, based on our findings the thesis, in line with several previous studies, affect- driven attention can be differentiated from the traditional dichotomy of goal- and stimulus- driven attention capture mechanisms (Munneke et al., 2015; Awh et al., 2012; Raymond, 2009). In the former, the goal of the task drives the attention toward goal-related information and in the latter the physical salience of the stimulus drives the attention. In affect driven attention, the affective stimuli attain salience and capture attention due to its emotional or motivational value. All the three appear to play a role in attention capture and share similar mechanisms. Similar to current goals and physical characteristics, affect also makes a stimulus salient, that is, gives it weightage when compared to other neutral stimuli. Previous research and the current study findings have shown that affective stimuli also modulate both automatic and voluntary attention capture (experiment 1, chapter II; experiment 3, chapter III; Raymond, 2009; Mohanty & Sussman, 2013; Le Pelley, Mitchell, Beesley & George, 2016). Overall, the current set of experiments adds theoretical power to the claim that the mechanisms underlying affect driven performance can be differentiated from the traditional dichotomy.

Lastly, there are several proofs of concept for attention- driving by multiple affective stimuli, such as emotion-induced blindness, emotional attention, anger/happiness superiority effects, reward-based attention, value-driven attention and even (Singh & Sunny, 2017; Anderson, 2016; Savage et al., 2016; Sahny-Ur et al., 2014; Ceccerini & Caudek, 2013; Vuilleumier & Huang, 2009). There has also been evidence of attention bias to other stimuli such as alcohol and substances (predominantly in clinical populations), and food cues (Verdejo-Garcia et al., 2019; Anderson, 2016b; Garcia-Garcia et al., 2014). This shows the importance of studying the processing of affective stimuli particularly in regards to attention capture in the context of widely used attention frameworks such as perceptual load theory.

Automaticity of Attention Capture by Affective Stimuli

The vast literature shows support for quick and adaptive attention bias to affective stimuli (Rajsic et al., 2017; Preciado & Theeuwes, 2014; Pourtois et al., 2012; Hohwy, 2012). This quick capture of attention could have varying levels of automaticity based on its demands of cognitive and attentional resources. Pessoa (2015) has delineated a strong and weak automaticity. Here, the former refers to an involuntary and automatic attention capture that is independent of cognitive resources and the latter refers to an unintentional processing that still requires cognitive resources (discussed broadly in Chapter 1; Pessoa, 2005; 2013). The thesis (experiments 1, 2, 3 and 5) shows that there is a trade-off in resource utilization. The affective distractors appear to involuntarily utilize attention resources even though the participants were asked to ignore the distractors. Thus, leaving less attentional resources for task processing and consequently poor task performance. Therefore, the current findings support the weak automaticity perspective.

Pervasiveness and Strength of Attention Capture by Affective Stimuli

The automaticity of affective stimuli is usually associated with its salience. First, at a neural level, emotion has been considered as a 'fundamental feature of cognition' that significantly affects information processing (Todd et al., 2020). Other studies and theoretical models have proposed motivation to also include emotion as a feature but have also shown that emotion can be affected by motivational value of a stimuli (Reeve 2016; Yokoyama et al., 2015; Kim, 2013; Rayomond, 2009). For example, a behavioral study by Yokoyama et al. (2015) showed that when presented simultaneously, highly predictable reward stimuli reduced the interference of negative emotional stimuli on task performance; thus, motivational stimuli can overshadow the negative effects of the emotional stimuli. The current findings can only show that at a behavioural level, affective stimuli are capable of shaping perception.

Furthermore, the results show that prioritized attention capture by affective stimuli is affected by the type of affective stimuli. For example, in contrast to emotional and value-learnt stimuli, food distractors did not affect task processing under high- load conditions . A possible reason could be the overlap of conceptual boundaries of affective stimuli. Despite affective stimuli in the current experiments having similar evaluative dimensions such as valence; they also had other different dimensions. Food cues were the most complex, compared to emotional and value learnt stimuli, as they had multiple evaluative dimensions and image variables (such as desire to eat and color) that could modulate perception (Dai et al., 2020). Overall, the relationship between emotion and motivation is complex and not all affective stimuli are processed in the same manner. The current thesis can only comment on the weak automaticity and salience of affective stimuli. We did not aim to, nor can comment on the comparability between emotional and motivational stimuli.

