Understanding the role of emotion, reward and food preference on the perception of sweet-tasting food using a novel classification task

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Abstract

Research demonstrates that humans tend to have behavioural biases toward calorie (kcal)-dense foods, particularly those that are sweet, although cognitive biases toward these foods are less well established. With major public health organisations highlighting the rising concerns surrounding excessive sugar intake, understanding these cognitive biases is of growing importance. Current knowledge about the cognitive and emotional influences on eating preferences is also inconsistent. This study aimed to explore implicit cognitive biases toward various sweet food categories and their connection with explicit behavioural and physiological responses. Using a within-subjects cross-sectional, factorial design, 102 participants (27 males, 74 females and one non-binary, average age 20.65) engaged in a novel food-based cognitive judgment task. Response time and accuracy in identifying sweet versus non-sweet foods were recorded, along with ratings of 'liking' and 'wanting' for each food stimulus. Foods were categorised into high-fat, high-carbohydrate, and high-protein groups. These measures were paired with questionnaire-based assessments of food preference, hunger and thirst, reward-related eating measured through the Reward-Related Eating Drive Scale (RED-13; Mason et al., 2017), and emotional eating tendencies measured through the Emotional Appetite Questionnaire (EMAQ; Nolan et al., 2010). Results revealed cognitive biases: participants were faster to respond to sweet foods, especially those high in fat and protein, and were less accurate in categorising sweet compared to non-sweet foods. Participants also reported greater liking and wanting for sweet foods overall. Furthermore, positive emotional eating was associated with quicker response times to sweet foods, and

higher reward-related eating scores were linked to faster responses and broader food preferences. Although liking and wanting were each associated with response time, these effects were analysed separately; therefore, the study does not provide direct evidence of their distinct or independent contributions. The results are consistent with the notion of separate systems for liking and wanting in food reward, but further research using combined modelling approaches is needed to test this more directly. These findings underscore the complexity of emotional and reward-driven eating behaviours and offer insight for future work on cognition, perception, and public health strategies to reduce excessive sugar consumption.

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1. Introduction

1.1 The Implications of Excess Sugar Consumption on Public Health

The adverse impact of consuming excess dietary sugars on health cannot be overstated, particularly added sugars. With both direct and indirect links between excess dietary sugar consumption and adverse health effects such as obesity (Ludwig et al., 2001; Magriplis et al., 2021; Malik et al., 2006; Yamakawa et al., 2020), cardiovascular disease and type two diabetes (Stanhope, 2016), the development of dental caries (Touger-Decker & van Loveren, 2003); especially when considering sweetened beverages (Valenzuela et al., 2021). As well as the development of non-alcoholic fatty-liver disease and non-alcoholic steatohepatitis (Jensen et al., 2018; Ma et al., 2015), additionally some research suggests a link with colon and pancreatic cancer (Larsson et al., 2006; Slattery et al., 1997) and all-cause mortality (Meng et al., 2021).

The terms free sugars and added sugars are sometimes used interchangeably in literature and vary geographically. The term added sugars refers to sugars added in the processing of foods such as sucrose, dextrose, honey, fruit juices etc. whilst the term free sugar typically refers to sugars that are readily available and quickly absorbed such as those in fruit juices, no longer contained in cells due to the processing of the fruit (British Heart Foundation, 2021; U.S. Food and Drug Administration, 2024; World Health Organization(WHO), 2015). Sugar in isolation, be it free or added is typically characterized by its minimal nutritional value, comprising 4 calories per gram, sugar on its own lacks many essential nutrients such as fibre, vitamins and minerals, fundamental for maintaining optimal health (Great Britain: Scientific Advisory Committee on Nutrition, 2015). This nutritional deficiency renders free or added sugar a relatively weak dietary component especially when added to foods and particularly when compared to other essential macronutrients such as fats, proteins and complex carbohydrates. The predominance of high-sugar foods in modern diets exacerbates the risk of nutritional imbalance, where high caloric intake is not accompanied by sufficient essential nutrients, underscoring the need for moderated sugar consumption within a balanced dietary regimen (Johnson et al., 2009). As a result, it comes with little surprise that tackling the overconsumption of sweet foods has become a primary goal of many public health organisations.

The literature on our consumption of added and free sugars is quite clear; we are simply consuming too much. Estimates place added sugars as contributing 16% of the total energy consumption in the diets of US citizens (McGuire, 2012), with sweet beverages and processed bakery products serving as the primary source of these added sugars (Bailey et al., 2018). Up to 13% in the Canadian diet (Brisbois et al., 2014), similarly, up to 13% in the British diet with sweet beverages, confectionary and processed grain products again serving as the primary contributors (Amoutzopoulos et al., 2020). The World Health Organisation's guidelines on free sugar consumption are similarly clear; added and free sugars should constitute less than 10% of an individual's total energy consumption, with this seeing a further recent recommendation for less than 5% (World Health Organization(WHO), 2015). In other terms, this constitutes no more than 200kcal or 50g of free sugar for a 2000kcal diet, or with the further recommendation of less than 5%, this is 100kcal or 25g of free sugars in the diet. Guidance from neighbouring health authorities mirrors this recommendation (American Heart Association, 2024; ESPGHAN, 2018; NHS, 2023). As evidenced, we are simply consuming significantly more than even the more lenient recommended dietary intake of 10%.

1.2 Evolutionary Mismatch: Our adeptness in a modern nutritional environment

As a result of the environmental pressures and food scarcity throughout our evolutionary history, we have developed tendencies to consume foods rich in calories, more so than expected of our size, especially those high in fats and sugars (Leonard & Robertson, 1994), and from a young age children tend to show a choice preference for comparatively sweeter, artificially sweetened foods compared to naturally sweet whole fruits and vegetables (Saavedra et al., 2013; Siega-Riz et al., 2011). Despite our exceptional metabolic acceleration over our evolution, we possess rather low Basal Metabolic Rates (BMR) especially when compared to similar sized mammals (Pontzer et al., 2014). This evolutionary adaptation has enabled more efficient allocation of energy, proving pivotal in the development of our growing primate brains, a comparatively energy-demanding organ consuming 20% of the calories obtained through food consumption (Balasubramanian, 2021). Linked to our BMR, we also have lower Total Energy Expenditures (TEE) when compared to similar-sized mammals, averaging just 50% of the expenditure expected (Pontzer et al., 2014). The lower expenditure of energy seen here does not reflect lower activity levels when compared to similar-sized placental mammals, rather it reflects our crucial biological adaptations for effective caloric use, once again, freeing much-needed energy for our brains (Simmen et al., 2015). Tied to our brain's thirst for energy, we humans have evolved adept mechanisms for storing energy, allowing us to outlast famine and food scarcity, and allowing our bodies and our brains to tap into a reserve energy store (Navarrete et al., 2011). For example, we, along with all vertebrate species evolved lipogenesis whereby excess glucose is converted into fatty acids and combined with glycerol to form triglycerides; making up our adipose tissue when glycogen stores reach their capacity (Young, 1976), however, humans have evolved particularly effectively at performing this process.

There is a wealth of research proposing neuropeptide Y (NPY) in the nucleus accumbens (NAc) may indeed be responsible for our propensity to seek out and consume unhealthy foods, particularly those that are sweet and fatty. Research from van den Heuvel et al. (2015) highlights that higher NYP levels in the NAc have an inhibitory effect, reducing neuronal firing and as a result suppressing the typical homeostatic drives of the NAc, in turn leading to more hedonistic eating behaviours, specifically toward more palatable foods. Raghanti et al. (2023) build on this concept, comparing humans with 12 other primate species. They demonstrated that, once accounting for brain size, humans possess significantly higher NYP innervation in the NAc compared to other similar primate species. The suggestion from research into NYP levels in the NAc is that we have a biological vulnerability for addictive behaviours such as gambling, drug dependence and key to the present study, highly palatable and sweet foods due to our comparably high levels of NYP innervation and its effects on how we experience reward.

What is clear is humans have developed to not only store energy exceedingly efficiently, we also are adept at efficiently utilizing this energy. Whilst serving us well during our evolutionary history, these adaptations prove in many instances to now serve as hindrances and ultimately damage our health as we have become biologically mismatched with our modern environment (Manus, 2018; Neel, 1962). For the majority, the food scarcity plaguing our history poses less of an issue with a modern abundant availability of calorically rich foods and this issue of the overconsumption of these foods is further compounded by a reduction in the availability of affordable and healthier food options in lower-income Western communities whilst the availability of calorically rich and nutrient-poor foods remains high, such as those containing added sugars (Ziso et al., 2022). This in turn culminates in further risk of the development of obesity and other dietary-related health risks, with some calling these areas "food deserts" with examples of these areas seeing up to a 30% increased risk of the development of obesity due to the imbalanced nutritional environment (Kelli et al., 2017; 2019; Walker et al., 2010). We face biological processes and tendencies which no longer serve to our benefit, these vulnerabilities are further compounded by personal factors, one of which is our emotions.

1.3 Overconsumption of Sweet-Tasting Food: the Role of Emotion

Our emotional state can play a large role in dictating how much food we consume. The term emotional eating refers to the propensity for consuming food in response to emotions, be they negative, or positive. Emotional eating is highly prevalent, with one sample of university students indicating 38% suffered from emotional eating behaviours, with those engaging in lower levels of activity or under more stress or higher in BMI being more likely to be an emotional eater (Grajek et al., 2022). There are difficulties in ascertaining a clear global prevalence rate. As noted by Stammers et al. (2020), the lack of clear diagnostic criteria and varying investigative measures which typically rely on self-report, large gaps in our knowledge result in only localized understandings of both the aetiology of these behaviours as well as the degree to which we as a populace suffer from this. Emotional eating has a strong positive relationship with Body Mass Index (BMI). In one sample, emotional eating was reported to affect more than half (58%) of people who were referred for obesity treatment (Wong et al. 2020). In disorders where overeating becomes maladaptive such as Binge Eating Disorder (BED) a positive relationship is typically observed between negative emotional states and additional food consumption (Reichenberger et al., 2020). Similarly, emotional eating is correlated with other disorders such as higher Emotional Eating Scores (EES) and binge eating patterns in Bulimia Nervosa (BN) and higher EES scores with restrictive eating behaviours in Anorexia Nervosa (Ricca et al., 2012). Additionally, depression seems to modulate eating behaviour in emotional eaters, with emotional eating being linked to higher consumption of sweet and highly-caloric foods (chocolate, pastries etc.), especially for those reporting depressive symptoms (Camilleri et al., 2014). Similar results are explored in a review by Fuente González et al. (2022) which suggests the dysregulation of emotion, and keenly, eating in response to negative emotional states typically results in the consumption of highly-palatable foods and posited emotional eating as a driving factor in weight gain. Interestingly, their findings similarly highlight positive emotions.

Continuing the move from negative emotions, the role positive emotion plays is explored further, such as in observations from Evers et al. (2013) indicating participants tended to increase their caloric intake simultaneously to positive emotions and situations. Additionally, noting that increases in snack consumption were more common in response to positive than negative emotions. Research from Bongers et al. (2013) reports similar findings with increases in food consumption in response to positive situations or emotions and noted the amount of calories consumed was also correlated with mood improvements after five minutes, suggesting perhaps somewhat of a feedback loop. Interestingly, this increase was seen more in those identified as emotional eaters (compared to non-emotional eaters). Similar notes in these studies are that the link between positive emotions and unhealthy food consumption remains an under-investigated area.

When linking this increase specifically to sweet-tasting foods, research here suggests again that emotional eaters tended to increase food consumption in both negative and positive emotional states more than non-emotional eaters, but also that those higher in emotional eating tended to consume more sweet foods, rather than salty foods (van Strien et al., 2013). Linking to a specific positive emotion, feelings of gratitude specifically were found to link with increases in food consumption, especially sweet-tasting foods compared to non-sweet foods (Schlosser, 2015). When seeking to explore which foods are most likely to be selected during episodes of emotional eating, the primary theme seems to be availability; what foods are readily available to the individual at that time. Typically, pre-prepared products that are highly-palatable and energy-dense. This was the case in research from Aguiar-Bloemer and Diez-Garcia (2018), who noted this observation, but found that normal-weight participants tended to increase their consumption of only sweeter foods, whilst overweight participants increased their consumption of both sweet and salty food types. Similarly, Ashurst et al. (2018) found participants were unlikely to consume healthy foods during these periods, selecting saltier foods during periods of negative emotion, sweet during positive emotion and both during periods of apathy, positing that palatable foods are chosen to divert attention away from the emotions by providing some positive sensory relief. This notion is supported by a theory from Heatherton and Baumeister (1991) which suggests we have a propensity to binge in response to negative stimuli in order to reduce our negative self-awareness as we narrow our focus from meaningfully negative stimuli toward immediate stimuli. In doing this, it is suggested our typical inhibition of overeating is disengaged, which explains our propensity for binging episodes. Another theory simply suggests the hedonic pleasure derived from consuming food, especially those that are highly-palatable or self-labelled as 'banned' and subsequently, higher in calories increases feelings of positive emotions such as joy, and as such counteracts the negative emotional state (Fairburn & Cooper, 1982; Lehman & Rodin, 1989). This theory offers a logical suggestion of emotion and food consumption, but fails to account for binging episodes that result in negative emotion, but does however explain why foods that are known to be unhealthy to an individual are consumed regardless due to their power on emotion.

Measuring the extent to which emotion can influence human eating behaviour is of keen interest to psychological research. Whilst scales exist to measure this relationship such as the emotional subsection of the Dutch Eating Behaviour Questionnaire (DEBQ) developed by van Strien et al. (1986), or the emotion-related questions of the Three-Factor Eating Questionnaire (TFEQ) developed by Stunkard and Messick (1985) these typically focus on contributions of negative emotional states to eating and neglect positive effects and do not include specific situations. The Emotional Eating Scale (EES) developed by Arnow et al. (1995) does address this issue by including some positive emotional states, it still fails to include examples of specific emotional situations. Similarly, the Adult Eating Behaviour Questionnaire (AEBQ) (Hunot et al., 2016) measures eating behaviour by assessing a broad range of traits that influence how individuals respond to food and internal cues like hunger and fullness. Although it includes subscales for emotional overeating and emotional undereating, these are just two elements within a much broader scale that also captures traits such as food responsiveness, satiety sensitivity, and enjoyment of food. As a result, the AEBQ does not focus specifically on emotional eating, but instead offers a general profile of eating behaviours across multiple domains. For the present study and it's aim to understand how emotions specifically influence food perception the AEBQ may be too broad, as its inclusion of non-emotional traits can limit its sensitivity. The Emotional Appetite Questionnaire (EMAQ) from Nolan et al. (2010) is an instrument developed to address these key shortcomings. The scale, comprising 22 questions measures the modulative capacity of both positive and negative emotional states and situations on the amount of food consumed. Whilst the EMAQ measures similar negative emotions to the DEBQ such as Loneliness or Frightened/ Afraid, positive emotional states are included such as happy, enthusiastic, confident etc. This questionnaire also notably includes eight questions referring specifically to changes to food consumption during positive and negative emotional situations. The EMAQ exhibits good construct validity, evidenced by its significant positive correlations with the emotional eating subscale of the DEBQ for negative emotions and situations, underscoring the EMAQ's efficacy in evaluating emotional eating associated with negative stimuli (Nolan et al., 2010). Furthermore, its discriminant validity is confirmed through minimal correlations between the EMAQ's scores for positive emotions and situations and the DEBQ's emotional eating subscale, demonstrating its capacity to distinguish between positive and negative emotional effects (Nolan et al., 2010). The EMAQ's validity and reliability are further demonstrated by similar convergent and discriminant validity against the DEBQ as well as negative EMAQ scores correlating with higher BMI and positive scores being negatively correlated with BMI, with good internal consistency and test-retest reliability (Bourdier et al., 2017). Building from this, our emotions are not the only contributor to this issue, indeed, the rewarding aspects of food play an equal role in driving our consumptive behaviours.

1.4 Overconsumption of Sweet-Tasting Food: The Role of Reward, Liking and Wanting

Predictably, reward possesses a great influence on eating behaviour. The model of operant conditioning (Skinner, 1963) offers some good explanations as to why we may seek out and exhibit a bias for sweet-tasting foods. The consumption of glucose-heavy foods provides positive reinforcement not only from the hedonic taste pleasure derived from its consumption but also in the form of glucose-enhanced augmentations to our cognitive performance (Peters et al., 2020). It is clear, humans have evolved a keen preference for sweet foods, finding these to be highly palatable and rewarding to consume. This rewarding aspect is considered to aid greatly in progressing feeding behaviours in early development toward sources rich in energy (Drewnowski et al., 2012; Mennella et al., 2016), and the rewarding aspects of sweet food play a crucial role in reinforcing this biological drive toward them (Ramirez, 1990). Under the context of our environmental evolutionary mismatch, reward causes us to eat unhealthy foods and too much food. The hedonistic factors of food subsequently play a pivotal role in abnormal eating behaviours such as binge eating disorder, where the primary foods consumed during objective binging episodes are rewarding hyper-palatable and high-calorie foods (Moraes et al., 2023). With higher consumption of highly rewarding and highly palatable foods leading to larger increases in weight gain (Fazzino et al., 2021). Indeed, the rewarding prospects of food exist even in anticipation of their consumption, with this experience of reward in anticipation is posited as a contributor and reinforcer to the development of abnormal eating behaviours such as binge eating disorder and can lead to overconsumption (Berridge, 2009; Pearson et al., 2016).

Two differing systems are suggested as being simultaneously involved in reward: wanting, and liking, with suggestions that liking and wanting work together forming a 'dual-process' account of food reward (Finlayson & Dalton, 2012). Wanting is generally considered a motivation toward the reward whilst liking refers to the hedonic impact or pleasantness of the reward. Wanting can also be proposed from an incentive salience perspective, the concept that predictive cues of a reward are used to help govern the motivational value linked to that reward and that motivation toward an outcome, or wanting may not be proportional to the pleasure attained once that outcome is achieved (Berridge & Robinson, 1998). For this reason, a pleasant food that may be 'liked' may not be 'wanted' as learned negative cues may cause an aversion for example (Freeman & Riley, 2008). Indeed, wanting as a motivational drive governs experiences such as cravings, elicited through sight, taste or smell of a food, even when imagined (Pelchat et al., 2004). Wanting alone is not enough to elicit reward, liking is needed simultaneously in order to experience reward properly. Liking similarly, is theorised to exist as an independent system within the brain. To investigate the neural systems behind the pleasure of rewards, researchers have studied observable 'liking' reactions to sweet tastes. These reactions, which include lip licking and tongue protrusions, appear in newborn humans and other primates such as orangutans, chimpanzees and monkeys. Conversely, bitter tastes trigger 'disliking' expressions such as gaping. These responses are controlled by brain systems in the forebrain and brainstem and are influenced by factors like hunger, satiety, and learned taste preferences (Berridge & Kringelbach, 2008; Kringelbach, 2005; Steiner et al., 2001). Regions for hedonic liking are also identified across the brain in the ventral pallidum, nucleus accumbens as well as the pons (Smith & Berridge, 2007). When considering the dual process view of liking and wanting, evidence suggests opioid transmission in the limbic forebrain causally these two systems to enhance taste and food reward (Levine & Billington, 2004).