Theoretical and Practical Implications

The current work has broad theoretical implications for understanding the mechanisms that underlie affective stimuli processing and how it shapes our perception from a limited attention capacity framework of perceptual load theory. The current studies show an interaction between perceptual load and affective stimuli on perception. The perceptual load theory is robust and constantly evolving to incorporate individual differences and factors that modulate load (Murphy et al., 2016). The current findings necessitate the updating of the perceptual load theory to include affective stimuli rather than only focusing on neutral stimuli. The thesis also adds support to affect driven attention as a unique and standalone concept. This complements the need for restructuring the traditional attention capture mechanisms to include affect driven attention. Furthermore, the weak automaticity concept helps further understand the involuntary attention capture by and processing of affective stimuli.

Specifically, the current body of work proposes the attention- constraint hypothesis to help better conceptualize the processing of value learnt stimuli and its variability based on evaluative dimensions. An enhanced understanding of the role of evaluative affect dimensions on performance could have practical implications such as incorporating these drivers of attention in instructional designs to capture a learner's attention (Stalbert, 2022). The findings not only show that affect- driven attention capture is modulated by evaluative dimensions, but also show that not all affective stimuli are processed the same. Furthermore, redefining the conceptual boundaries to elucidate differences in the processing of affective stimuli could help in drawing out clinical implications and generalizations of aberrant processing of affective stimuli. For example, aberrant reward processing and significant attention biases to non-drug-related positive stimuli have been observed in individuals with substance addiction (Verdejo-Garcia et al., 2019; Anderson, 2016b, Anderson et al., 2013). The current study paradigm used non-drug related stimuli in a non- clinical population (experiment 2, chapter III). Similarities between non-drug and drug-related stimuli could help potentially define the pervasiveness of aberrations in reward processing in clinical and non-clinical populations. The study findings could also have practical implications. Specifically, actively reducing perceptual clutter (load) and negative affective stimuli from the environment might facilitate information processing.

Limitations and Future Directions

The results obtained in the current studies are subject to some limitations. First, the findings should be generalised cautiously as the in-person data largely consisted of student populations; and, the online data is subjected to a larger variability in terms of sample characteristics and non-response bias (Cheung et al., 2017; Hanel & Vione, 2016). Second, the cognitive paradigm used in Experiments 1 and 2 especially, incorporated multiple factors such as attention, affective stimuli and personality; however, simpler designs would enable robust conclusions, because complicated tasks take time to complete, for example, the using of positive and negative value-learnt stimuli in different experimental blocks could be temporally well-spaced. Similarly, the current thesis (except experiment 4) used a neutral emotional distractor condition; future studies could use no distractor conditions or manipulate arousal to clarify and replicate our findings. Third, the study recruited a healthy sample of young adults. Future studies could actively recruit samples with maladaptive eating behaviours or those with high- and low- levels of personality traits and individual differences (impulsivity, anxiety, reward- seeking behaviours). This thesis attempted to understand the role of affective stimuli at an early level of information processing. Thus, future studies could incorporate higher cognitive processes such as decision making to understand the process of affective stimuli and its impact on performance.

Overall, future studies could extend the current findings by comparing multiple affective stimuli to provide commonalities and differences between them. This would help define the preliminary concept of affect- driven attention. Some studies have shown that the perceptual capacity can be increased with practice so that even when the task load increases there are less or no deleterious effects of distractors on the task performance (Murphy et al., 2016). The current body of work has not considered individual variability in perceptual load capacity or accounted for its apparent plasticity. Future studies could attempt to determine if neutral and affective stimuli are processed differently based on individual differences in perceptual load capacity. The current study adapted a visual inattentional blindness paradigm in Experiments 1 and 2; chapters II and III respectively (Macdonald & Lavie, 2008). It would be interesting to explore if the current study findings generalise across sensory systems since inattentional blindness appears to affect the auditory senses (inattentional deafness; Causse et al., 2016).

Summary and Conclusion

The current work demonstrated that when attentional demands increase (a) angry and loss-related distractors reduce the ability to perceive target stimuli consciously in a sample of healthy adults; and, (b) the distraction by food cues that was present during low attention demanding conditions, vanishes. Preliminary evidence indicates that (a) impulsivity modulated the interaction between perceptual load and emotional distractors; (b) there is partial evidence for the attention- constraint hypothesis of value- learning which showed that valence of the distractor influences the task performance under high attention demanding conditions. However, the influence of predictability on task performance during low- load conditions is unclear; and (c) task performance is significantly poorer in the presence of food distractors, especially low-caloric density food. Overall, affective stimuli and perceptual load shape our perception and their role should be emphasised in theoretical frameworks of attention and perception.