With reward serving such large governance overeating behaviour, having measures of the extent to which reward impacts individuals' eating is pivotal to investigation in this area. Different measures exist to assess the impact of the hedonic properties of food on one’s consumption, particularly their ability to regulate and control their eating. Whilst the previously mentioned TFEQ and DEBQ instruments contain subsections relating to reward and eating restraint they do not focus on this dimension of eating solely. The Yale Food Addiction Scale (YFAS) and YFAS2 measure traits in this area of reward-related eating (RRE) building on guidelines and criteria from the DSM-IV and DSM-V respectively (Gearhardt et al., 2009; 2016). These measures capture a broad range of eating behaviours such as preoccupation with food, binging behaviours as well as withdrawal symptoms from non-consumption of certain foods. Despite being well-tested and valid (Horsager et al., 2020), these measures typically assess the extremes of pathological eating behaviours with respect to reward, similarly, clinical populations are where these scales are most routinely applied. As such, application to a non-clinical population such as in the present study may prove ineffective in measuring non-pathological reward-related eating.

The Reward-Based Eating Drive Scale is a measure, developed to address key shortcomings in previous scales, notably, their insufficiency in more broadly capturing a full spectrum of reward-related eating. The RED scale has three iterations: the 13-item RED-13 (Mason et al., 2017), the 9-item original RED scale (Epel et al., 2014) and the 5-Item RED-X5 (Vainik et al., 2019). The RED-13 considered the improved version by the authors, provides the most comprehensive measure with 13 statements asked across a five-point Likert scale from which participants are required to indicate whether they agree or disagree with that statement. Questions asked can be broken down into three themes: a preoccupation with food, a lack of control over consumption and a lack of satiety in eating. The RED scale shows good validity across its iterations, with a good ability to measure reward-related eating across the lower to middle ranges of the spectrum of disordered eating. As a measure of reward-related eating and drives it has also seen broad applications such as showing good predictive power for weight loss in dietary interventions (Mason et al., 2016), applications in measuring the effectiveness of pharmaceutical interventions such as Naltrexone in reducing the intensity of reward-related eating (Mason et al., 2015) as well as use in predicting children's ultra-processed food consumption based on the reward-eating drive of parents (Dolwick & Persky, 2021). When comparing this to the TFEQ Restraint Scale subsection, the TFEQ emphases the cognitive and behavioural strategies individuals use to control their food intake, particularly in the context of weight management. While the RED-13 scale specifically targets reward sensitivity and the drive to eat in response to palatable or highly rewarding food cues. The TFEQ Restraint Scale does capture how individuals actively attempt to manage or suppress these urges, offering insight into real-world dieting behaviours and the tension between control and desire. However, the TFEQ also includes measures across its subscales that incorporate emotional influences on eating behaviour, particularly through constructs like disinhibition and hunger, which may blur the line between emotional and reward-driven eating. In contrast, the RED scale intentionally separates reward drive from emotional triggers, which aligns better with the present study aiming to disentangle the distinct roles of emotion and reward in eating behaviour. As such, while the TFEQ offers a broader behavioural profile, it may not be optimal when a clear separation between emotional and reward-related processes is required. Another scale considered here is the Self-Regulation of Eating Behaviour Questionnaire (SREBQ) (Kliemann et al., 2016). The SREBQ measures self-regulation of eating, focusing on an individual's ability to control their intake in line with health goals, including monitoring, resisting temptation, and staying on track. In contrast, the RED scale specifically targets reward-based eating, assessing the drive to eat in response to cravings, palatable foods, and loss of control around food. It captures hedonic motivation directly through items that reflect strong urges to eat when not hungry, difficulty stopping once eating has started, and a persistent desire for highly rewarding foods. These features make the RED scale particularly well-suited for measuring sensitivity to food reward, while the SREBQ reflects the capacity to regulate eating rather than the pull of food itself.

When linking the two, emotions may indeed contribute to the rewarding gratification obtained from eating by altering the reward value of food. Research from Noel and Dando (2015) demonstrates how positive mood states can enhance the sweetness of foods and reduce the perception of bitter tastes. As explored previously, when considering negative mood states such as anxiety, stress or depression can lead to the consumption of comfort foods that are typically highly palatable and consequently are typically higher in salt, fats and sugar. Due to the rewarding gratification of these stimuli during a time of negative emotion, comfort eating becomes positively reinforced as pleasure and reward centres are activated leading to positive and rewarding feelings (Klatzkin et al., 2022). As a result of this people are more likely to turn to highly-palatable, gratifying and rewarding food stimuli, such as those foods that are higher in sugar and fat for comfort and reprieve, especially during times of stress and negative emotion (Maniam & Morris, 2012; Singh, 2014). This body of research might suggest links between the processes of emotion and reward, especially in the context of eating. As well as measuring reward through purpose-built scales, measuring rewards' constituent parts both liking, and wanting may prove useful in better understanding its power over our behaviours.

1.5 The Measurement of Liking, Wanting and Biases

Liking and wanting are important processes involved in reward and food choice and as such understanding how best to operationalize and measure these processes is paramount to research in this field. The measuring of liking and wanting throughout research is inconsistent. Highlighted in a review by Pool et al. (2019) there are key discrepancies in the way both wanting and liking are operationalized in studies. Due to reward being such a large and integrative process, and problems surrounding the confusion when asked to introspectively assess one's 'liking' of a stimuli, it is suggested that immediate and reactionary measures are better at assessing true liking of a stimuli as introspective measures may confuse or synonymise liking and wanting in participants (Kringelbach & Berridge, 2009). Preference choice tasks show promising ability to assess measures of liking and wanting. Research from Finlayson et al. (2007) utilized a protocol involving a computer-based 'forced-choice procedure' utilising photographs of pictures whereby two food photographs were presented simultaneously with participants required to choose from the two which they wanted the most. In turn, this procedure indicated participants reported wanting sweet foods significantly more than savoury foods, and participants were faster at responding to sweet foods (Finlayson et al., 2008). Indeed preference-based methods such as those in liking and wanting typically involve judgement tasks by which participants are forced to make decisions about stimuli seem to serve the best method of operationalizing these variables. This paradigm employed in research by Finlayson saw great impact and influence on the paradigm employed in the present study. The use of a forced-choice task (in the present study a ‘Food Judgement Task’ in particular is mirrored in our approach, especially when concerning its application in measuring implicit wanting (Finlayson et al. 2011). Where the present study differs here is in the measurement of accuracy in correct categorisation of foods, and in the measurement of implicit liking. The study distinguished explicit liking (what people say they enjoy) from implicit wanting (what they’re drawn to quickly and automatically), but implicit liking was not directly measured. A body of literature suggests implicit liking (a non-conscious evaluative response) may indeed be separate from motivational drives such as those found in wanting (Tibboel et al., 2011; Tibboel et al., 2015). Important to state here however is that these findings are inconsistent and methodologies across the studies reviewed vary greatly. With this detail in mind, the present study looks to build on the previous research by employing measures to evaluate explicit wanting, explicit liking, implicit wanting and implicit liking as distinct constructs. Studies utilising cognitive and choice-based tasks typically demonstrate inconsistent findings occasionally with some preferences and biases toward different foods. Gibson and Wardle (2003) observed a liking preference in children for calorically denser foods, whilst follow-up research from Brunstrom et al. (2018) for example, attempted to assess the ability of individuals to distinguish between higher and lower caloric foods and attempted to explore any preference or liking of these foods. They saw participants were poor at distinguishing between the caloric density of foods, and contrary to expectations showed no liking preference based on caloric amount.

The research examined here uses measures to demonstrate explicit biases. When considering the exploration of implicit biases, results are more inconsistent, and limited when considering sweet foods. Research from Mason et al. (2019) utilized the n-back task to assess attentional food biases. They concluded obese participants might possess a "sweet cognition" due to seeing greater attentional biases toward food after consuming sugar, than leaner participants. Research employing a flicker paradigm showed attentional biases toward food items compared to non-food items, with higher attentional biases in overweight participants (Favieri et al., 2020), however, the stimuli in these studies were of a range of foods with no sweetness distinction. Research utilizing a pictorial visual probe paradigm involving eye tracking saw participants who with higher BMIs typically showed more initial visual orientation toward high-fat foods, but interestingly were quicker at retracting their gaze from these images suggesting somewhat of an approach-avoidance behaviour pattern toward those higher-fat foods (Werthmann et al., 2011). This shows a distinction between high-fat and low-fat foods, but still does not account for stimuli sweetness. Research attempting to examine the ideal measure of food biases saw pictorial tasks achieved the greatest ability to capture attentional biases, stressing the large variation in ability to capture attentional biases throughout literature may be due to a lack of standard methods (Franja et al., 2021). Meta analyses in this area tend to either focus on attentional bias differences between healthy and overweight individuals (Hagan et al., 2020), or differences in attentional/ cognitive biases in individuals with eating disorders (Brooks et al., 2011; Stott et al., 2021). Research offers a broad range of methodologies when attempting to capture biases to different foods, and how different individuals may perceive food however, a gap from this area comes when considering the application of cognitive tasks in measuring response biases specifically focused on sweet foods and non-sweet foods in particular.

1.6 The Present Study

The primary objective of this study is to investigate the effects of emotion, reward, and food preference on the perception of sweet-tasting foods measured through response times, response type and accuracy of correct categorisation. Existing literature indicates that hedonic (liking) and motivational (reward) factors can influence food perception, but has not yet considered their impacts on how to process and perceive sweet and non-sweet foods. Consequently, this study observes the responses to sweet and non-sweet foods by instructing participants to explicitly indicate their liking (versus disliking) and wanting (versus not wanting) of the displayed foods.

We hypothesize that liking and wanting will influence responses, resulting in facilitated perception, characterized by faster response times for foods that are liked and wanted (H1). It is important to note that the taste-judgment task is not considered a control task for direct comparisons with the liking and wanting tasks due to the differing cognitive functions involved in taste judgment, liking, and wanting. Nevertheless, we expect that cognitive performance in the taste task, in terms of accuracy and response time, will correlate with food preferences (H2 a). Furthermore, we designed a task requiring participants to judge whether a displayed food is sweet or non-sweet, devoid of emotional or rewarding connotations, serving as a reference task. We hypothesize that classifying food as sweet or non-sweet should not involve emotional or reward facilitation, and thus, we do not anticipate effects of sweet and non-sweet classifications on accuracy and response time. (H2 b)

Task responses and response speed was subsequently analysed in relation to measures of emotional eating and reward-related eating. Specifically, we systematically tested whether emotional eating and reward-related eating could predict responses and speed across the like and want tasks. We hypothesize that emotional eating will account for variability of liking and response time in the liking task, while reward-related eating will explain response time and levels of wanting in the wanting task (H3).

This study does not directly compare the effects of emotion, reward, and food preference across all tasks simultaneously due to inconsistent evidence regarding the interaction or overlapping neurobiological mechanisms for liking and wanting. Thus, our hypotheses test the effects of emotion, reward, and food preferences in each task independently. To ensure the reliability of our findings, we incorporated control variables such as hunger and thirst. Participants' levels of hunger and thirst were measured prior to the tasks to account for their potential influence on food perception and cognitive performance. By controlling for these variables, we aimed to isolate the specific effects of liking, wanting, and taste on food perception and cognitive performance. Analyses of physiological state and task outcomes can be seen across supplementary materials items 7.1.3, 7.2.2 and 7.3.2.

In addition to the hypotheses outlined, exploratory analyses were also carried out to examine patterns in the data not initially anticipated. These analyses were not theory-driven but were included to better understand the broader dataset and to identify potentially meaningful relationships that might inform future research. Given the complexity of food-related behaviours and the overlapping constructs of liking, wanting, emotional eating, and reward-driven tendencies, such exploratory work was considered appropriate for highlighting directions that may warrant further investigation.

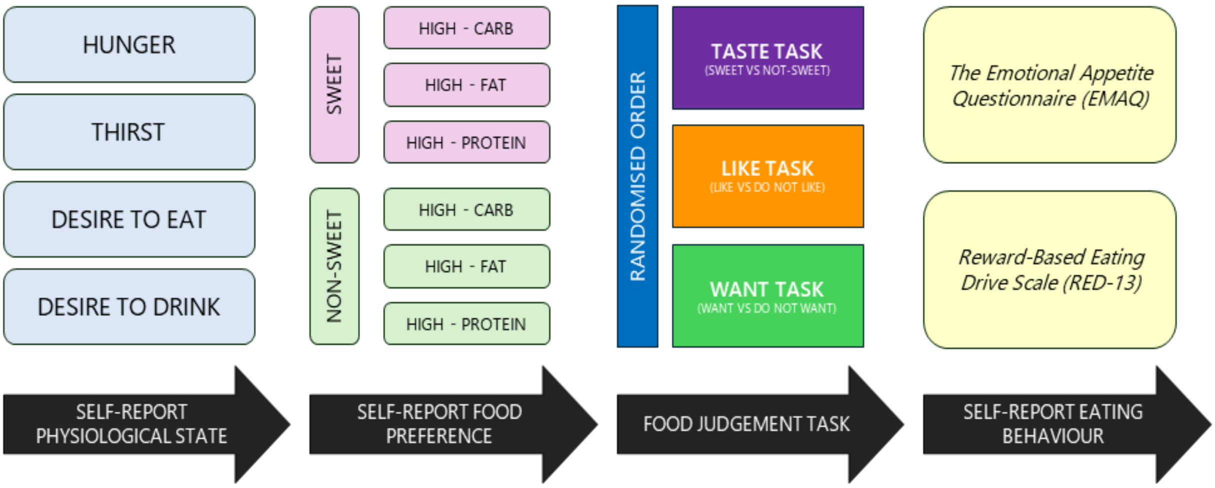
2. Methods

2.1 Design

The present study implemented a within-participants cross-sectional design.

Figure 1

Experimental design and measurements of the current study.



This figure depicts the full study design. Beginning with self-report measures of hunger, thirst and desire to eat and drink. This is followed by the food preference questionnaire with 60 foods broken down into six subcategories. Following this questionnaire is the food judgement task with three distinct blocks of 120 trials within each participant made different judgements. Each block of trials contained the same 60 food stimuli (30 sweet, 30 non-sweet) presented in a randomised order. Finally, participants completed the EMAQ and RED-13 questionnaires.

2.2 Participants

One hundred and two adults from Bournemouth University, UK with a mean age of 20.65 years old (ranging 18 and 40 years of age) participated in the present study (74 female, 27 male and one non-binary). Participants volunteered for the study and were recruited through the SONA recruitment platform (Sona Systems, 2023). Eligibility requirements consisted of having normal or corrected-to-normal vision (e.g. contact lenses, glasses etc.), English fluency, an intact and unobstructed sense of taste and smell, no current or previously diagnosed substance-use disorders and not following any large dietary restriction medically prescribed or otherwise (low sugar, low fat, vegan, vegetarian, keto etc.). No participants withdrew from the study.

Utilizing G*Power (V 3.1), the study estimated the necessary sample size to discern correlations between questionnaire responses and explicit cognitive task measurements, targeting a minimal effect size of .03, with an alpha of .05 and a power of .80, resulting in a required sample of 80 participants. The actual sample size surpassed this minimum, thus providing robust power for the study. This conservative effect size estimation was chosen in response to the varied outcomes in effect sizes reported in prior research (Finlayson et al., 2008).

2.3 Materials

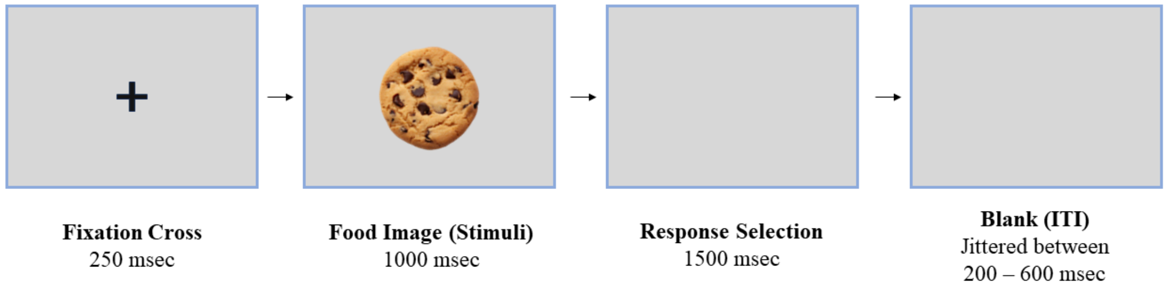
2.3.1 Food judgement task

This judgement task was created to measure accuracy and response time for pictures displaying non-sweet and sweet food when asked to classify pictures based on their taste (sweet or not-sweet), or response time and response type when asked to indicate whether the food was wanted (want or not-want) or whether it was liked (like or not-like).

This task consisted of four distinct blocks of 120 trials (Practice, Taste, Like and Want). After completing the practice block, the order in which the following three blocks were delivered was randomised to prevent any effect of task order. For each block, there are 120 trials, with 60 distinct food stimuli presented consecutively in a random order with each stimulus presented twice in total for each block of trials. The trial structure begins with a 250 msec presentation of a fixation cross to focus attention, immediately followed by a food image for 1000 msec, immediately followed by a 1500 msec response selection window (see Figure 2). Following their response or the lapse of the response window, a variable inter-stimulus interval (ISI) of 200-600 msec precedes the next trial. This design aims to measure response times and accuracy efficiently while minimizing cognitive fatigue. Each block of 120 trials typically lasted three to four minutes to complete with breaks offered to participants between trials. The three main tasks consisted of three different classifications the participants were asked to make: Sweet/ Not Sweet, Liked/ Not Liked and Wanted/ Not Wanted. In order to provide a classification, responses were bound to the '*n*' and '*m*' keys on the keyboard, for each participant and block, the response upon which each key corresponds was randomised throughout to avoid any impact the key input might have. Of the 60 stimuli presented 30 were classed as sweet, and 30 non-sweet. This was further broken down into six subgroups: sweet-high-carbohydrate (SHC), sweet-high-protein (SHP), sweet-high-fat (SHF), non-sweet-high-carbohydrate (SAHC), non-sweet-high-protein (SAHP) and non-sweet-high-fat (SAHF). The study employed uniformly edited food photographs, each with the same resolution (600 x 450 pixels), colour depth, and identical white backgrounds. All images were consistently positioned on the screen, and uniformity was maintained using GIMP software for image editing.

Figure 2

Illustration depicting one cognitive task trial.



Note. The trial structure begins with a 250 msec presentation of a fixation cross to focus attention, immediately followed by a food image for 1000 msec, following this a 1500 msec response window appears in which participants classify the stimulus. Following their response or the lapse of the response window, a variable inter-trial interval (ITI) of 200-600 msec precedes the next trial. This design aims to measure response times and accuracy efficiently while minimizing cognitive fatigue.

2.3.2 Food preference questionnaire

The Food Preference Questionnaire (FPQ) assesses participants' desire to consume different types of food. This questionnaire was designed to be representative of the food stimuli presented in the judgement task, with every food in the task matched with a score in the preference questionnaire. The questionnaire itself contains 60 different foods, of which 30 are categorized as sweet whilst 30 are categorized as non-sweet. From these 60 foods, they can be further broken down into six subcategories (both sweet and non-sweet: high-fat, high-carb and high-protein). Participants were given the instruction "Please rate: how strong is your desire to eat each of the following foods RIGHT NOW, on a scale of 0-6 where: 0 refers to no desire at all and, 6 refers to a very high desire. Please think about the food as an individual item – do not combine the food with others or think of the food as part of a meal."