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Informed consent: Informed consent was obtained from all individual participants included in the study.

Appendix A: Additional measures from Chapter III

We were also interested in the association between detection sensitivity and the personality traits of impulsivity, sensitivity to reward/punishment, and attention to reward; since these traits influence attention capture and value-learning (Perri, 2020; Anderson, Kim et al., 2019; Padmala & Pessoa, 2010; Hickey et al., 2010a,b; Poy et al., 2004).

Trait impulsivity

The UPPS-P Impulsive Behaviour scale (Lynam et al., 2009) was used to measure trait impulsivity. The questionnaire is based on Whiteside and Lyman's (2001) proposal that impulsive behaviour has five facets or pathways (the internal consistency/Cronbach alpha's (α) of the facet in the current study sample is given in parenthesis): (a) urgency refers to the tendency to act rashly when under extreme negative (negative urgency; α= .84) or positive (positive urgency; α= .93) emotions, (b) lack of premeditation (α= .80) implies a tendency to act with no or less thinking and planning, (c) lack of perseverance (α= .83) connotes the lack of ability to sustain focus on the current task, and (d) sensation-seeking (α= .92) is the tendency to seek activities that are novel or thrilling. The UPPS-P consists of 49 questions rated on a four-point Likert scale that ranges from 'strongly disagree' to 'strongly agree', with a higher total reflecting higher impulsivity. The UPPS-P has been reported to have good construct validity (CFI is 0.99) and internal consistency across subscales (α ranging from .82-.95) (Smith et al., 2007; Cyders et al., 2007).

Value-Driven Attention Questionnaire (VDAQ)

The VDAQ (Anderson, Kim, et al., 2019) measures trait attention to rewards. This recently developed scale measures attention to reward outside the traditional psychophysical laboratory measures. The VDAQ comprises 16-items rated on a four-point scale ranging from 1 = 'the opposite of me', 2 = 'does not describe me well', 3= 'somewhat true of me', and 4 = 'very true of me'. The scale demonstrated good internal consistency in the current sample (α=

.78). The scale has shown to have convergent validity with relevant scales (for example, moderate correlations from r= .3-.5 with BIS/BAS scale; Carver & White, 1995) and acceptable reliability (α= .76 and test-retest correlations for a month was r= .69).

Sensitivity to Punishment and Reward Questionnaire (SPSRQ)

The SPSRQ (Torrubia et al., 2001) is derived from Gray's model of personality who proposed that individuals possess behavioural inhibition (signals aversion and results in avoidance behaviour and the behavioural approach system (signals reward and results in approach behaviour). The scale contains two facets (the internal consistency of the facet in the current study sample is given in parenthesis): sensitivity to reward (SR; α= .83) and sensitivity to punishment (SP; α= .8). Each of the facets has 24 yes/no questions. The scale has shown good convergent and divergent validity with many scales (for example, moderate to high correlation of .4 with impulsivity subscale of Eysenck's personality inventory; Eysenck, 1965) and good reliability (α ranging from .76–.84 and test-retest correlations for a three-month was .89) (Torrubia et al., 2001; Caseras et al., 2003).

Table 17

The descriptive statistics for age and the questionnaire scores.

	Range	Mean (SD)	Standard Error
Age	20	24.18 (4.5)	0.64
UPPS-P scores	104	134.2 (22.62)	3.23
VDA scores	33	42.2 (7.37)	1.05
SR scores	18	11.55 (4.66)	0.66
SP scores	19	14.65 (5.24)	0.74

Note: N= 49

Table 18

Pearson correlation coefficients for the relationship between the overall detection sensitivity in each high- and low-load with the questionnaire scores

	UPPS-P scores	VDA scores	SR scores	SP scores
High-load mean *d’*	.160	.041	.164	.128
Low-load mean *d’*	.063	.125	.077	.102

There were no significant correlations between the overall detection sensitivities (*d’*) in high- and low-load conditions, and the personality traits of impulsivity, attention to rewards, and, sensitivity to punishment and reward (UPPS-P, VDA, and SPSRQ scores respectively) (refer to table 18).