Participants reported their responses on a 7-point Likert scale with the anchors "0-No Desire" and 6-Very High Desire". (See Appendix item N).

2.3.3 Emotional Appetite Questionnaire (EMAQ)

The EMAQ is employed in the present study to measure how participants' eating behaviour is altered by emotion, specifically how their amount of consumption changes. The questionnaire is split into two, with the first half focused on emotional states, and the second half focusing on specific emotional situations. Of the 14 states, nine are negative ("Sad", "Anxious", "Lonely" etc.) whilst five are positive ("Confident", "Playful", "Relaxed" etc.). Similarly, of the eight situations given, five are negative ("When under pressure", "After ending a relationship" etc.) and three are positive ("When falling in love", After receiving good news" etc.). Answers to the question "As compared to usual, do you eat: Much less, The Same or Much More when you are…" are provided by participants on a 9-point Likert scale with the anchors 1-Much less, 5-The same and 9-Much more. Questions can be broken down for analysis into six sections: positive/ negative emotional situations (questions relating to the change in eating behaviour in response to specific situations), positive/ negative emotional states (questions relating to the change in response to specific states of emotion) and overall positive/ negative scores (encompassing both negative situations and states, or positive situations and states respectively). The EMAQ shows strong construct validity, correlating positively with the DEBQ's emotional eating subscale for negative emotions, and discriminant validity, with minimal correlations to positive emotions (Nolan et al., 2010). It also demonstrates good convergent and discriminant validity, with negative scores correlating with higher BMI, positive scores with lower BMI, and high internal consistency and test-retest reliability (Bourdier et al., 2017). (See Appendix item P).

2.3.4 Reward-Based Eating Drive Questionnaire (RED-13)

The RED-13 is implemented in the present study to assess the influence that the hedonic factors of food consumption have on participants' food consumption. This 13-item scale assesses three different dimensions of reward-related eating, those being a lack of control over our eating such as controlling the level of food consumption, a lack of satiety such as the absence of fullness and a preoccupation with food such as a constant thinking about food. Each of the 13 questions poses a statement from which the participant has to indicate on a 5-point Likert scale (0-4) whether they "Strongly Disagree", "Disagree", "Neither Agree nor Disagree", "Agree" or "Strongly Agree" with the statement. The RED scale exhibits good validity in the measurement of reward-related eating (RRE) particularly in the mid-lower ranges of disordered eating behaviour, with reliability shown in its applications as a measurement of RRE in dietary intervention research (Mason et al., 2016), medication effectiveness (Mason et al., 2015) and shows good predictive power of childhood eating patterns (Dolwick & Persky, 2021). (See Appendix item O).

2.3.5 Physiological state questionnaire

In order to understand and account for individual differences in participants' physiological state, four questions were asked to measure their current level of hunger and thirst, as well as their current desire to both eat and drink. The participants were given the instruction "Please mark the following scales according to how you feel RIGHT NOW. Please answer each question independently and as accurately as possible" and provided this information by indicating a score on a 100-point scale with the anchors "0-Not at all" and "100-Extreemely". Despite previous literature typically using the terms hunger and desire to eat synonymously, evidence suggests these subjective measurements may be different constructs, each with their own distinct underlying drives (Appleton & Soysa, 2008).

2.4 Procedure

Prior to engaging in the study, participants received a detailed participant information sheet and were required to sign a participant agreement form. The information sheet thoroughly explained the research procedures, participant expectations, and the types of data collected, including data storage and anonymization protocols. This ensured participants were fully informed about the study's scope and their role within it. The agreement form facilitated informed consent, affirming their understanding and agreement to the outlined activities. Participants had the chance to ask any questions before providing their age and gender. The participants then completed a short four-question physiological state questionnaire relating to participants levels of Hunger and Thirst as well as their Desire to Eat and Desire to Drink. The participants were then asked to complete the food preference questionnaire designed to indicate their preferences for/ current desire to consume food from the six different food subgroups. Following the completion of the food preference questionnaire, the participants then commenced the food classification task. This task was conducted on a Hewlett-Packard EliteDesk 800 G1 SFF, 8GB RAM with a Windows 7, 64bit operating system. The monitor used was a 24" BENQ XL2411, 1920 x 1080 pixels, 60 Hz refresh rate. The task was delivered to participants using the open-source experiment builder and runner PsychoPy version 2023.2.3 for 64-bit Windows (using Python3.8) (Pierce et al., 2019; 2022). This task consisted of four distinct blocks of 120 trials (Practice, Taste, Like and Want). After completing the practice block, the order in which the following three blocks were delivered was randomised to prevent any effect of task order. For each task there are 120 trials, with 60 distinct food stimuli presented consecutively in a random order with each stimulus presented twice in total for each block of trials. After completing the classification task participants then completed the Emotional Appetite Questionnaire (EMAQ) (Nolan et al., 2010), followed by the Reward-based Eating Drive (RED-13) scale (Mason et al., 2017). The order of the study was dictated by two factors. Firstly, it was necessary for hunger and thirst measurements to be taken before food preference and cognitive task measures as not to influence the hunger feelings or thirst of participants. Secondly, the EMAQ and RED-13 were conducted after completing the cognitive task, and importantly, the food preference questionnaire as these assessments may have led to different responding due to their introspective and personal nature. As such, they were the final measures of the study.

2.5 Ethics

This study received approval from the Bournemouth University Research Ethics Code of Practice board, adhering to the British Psychological Society's Code of Ethics and Conduct (2021), ensuring compliance with ethical standards, researcher professionalism, and data protection. Participants were given detailed information sheets and participant agreement forms, clarifying the study's aims and requiring their signed consent. Recruitment was conducted via the secure SONA Participant Recruitment platform (Sona Systems, 2023), ensuring no personal data retention by the research team. To safeguard anonymity and data privacy, participants were assigned randomly generated numerical codes linking their questionnaire responses to their judgment tasks.

2.6 Data pre-processing

2.6.1 Food judgement task pre-processing

Missed trials that lapsed the response window in the food judgement task were automatically coded as blank and as such were not factored into the analysis. The number and proportion of these missed responses removed for each trial were: Taste (80/ 0.6%), Like (102/ 0.83%) and Want (119/ 0.97%). In addition, fast responses (trails answered with a

Response Time of <100msec) were similarly excluded from analysis. The number and proportion of these responses were: Taste (0/ 0%), Like (15/ 0.1%) and Want (8/ 0.06%).

2.6.2 Questionnaire pre-processing

Answers were mandatory for all questionnaire responses in the Physiological State Questionnaire, Food Preference Questionnaire and Reward Eating Drive Scale (RED-13). Therefore, no responses required removal. In the Emotional Appetite Questionnaire if a situation or emotional state did not apply to the participant, or they did not know how they would feel, they could indicate this. The responses D/K (don't know) or N/A (not applicable) were coded as blank, and as such, were not interpreted in the analysis. Of the responses, 72/ 3.2% were removed for stating D/K or N/A. For the Physiological State Questionnaire, 9/ 2.2% of responses in total were missing (4 'Hunger' ratings and 5 'Desire to Eat' ratings), similarly, these were coded as blank and were not factored into the analysis.

2.7 Data analysis

2.7.1 Descriptive statistics and assumption checks

Mean and standard error was calculated to assess the metrics for each assessment. In addition, the normality of the distribution of the data was calculated for each metric utilizing a Shapiro-Wilk test (Shapiro & Wilk, 1965) (see Appendix items A1, A2, A3 & A4). Durbin-Watson tests, data homoscedasticity and normality checks are calculated and reported in linear regression analyses.

2.7.2. Analysis for Hypothesis 1: Liking and wanting will influence response times

To test Hypothesis 1 that participants would respond more quickly to foods they liked and wanted, two separate Linear Mixed Models (LMMs) were conducted. One model included liking (liked vs. not-liked) as a fixed effect; the other included wanting (wanted vs. not-wanted). In both models, response time served as the dependent variable, and participant ID was entered as a random effect to account for individual variation. This allowed examination of whether affective (liking) and motivational (wanting) judgments influenced decision speed. These specifications included participant-specific intercepts (to allow each participant their own overall response speed) and participant-specific slopes for Sweetness, Liking and Wanting (to allow the sweetness, liking and wanting effects to vary between participants). Models were estimated using restricted maximum likelihood (REML), and fixed-effect tests employed the Satterthwaite approximation for denominator degrees of freedom. The denominator degrees of freedom reflects the Satterthwaite approximation, which provides an effective rather than exact df based on the participant sample size and random-effects structure.

2.7.3. Analysis for Hypothesis 2a: Food preferences will correlate with taste task performance

To assess Hypothesis 2a that explicit food preferences would relate to performance in the taste categorisation task, Pearson's correlation analyses were conducted. Preference scores from the Food Preference Questionnaire (FPQ) were correlated with each participant's mean accuracy and mean response time in the taste task. Correlations were calculated for overall sweet and non-sweet food preferences, as well as for each food subgroup, to explore whether stronger preferences were associated with better performance.

2.7.4. Analysis for Hypothesis 2b: Sweetness will not influence taste task performance

Hypothesis 2b proposed that food sweetness would not significantly influence performance on the taste categorisation task. To evaluate this, accuracy was analysed using a Generalised Mixed Model (GMM) with sweetness (sweet vs. non-sweet) as a fixed effect and participant as a random effect, using a binomial distribution and logit link function. Response time was analysed using a Linear Mixed Model (LMM) with the same fixed and random structure. These models assessed whether sweet foods were categorised differently in terms of speed or accuracy.

2.7.5. Analysis for Hypothesis 3: Emotional and reward-related eating will predict liking and wanting performance

To test Hypothesis 3 that emotional eating would predict responses in the liking task and reward-based eating would predict responses in the wanting task, Pearson's correlations were conducted. Scores from the Emotional Appetite Questionnaire (EMAQ) were correlated with each participant's liking proportions and mean liking response time. Scores from the Reward-Based Eating Drive Scale (RED-13) were correlated with wanting proportions and mean wanting response time. This approach allowed direct examination of how individual differences in eating tendencies related to hedonic (liking) and motivational (wanting) components of food reward.

3. Results

3.1 Hypothesis 1: Liking and wanting will influence response time

Hypothesis 1 predicted that liking and wanting would influence responses, such that participants would respond more quickly to foods they liked and wanted compared to those they did not.

3.1.1 Liking and Response Time

Table 1

Descriptive statistics of the response time of liked and not-liked stimuli

Descriptive Statistics

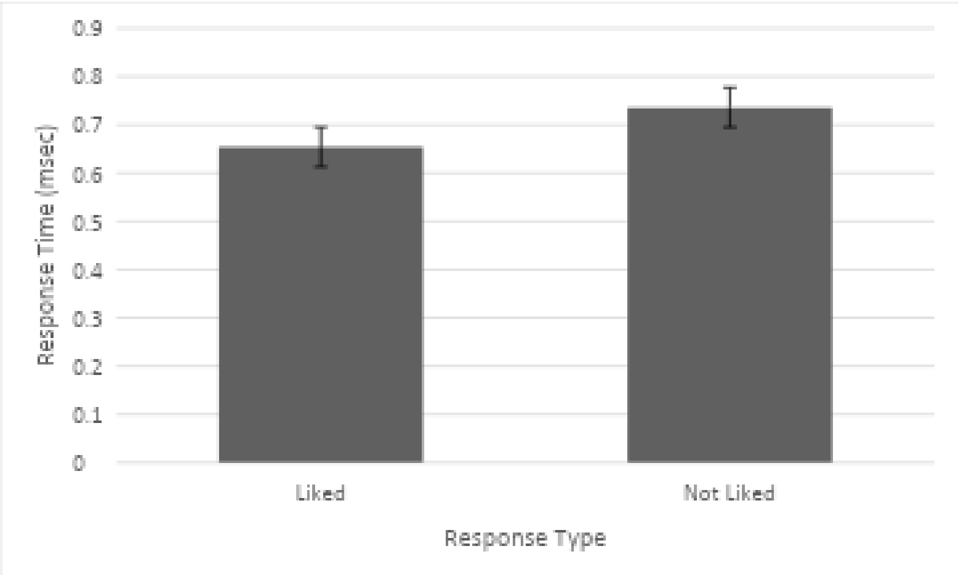
	Valid	Missing	Mean	Std. Error of Mean	Std. Deviation	Shapiro-Wilk	P-value of Shapiro-Wilk	Minimum	Maximum
Like RT	102	0	0.654	0.009	0.087	0.973	0.036	0.306	0.908
Not-Like RT	102	0	0.736	0.009	0.090	0.990	0.627	0.457	0.973

Note. This table displays the descriptive statistics, standard deviation, and Shapiro-Wilk test results for the average response time when indicating a stimuli is liked, or not-liked.

A Linear Mixed Model (LMM) was used to examine whether liking affected response time. Results showed a main effect of liking ($F = 92.1$, Den $df = 82$, $p < .001$), with faster responses for "liked" foods ($M = 654$ ms) compared to "not-liked" foods ($M = 736$ ms). The fixed effect coefficient was $B = -0.0696$, $SE = 0.00736$, 95% CI [-0.0838, -0.0564], $t = -9.60$, $p < .001$. Participant differences accounted for 29% of the variance in response times. (See Table 1 and Figure 3).

Figure 3

Column chart of response time for liked and not-liked responses



Note. This line-plot visualises the differences in response time indicated by participants in the judgement task. Liking responses are markedly faster than responses indicating the stimuli is not liked.

3.1.2 Wanting and Response Time

Table 2

Descriptive statistics of the response time of wanted and not-wanted stimuli

Descriptive Statistics

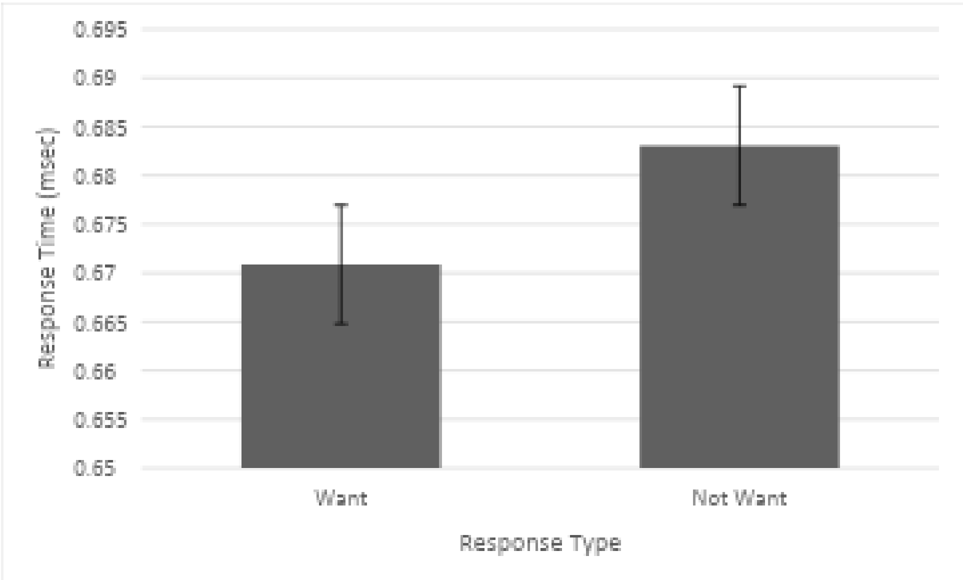
	Valid	Missing	Mean	Std. Error of Mean	Std. Deviation	Shapiro-Wilk	P-value of Shapiro-Wilk	Minimum	Maximum
Want RT	102	0	0.671	0.008	0.083	0.988	0.504	0.451	0.874
Not-Want RT	102	0	0.683	0.008	0.077	0.989	0.542	0.440	0.902

Note. This table displays the descriptive statistics, standard deviation, and Shapiro-Wilk test results for the average response time when indicating a stimuli is wanted, or not-wanted.

An LMM was also run for wanting, which revealed a main effect of wanting (F = 6.78, Den df = 86.8, p < .001), with "wanted" foods responded to more quickly (M = 671 ms) than "not-wanted" foods (M = 683 ms). The fixed effect coefficient was B = 0.0220, SE = 0.00844, 95% CI [0.00544, 0.0385], $t = 2.60$, $p < .001$. Participant differences explained 16.8% of the variance. (See Table 2 and Figure 4).

Figure 4

Column chart for the average response time of wanted and not-wanted stimuli.



Note. This column chart visualises the differences in response time indicated by participants in the judgement task. Wanting responses are markedly faster than responses indicating the stimuli is not wanted.

3.2 Hypothesis 2a: Cognitive performance in the taste task will correlate with food preferences

Hypothesis 2a predicted that explicit food preferences would relate to performance in the taste categorisation task, with higher preferences being associated with greater accuracy and faster response times.

3.2.1 Food Preference and Accuracy

Pearson correlations were used to examine whether food preferences (measured via FPQ) were related to categorisation accuracy. No significant associations were found between preference scores and accuracy for sweet, non-sweet, or subgrouped foods. (See Appendix Q. and R)

3.2.2 Food Preference and Response Time

Similarly, no significant correlations emerged between food preferences and response time across any food categories. (See appendix S. and T.)

3.3 Hypothesis 2b: Sweet/non-sweet classification should not influence accuracy or response time

Hypothesis 2b predicted that sweet/non-sweet classification would not impact performance, given the task's neutral nature with respect to reward or emotion.

3.3.1 Accuracy by Sweetness

Table 3

Descriptive statistics of taste task accuracy proportion (%) and average EMAQ scores

	Sweet_ACC_Taste	Not_Sweet_ACC_Taste	SAHC_ACC_Taste	SAHP_ACC_Taste	SAHF_ACC_Taste	SHC_ACC_Taste	SHF_ACC_Taste	SHP_ACC_Taste	EMAQ_POS_Emo	EMAQ_NEG_Emo	EMAQ_POS_Situ	EMAQ_NEG_Situ
Valid	102	102	102	102	102	102	102	102	102	102	102	102
Missing	0	0	0	0	0	0	0	0	0	0	0	0
Mean	90.392	93.546	94.020	94.216	92.402	81.618	94.118	95.441	5.476	4.511	5.558	3.462
Std. Error of Mean	0.800	0.694	0.845	1.021	1.061	1.715	0.764	0.919	0.106	0.132	0.110	0.165
Std. Deviation	8.078	7.011	8.532	10.311	10.711	17.323	7.721	9.284	1.073	1.330	1.112	1.664
Shapiro-Wilk	0.859	0.774	0.633	0.577	0.711	0.877	0.726	0.472	0.946	0.975	0.981	0.941
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	0.048	0.157	< .001
Minimum	51.667	63.333	35.000	30.000	45.000	30.000	60.000	20.000	1.800	1.667	2.333	1.000
Maximum	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000	9.000	7.889	8.000	9.000

Note. This descriptives table provides the descriptive statistics, standard deviation, and Shapiro-Wilk test results for the average accuracy proportion (%) of correct categorizations and average EMAQ subscale scores.