Appendix B: Images used from food.pics_extended database in chapter IV

Images used in the study are 0001, 0003, 0004, 0005, 0006, 0010, 0014, 0015, 0016, 0020, 0022, 0024, 0025, 0026, 0027, 0028, 0029, 0030, 0032, 0038, 0039, 0048, 0049, 0053, 0055, 0059, 0060, 0061, 0062, 0063, 0064, 0066, 0067, 0068, 0083, 0084, 0087, 0089, 0090, 0094, 0097, 0101, 0102, 0104, 0110, 0111, 0115, 0116, 0117, 0118, 0121, 0124, 0125, 0131, 0138, 0141, 0143, 0145, 0147, 0148, 0149, 0152, 0154, 0155, 0156, 0157, 0158, 0160, 0168, 0171, 0175, 0176, 0180, 0181, 0182, 0183, 0184, 0185, 0186, 0187, 0188, 0189, 0190, 0192, 0194, 0197, 0198, 0199, 0200, 0202, 0203, 0205, 0206, 0208, 0211, 0212, 0215, 0216, 0217, 0219, 0220, 0226, 0227, 0228, 0235, 0237, 0241, 0244, 0247, 0249, 0250, 0251, 0252, 0253, 0254, 0255, 0256, 0257, 0258, 0259, 0260, 0261, 0262, 0263, 0264, 0265, 0266, 0267, 0268, 0269, 0270, 0271, 0272, 0273, 0274, 0275, 0276, 0277, 0279, 0280, 0281, 0282, 0283, 0284, 0285, 0287, 0288, 0289, 0290, 0291, 0292, 0293, 0294, 0295, 0297, 0298, 0299, 0302, 0304, 0306, 0307, 0308, 0311, 0313, 0315, 0316, 0317, 0320, 0321, 0323, 0324, 0325, 0327, 0330, 0332, 0333, 0335, 0342, 0343, 0344, 0347, 0348, 0349, 0350, 0352, 0353, 0358, 0362, 0366, 0373, 0377, 0380, 0384, 0388, 0389, 0390, 0393, 0396, 0398, 0400, 0401, 0407, 0416, 0422, 0433, 0435, 0436, 0450, 0454, 0471, 0475, 0476, 0480, 0482, 0483, 0484, 0488, 0490, 0493, 0503, 0513, 0520, 0521, 0525, 0526, 0527, 0528, 0539, 0550, 0551, 0554, 0560, 0566, 0575, 0576, 0579, 0585, 0586, 0589, 0595, 0598, 0599, 0603, 0604, 0605, 0607, 0610, 0613, 0614, 0619, 0621, 0622, 0625, 0629, 0631, 0635, 0636, 0638, 0639, 0645, 0647, 0650, 0653, 0654, 0661, 0667, 0677, 0680, 0684, 0689, 0693, 0700, 0701, 0704, 0707, 0711, 0715, 0719, 0739, 0740, 0759, 0801, 0805, 0809, 0850, 0859, 0863, 0874, 0882, 0884, 0885, 0886, 0887, 0888, 0889, 0890, 0891, 0893, 0895, and 0896.

Appendix C: Supplementary analyses of chapter IV

We explored cultural differences on a smaller subset of 101 food images previously rated for French (Bonin et al. 2021), predominantly German-speaking (food.pics_extended norms; Blechert et al. 2019) and Portuguese (Prada et al. 2017) samples. This was achieved by performing a 4 (Sample: ours, Bonin et al., 2021; Blechert et al., 2019; Prada et al. 2017) × 2 (Caloric density: low versus high) ANOVA for the common images across each of the four evaluative dimensions: arousal, valence, desire to eat and palatability (noted as tastiness in Prada et al., 2017). Experiment 4 and the norms from the food.pics_extended database for the evaluative dimensions are present on a scale of 0-100; however the norms available for the French and Portuguese sample are on a scale of 0-10 (Bonin et al., 2021; Prada et al., 2017). To harmonise data across studies, we converted all the ratings on a scale of 0-10 and proceeded with the analysis.

Multi-cultural comparison: Univariate 4 (Sample: Indian, Original, French, Portuguese) x 2 (Caloric density: high vs. low) ANOVA