A Generalised Mixed Model (GMM) with a binomial distribution and logit link function was used to assess accuracy differences. Results showed a significant effect of sweetness ($\chi^2 = 48.5$, df = 1.0, $p < .001$), with lower accuracy for sweet (M = 90.4%) than non-sweet foods (M = 93.5%). The fixed effect coefficient was B = -0.487, SE = 0.0713, 95% CI [-0.636, -0.357], z = -6.97, $p < .001$. Participant-level variance accounted for 14% of the variability.

3.3.2 Response Time by Sweetness

An LMM showed a main effect of sweetness on response time (F = 22.3, df = 101, $p < .001$), with faster responses for sweet foods (B = -0.0177, SE = 0.00374, 95% CI [-0.0250, -0.0103], t = -4.72, $p < .001$). Random effects showed participant differences accounted for 17.7% of the variance.

3.4 Hypothesis 3: Emotional eating will predict liking and response time in the liking task, and reward-related eating will predict wanting and response time in the wanting task

3.4.1 Emotional Eating and Liking Performance

Descriptive statistics for EMAQ subscales were: Negative Emotions (M = 21.4, SD = 5.9), Positive Emotions (M = 24.7, SD = 5.5), Negative Situations (M = 19.8, SD = 5.7), and Positive Situations (M = 22.6, SD = 6.2).

Negative emotion scores were positively associated with categorisation accuracy for sweet foods (r = .338, $p < .001$) and SHC foods (r = .391, $p < .001$). Positive situation scores correlated positively with wanting of non-sweet high-protein foods (r = .226, p = .022) and overall non-sweet foods (r = .204, p = .039). Negative emotion scores were also associated with faster wanting responses for sweet foods (r = -.215, p = .031).

3.4.2 Reward-Related Eating and Wanting Performance

RED-13 descriptive statistics: Lack of Control (M = 13.2, SD = 3.8), Food Preoccupation (M = 11.5, SD = 4.0), and Lack of Satiety (M = 12.7, SD = 3.6).

Lack of Control was associated with greater liking proportions (r = .261, p = .009) and faster liking RTs (r = -.238, p = .016). Food Preoccupation also correlated with liking proportions (r = .249, p = .012) and faster wanting RTs (r = -.198, p = .048). These patterns suggest some overlap between reward-based eating and both hedonic and motivational responses.

4. Discussion

4.1 Overview of Findings

The current study aimed to explore the cognitive biases towards sweet foods and their relationships with reward, emotion, liking, and wanting. This was accomplished by utilizing the Emotional Appetite Questionnaire (EMAQ) (Nolan et al. 2010), the Reward-Based Eating Drive scale (RED-13) (Mason et al., 2017), both a food preference questionnaire and physiological state questionnaire and pivotally, a novel food judgement task. Using this method our study suggests some relationships between both susceptibility toward emotional eating, and reward-related eating and cognitive biases, particularly relating to response time.

4.2 Liking, wanting and response time (H1)

We hypothesised that liking and wanting would influence responses, resulting in facilitated perception, characterized by faster response times for foods that are liked and wanted. The results of the present study confirmed that participants exhibited significantly faster response times when categorizing foods they liked compared to foods they did not like. Similarly, participants showed faster response times for foods they wanted compared to those they did not want. These findings align with previous research by Finlayson et al. (2007, 2008), which demonstrated that participants responded more quickly to foods they liked and wanted. This supports the notion that both hedonic value (liking) and motivational drive (wanting) enhance cognitive processing efficiency. Further, the distinction between liking and wanting in food reward has been emphasized in the literature (Pool et al., 2019), and our findings support this distinction by showing that both factors facilitate perception. The results are consistent with the dual-process theory of food reward, which whilst positing that liking (hedonic pleasure) and wanting (motivational drive) may be distinct elements, they are interrelated processes

(Berridge & Robinson, 1998). The observed faster response times for liked and wanted foods suggest that both processes enhance attentional and cognitive processing. Neuroimaging studies (Berridge & Kringelbach, 2008; Kringelbach, 2005; Smith and Berridge (2007) indicate that separate neural circuits are involved in liking and wanting. The present findings indicate that both liking and wanting responses were associated with faster categorisation times compared to not-liked and not-wanted responses. While this aligns with existing literature suggesting that liking and wanting play important roles in food-related decision making (e.g., Berridge & Robinson, 1998; Finlayson & Dalton, 2012), these constructs were analysed separately in the current study. As such, the results do not provide direct evidence that liking and wanting are distinct or independently contributing factors in food reward processing. Demonstrating such a distinction would require a statistical model in which both variables are included simultaneously to control for any shared variance. Without this, it is not possible to determine whether one construct explains variance in behaviour beyond the other. Therefore, the current results should be interpreted as consistent with, rather than confirmatory of, the dual-process model of food reward. Future work may benefit from using a combined modelling approach such as the Linear Mixed Modelling approach used to assess other variables in the present study to further clarify the independent contributions of liking and wanting to cognitive and behavioural responses toward food.

4.3 FPQ responses and taste task performance (H2a)

Whilst our results did reveal significantly better accuracy for categorising non-sweet foods, and significantly faster response times to sweet foods, these results were not seen to correlate with food preferences indicated in the preference questionnaire. This would suggest the explicitly indicated wanting of the food did not impact participants' ability to categorize these, nor did this significantly affect the speed of their responses to these foods. This counters our second hypothesis (H2) as explicit food preferences did not impact participants' ability to categorise foods, nor did it impact the speed at which they were able to achieve this. The lack of a significant impact of food preference questionnaire responses on accuracy and response time in the taste task suggests that the cognitive mechanisms underlying taste perception operate independently of subjective food preferences. This may indicate that the ability to categorize foods as sweet or not sweet might serve as a more fundamental cognitive process not strongly influenced by individual likes or dislikes. From this, the cognitive processes responsible for basic taste recognition are likely distinct from those involved in processing the hedonic value of food. This separation could be facilitating objective taste categorization that is not biased by individual preferences. Whilst food preferences were not seen to result in changes to the outcomes of the taste task, this can not be said for the like and want task where quite consistent correlations were indeed seen (see supplementary materials 7.2.3 and 7.3.4 for more detail).

4.4 Taste task accuracy, response time, emotional eating and reward related eating (H2b)

When considering the impact of emotional eating on task performance, a key trend was observed. Participants on average who reported increasing their food consumption in response to negative emotions saw significantly better accuracy when categorizing sweet foods, especially sweet foods that are, once again, high in carbohydrates despite this subgroup being on average the hardest to correctly categorize. Interestingly, those who increased their food consumption in response to positive emotions were significantly faster at responding to sweet foods. With previous research suggesting people may tend to eat more sweet food in response to positive emotions (Ashurst et al., 2018; van Strien et al., 2013), it could be suggested that familiarity with these foods in these participants might have led them to react faster. It is important to note that participant familiarity with different stimuli and the impact this may have had on our results is not yet understood and could pose a wider impact than this. Different stimuli and potentially entire food subgroups may be more or less familiar to participants, and perhaps greatly so. Variation in individual differences in familiarity might introduce effects specifically to accuracy measures in the taste task and potentially response time measures across all tests, potentially biasing these measures toward familiar foods or groups. To address this issue, future research should look to incorporate more systematic approaches to control for familiarity. Achieving this might come through the use of more controlled stimuli from a more rigorously tested database that are better matched across categories for familiarity, ensuring that differences in task outcomes are not due to prior exposure (Blechert et al., 2019). Additionally, providing participants with prior exposure or training on less familiar food types prior to testing could help reduce the impact of unfamiliarity allowing for more reliable assessment. This was partially the case in the present study, as a practice block was used prior to the primary block of measured trials to give participants the opportunity to familiarise themselves with the task format and stimuli used. This could indeed be made longer to better pre-train participants' familiarity to stimuli, but this in itself risks introducing practice and repetition effects. A balanced approach of these controls as well as potentially measuring familiarity directly with a pre-testing assessment of stimuli could better address this issue.

RED-13 measures relating to participants having lower control over their eating behaviours saw markedly faster response times to sweet foods, especially those sweet foods that were also high in fat and high in protein. This interesting finding demonstrates a key link between explicit measures of control and implicit measures of reactivity. With previous research highlighting the great power reward has over our eating habits, even in anticipation of food (Berridge, 2009; Pearson et al., 2016), we theorize individuals who exert lower levels of control over their day-to-day eating, might exhibit cognitive biases toward highly palatable foods, such as these and as such are more reactive to these foods primed by anticipation of these, and lack some of the inhibitory power others have over both their consumption and reactivity to these foods.

4.5 Emotional eating, reward-related eating, liking and wanting (H3)

In direct relation to our hypothesis, our analysis showed that emotional eating, as measured by EMAQ negative emotion scores, predicted liking and accuracy for sweet foods, indicating that individuals who eat more in response to negative emotions were better at identifying and more likely to like sweet foods. Furthermore, reward-related eating, particularly RED Lack of Control scores, predicted faster response times for sweet foods, especially those high in fat or protein, and negatively correlated with the wanting of sweet foods. The hypothesis predicted that emotional eating would primarily impact the liking task, while reward-related eating would influence the wanting task. However, the results demonstrated that emotional eating also had a significant impact on wanting, and reward-related eating affected liking as well. This indicates that the relationship between these constructs is more intricate than initially anticipated. Specifically, EMAQ positive situation scores were positively correlated with the wanting of non-sweet high-protein foods (SAHP) and overall non-sweet foods, suggesting that individuals who eat more in response to positive emotional situations are more likely to report wanting non-sweet foods. This was contrary to the expectation that emotional eating would primarily influence the liking task. These findings suggest that emotional eating and reward-related eating are not mutually exclusive in their effects on liking and wanting tasks. Emotional eating can influence both liking and wanting, depending on the type of emotional trigger (positive vs. negative) and the specific food attributes (sweet vs. non-sweet). The significant prediction of wanting by positive situation scores (EMAQ) implies that positive emotions and situations can enhance the motivational drive for non-sweet foods, particularly those high in protein. This aligns with theories suggesting that positive emotions can enhance cognitive and perceptual processes related to food (Noel & Dando, 2015). The influence of reward-related eating on liking suggests that individuals with higher RED scores, especially in lack of control and food preoccupation, are more likely to report liking a broader range of foods. This pattern is consistent with theoretical accounts of liking and wanting as separate but interacting systems within the food reward process (e.g., Smith & Berridge, 2007), though the current study does not provide direct evidence for their independence. In conclusion, while Hypothesis 3 is partially supported, the results highlight the complex and intertwined nature of emotional and reward-related eating behaviours on both liking and wanting processes. This further underscores the need for further research to disentangle these relationships and refine our understanding of their impact on food perception and consumption.

4.6 Limitations

Liking was measured both through introspective self-report measures (food preference questionnaire) as well as through more immediate means such as through the food judgement task. This was important with speculation as to the reliability of introspectively assessing the extent to which one likes a reward (Kringelbach & Berridge, 2009). In a review from Pool et al. (2016) it was noted that rapid preference tasks, similar to the procedure used in the present study, whilst used to measure liking and wanting throughout literature, may actually just reflect wanting. With liking existing as an explicit measure, rapid assessments such as the food judgement task in this study might not give participants enough time to make decisions as to the liking of a food, and thus their responses given may better reflect wanting again. Finlayson et al. (2007) also noted this possibility in their experimental setup, stating liking measures may always contain a portion of wanting and vice versa. They stated this is fundamental to incentive salience, suggesting it may not be possible to entirely separate the two in tasks such as these, but highlights, contrary to Pool et al. (2016), that they are not the same. Despite differences in the liking and wanting outcomes of the present study, the food preference questionnaire, an explicit measure of wanting was seen to correlate fairly consistently with both the implicit measures of liking, as well as wanting. As a result, it is certainly plausible that liking and wanting measures in the present study are interlinked, but due to the fundamental differences in implicit liking and wanting in this study (indicated by judgement task outcomes) we do not believe they measure the same edxact desire or process.

Another limitation of the present study was the omission of the collection of BMI data from participants. BMI has been shown to have good correlates with eating behaviour, specifically in emotional (Wong et al. 2020) and reward-related eating (Fazzino et al., 2021). The collection of this data would have allowed for further comparison in this study and could reveal further effects on the perception of sweet foods. Future research should consider physiological factors such as this to strengthen understanding and investigate the potential impact of BMI on response time to sweet vs. non-sweet foods as well as correlating BMI with RED-13 and EMAQ measures. Linked to these physiological differences and their potential impacts on data, an additional issue present was the impact physiological state had on the results. Whilst the participants' physiological state was not seen to correlate with taste task measures, correlations were seen in both the like task, and want task (see supplementary materials items 7.1.3 and 7.2.2). In particular, desire to eat and hunger saw correlations with both increased, and decreased proportions of wanting and liking of different foods. This facet of individual differences could see further control in participants. By seeking to make this variable more consistent across participants, such as having participants arrive fasted and therefore hungry, or indeed by providing a breakfast meal to participants, future research may be better able to account for these physiological factors.

One concern relates to the number of tests conducted and the assocated risks of false positives. This is particularly relevant when considering the exploratory aspects of the present study, where multiple comparisons were made. It is important to acknowledge that some of the effects reported may not withstand more stringent statistical correction and should therefore be interpreted with caution. In future research, greater emphasis will be placed on applying formal procedures such as Bonferroni adjustments or false discovery rate (FDR) control, particularly when testing a large number of variables and applying a range of statistical tests, like found in the present study. These approaches, whilst potentially reducing statistical power and may lead to Type II errors, offer a more robust safeguard against Type I error and will be important in ensuring that findings are both reliable and replicable. Taken together, a more cautious, balanced and controlled approach to analysis may help reduce overinterpretation and allow for stronger conclusions to be drawn.

Another limitation of the present study comes as due to the stimuli used in the present study, key exclusion criterion were stipulated in recruitment. Specifically, those following controlled diets such as vegetarians or vegans were ineligible to take part due to the use of meat and animal-based stimuli which was feared would see disproportionately lower levels of wanting and liking and as such would result in unwanted confounding factors impacting the data collected. Dietary restrictions, be them a result of dietary choices or medically advised avoidance represent a significant group of the population, as a result, future research may seek to implement a more representative and inclusive set of both visual stimuli and items in a food preference questionnaire in order to broaden the sample population of participants.

A question arises when considering the way in which ‘food preference’ was measured in the present study. With the instruction to indicate ‘Desire to eat’ it is certainly possible that what was measured in our Food Preference Questionnaire was instead an indication of current wanting rather than a general preference for different foods. Evidenced here in exploratory analyses however is a general lack of a correlation between indications of ‘wanting’ in the want task, and measures of ‘food preference’ in the FPQ. If ‘food preference’ in the present study is indeed synonymous with wanting, we would expect to see clearer correlations between these measures. However, the lack of a relationship here might suggest our current FPQ is measuring a different concept entirely, perhaps just ‘Desire to eat’. Future research should seek to employ better ratified and operationalized measures to more accurately capture food preferences. The Leeds Food Preference Questionnaire (LFPQ) (Finlayson et al., 2007) might prove the best suited here, reliably measuring food preference by assessing how much individuals like and want foods varying in fat and taste. Using food images and reaction-time tasks, it captures both conscious ratings and implicit motivation, offering a detailed profile of reward-driven food preferences.

4.7 Future Research Directions

Future research might seek to explore the longitudinal effects of cognitive biases on eating behaviour and weight gain. Studies may also investigate the efficacy of interventions designed to alter these biases, or indeed treat emotional and reward-related eating issues. Interventions such as behaviour modification training, cognitive training programs and given the nature of emotional eating, mindfulness programmes could have their efficacy measured using tools such as a version of the judgement task in the present study. Measures of response time, categorization accuracy and the wanting and liking of foods could offer unique insight as to the progress of these treatments over time. Similarly, longitudinal studies exploring cognitive biases toward food, and how this interacts with consumption could be useful when following children through adolescence into adulthood. Insights here could prove beneficial in understanding the cumulative effect of these biases on the development of conditions such as type 2 diabetes, obesity and cardiovascular disease, especially under the context of emotional and reward-related eating, identified as key contributors to weight gain (Fazzino et al., 2021; Moraes et al., 2023; Wong et al., 2020). By seeking to understand this trajectory, research may be able to inform early intervention strategies through patterns in biases and eating behaviours. Behaviour patterns, or patterns in the cognitive perception of different foods could serve as important early indicators of maladaptive predispositions toward unhealthy coping mechanisms in later life.

A key point highlighted was that the scarcity of fresh and whole foods disproportionately impacts different communities across the world, evidenced by concepts such as ‘food deserts’ (Kelli et al., 2017; 2019; Walker et al., 2010; Ziso et al., 2022). From this, future study into this area may seek to understand the environmental and socio-economic factors implicated in different contexts. Understanding the nuanced contribution dietary imbalance, and the scarcity of fresh and whole foods has on the development of cognitive biases would serve a pivotal tool in advancing our knowledge of how different communities may be differentially impacted by their nutritional environment. Individuals cannot be held wholly responsible for their nutrition when living under these contexts, but by understanding the cognitive underpinnings of eating behaviours, we can better understand how to mitigate some of the issues contributing to increased obesity rates and cardiovascular disease amongst these communities. Again, longitudinal studies following children into adulthood, measuring diet, nutrition and the availability of healthy foods may help to expand our knowledge of how different societal contexts may affect cognition. Evidenced in this research was how different participants all have different biases toward foods. Future research, such as the suggestions explored has the potential to provide important insight as to the environmental factors that contribute to the development of these differential biases.

Like many studies before, explicit behaviours were measured through self-report. Evidenced by prior critiques of understanding emotional eating behaviours (Stammers et al., 2020), self-report is considered by many to simply lack the rigor and validity needed. Similarly stated by Stammers et al. (2020) however, alternatives to these measures are scarce, with attempts to better operationalize and measure these processes still relying on self-reporting such as the use of standardized scales and questionnaires, like the EMAQ and RED-13 used in the present study. Future research in this area may look to move away from self-report for the measurement of some explicit measures, to attempt to mitigate the aforementioned limitations associated. Future research may for example, complement a food preference questionnaire with observational measures such as the provision of a controlled and measured meal to understand food choices and infer liking and wanting, or indeed the application of eye tracking to understanding the attentional biases given to different stimuli, this could be paired well with a judgement-based task to offer an additional measure (Krabbe, 2017).

In the present study we selected the RED-13 scale due to its focused assessment of reward-related eating however, it may not adequately capture dietary restraint, a key aspect of eating behaviour relevant to our research aims. The RED scale isolates the hedonic drive to eat, offering clarity in distinguishing reward sensitivity from emotional influences however, it does not assess the regulatory efforts individuals make to resist or control these urges. This limitation became apparent in our analysis and interpretation of our results where measures of restraint appeared underrepresented. In contrast, the TFEQ, particularly its Restraint subscale directly assesses the cognitive control mechanisms that individuals employ to manage their eating in the face of both internal and external cues. Although it investigates both emotional and reward processes across its subscales, the TFEQ provides a more comprehensive behavioural profile, especially valuable when examining the interaction between dieting, self-control, and reward exposure. Future research aiming to explore these dynamics in greater depth may benefit from incorporating the TFEQ, especially the restraint subscale alongside or in place of the RED scale to more fully capture the balance between drive and regulation in eating behaviour.

4.8 Implications

The present findings propose some real-world applications that serve good contributions to both our understanding of the cognition in food choice and behaviour, as well as the impact of emotion and reward on these processes. We understand individuals are vulnerable to overconsuming unhealthy, and sugary foods under periods of negative emotion and stress, evidenced by previous research (Camilleri et al., 2014; Fuente González et al. 2022) and the present studies insights as to our cognitive biases and EMAQ outcomes. The findings emphasize the pressing public health issue of excess sugar consumption. The speed and accuracy with which participants identified sweet foods, coupled with their preference for these foods, reflect broader dietary patterns that contribute to obesity, cardiovascular disease, and type 2 diabetes. This underscores the need for public health initiatives to reduce sugar intake, particularly focusing on interventions that account for cognitive biases and preferences, focusing on moving towards healthier food options. Regulating both the availability and marketing of high-sugar foods, particularly in environments where individuals may be more likely to experience stress, or negative emotions, and particularly toward vulnerable groups such as children may help to mitigate some of the overconsumption of these foods. Additionally, research such as ours may help in the production of education and public health guidance increasing the awareness of cognitive biases toward foods, empowering individuals to recognise their predispositions and in turn focus on making healthier food choices, with the aim to reduce sugary food consumption at the population level. The provision of educational campaigns would be most crucial to young people and children. Schools could implement programs helping children to not only understand nutrition, but how their emotions impact their eating habits. Additionally, they could be provided the tools to critically evaluate marketing information and strategies as to how they can regulate their emotions would serve important skills to be taken forward into adulthood. Paired with this, programs aimed at parents and caregivers to understand how their children's eating habits and food choices may be impacted by these factors could help reinforce this education.

The present study also provides important implications for understanding the aetiology and maintenance of more severe disordered eating patterns. Previously explored research highlights the pivotal role both emotions and the rewarding properties of food consumption have on the development and maintenance of disordered eating patterns (Moraes et al., 2023; Reichenberger et al., 2020; Ricca et al., 2012). The use of judgement tasks, similar to the present research applied to clinical populations could benefit the production of cognitive assessment tools to aid in the diagnosis and formation of treatments for eating-related conditions. Similarly, the procedure implemented in the present study; utilizing overt explicit measures, applying tested and rigorous self-report assessment and coupling this with implicit cognitive judgement tools could see good applications outside of eating behaviour research such as in gambling behaviours, and substance abuse conditions. Measuring how emotion and reward play key factors in guiding maladaptive behaviour patterns, and exploring this under the context of cognitive bias could serve greatly in understanding and treating these behaviours.

4.9 Conclusion

In conclusion, this study sheds light on the complex interplay between cognitive biases, emotional states, and reward-based eating in shaping food preferences and consumption patterns. By understanding these relationships, more effective strategies can be developed to combat the overconsumption of sugar and improve public health outcomes. Public health guidelines are paramount to informing the populace on nutrition, health and wellbeing. What is evidenced by growing negative health outcomes and spiking obesity rates is that the current health advice simply is either, not reaching those who need it, not being properly understood or does not properly reflect our modern nutritional environment and requires more development. I believe a complex relationship between these conclusions is the case. We need to greatly improve our understanding of nutrition and its interplay with human behaviour, how advice can best reach those who need it and how we can best tackle the complex issue of nutritional imbalance and an ever too prevalent lack in availability of good quality whole foods.

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6. Appendices

Descriptive Statistics

	Mean	Std. Error of Mean	Std. Deviation	Shapiro-Wilk	P-value of Shapiro-Wilk
Hunger	37.898	2.296	22.728	0.943	< .001
Thirst	48.608	2.132	21.530	0.956	0.002
Desire_Eat	34.691	2.550	25.114	0.928	< .001
Desire_Drink	50.243	2.395	24.303	0.968	0.014
FPQ_Sweet	1.690	0.097	0.977	0.976	0.064
FPQ_Not_Sweet	1.568	0.093	0.937	0.962	0.005
FPQ_SHC	1.590	0.090	0.913	0.972	0.029
FPQ_SHF	1.915	0.132	1.334	0.959	0.003
FPQ_SHP	1.565	0.114	1.151	0.945	< .001
FPQ_SAHC	1.412	0.092	0.928	0.963	0.006
FPQ_SAHF	1.377	0.120	1.209	0.906	< .001
FPQ_SAHP	1.916	0.118	1.192	0.971	0.023
RED_Lack_Control	13.206	0.456	4.608	0.987	0.399
RED_Food_Preoccupation	5.225	0.236	2.384	0.978	0.081
RED_Lack_Satiety	5.392	0.330	3.336	0.961	0.004
RED_Total	23.824	0.762	7.699	0.987	0.414
EMAQ_POS_Emo	5.476	0.106	1.073	0.946	< .001
EMAQ_NEG_Emo	4.511	0.132	1.330	0.975	0.048
EMAQ_POS_Situ	5.558	0.110	1.112	0.981	0.157
EMAQ_NEG_Situ	3.462	0.165	1.664	0.941	< .001
EMAQ_POS_Ave	5.501	0.098	0.987	0.968	0.013
EMAQ_NEG_Ave	4.144	0.131	1.319	0.981	0.146

Appendix A1. *Descriptive statistics and Shapiro-wilk test results for questionnaire responses*

Descriptive Statistics

	Mean	Std. Error of Mean	Std. Deviation	Shapiro-Wilk	P-value of Shapiro-Wilk
Sweet_RT	0.630	0.006	0.058	0.982	0.191
Not_Sweet_RT	0.650	0.006	0.065	0.980	0.116
SAHC_RT_Taste	0.650	0.007	0.071	0.975	0.047
SAHP_RT_Taste	0.648	0.007	0.067	0.940	< .001
SAHF_RT_Taste	0.654	0.008	0.077	0.973	0.035
SHC_RT_Taste	0.659	0.007	0.073	0.976	0.057
SHF_RT_Taste	0.620	0.006	0.059	0.973	0.037
SHP_RT_Taste	0.618	0.006	0.062	0.979	0.096
Sweet_ACC_Taste	90.392	0.800	8.078	0.859	< .001
Not_Sweet_ACC_Taste	93.546	0.694	7.011	0.774	< .001
SAHC_ACC_Taste	94.020	0.845	8.532	0.633	< .001
SAHP_ACC_Taste	94.216	1.021	10.311	0.577	< .001
SAHF_ACC_Taste	92.402	1.061	10.711	0.711	< .001
SHC_ACC_Taste	81.618	1.715	17.323	0.877	< .001
SHF_ACC_Taste	94.118	0.764	7.721	0.726	< .001
SHP_ACC_Taste	95.441	0.919	9.284	0.472	< .001

Appendix A2. Descriptive statistics and Shapiro-wilk rest results for Taste Task responses

Descriptive Statistics

	Mean	Std. Error of Mean	Std. Deviation	Shapiro-Wilk	P-value of Shapiro-Wilk
Sweet_Like%	71.176	1.935	19.546	0.949	< .001
Not_Sweet_Like%	61.765	1.823	18.409	0.986	0.339
SAHC_Like%	57.745	2.323	23.459	0.974	0.038
SAHP_Like%	70.245	2.455	24.790	0.903	< .001
SAHF_Like%	57.304	2.661	26.872	0.964	0.007
SHC_Like%	72.255	1.849	18.677	0.957	0.002
SHF_Like%	75.882	2.313	23.361	0.874	< .001
SHP_Like%	65.392	2.995	30.252	0.900	< .001
Sweet_NotLike%	28.824	1.935	19.546	0.949	< .001
Not_Sweet_NotLike%	38.235	1.823	18.409	0.986	0.339
SAHC_NotLike%	42.255	2.323	23.459	0.974	0.038
SAHP_NotLike%	29.755	2.455	24.790	0.903	< .001
SAHF_NotLike%	42.696	2.661	26.872	0.964	0.007
SHC_NotLike%	27.745	1.849	18.677	0.957	0.002
SHF_NotLike%	24.118	2.313	23.361	0.874	< .001
SHP_NotLike%	34.608	2.995	30.252	0.900	< .001
Sweet_Like_RT	0.637	0.009	0.093	0.971	0.025
Not_Sweet_Like_RT	0.671	0.009	0.091	0.962	0.005
SAHC_Like_RT	0.678	0.011	0.111	0.970	0.019
SAHP_Like_RT	0.664	0.009	0.087	0.986	0.396
SAHF_Like_RT	0.669	0.011	0.114	0.979	0.110
SHC_Like_RT	0.640	0.008	0.081	0.984	0.257
SHF_Like_RT	0.620	0.010	0.098	0.971	0.023
SHP_Like_RT	0.651	0.013	0.127	0.904	< .001
Sweet_NotLike_RT	0.751	0.011	0.107	0.960	0.004
Not_Sweet_NotLike_RT	0.721	0.009	0.095	0.991	0.739
SAHC_NotLike_RT	0.717	0.012	0.117	0.948	< .001
SAHP_NotLike_RT	0.724	0.013	0.126	0.916	< .001
SAHF_NotLike_RT	0.714	0.011	0.110	0.983	0.243
SHC_NotLike_RT	0.731	0.012	0.116	0.969	0.023
SHF_NotLike_RT	0.748	0.014	0.129	0.955	0.007
SHP_NotLike_RT	0.757	0.013	0.125	0.941	< .001

Appendix A3. Descriptive statistics and Shapiro-wilk test results for Like Task responses

Descriptive Statistics

	Mean	Std. Error of Mean	Std. Deviation	Shapiro-Wilk	P-value of Shapiro-Wilk
Sweet_Want%	56.127	1.657	16.738	0.977	0.070
Not_Sweet_Want%	39.493	2.124	21.449	0.985	0.303
SAHC_Want%	33.529	2.404	24.278	0.949	< .001
SAHP_Want%	50.882	3.136	31.673	0.935	< .001
SAHF_Want%	34.069	2.605	26.305	0.935	< .001
SHC_Want%	50.343	2.158	21.792	0.969	0.017
SHF_Want%	52.549	3.006	30.359	0.939	< .001
SHP_Want%	65.490	3.160	31.915	0.885	< .001
Sweet_NotWant%	55.278	2.388	24.116	0.957	0.002
Not_Sweet_NotWant%	60.507	2.124	21.449	0.985	0.303
SAHC_NotWant%	66.471	2.404	24.278	0.949	< .001
SAHP_NotWant%	49.118	3.136	31.673	0.935	< .001
SAHF_NotWant%	65.931	2.605	26.305	0.935	< .001
SHC_NotWant%	49.657	2.158	21.792	0.969	0.017
SHF_NotWant%	51.667	3.012	30.421	0.940	< .001
SHP_NotWant%	64.510	3.206	32.377	0.888	< .001
Sweet_Want_RT	0.677	0.009	0.089	0.994	0.946
Not_Sweet_Want_RT	0.665	0.009	0.087	0.980	0.120
SAHC_Want_RT	0.673	0.010	0.099	0.982	0.180
SAHP_Want_RT	0.688	0.011	0.111	0.985	0.323
SAHF_Want_RT	0.653	0.010	0.097	0.980	0.133
SHC_Want_RT	0.676	0.010	0.106	0.990	0.669
SHF_Want_RT	0.686	0.011	0.112	0.977	0.077
SHP_Want_RT	0.676	0.010	0.100	0.988	0.515
Sweet_NotWant_RT	0.680	0.009	0.091	0.993	0.871
Not_Sweet_NotWant_RT	0.687	0.008	0.083	0.986	0.362
SAHC_NotWant_RT	0.718	0.011	0.108	0.982	0.244
SAHP_NotWant_RT	0.704	0.013	0.125	0.898	< .001
SAHF_NotWant_RT	0.650	0.010	0.095	0.979	0.127
SHC_NotWant_RT	0.677	0.010	0.105	0.990	0.628
SHF_NotWant_RT	0.685	0.012	0.113	0.977	0.092
SHP_NotWant_RT	0.674	0.010	0.102	0.987	0.456

Appendix A4. Descriptive statistics and Shapiro-wilk test results for Want Task responses

	Taste-ACC-Sweet	Taste_ACC-Not sweet
N	102	102
Missing	0	0
Mean	90.4	93.5
95% CI mean lower bound	88.8	92.2
95% CI mean upper bound	92.0	94.9
Median	93.3	95.0
Standard deviation	8.08	7.01
Minimum	51.7	63.3
Maximum	100	100
Shapiro-Wilk W	0.859	0.774
Shapiro-Wilk p	< .001	< .001

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the proportion of accurate responses for sweet and non-sweet foods.

Appendix B. *Descriptive statistics for accuracy of sweet and not-sweet foods*

	Taste_ACC-SAHC	Taste_ACC-SAHP	Taste_ACC-SAHF	Taste_ACC-SHC	Taste_ACC-SHF	Taste_ACC-SHP
N	102	102	102	102	102	102
Missing	0	0	0	0	0	0
Mean	94.0	94.2	92.4	81.6	94.1	95.4
95% CI mean lower bound	92.3	92.2	90.3	78.2	92.6	93.6
95% CI mean upper bound	95.7	96.2	94.5	85.0	95.6	97.3
Median	95.0	95.0	95.0	85.0	95.0	100
Standard deviation	8.53	10.3	10.7	17.3	7.72	9.28
Minimum	35	30	45	30	60	20
Maximum	100	100	100	100	100	100
Shapiro-Wilk W	0.633	0.577	0.711	0.877	0.726	0.472
Shapiro-Wilk p	< .001	< .001	< .001	< .001	< .001	< .001

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the average proportion of accurate responses across all food subgroups: non-sweet high carbohydrate (SAHC), non-sweet high fat (SAHF), non-sweet high protein (SAHP), sweet high carbohydrate (SHC), sweet high fat (SHF) and sweet high protein (SHP).

Appendix C. Descriptive statistics for taste trial accuracy across food subgroups

	Taste-RT-Sweet	Taste-RT-Not_sweet
N	102	102
Missing	0	0
Mean	0.630	0.650
95% CI mean lower bound	0.619	0.637
95% CI mean upper bound	0.642	0.662
Median	0.621	0.645
Standard deviation	0.0577	0.0645
Minimum	0.499	0.520
Maximum	0.791	0.839
Shapiro-Wilk W	0.982	0.980
Shapiro-Wilk p	0.191	0.116

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the response-time for correctly categorized sweet and non-sweet foods

Appendix D. Descriptive statistics for taste-task response time

	Taste-RT-SAHC	Taste-RT-SAHP	Taste-RT-SAHF	Taste-RT-SHC	Taste-RT-SHF	Taste-RT-SHP
N	102	102	102	102	102	102
Missing	0	0	0	0	0	0
Mean	0.650	0.648	0.654	0.659	0.620	0.618
95% CI mean lower bound	0.636	0.634	0.639	0.645	0.608	0.605
95% CI mean upper bound	0.664	0.661	0.669	0.673	0.631	0.630
Median	0.640	0.645	0.642	0.652	0.612	0.609
Standard deviation	0.0705	0.0671	0.0765	0.0728	0.0589	0.0623
Minimum	0.505	0.516	0.510	0.518	0.514	0.465
Maximum	0.878	0.940	0.853	0.934	0.792	0.814
Shapiro-Wilk W	0.975	0.940	0.973	0.976	0.973	0.979
Shapiro-Wilk p	0.047	< .001	0.035	0.057	0.037	0.096

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the response-time for correctly categorized sweet and non-sweet foods across the six food subgroups: non-sweet high carbohydrate (SAHC), non-sweet high fat (SAHF), non-sweet high protein (SAHP), sweet high carbohydrate (SHC), sweet high fat (SHF) and sweet high protein (SHP).

Appendix E. Descriptive statistics for response-time across food subgroups

	Like_Prop_Sweet	Like_Prop_Not_Sweet	NL_Prop_Sweet	NL_Prop_Not_Sweet
N	102	102	102	102
Missing	0	0	0	0
Mean	71.2	61.8	28.8	38.2
95% CI mean lower bound	67.3	58.1	25.0	34.6
95% CI mean upper bound	75.0	65.4	32.7	41.9
Median	75.0	62.5	25.0	37.5
Standard deviation	19.5	18.4	19.5	18.4
Minimum	16.7	16.7	0.00	0.00
Maximum	100	100	83.3	83.3
Shapiro-Wilk W	0.949	0.986	0.949	0.986
Shapiro-Wilk p	< .001	0.339	< .001	0.339

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the proportion of liked and not-liked participant responses for sweet and non-sweet food stimuli.

Appendix F. Desriptive statistics for the proportion of liked and not-liked responses for sweet and non-sweet foods

	Like%_ SAHC	Like%_ SAHP	Like%_ SAHF	Like%_ SHC	Like%_ SHF	Like%_ SHP
N	102	102	102	102	102	102
Missing	0	0	0	0	0	0
Mean	57.7	70.2	57.3	72.3	75.9	65.4
95% CI mean lower bound	53.1	65.4	52.0	68.6	71.3	59.5
95% CI mean upper bound	62.4	75.1	62.6	75.9	80.5	71.3
Median	57.5	80.0	55.0	75.0	80.0	75.0
Standard deviation	23.5	24.8	26.9	18.7	23.4	30.3
Minimum	5	0	0	15	0	0
Maximum	100	100	100	100	100	100
Shapiro-Wilk W	0.974	0.903	0.964	0.957	0.874	0.900
Shapiro-Wilk p	0.038	< .001	0.007	0.002	< .001	< .001

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the proportion of liked participant responses across the different food subgroups.

*Like and not-liked tables have been separated for readability.

Appendix G. Descriptive statistics for the proportion of liked responses across food subgroups

	NTLike%_SAHC	NTLike%_SAHP	NTLike%_SAHF	NTLike%_SHC	NTLike%_SHF	NTLike%_SHP
N	102	102	102	102	102	102
Missing	0	0	0	0	0	0
Mean	42.3	29.8	42.7	27.7	24.1	34.6
95% CI mean lower bound	37.6	24.9	37.4	24.1	19.5	28.7
95% CI mean upper bound	46.9	34.6	48.0	31.4	28.7	40.5
Median	42.5	20.0	45.0	25.0	20.0	25.0
Standard deviation	23.5	24.8	26.9	18.7	23.4	30.3
Minimum	0	0	0	0	0	0
Maximum	95	100	100	85	100	100
Shapiro-Wilk W	0.974	0.903	0.964	0.957	0.874	0.900
Shapiro-Wilk p	0.038	< .001	0.007	0.002	< .001	< .001

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the proportion of not-liked participant responses across the different food subgroups.

*Like and not-liked tables have been separated for readability.

Appendix H. Descriptive statistics for the proportion of not-liked responses across food subgroups

	Like_RT_Sweet	Like_RT_Not-Sweet	NTLike_RT_Sweet	NTLike_RT_Not-Sweet
N	102	102	100	101
Missing	0	0	2	1
Mean	0.637	0.671	0.750	0.721
Std. error mean	0.00922	0.00898	0.0107	0.00948
Median	0.628	0.676	0.743	0.721
Standard deviation	0.0931	0.0907	0.107	0.0953
Minimum	0.309	0.304	0.472	0.443
Maximum	0.963	0.852	1.11	0.994
Shapiro-Wilk W	0.971	0.962	0.956	0.991
Shapiro-Wilk p	0.025	0.005	0.002	0.739

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the average response time for liked and not-liked responses for sweet and not-sweet foods.