Valence

The interaction between study and caloric density was significant, F (3, 396) = 42.13, MSE = 1.180, p < .001, ηp^2 = .242. The main effect of study was significant, F (3) = 27.15, p < .001, ηp^2 = .171. The main effect of caloric density was also significant, F (1) = 41.2, p < .001, ηp^2 = .094, where participants rated low- calorie food (M= 6.3, SD= 1.4) more positively than high- calorie food (M= 5.6, SD= 1.2). In specific, the Indian sample (M= 6.3, SD= .92) had rated food images significantly more positive than the German (M= 5.38, SD= .99, t(200) = 6.553, p< .001, d= 0.922) and French (M= 5.61, SD= .81, t(200) = 5.435, p< .001, d= 0.765) sample. Further sensitivity analysis was performed in low- and high- calorie groups comparing Indian sample with the others. Independent sample t-tests revealed that Indian samples rated low- calorie foods as significantly more positive (M= 6.07, SD= 0.94) than French sample (M= 5.47, SD=0.89; *t*(108) = 3.405, *p*= 0.003, *d*= 0.649; and significantly less than the Portuguese sample (M= 7.85, SD=1.50; *t*(108) = 7.471, *p*< .001, *d*= 1.425). In the high- calorie group, Indian sample (M= 6.51, SD=0.85) rated the food more positively than Food.pics_extended (predominantly German; M= 4.88, SD=0.76, *t*(90) = 9.723, *p*< .001, *d*= 2.027), French (M= 5.77, SD=0.66, *t*(90) = 4.68, *p*< .001, *d*= 0.976) and Portuguese samples (M= 5.26, SD=1.67, *t*(90) = 4.54, *p*< .001, *d*= 0.947).

Arousal

The interaction between study and caloric density was significant, *F* (3, 396) = 7.3, *MSE* = .912, *p* < .001, ηp^2 = .052. The main effect of study was also significant, *F* (3) = 144.68, *p* < .001, ηp^2 = .523. The main effect of caloric density was not significant (*p*=.162). In specific, the Indian sample (M= 5.08, SD= 1.15) found the food to be significantly less emotionally arousing than the Portuguese (M= 5.55, SD= 1.01, *t*(200) =3.089, *p*= 0.006, *d*= 0.435) and more arousing than the German (M= 3.19, SD= .73, *t*(200) =13.951, *p*< .001, *d*= 1.963) and French (M= 3.55, SD=.98, *t*(200) =10.18, *p*< .001, *d*= 1.433) samples. Further sensitivity analysis performed using independent sample *t*-tests revealed that Indian samples rated low-calorie foods as significantly as more arousing (M= 4.80, SD=1.08) than German (M= 3.38, SD=0.79, *t*(108) = 8.173, *p*< .001, *d*= 1.559) and French samples (M= 3.31, SD=1.03; *t*(108) = 7.378, *p*< .001, *d*= 1.407); and significantly less than the Portuguese sample (M= 5.70, SD=1.03, *t*(108) = 4.481, *p*< .001, *d*= 0.855). In the high calorie group, Indian sample (M= 5.42, SD= 1.14) rated the food as significantly more arousing than German (M= 3.03, SD=0.63, *t*(90) = 12.38, *p*< .001, *d*= 2.581) and French (M= 3.84, SD=0.84, *t*(90) = 7.565, *p*< .001, *d*= 1.577) samples.