Appendix I. Descriptive statistics for the response time of liked and not-liked foods by sweetness.

	Like_RT_ SAHC	Like_RT_ SAHP	Like_RT_ SAHF	Like_RT_ SHC	Like_RT_ SHF	Like_RT_ SHP
N	102	101	102	102	102	102
Missing	0	1	0	0	0	0
Mean	0.678	0.664	0.669	0.640	0.620	0.651
95% CI mean lower bound	0.657	0.647	0.647	0.624	0.601	0.626
95% CI mean upper bound	0.700	0.682	0.692	0.656	0.639	0.676
Median	0.686	0.662	0.659	0.640	0.612	0.636
Standard deviation	0.111	0.0872	0.114	0.0814	0.0976	0.127
Minimum	0.282	0.370	0.259	0.342	0.316	0.269
Maximum	0.979	0.882	1.06	0.827	0.998	1.23
Shapiro-Wilk W	0.970	0.986	0.979	0.984	0.971	0.904
Shapiro-Wilk p	0.019	0.396	0.110	0.257	0.023	< .001

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the average response time for liked responses across the different food subgroups.
*Like and not-liked tables have been separated for readability.

Appendix J. Descriptive statistics for the response time of liked foods across food subgroups

	NL_RT_SAHC	NL_RT_SAHP	NL_RT_SAHF	NL_RT_SHC	NL_RT_SHF	NL_RT_SHP
N	100	94	94	94	80	85
Missing	2	8	8	8	22	17
Mean	0.717	0.724	0.714	0.731	0.748	0.755
Std. error mean	0.0117	0.0129	0.0113	0.0120	0.0145	0.0135
Median	0.711	0.714	0.718	0.725	0.745	0.743
Standard deviation	0.117	0.126	0.110	0.116	0.129	0.124
Minimum	0.439	0.448	0.443	0.482	0.419	0.514
Maximum	1.20	1.37	1.07	1.19	1.15	1.24
Shapiro-Wilk W	0.948	0.916	0.983	0.969	0.955	0.936
Shapiro-Wilk p	< .001	< .001	0.243	0.023	0.007	< .001

Note. The CI of the mean assumes sample means follow a t-distribution with N - 1 degrees of freedom

Note. **This table displays the descriptive statistics, standard deviation, 95% confidence intervals and Shapiro-Wilk test results for the average response time for liked responses across the different food subgroups.**
***Like and not-liked tables have been separated for readability.**

Appendix K. Descriptive statistics for the response time of not-liked foods across food subgroups

	Sweet Want%	Not_Sweet_ Want%	SAHC_ Want%	SAHP_ Want%	SAHF_ Want%	SHC_ Want%	SHF_ Want%	SHP_ Want%
N	102	102	102	102	102	102	102	102
Missing	0	0	0	0	0	0	0	0
Mean	55.3	60.5	33.5	50.9	34.1	50.3	52.5	65.5
Std. error mean	2.39	2.12	2.40	3.14	2.60	2.16	3.01	3.16
Median	54.2	60.8	35.0	50.0	30.0	50.0	55.0	72.5
Standard deviation	24.1	21.4	24.3	31.7	26.3	21.8	30.4	31.9
Minimum	10.0	5.00	0	0	0	10	0	0
Maximum	95.0	100	90	100	100	95	100	100

Appendix L. Descriptive statistics for wanting proportions for sweet/not sweet and food subcategories

Pearson's Correlations

Variable		RED_Lack_Control	RED_Food_Preoccupation	RED_Lack_Satiety	RED_Total	Sweet_ACC_Taste	Not_Sweet_ACC_Taste	SAHC_ACC_Taste	SAHP_ACC_Taste	SAHF_ACC_Taste	SHC_ACC_Taste	SHF_ACC_Taste	SHP_ACC_Taste
1. RED_Lack_Control	Pearson's r	—											
	p-value	—											
2. RED_Food_Preoccupation	Pearson's r	0.381	—										
	p-value	< .001	—										
3. RED_Lack_Satiety	Pearson's r	0.278	0.271	—									
	p-value	0.005	0.006	—									
4. RED_Total	Pearson's r	0.837	0.655	0.684	—								
	p-value	< .001	< .001	< .001	—								
5. Sweet_ACC_Taste	Pearson's r	0.154	0.148	−0.085	0.038	—							
	p-value	0.122	0.138	0.394	0.706	—							
6. Not_Sweet_ACC_Taste	Pearson's r	0.041	−0.020	0.136	0.125	0.079	—						
	p-value	0.682	0.844	0.174	0.211	0.428	—						
7. SAHC_ACC_Taste	Pearson's r	0.030	0.130	0.101	−0.042	0.420	0.733	—					
	p-value	0.762	0.192	0.311	0.672	< .001	< .001	—					
8. SAHP_ACC_Taste	Pearson's r	−0.026	−0.122	0.172	−0.156	0.123	0.704	0.351	—				
	p-value	0.797	0.223	0.083	0.118	0.220	< .001	< .001	—				
9. SAHF_ACC_Taste	Pearson's r	0.081	0.181	0.054	3.885×10^{-4}	0.253	0.702	0.305	0.596	—			
	p-value	0.417	0.068	0.592	0.997	0.010	< .001	0.002	< .001	—			
10. SHC_ACC_Taste	Pearson's r	0.181	0.101	0.038	0.156	0.833	0.131	0.106	−0.023	0.195	—		
	p-value	0.068	0.311	0.706	0.117	< .001	0.189	0.288	0.816	0.050	—		
11. SHF_ACC_Taste	Pearson's r	−0.085	0.172	0.125	0.056	0.515	0.302	0.363	0.240	0.074	0.118	—	
	p-value	0.394	0.083	0.211	0.573	< .001	0.002	< .001	0.015	0.461	0.237	—	
12. SHP_ACC_Taste	Pearson's r	0.136	0.054	−0.042	0.079	0.627	0.442	0.596	0.164	0.236	0.211	0.292	—
	p-value	0.174	0.592	0.672	0.428	< .001	< .001	< .001	0.100	0.017	0.033	0.003	—

Appendix M. Pearson's correlation output table for RED-13 scores and accuracy in the taste task.

Please mark the following scales according to how you feel RIGHT NOW. Please answer each question independently and as accurately as possible.

1. How hungry are you?

Not at all ____ Extremely

2. How thirsty are you?

Not at all ____ Extremely

3. How strong is your desire to eat

Not at all ____ Extremely

4. How strong is your desire to drink?

Not at all ____ Extremely

Please rate: how strong is your desire to eat each of the following foods right now, on a scale of 0-6 where 0 refers to no desire at all, and 6 refers to a very high desire.

Please think about the food as an individual item – do not combine the food with others or think of the food as part of a meal.

1. Bacon	0	1	2	3	4	5	6
2. Baked potato	0	1	2	3	4	5	6
3. Banana	0	1	2	3	4	5	6
4. Bbq chicken	0	1	2	3	4	5	6
5. Bread roll	0	1	2	3	4	5	6
6. Carrot	0	1	2	3	4	5	6
7. Cheese biscuits	0	1	2	3	4	5	6
8. Cheese sandwich biscuits	0	1	2	3	4	5	6
9. Cheesecake	0	1	2	3	4	5	6
10. Chips	0	1	2	3	4	5	6
11. Chocolate chip cookies	0	1	2	3	4	5	6
12. Chocolate fingers	0	1	2	3	4	5	6
13. Chocolate milkshake	0	1	2	3	4	5	6
14. Custard	0	1	2	3	4	5	6
15. Digestive biscuits	0	1	2	3	4	5	6
16. Doughnut	0	1	2	3	4	5	6
17. Flapjack	0	1	2	3	4	5	6
18. Fried bread	0	1	2	3	4	5	6
19. Fromage frais	0	1	2	3	4	5	6
20. Fruit pie	0	1	2	3	4	5	6
21. Fruit yoghurt	0	1	2	3	4	5	6
22. Fudge cake	0	1	2	3	4	5	6
23. Garlic bread	0	1	2	3	4	5	6
24. Green salad	0	1	2	3	4	5	6
25. Honey	0	1	2	3	4	5	6
26. Honeydew melon	0	1	2	3	4	5	6
27. Jelly babies	0	1	2	3	4	5	6
28. Kebab	0	1	2	3	4	5	6
29. Marshmallows	0	1	2	3	4	5	6
30. Mashed potato	0	1	2	3	4	5	6
31. Meat curry	0	1	2	3	4	5	6
32. Milk chocolate	0	1	2	3	4	5	6
33. Muffin	0	1	2	3	4	5	6
34. Orange	0	1	2	3	4	5	6

35. Pizza	0	1	2	3	4	5	6
36. Plain crackers	0	1	2	3	4	5	6
37. Plain omelette	0	1	2	3	4	5	6
38. Plain crisps	0	1	2	3	4	5	6
39. Pringles	0	1	2	3	4	5	6
40. Profiteroles	0	1	2	3	4	5	6
41. Rice pudding	0	1	2	3	4	5	6
42. Salted nuts	0	1	2	3	4	5	6
43. Salted popcorn	0	1	2	3	4	5	6
44. Sausages	0	1	2	3	4	5	6
45. Savoury biscuits	0	1	2	3	4	5	6
46. Smoked salmon	0	1	2	3	4	5	6
47. Steak	0	1	2	3	4	5	6
48. Strawberry blancmange	0	1	2	3	4	5	6
49. Sushi	0	1	2	3	4	5	6
50. Sweet pancakes	0	1	2	3	4	5	6
51. Tiramisu	0	1	2	3	4	5	6
52. Toffee popcorn	0	1	2	3	4	5	6
53. Tomato	0	1	2	3	4	5	6
54. Twiglets	0	1	2	3	4	5	6
55. Tuna	0	1	2	3	4	5	6
56. Vanilla ice cream	0	1	2	3	4	5	6
57. Vanilla mousse	0	1	2	3	4	5	6
58. Vegetable curry	0	1	2	3	4	5	6
59. White chocolate	0	1	2	3	4	5	6
60. Yorkshire pudding	0	1	2	3	4	5	6

Appendix N. Food Preference Questionnaire (FPQ)

The Reward Based Eating Drive (RED) Scale

DIRECTIONS: Please read every question and indicate how much you agree or disagree.	
0 Strongly Disagree; 1 Disagree; 2 Neither Agree nor Disagree; 3 Agree; 4 Strongly Agree	
1. I feel out of control in the presence of delicious food	0 1 2 3 4
2. When I start eating, I just can't seem to stop	0 1 2 3 4
3. It is difficult for me to leave food on my plate	0 1 2 3 4
4. When it comes to foods I love, I have no willpower	0 1 2 3 4
5. I get so hungry that my stomach often seems like a bottomless pit	0 1 2 3 4
6. I don't get full easily	0 1 2 3 4
7. It seems like most of my waking hours are preoccupied by thoughts about eating or not eating	0 1 2 3 4
8. I have days when I can't seem to think about anything else but food	0 1 2 3 4
9. Food is always on my mind	0 1 2 3 4
10. I feel hungry all the time	0 1 2 3 4
11. I can't stop thinking about eating no matter how hard I try	0 1 2 3 4
12. I find myself continuing to consume certain foods even though I am no longer hungry	0 1 2 3 4
13. If food tastes good to me, I eat more than usual	0 1 2 3 4

Appendix O. Thirteen-Point Reward Based Eating Drive Scale (RED-13)

Appetite Questionnaire (EMAQ)

Please tell us first how your eating behavior is affected by certain emotional states and situations by **circling** a number on the scale below. The scale ranges from 1 to 9, where 1 represents much less food intake than usual, 9 much more than usual, and 5 the same as usual. If the specific question does not apply, please circle NA. If you don't know the answer, please circle DK.

The following refer to EMOTIONS

As compared to usual, do you eat:		**Much less**				**The same**				**Much more**		
When you are:	Sad	1	2	3	4	5	6	7	8	9	NA	DK
	Bored	1	2	3	4	5	6	7	8	9	NA	DK
	Confident	1	2	3	4	5	6	7	8	9	NA	DK
	Angry	1	2	3	4	5	6	7	8	9	NA	DK
	Anxious	1	2	3	4	5	6	7	8	9	NA	DK
	Happy	1	2	3	4	5	6	7	8	9	NA	DK
	Frustrated	1	2	3	4	5	6	7	8	9	NA	DK
	Tired	1	2	3	4	5	6	7	8	9	NA	DK
	Depressed	1	2	3	4	5	6	7	8	9	NA	DK
	Frightened	1	2	3	4	5	6	7	8	9	NA	DK
	Relaxed	1	2	3	4	5	6	7	8	9	NA	DK
	Playful	1	2	3	4	5	6	7	8	9	NA	DK
	Lonely	1	2	3	4	5	6	7	8	9	NA	DK
	Enthusiastic	1	2	3	4	5	6	7	8	9	NA	DK

The following refer to SITUATIONS

As compared to usual, do you eat:	**Much less**				**The same**				**Much more**		
When under pressure	1	2	3	4	5	6	7	8	9	NA	DK
After a heated argument	1	2	3	4	5	6	7	8	9	NA	DK
After a tragedy of someone close to you	1	2	3	4	5	6	7	8	9	NA	DK
When falling in love	1	2	3	4	5	6	7	8	9	NA	DK
After ending a relationship	1	2	3	4	5	6	7	8	9	NA	DK
When engaged in an enjoyable hobby	1	2	3	4	5	6	7	8	9	NA	DK
After losing money or property	1	2	3	4	5	6	7	8	9	NA	DK
After receiving good news	1	2	3	4	5	6	7	8	9	NA	DK

Appendix P. Emotional Appetite Questionnaire (EMAQ)

	FPQ_Sweet	FPQ_Not_Sweet	FPQ_SHC	FPQ_SHF	FPQ_SHP	FPQ_SAHC	FPQ_SAHF	FPQ_SAHP	Sweet_ACC_Taste	Not_Sweet_ACC_Taste	SAHC_ACC_Taste	SAHP_ACC_Taste	SAHF_ACC_Taste	SHC_ACC_Taste	SHF_ACC_Taste	SHP_ACC_Taste
Valid	102	102	102	102	102	102	102	102	102	102	102	102	102	102	102	102
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	1.690	1.568	1.590	1.915	1.565	1.412	1.377	1.916	90.392	93.546	94.020	94.216	92.402	81.618	94.118	95.441
Std. Error of Mean	0.097	0.093	0.090	0.132	0.114	0.092	0.120	0.118	0.800	0.694	0.845	1.021	1.061	1.715	0.764	0.919
Std. Deviation	0.977	0.937	0.913	1.334	1.151	0.928	1.209	1.192	8.078	7.011	8.532	10.311	10.711	17.323	7.721	9.284
Shapiro-Wilk	0.976	0.962	0.972	0.959	0.945	0.963	0.906	0.971	0.859	0.774	0.633	0.577	0.711	0.877	0.726	0.472
P-value of Shapiro-Wilk	0.064	0.005	0.029	0.003	< .001	0.006	< .001	0.023	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
Minimum	0.048	0.095	0.000	0.000	0.000	0.000	0.000	0.000	51.667	63.333	35.000	30.000	45.000	30.000	60.000	20.000
Maximum	4.667	4.429	4.143	5.167	5.333	4.429	5.000	5.143	100.000	100.000	100.000	100.000	100.000	100.000	100.000	100.000

Appendix Q. Descriptive statistics of food preference questionnaire responses and taste task accuracy proportion (%)

Variable		FPQ_Sweet	FPQ_Not_Sweet	FPQ_SHC	FPQ_SHF	FPQ_SHP	FPQ_SAHC	FPQ_SAHF	FPQ_SAHP	Sweet_ACC_Taste	Not_Sweet_ACC_Taste	SAHC_ACC_Taste	SAHP_ACC_Taste	SAHF_ACC_Taste	SHC_ACC_Taste	SHF_ACC_Taste	SHP_ACC_Taste
1. FPQ_Sweet	Pearson's r	—															
	p-value	—															
2. FPQ_Not_Sweet	Pearson's r	0.645***	—														
	p-value	< .001	—														
3. FPQ_SHC	Pearson's r	0.794***	0.464***	—													
	p-value	< .001	< .001	—													
4. FPQ_SHF	Pearson's r	0.896***	0.608***	0.180	—												
	p-value	< .001	< .001	0.070	—												
5. FPQ_SHP	Pearson's r	0.877***	0.567***	0.073	0.021	—											
	p-value	< .001	< .001	0.466	0.831	—											
6. FPQ_SAHC	Pearson's r	0.583***	0.823***	0.145	0.141	0.132	—										
	p-value	< .001	< .001	0.146	0.156	0.187	—										
7. FPQ_SAHF	Pearson's r	0.462***	0.597***	0.007	0.089	0.853***	0.030	—									
	p-value	< .001	< .001	0.946	0.373	< .001	0.768	—									
8. FPQ_SAHP	Pearson's r	0.597***	0.853***	0.418***	0.492***	0.617***	0.581***	0.551***	—								
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—								
9. Sweet_ACC_Taste	Pearson's r	0.180	0.030	0.196*	0.090	0.198*	−0.139	0.048	0.130	—							
	p-value	0.070	0.768	0.048	0.369	0.046	0.163	0.635	0.194	—							
10. Not_Sweet_ACC_Taste	Pearson's r	0.073	0.047	-6.099×10^{-4}	0.032	0.149	−0.077	0.071	0.098	0.359***	—						
	p-value	0.466	0.639	0.995	0.750	0.134	0.444	0.478	0.325	< .001	—						
11. SAHC_ACC_Taste	Pearson's r	0.145	0.072	0.120	0.092	0.167	−0.013	0.100	0.078	0.420***	0.733***	—					
	p-value	0.146	0.472	0.229	0.358	0.093	0.898	0.317	0.436	< .001	< .001	—					
12. SAHP_ACC_Taste	Pearson's r	0.007	0.051	−0.089	0.013	0.072	0.024	0.055	0.045	0.123	0.704***	0.351***	—				
	p-value	0.946	0.613	0.376	0.896	0.470	0.807	0.583	0.656	0.220	< .001	< .001	—				
13. SAHF_ACC_Taste	Pearson's r	0.021	−0.014	−0.012	−0.023	0.090	−0.164	0.007	0.088	0.253*	0.702***	0.305**	0.141	—			
	p-value	0.831	0.889	0.907	0.818	0.366	0.100	0.947	0.379	0.010	< .001	0.002	0.159	—			
14. SHC_ACC_Taste	Pearson's r	0.141	−0.007	0.231*	0.045	0.125	−0.146	0.017	0.080	0.833***	0.131	0.106	−0.023	0.195*	—		
	p-value	0.156	0.945	0.019	0.657	0.212	0.144	0.868	0.422	< .001	0.189	0.288	0.816	0.050	—		
15. SHF_ACC_Taste	Pearson's r	0.089	0.034	−0.067	0.122	0.139	−0.022	−0.045	0.143	0.515***	0.302**	0.363***	0.240*	0.074	0.118	—	
	p-value	0.373	0.733	0.504	0.223	0.164	0.828	0.654	0.151	< .001	0.002	< .001	0.015	0.461	0.237	—	
16. SHP_ACC_Taste	Pearson's r	0.132	0.061	0.137	0.050	0.169	−0.073	0.131	0.069	0.627***	0.442***	0.596***	0.164	0.236*	0.211*	0.292**	—
	p-value	0.187	0.540	0.171	0.615	0.090	0.466	0.191	0.489	< .001	< .001	< .001	0.100	0.017	0.033	0.003	—

* p < .05, ** p < .01, *** p < .001

Appendix R. Pearsons's correlation matrix of the relationship between food preference questionnaire responses and taste task accuracy proportion (%)

	FPQ_Sweet	FPQ_Not_Sweet	FPQ_SHC	FPQ_SHF	FPQ_SHP	FPQ_SAHC	FPQ_SAHF	FPQ_SAHP	Sweet_RT	Not_Sweet_RT	SAHC_RT_Taste	SAHP_RT_Taste	SAHF_RT_Taste	SHC_RT_Taste	SHF_RT_Taste	SHP_RT_Taste
Valid	102	102	102	102	102	102	102	102	102	102	102	102	102	102	102	102
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	1.690	1.568	1.590	1.915	1.565	1.412	1.377	1.916	0.630	0.650	0.650	0.648	0.654	0.659	0.620	0.618
Std. Error of Mean	0.097	0.093	0.090	0.132	0.114	0.092	0.120	0.118	0.006	0.006	0.007	0.007	0.008	0.007	0.006	0.006
Std. Deviation	0.977	0.937	0.913	1.334	1.151	0.928	1.209	1.192	0.058	0.065	0.071	0.067	0.077	0.073	0.059	0.062
Shapiro-Wilk	0.976	0.962	0.972	0.959	0.945	0.963	0.906	0.971	0.982	0.980	0.975	0.940	0.973	0.976	0.973	0.979
P-value of Shapiro-Wilk	0.064	0.005	0.029	0.003	< .001	0.006	< .001	0.023	0.191	0.116	0.047	< .001	0.035	0.057	0.037	0.096
Minimum	0.048	0.095	0.000	0.000	0.000	0.000	0.000	0.000	0.499	0.520	0.505	0.516	0.510	0.518	0.514	0.465
Maximum	4.667	4.429	4.143	5.167	5.333	4.429	5.000	5.143	0.791	0.839	0.878	0.940	0.853	0.934	0.792	0.814

Appendix S. Descriptive statistics of food preference questionnaire responses and taste task response time (msec)

Variable		FPQ_Sweet	FPQ_Not_Sweet	FPQ_SHC	FPQ_SHF	FPQ_SHP	FPQ_SAHC	FPQ_SAHF	FPQ_SAHP	Sweet_RT	Not_Sweet_RT	SAHC_RT_Taste	SAHP_RT_Taste	SAHF_RT_Taste	SHC_RT_Taste	SHF_RT_Taste	SHP_RT_Taste
1. FPQ_Sweet	Pearson's r	—															
	p-value	—															
2. FPQ_Not_Sweet	Pearson's r	0.645***	—														
	p-value	< .001	—														
3. FPQ_SHC	Pearson's r	0.794***	0.464***	—													
	p-value	< .001	< .001	—													
4. FPQ_SHF	Pearson's r	0.896***	0.608***	0.565***	—												
	p-value	< .001	< .001	< .001	—												
5. FPQ_SHP	Pearson's r	0.877***	0.567***	0.572***	0.671***	—											
	p-value	< .001	< .001	< .001	< .001	—											
6. FPQ_SAHC	Pearson's r	0.583***	0.823***	0.464***	0.553***	0.476***	—										
	p-value	< .001	< .001	< .001	< .001	< .001	—										
7. FPQ_SAHF	Pearson's r	0.462***	0.853***	0.312**	0.505***	0.344***	0.572***	—									
	p-value	< .001	< .001	0.001	< .001	< .001	< .001	—									
8. FPQ_SAHP	Pearson's r	0.597***	0.853***	0.418***	0.492***	0.617***	0.581***	0.551***	—								
	p-value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—								
9. Sweet_RT	Pearson's r	−0.042	−0.108	−0.064	−0.008	−0.046	0.019	−0.170	−0.097	—							
	p-value	0.678	0.281	0.523	0.937	0.646	0.849	0.087	0.334	—							
10. Not_Sweet_RT	Pearson's r	0.075	−0.014	0.058	0.090	0.040	0.131	−0.104	−0.030	0.800***	—						
	p-value	0.453	0.886	0.562	0.366	0.688	0.189	0.297	0.765	< .001	—						
11. SAHC_RT_Taste	Pearson's r	0.088	0.006	0.077	0.091	0.059	0.154	−0.115	0.011	0.756***	0.939***	—					
	p-value	0.377	0.951	0.442	0.363	0.559	0.121	0.250	0.913	< .001	< .001	—					
12. SAHP_RT_Taste	Pearson's r	0.019	−0.092	0.021	0.037	−0.012	0.071	−0.146	−0.124	0.745***	0.912***	0.811***	—				
	p-value	0.853	0.359	0.834	0.712	0.903	0.478	0.144	0.215	< .001	< .001	< .001	—				
13. SAHF_RT_Taste	Pearson's r	0.084	0.022	0.051	0.113	0.042	0.132	−0.054	0.003	0.704***	0.922***	0.806***	0.739***	—			
	p-value	0.403	0.828	0.610	0.259	0.678	0.187	0.591	0.974	< .001	< .001	< .001	< .001	—			
14. SHC_RT_Taste	Pearson's r	0.010	−0.112	−0.033	0.005	0.046	0.041	−0.197*	−0.097	0.869***	0.761***	0.696***	0.730***	0.675***	—		
	p-value	0.920	0.260	0.745	0.963	0.645	0.685	0.047	0.334	< .001	< .001	< .001	< .001	< .001	—		
15. SHF_RT_Taste	Pearson's r	−0.045	−0.045	−0.023	−0.025	−0.067	0.054	−0.100	−0.047	0.920***	0.737***	0.705***	0.653***	0.665***	0.689***	—	
	p-value	0.653	0.653	0.819	0.802	0.502	0.590	0.317	0.639	< .001	< .001	< .001	< .001	< .001	< .001	—	
16. SHP_RT_Taste	Pearson's r	−0.090	−0.119	−0.141	−0.010	−0.104	−0.012	−0.156	−0.114	0.922***	0.702***	0.671***	0.662***	0.606***	0.689***	0.809***	—
	p-value	0.371	0.232	0.157	0.917	0.300	0.905	0.117	0.254	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—

* p < .05, ** p < .01, *** p < .001

Appendix T. Pearsons's correlation matrix of the relationship between food preference questionnaire responses and taste task response time (msec)

7. Exploratory Analyses

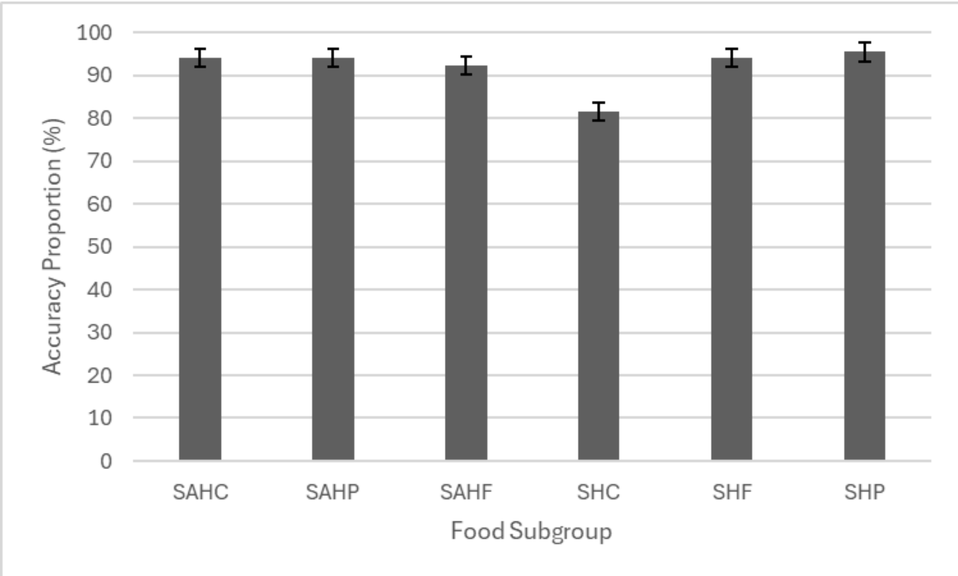
7.1 Taste Task additional analyses

7.1.1 Accuracy of correct categorizations by subgroup

A generalized mixed model (GMM) with a Binomial distribution with a logit link function was employed to test the impact of taste on accuracy at the group level. We tested a GMM with one fixed effect (Food Group) and a random effect of Participant. A fixed effect of food group was identified ($\chi^2 = 350$, df = 5.0, p <.001). The random effect of Participant indicated that 15% of the variability found in the data can be explained by individual differences seen in the accuracy between the subjects. (See Appendix C for descriptive statistics). This revealed that the significantly lower levels of accuracy toward sweet foods were a result of foods that were sweet and high in carbohydrates which saw the lowest levels of accuracy (B = -1.44, SE = 0.22, 95% CI [-1.87, -1.00], z = -6.45, p < .001).

Figure 9

Mean accuracy score across the six food subgroups.



Note. This column chart visualizes the differences in average accuracy across the six different food subcategories: non-sweet high carbohydrate (SAHC), non-sweet high fat (SAHF), non-sweet high protein (SAHP), sweet high carbohydrate (SHC), sweet high fat (SHF) and sweet high protein (SHP). A markedly lower accuracy for sweet foods high in carbohydrates can be visualized here.

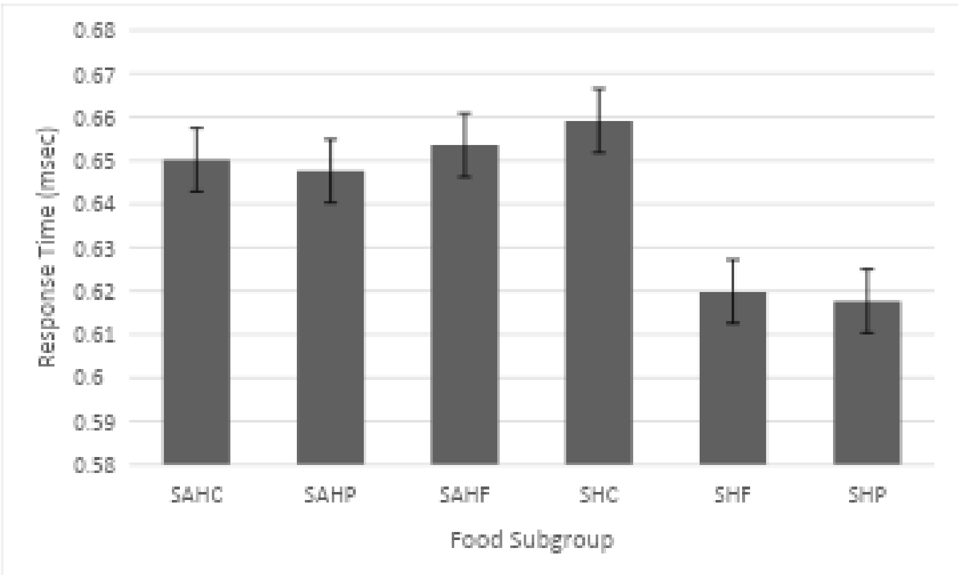
7.1.2 Response time between food subgroups

In order to further investigate this effect of sweetness on response time, an LMM analysis with a fixed effect of Food Group and a random effect of participant was conducted. A main effect of food group was identified (F = 41.8, df = 5.0, p <.001). Bonferroni corrected post-hoc comparisons indicated participants were significantly faster at responding to sweet foods that were high fat when compared to high carbohydrate (t(12053) = 10.49, p < .001) as well as high protein compared to high carbohydrate (t(12053) = 10.68, p < .001). High-fat sweet foods (SHF) were responded to significantly faster when compared to all non-sweet food groups: SAHC (t(12053) = 7.50, p < .001); SAHF (t(12053) = 8.70, p <

.001); SAHP ($t(12053) = 7.27$, $p < .001$). The same can be seen for high-protein sweet foods (SHP), with significantly faster response time when compared to SAHC ($t(12053) = 7.60$, $p < .001$); SAHF ($t(12053) = 8.89$, $p < .001$); SAHP ($t(12053) = 7.46$, $p < .001$). Sweet foods that were high-carbohydrate (SHC) however saw significantly slower response times when compared to SAHC ($t(12053) = -3.09$, $p = .030$); SAHP ($t(12053) = -3.24$, $p = .018$); SHF ($t(12053) = 10.49$, $p < .001$); SHP ($t(12053) = 10.68$, $p < .001$). The random effect of Participant indicated that 17.7% of the variability found in the data can be explained by individual differences seen in response time between the subjects.

Figure 10

Response time between food groups.



Note. This column chart visualizes the differences in average speed of response across the six different food subcategories: non-sweet high carbohydrate (SAHC), non-sweet high fat (SAHF), non-sweet high protein (SAHP), sweet high carbohydrate (SHC), sweet high fat (SHF) and sweet high protein (SHP). A markedly faster response time is apparent here for sweet foods high in fats and proteins.

7.1.3 Physiological state questionnaire and taste task accuracy and response time

In order to interpret the impact participants' physiological state had on their performance and response time for the taste task, a Pearson's correlation was conducted. Results indicated no significant correlations between physiological state measurements and taste task accuracy for neither sweet, non-sweet, or their respective subgroups. Similarly, no significant correlations were observed in response time for these groups. This demonstrates physiological state, be it hunger, thirst or desire to eat or drink, had no significant correlation on response time or accuracy.

7.1.4 Emotional appetite questionnaire and response time

In order to understand the relationship between EMAQ scores and response time in the taste task a Pearson's correlation was employed. Only one significant negative correlation was seen between sweet food response time and EMAQ positive emotion (PE) scores (r(101) = -.214, p = .031). This would suggest that participants who increased their food consumption in response to PE had faster response times when responding to sweet foods, but not for non-sweet foods. A linear regression showed EMAQ PE score significantly predicted sweet RT, F (1, 101) = 4.79, p =.031, accounting for 3.6% of the variability in response time with adjusted R^2 = 0.036. This is a relatively weak predictive relationship. The regression equation for predicting the RT from EMAQ PE score was ŷ = 0.693 - -0.011x. The confidence interval for the slope to predict RT from EMAQ PE score was 95% CI [-0.022, -0.001] with a B = -0.011; thus for each one unit increase in EMAQ PE score, sweet RT reduces by about 11 milliseconds.

7.1.5 RED scores and Response Time

Pearson's correlations revealed a significant negative correlation between Sweet RT and RED LoC r(100) = -.239, p = .016. A linear regression was conducted to analyse how well the RED Lack of Control (LoC) scores could predict response time of sweet foods in the judgement task. RED LoC score significantly predicted Sweet RT, F (1, 100) = 6.052, p = .016, accounting for 4.8% of the variability in the RT with adjusted R^2 = 0.048. This is a weak predictive relationship (Cohen, 1988). The regression equation for predicting the RT from RED LoC score was ŷ = 0.670 - -0.003x (RED LoC). The confidence interval for the slope to predict response time from the RED LoC score was 95% CI [-0.005, -0.00058] with a B = -0.003; thus for each one unit increase in RED LoC score, response time of sweet food is faster by about 0.003 points, or three milliseconds. The results here would indicate some ability to predict RT, with the higher RED LoC score, the faster the response time to sweet foods.

A significant negative correlation was seen between RED LoC scores and RT to SHF foods r(100) = -.232, p = .019. A linear regression was conducted to further analyse this relationship. RED LoC score significantly predicted Sweet RT, F (1, 100) = 5.704, p = .019, accounting for 4.5% of the variability in the RT with adjusted R^2 = 0.045. The regression equation for predicting the RT from RED LoC score was ŷ = 0.659 - -0.003x (RED LoC). The confidence interval for the slope to predict response time from the RED LoC score was 95% CI [-0.005, -0.0005] with a B = -0.003; thus for each one unit increase in RED LoC score, response time of SHF foods is faster by about 0.003 points, or three milliseconds. The results here would indicate some ability to predict RT, with the higher RED LoC score, the faster the response time to sweet foods high in fat.

Finally, a significant negative correlation was demonstrated between RED LoC scores and RT to SHP foods r(100) = -.267, p = .007. Similarly, a linear regression was conducted. RED LoC score significantly predicted Sweet RT, F (1, 100) = 7.7, p = .007, accounting for 6.2% of the variability in the RT with adjusted R^2 = 0.062. This is a weak predictive relationship (Cohen, 1988). The regression equation for predicting the RT from RED LoC score was ŷ =

0.665 - -0.004x (RED LoC). The confidence interval for the slope to predict response time from the RED LoC score was 95% CI [-0.006, -0.001] with a B = -0.004; thus for each one unit increase in RED LoC score, response time of SHP foods is faster by about 0.004 points, or four milliseconds. The results here would indicate some ability to predict RT, with the higher RED LoC score, the faster the response time to SHP foods

This would suggest only elements of reward-based eating that relate to having a lack of control pose an impact on response times. With typically, those higher in lack of control scores resulting in faster response times to sweet foods overall, and especially those high in fat or protein.

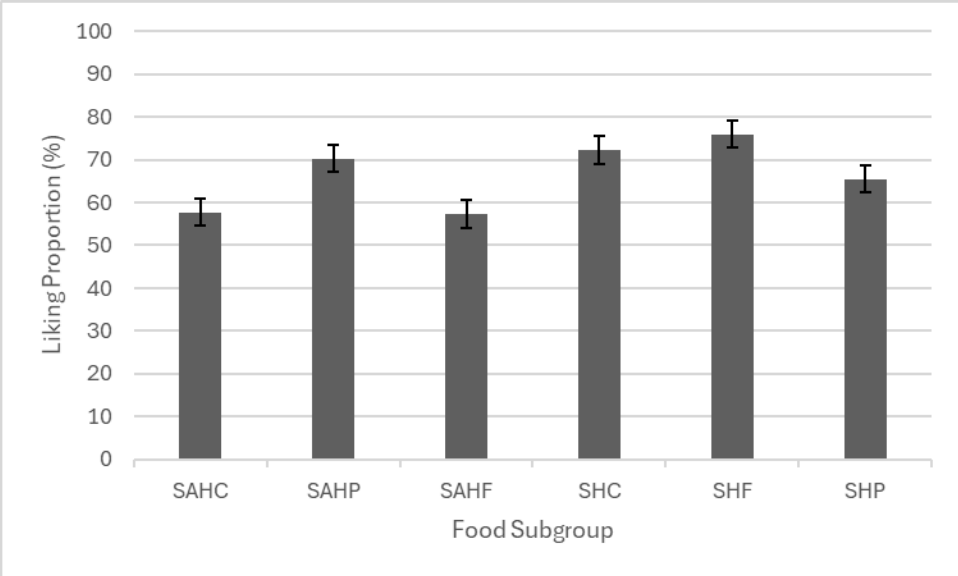
7.2 Like Task additional analyses

7.2.1 Proportions of liked foods, by food subgroup

In order to further investigate this effect of sweetness on liking, an GMM analysis with a fixed effect of Food Group and a random effect of participant was conducted. A main effect of food group was identified (χ^2 = 273.17, df = 5.0, p <.001). Participants indicated liking SHF foods significantly more frequently than SAHC foods (B = 0.834, SE = 0.0685, 95% CI [0.70044, 0.969], z = 12.183, p <.001), SAHP stimuli significantly more frequently than SAHC (B = 0.5469, SE = 0.066, 95% CI [0.41777, 0.677], z = 8.28, p <.001), SHC significantly more frequently than SAHC (B = 0.645, SE = 0.0668, 95% CI [0.5145, 0.776], z = 9.664, p <.001) and SHP significantly more frequently than SAHC (B = 0.324, SE = 0.0646, 95% CI [0.197, 0.451], z = 5.015, p <.001). For descriptive statistics see Appendix items G and H.