Palatability/ Tastiness

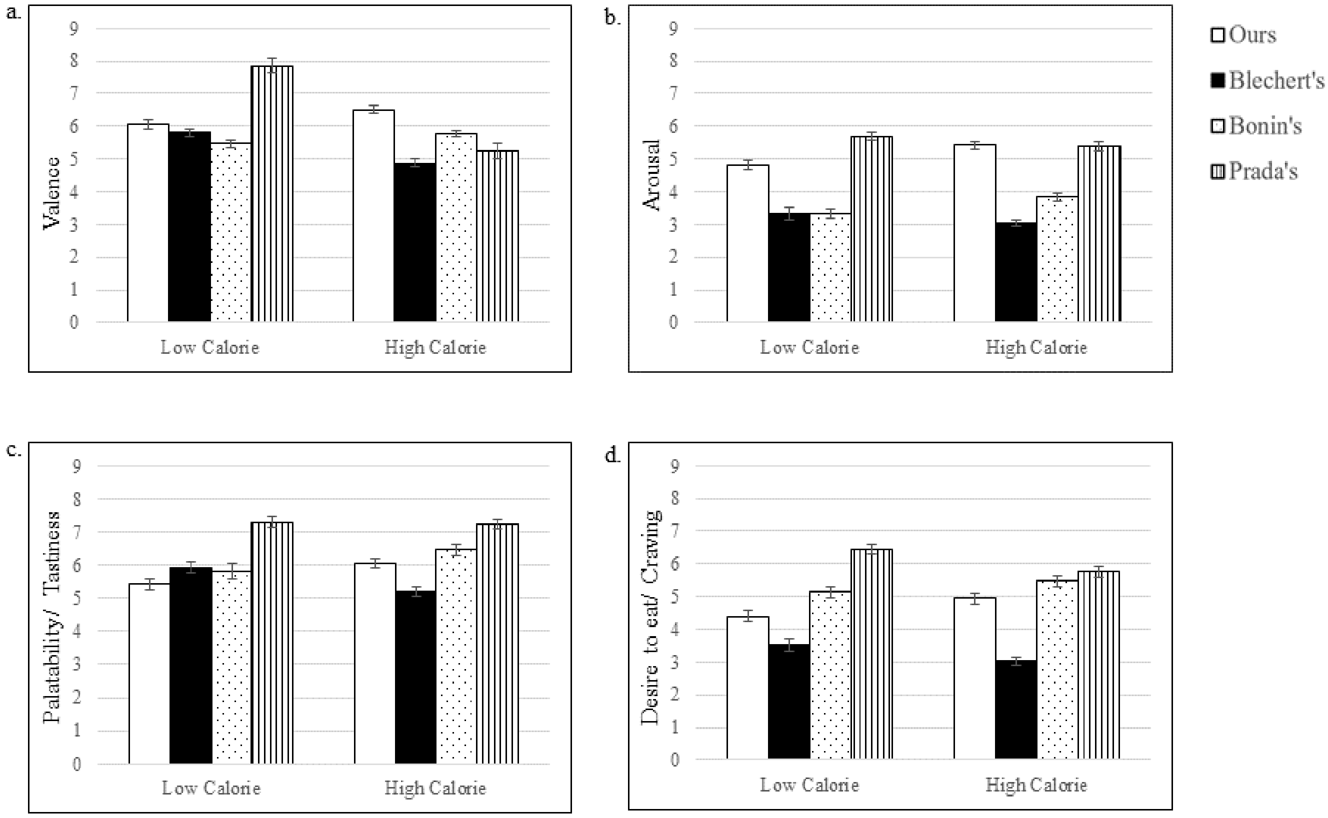
The interaction between study and caloric density was significant, F (3, 396) = 7.45, MSE = 1.446, p < .001, ηp^2 = .053. The main effect of study was also significant, F (3) = 40.92, p < .001, ηp^2 = .237. The main effect of caloric density was not significant (p=.294). In specific, the Indian sample (M= 5.71, SD= 1.31) had rated food significantly less palatable than Portuguese (M= 7.28, SD=1.05, t(200) = 9.388, p< .001, d= 1.321) sample. Further sensitivity analysis performed using independent sample t-tests revealed that Indian samples rated low-calorie foods as significantly as less palatable (M= 5.41, SD=1.34) than the Portuguese sample (M= 7.31, SD=1.11, t(108) = 4.481, p< .001, d= 0.855). In the high- calorie group, Indian sample (M= 6.05, SD= 1.21) rated the food as significantly more palatable than German (M= 5.21, SD= 0.92, t(90) = 3.766, p< .001, d= 0.785) sample and less palatable than the Portuguese (M= 7.24, SD= 0.98, t(90) = 5.194, p< .001, d= 1.083) sample.

Desire to eat/ Craving

The interaction between study and caloric density was significant, F (3, 396) = 6.55, MSE = 1.382, p < .001, ηp^2 = .047. The main effect of study was also significant, F (3) = 103.97, p < .001, ηp^2 = .441. The main effect of caloric density was not significant (p=.535). In specific, the Indian sample (M= 4.64, SD= 1.30) reported significantly more craving for the food when compared to the German (M= 3.29, SD=1.03, t(200) = 8.209, p< .001, d= 1.155) sample and less craving when compared to the French (M= 5.28, SD= 1.28, t(200) = 3.522, p= 0.003, d= 0.496) and Portuguese (M=6.13, SD=1.16, t(200) = 8.558, p< .001, d= 1.204) samples.

Figure 11

Caloric density comparisons of 101 food images for the Indian, German, French and Portuguese study samples across the common 4 evaluate dimensions.