Figure 11

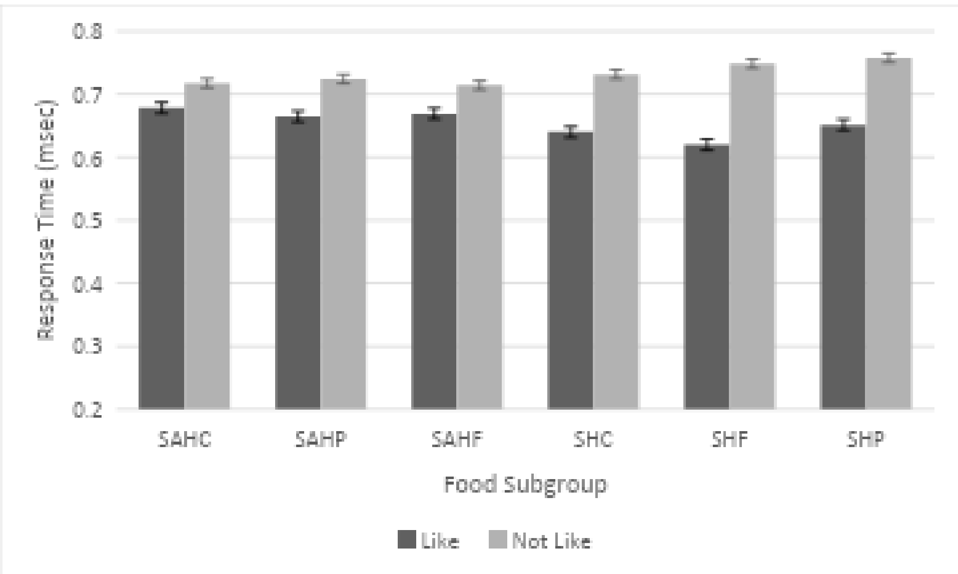
Liking Proportion between the six Food Subgroups.



Note. This chart displays the differences in Liking Proportion (%) between the six different Food Subgroups (Non-Sweet: High-Carb/Protein/Fat, Sweet: High-Carb/Protein/Fat). The vertical axis indicates the proportion of "Liked" responses.

Figure 12

Participant response time for liked and not liked response time across food subgroups



Note. This column chart displays the average participant response time separated into "liked" or "not-liked" responses across the six food subgroups. The figure displays the faster response times for liked compared to not-liked foods, as well as particularly faster response times for liked sweet foods.

7.2.2 Physiological state questionnaire and liking

In order to interpret the impact participants' physiological state had on their reporting of liking in the judgement task, a Pearson's correlation was conducted. Results indicated self-report measures of Hunger, Thirst and Desire to Drink were not significantly correlated with any measurements of liking in the task. Significant correlations were seen with Desire to Eat however, with a significant positive correlation with liking of sweet food (r(95) = .262, *p* = .009, and a moderate positive correlation with liking of SHP foods (*r*(95) = .367, *p* < .001). Linear regressions were conducted to better understand these relationships. Desire to Eat score significantly predicted Sweet Liking, F (1, 100) = 7.024, *p* = .009, accounting for 5.9% of the variability in the liking proportion with adjusted R2 = 0.059. This is a weak predictive relationship (Cohen, 1988). The regression equation for predicting liking from Desire to Eat score was ŷ = 63.748 + 0.204x. The confidence interval for the slope to predict response time from the Desire score was 95% CI [0.051, 0.358] with a B = 0.204; thus for each one unit increase in Desire to Eat score, the liking of sweet foods increases by about 0.2 points. Similarly, Desire to Eat score significantly predicted the liking of SHP foods, *F* (1, 100) = 14.812, *p* < .001, accounting for 12.6% of the variability in liking with adjusted R^2 = 0.126. This is a fair predictive relationship (Cohen, 1988). The regression equation for predicting SHP liking from desire to eat score was ŷ = 49.141 + 0.448x. The confidence interval for the slope to predict liking from the desire score was 95% CI [0.217, 0.679] with a B = -0.448; thus for each one unit increase in Desire to Eat score, the proportion of liking of SHP foods increases by about 0.45 points, or 0.45%.

7.2.3 Food preference questionnaire responses and liking

To understand the impact the participant's food preference questionnaire responses had on their reporting of liking in the judgement task, a Pearson's correlation was employed. Analyses showed that higher proportions of liking of sweet foods indicated in the judgement task was positively correlated with a self-reported preference for sweet food ($r(100) = .327$, $p < .001$), SHF foods ($r(100) = .336$, $p < .001$), and SHP foods ($r(100) = .267$, $p = .007$) in the food preference questionnaire. Similarly, a higher proportion of liking of non-sweet foods in the judgement task was positively correlated with higher food preference for SAHP foods ($r(100) = .269$, $p = .006$). Proportions of liking of SAHP foods were positively correlated with a preference for non-sweet food ($r(100) = .284$, $p = .004$) and a preference for SAHP foods ($r(100) = .515$, $p < .001$). The liking of SHC foods was positively correlated with a self-report preference for SHC foods ($r(100) = .311$, $p = .001$). The liking of SHF foods was positively correlated with a preference for SHF foods ($r(100) = .288$, $p = .003$). Finally, the liking of SHP foods in the task was positively correlated with an overall preference for sweet foods ($r(100) = .334$, $p < .001$), as well as a preference for SHF foods ($r(100) = .311$, $p = .001$), and SHP foods ($r(100) = .348$, $p < .001$). The results here demonstrate consistent positive correlations between the explicit measure of self-report preference for sweet foods, and their respective implicit measures of liking in the judgement task. This is less consistent when considering non-sweet foods.

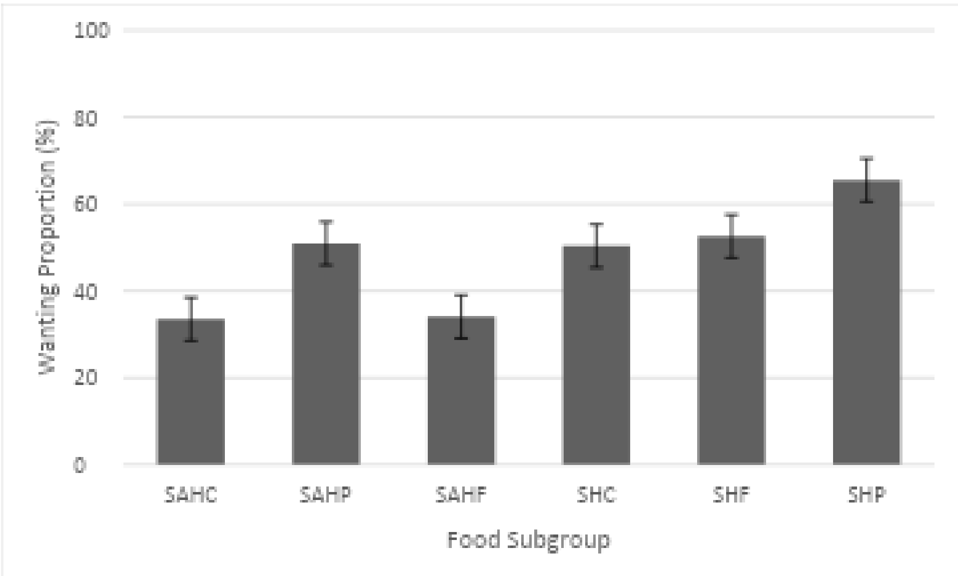
7.3 Want Task additional analyses

7.3.1 Proportions of wanted foods, by food subgroup

In order to further investigate this effect of sweetness on wanting, an GMM analysis with a fixed effect of Food Group and a random effect of participant was conducted. A main effect of food group was identified (χ^2 = 347, df = 5.0, p <.001). Participants indicated wanting SHF foods significantly more frequently than SAHC foods (B = 0.714, SE = 0.0694, 95% CI [0.0578, 0.85], z = 10.29, p <.001), SAHP stimuli significantly more frequently than SAHC (B = 0.833, SE = 0.069, 95% CI [0.697, 0.969], z = 11.99, p <.001) and SHC foods significantly more frequently than SAHC (B = 0.0.809, SE = 0.069, 95% CI [0.672, 0.944], z = 11.638, p <.001). (For descriptive statistics, see Appendix L). The random effect of Participant indicated that 19.6% of the variability in the data could be explained by individual differences in responses between participants.

Figure 13

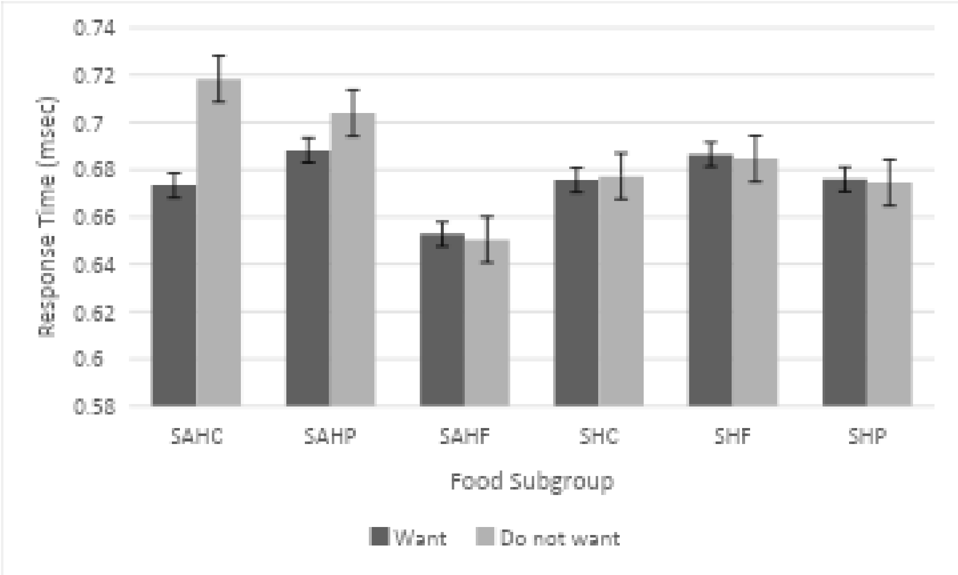
Column chart displaying the proportion of wanting, across the six food subgroups.



Note. This chart visualises the differences wanting proportions indicated by participants in the judgement task. Wanting is generally higher in food stimuli that is sweet, especially food that is sweet and high in protein.

Figure 14

Average response times of want and not want responses across food subgroups.



Note. The column chart here shows the differences in response times between wanted and not wanted foods, separated by the food subgroups. On average, although wanted responses were faster as noted prior, this may only be due to the markedly faster responses to SAHC and SAHP food groups, as visualised here.

7.3.2 Physiological state questionnaire and wanting

In order to interpret the impact participants' physiological state had on their reporting of wanting in the judgement task, a Pearson's correlation was conducted. Hunger was seen to have a moderately positive correlation with wanting of non-sweet foods ($r(96) = .303$, $p = .002$) and SAHP foods ($r(96) = .364$, $p < .001$). When considering reported Desire to Eat, significant positive correlations were seen with wanting of non-sweet foods ($r(95) = .417$, $p < .001$), SAHP foods ($r(95) = .407$, $p <.001$) and SAHF foods ($r(95) = .406$, $p < .001$). Interestingly, Desire to Eat was significantly negatively correlated with the wanting of sweet foods ($r(95) = -.32$, $p = .001$), SHF foods ($r(95) = -.283$, $p = .005$) and SHP foods ($r(95) = -.374$, $p < .001$). Both Thirst, and Desire to Drink were not significantly correlated with any measures of wanting. The results here indicate that explicit self-report measures of hunger and desire to eat impacted the results in the want judgement task. Interestingly, hunger and desire to eat correlated positively with different non-sweet food measures, suggesting those who were more hungry, or had a stronger desire to eat were more likely to want non-sweet foods, especially those high in protein or fat, whilst being less likely to want sweet foods, evidenced by negative correlations with wanting of sweet food measurements.

7.3.4 Food preference questionnaire responses and wanting

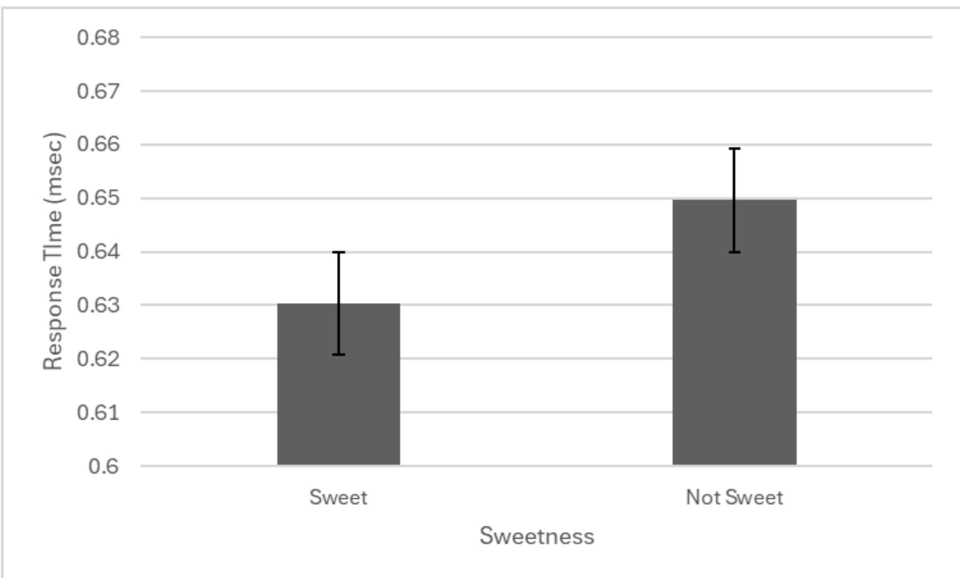
Higher ratings of wanting of sweet foods were significantly negatively correlated with a preference for sweet food ($r(100) = -.381$, $p < .001$), negatively correlated with a preference for SHF foods ($r(100) = .444$, $p < .001$) and SHP foods ($r(100) = -.334$, $p < .001$). Ratings of the wanting of non-sweet foods were positively correlated with a preference for sweet foods ($r(100) = 0.286$, $p = .004$), a preference for non-sweet foods ($r(100) = .596$, $p < .001$), a preference for food groups SHF ($r(100) = .275$, $p = .005$), SHP ($r(100) = .284$, $p = .005$), SAHC ($r(100) = .567$, $p < .001$), SAHF ($r(100) = .392$, $p < .001$) and SAHP ($r(100) = 0.556$, $p < .001$). The wanting of non-sweet foods was positively correlated with a preference for sweet foods ($r(100) = .286$, $p = .004$), non-sweet foods ($r(100) = .316$, $p = .001$) and SAHC foods ($r(100) = .482$, $p < .001$). Wanting of SAHP foods were positively correlated with a preference for both sweet foods ($r(100) = .390$, $p < .001$) and non-sweet foods ($r(100) = .557$, $p < .001$). As well as SHF foods ($r(100) = .346$, $p < .001$), SHP foods ($r(100) = .422$, $p < .001$), SAHC foods ($r(100) = .436$, $p < .001$), SAHF foods ($r(100) = .311$, $p = .001$) and SAHP foods ($r(100) = .706$, $p < .001$). Wanting of SAHF foods were positively correlated with a preference for non-sweet foods ($r(100) = .471$, $p < .001$), SAHC foods ($r(100) = .417$, $p < .001$), SAHF food ($r(100) = .472$, $p < .001$) and SAHP foods ($r(100) = .307$, $p = .002$). The wanting of SHC foods were positively correlated with an overall preference for sweet food ($r(100) = .316$, $p = .001$) and a preference for SHC foods ($r(100) = .454$, $p < .001$). Wanting of SHF foods were significantly negatively correlated a preference for sweet food ($r(100) = -.354$, $p < .001$) and SHF foods ($r(100) = -.429$, $p < .001$). Finally, the wanting of

SHP foods were significantly negatively correlated with a preference for sweet food ($r(100) = -.477, p < .001$), non-sweet food ($r(100) = .313, p = .001$), SHC food ($r(100) = -.346, p < .001$), SHF foods ($r(100) = -.424$ $p < .001$), SHP food ($r(100) = -.448, p < .001$), SAHF food ($r(100) = -.273, p = .006$) and SAHP food ($r(100) = -.291, p = .003$).

7.4 Response time between sweet and non-sweet food stimuli

Before assessing the effect of food preference on response time in the taste task, we assessed the impact of sweetness on Response Time. In this we employed a Linear Mixed Model (LMM) that included one fixed effect (Sweet/ Not-Sweet) and a random effect of Participant. A main effect of sweetness was identified ($F = 56.5$, df = 1.0, $p <.001$). This effect indicated participants were significantly quicker at correctly identifying Sweet Food compared to Non-Sweet Food (B = -0.0176, SE = 0.00235, 95% CI [-0.0222, -0.0130], $t = -7.51$, $p <.001$). The random effect of Participant indicated that 17.5% of the variability found in the data can be explained by individual differences seen in response time between the subjects. (Further response time assessments including all food subgroups can be found in supplementary materials item 7.1.2)

Response time between sweet and non-sweet foods.



Note. This column chart visualizes the differences in average speed of response between sweet food and non-sweet food stimuli. The significantly faster response time for sweet foods can be visualized here when compared to non-sweet.

8. Supplemental Glossary

Term	Definition	Method of Operationalization
Emotional Eating	Eating behaviour and consumption in response to emotions.	Propensity toward Emotional Eating is measured through the Emotional Appetite Questionnaire on a 9-point Likert scale.
Food Preference	Current desire to consume a specific food.	Measured through the Food Preference Questionnaire on a 7-point Likert scale.
Implicit Liking	Measure of the subconscious indication of whether a food is liked or not liked.	Measured through the Food Judgement Task ‘Like’ block of trials. Measured in binary of response (liked or not liked) and in msec response time.
Implicit Wanting	Measurement of a participants implicit/ subconscious desire to consume a food.	Measured through the Food Judgement Task ‘Want’ block of trials. Measured in binary of response (wanted/ not wanted) and in msec response time.
Perception/ Food Perception	How a food is perceived, understood and interpreted.	Measured through response time, and accuracy in the Food Judgement Task ‘Taste’ task.

Reward-Related Eating	Eating behaviours or consumption of food undertaken to satisfy hedonic factors such as pleasure and satisfaction.	Propensity toward reward-related eating is measured through the use of the RED-13 (Reward