Further sensitivity analysis performed using independent sample *t*-tests revealed that Indian samples rated significantly more craving for low- calorie foods (M= 4.40, SD=1.32) than the German (M= 3.51, SD=1.10, $t(108) = 3.825$, $p < .001$, $d = 0.729$) and French (M= 5.12, SD= 1.41, $t(108) = 2.801$, $p = 0.009$, $d = 0.534$) samples; and significantly less craving than the Portuguese (M= 6.43, SD=1.10, $t(108) = 8.787$, $p < .001$, $d = 1.676$) sample. In the high- calorie group, Indian sample (M= 4.94, SD= 1.22) rated significantly more craving than German (M= 3.02, SD= 0.89, $t(90) = 8.606$, $p < .001$, $d = 1.794$) sample and less craving than the Portuguese (M= 5.76, SD= 1.14, $t(90) = 3.344$, $p = 0.003$, $d = 0.697$) sample.

Table 19

Comparison between Indian and other cultural norms of the four common dimensions

		Valence	Arousal	Palatability	Desire to eat
t-test between Indian norms and	Food.pics (predominantly German) sample	$t(200)= 6.553, p< .001, d= 0.922$	$t(200)= 13.951, p< .001$, d= 1.963	$t(200)= 0.616, p= 1.617, d= 0.087$	$t(200)= 8.209, p< .001, d= 1.155$
	French sample	$t(200)= 5.435, p< .001, d= 0.765$	$t(200)= 10.18, p< .001, d= 1.433$	$t(200)= 2.101, p= 0.111, d= 0.296$	$t(200)= 3.522, p= 0.003, d= 0.496$
	Portuguese sample	$t(200)= 1.802, p= 0.219, d= 0.254$	$t(200)= 3.087, p= .006, d= 0.434$	$t(200)= 9.388, p< .001, d= 1.321$	$t(200)= 8.558, p< .001, d= 1.204$
t-test between Low caloric density food norms: Indian sample and	Food.pics sample	$t(108)= 1.408, p= 0.486, d= 0.268$	$t(108)= 8.173, p< .001, d= 1.559$	$t(108)= 2.236, p= 0.081, d= 0.426$	$t(108)= 3.825, p< .001, d= 0.729$
	French sample	$t(108)= 3.405, p= 0.003, d= 0.649$	$t(108)= 7.378, p< .001, d= 1.407$	$t(108)= 1.416, p= 0.48, d= 0.27$	$t(108)= 2.801, p= 0.009, d= 0.534$
	Portuguese sample	$t(108)= 7.471, p< .001, d= 1.425$	$t(108)= 4.481, p< .001, d= 0.855$	$t(108)= 8.042, p< .001, d= 1.534$	$t(108)= 8.787, p< .001, d= 1.676$
t-test between High caloric density food norms: Indian sample and	Food.pics sample	$t(90)= 9.723, p< .001, d= 2.027$	$t(90)= 12.38, p< .001, d= 2.581$	$t(90)= 3.766, p< .001, d= 0.785$	$t(90)= 8.606, p< .001, d= 1.794$
	French sample	$t(90)= 4.68, p< .001, d= 0.976$	$t(90)= 7.565, p< .001, d= 1.577$	$t(90)= 1.714, p= 0.27, d= 0.357$	$t(90)= 2.196, p= 0.093, d= 0.458$
	Portuguese sample	$t(90)= 4.54, p< .001, d= 0.947$	$t(90)= 0.219, p= 0.481, d= 0.046$	$t(90)= 5.194, p< .001, d= 1.083$	$t(90)= 3.344, p= 0.003, d= 0.697$

In the multicultural comparison we found an interaction between study and caloric density for all 4 evaluative dimensions: valence, arousal, palatability, and desire to eat (craving). The main effect of the study was found in all four dimensions, and the main effect of caloric density was found only for valence. This reflects the underlying cultural differences between Indian and the European samples. In exploring differences between Indian and other cultures, the Portuguese sample rated the food as significantly more arousing, palatable and desirable.

Specifically, both low-calorie foods were consistently rated more arousing and desirable by the Portuguese sample when compared to the Indian sample. However, the Indian sample rated high-calorie food more positively and low-calorie foods less positively than their Portuguese counterparts. The differences could reflect the healthiness and food preferences in their respective cultural diets. The Portugal-Mediterranean diet is considered healthy and encouraged widely for its health benefits (Gregório et al., 2018; Rodrigues et al., 2008). However, the Indian cohort show an increased prevalence of a 'western-like diet' which involves overconsumption of sweets, soft drinks, processed meat and other unhealthy food (Janssen et al., 2018).

We also found a lack of difference between the Indian and French samples in terms of palatability and desire to eat high-caloric density food despite the French sample rating these foods less positively and less arousing than the Indian sample. This is particularly interesting as both the French and Indian food consumption patterns are both energy-dense, where the French diet usually contains a smaller portion size, high amounts of dietary cholesterol and saturated fat; whereas the Indian diet consists of rich carbohydrates and poor nutrient value (Sharma et al., 2020; De Lorgeril et al., 2002; Drewnowski et al., 1996). Further, the differences in valence ratings are in accordance with a study that showed that, while describing foods, Indians tend to use more evaluatively positive words than their French and American counterparts (Rozin, & Holtermann, 2021). Overall, many noteworthy cross-cultural differences were observed; however, the differences or lack thereof in the multi-cultural comparisons should be taken with caution as the results are from a small sample of images from the food.pics_extended database.

Appendix D: Self-Report Measures from chapter V

Self-Report Measures

Grand's Hunger Scale

The Grand (1988) hunger scale measures hunger using a 4-item scale. Participants reported hours since their last meal and time until their next expected meal (estimated to the nearest 15 minutes). They also rated subjective hunger on a 7-point Likert scale from not hungry at all to extremely hungry and craving for their favourite food on a 6-point Likert scale from none at all to as much as I could get. Although the scale has not undergone formal validation, it has been widely used in appetite research (Tappar & Pothos, 2010; Kakoschke et al., 2015).

Food Cravings Questionnaire (Trait)

The 15-item food cravings trait questionnaire (FCQ-T; Meule et al., 2014) measures lack of control over eating, preoccupation with food, planning and intentions to eat food, emotions before or during food craving, and, possible food triggering cues. Participants rated items on a 6-point Likert scale (1 = never/ not applicable; 6 = always). The questionnaire has previously demonstrated good internal consistency reliability, test-retest reliability, convergent validity, and discriminant validity (Cronbach's α=.94, Meule et al., 2014; Meule, Teran et al., 2014; Richard, Meule, Reichenberger, & Blechert, 2017).

Reward-Based Eating Drive (RED) Scale

Participants completed the 13-item RED scale, which assesses a loss of control over eating, a lack of satiety, and preoccupation with food (Mason et al., 2017). Participants rated items on a scale from strongly disagree (1) to strongly agree (5). Total score is the sum of individual statements, with higher scores corresponding to a higher reward-based eating drive.

The scale has previously demonstrated good construct validity and internal- consistency (Cronbach's α=.82, CFI = .92 for a single factor solution, Epel et al., 2014; correlated with other similar scales *r* between .33 and .46, Mason et al., 2017).

Overall Diet Quality

The Prime Diet Quality Score 30-day measure (PDQS-30D; Gicevic, et al., 2021) measures the overall diet quality by focusing on the frequency of food consumption in the past month. The food groups on the scale are divided into healthy and unhealthy foods. The 14 healthy foods include various vegetables and fruits, legumes, nuts and seeds, liquid oils, low-fat dairy, fish and poultry. The 7 unhealthy foods include red and processed meat, refined grains, sweets, fried food, tubers and white root vegetables. To calculate the diet quality index, responses were scored according to the following criteria: (a) 0 point = 1 time per month or less, 2-3 times per month, (b) 1 point = 1-2 times per week, 3-4 times per week, (c) 2 points = 5-6 times per week, 1 time per day, ≥2 times per day. For the unhealthy components, the scores are reversed. The scale has shown good construct validity with other relevant diet quality measures (r = .60; Gicevic et al., 2021).

Table 20

Pearson correlation coefficients for the relationship between the additional measures.

		1	2	3	4	5	6
1. BMI	*r*	1					
	p value						
2. RED	*r*	.062	1				
	p value	.635					
3. FCQ-T	*r*	.149	.822**	1			
	p value	.251	<.001				
4. PDQS-U	*r*	-.002	-.400**	-.435**	1		
	p value	.987	.001	<.001			
5. PDQS-H	*r*	-.179	.138	.169	-.395**	1	
	p value	.167	.290	.194	.002		
6. PDQS	*r*	-.190	-.119	-.110	.244	.794**	1
	p value	.142	.359	.399	.058	<.001	

Note: BMI= Body Mass Index, RED= Reward Based Eating Drive Scale, FCQ-T= Food Craving Questionnaire (trait), PDQS-U= Prime Diet Quality- Unhealthy subscale Score, PDQS-H= Prime Diet Quality- Healthy subscale Score, PDQS= Prime Diet Quality Total Score

Experiment 5 showed that BMI is not associated with any of the other self-report measures ($p > .142$, for all). The reward-based eating drive scores appear to be positively associated with trait food craving and negatively associated with unhealthy diet.