Appetite control and dietary adherence during intermittent energy restriction in naturalistic settings using Ecological Momentary Assessment

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy by Mark Randle

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This thesis is submitted in partial fulfilment of the conditions for a PhD by published papers. In accordance with the University of Liverpool guidelines and regulations the chapters of this thesis will take the form of journal article manuscripts, which have either been published during the preparation of this thesis, are under review in a peer-reviewed journal, or are being read by co-authors before submission to a peer-reviewed journal. Specific details with regards to journal submission and contribution of authors are given at the beginning of each chapter, as required.

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Mark Randle

Abstract

Appetite is a biologically driven process expressed in a socio-cultural environment, though it is seldom measured within naturalistic settings. Previous investigations of appetitive responses to manipulations of energy balance suffer from various limitations: i) Laboratory-based environments constrain eating behaviour; ii) Retrospective recall methods are influenced by recall biases. These limit the ability to understand the role of momentary fluctuations in appetite in determining eating behaviour for individuals engaging in dieting within the real-world where barriers to successful weight control are encountered. This thesis uses Ecological Momentary Assessment (EMA) to examine the relationship between energy restriction (ER), appetite regulation, and dietary adherence in overweight and obesity under naturalistic settings.

I conducted the first systematic review and meta-analyses of appetitive and affective responses during moments of dietary temptation and lapses during ER using EMA (Chapter Three). Heightened responses accompany these momentary states, though engagement with coping strategies distinguished temptations from lapses. Within and between-person differences in responses also increased the likelihood of temptations and lapses occurring.

I developed a smartphone testing application to measure within-person fluctuations in appetitive processes in naturalistic settings as participants engaged in intermittent ER (IER). This was comprised of random and event-based assessments so that a comparison of outcomes under different momentary states could be conducted.

I conducted two of the first intermittent ER studies employing real-time measures of subjective sensations of appetite and affect, and objective measures of reward-reactivity and behavioural control. Individual differences in appetitive responses to ER were predicted using various baseline measures (Chapters Four and Five). Furthermore, raised sensations were found in the moments leading up to an eating event (Chapter Four) as well as during temptations and lapses, but these were distinguished by the extent of engagement with coping strategies (Chapter Five). Finally, changes in retrospective measures of appetite do not relate to real-world accounts of these sensations (Chapter Four) and display varying degrees of correlation (Chapter Five) which may have implications for future investigations into the impact of ER on appetite.

The findings in this thesis provide some of the first evidence that baseline measures of appetite and eating behaviours can predict individual differences in real-time appetite responses to intermittent ER in individuals with overweight and obesity. Additionally, support was provided that retrospective and real-time accounts of appetite are not consistent. Finally, support was found that momentary raises in sensations pose a problem for dietary adherence as these are associated with energy intake and experiences of temptations and lapses. Personalised interventions which identify appetitive processes at baseline that pose as problems for dietary adherence could be used to tailor strategies to cope with momentary increases during ER. This may prove useful towards increasing compliance with weight loss regimens.

Declaration

No part of this work was submitted in support of any other applications for degree or qualification at this or any other university or institute of learning.

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Many thanks to the study participants for their time and effort as well as their valuable insights into their experiences throughout the investigations of this thesis. I was informed that fasting studies are worse than participating in 3-hour long visual perception studies. I’ve done the latter and came out thinking it was a study into a novel form of torture, so I am massively grateful for the dedication and effort provided by these individuals.

Finally, I’d like to give special thanks to friends and family who have helped me tremendously during undertaking this PhD. I couldn’t have managed without all of your support throughout this process. Thank you all so much.

Chapter One

General Introduction

1.1 Thesis overview

The ‘Obesity Crisis’ poses the most significant global health problem of modern day. Importantly, obesity is preventable through lifestyle modification to dietary intake and physical exercise. A calorie-reduced diet is the most important component for initial weight loss; however, losses are seldom maintained in the long-term (Maclean, Higgins, Giles, Sherk, & Jackman, 2015). Understanding the behavioural and psychological mechanisms influencing dietary adherence will help the development of effective forms of behavioural weight management strategies (Casanova, Beaulieu, Finlayson & Hopkins, 2019).

Historically, investigations of the impact of energy restriction upon appetitive processes have largely been conducted in the confines of lab-based environments and have also relied on retrospective recall of past experiences. This limits our understanding of appetitive processes which occur in highly controlled environments or as snapshots of changes that occur throughout an investigation.

More recent advancements into smartphone technology have paved the way for near real-time measurement of appetite and eating behaviours under naturalistic settings. However, there have only been a few studies using these methods during engagement with dieting attempts. A systematic investigation and meta-analysis was required to summarise this current evidence-base which used EMA during dietary interventions to identify observational methods commonly used in this methodology. This study also evaluated the current findings on the momentary fluctuations in appetite and affect during ER as well as their implications on moments which pose as barriers to successful dietary adherence (Chapter Three).

Previous investigations of appetitive processes reveal large individual variation in responses to manipulations of energy intake which may explain the large diversity in eating behaviours. Many of these investigations have been conducted in laboratory-based environments or have relied on retrospective accounts of appetite. Both impact validity as appetite is environmentally mediated, and retrospective methods only provide snapshots of change that may be influenced by recall bias. The investigations in this thesis are among the first real-world investigations of fluctuations in appetite phenomena and their impact on proximal eating occurrences (Chapter Four) as well as momentary subjective states of dietary temptation and lapses (Chapter Five). These used Ecological Momentary Assessment (EMA) and N-of-1 methods to better understand individual variation in appetitive responses to ER whilst under naturalistic settings.

Currently, there is a lack of investigations which employ real-time measures to examine within person fluctuates of appetite during intermittent energy restriction (IER) (Chapters Four and Five). Furthermore, baseline measures of appetite and eating behaviours have not often been employed in IER interventions. These may aid in identifying individuals at baseline who will experience problems in adherence due to strong sensations of appetite that may impact control over eating behaviour. Evidence of the role of appetite during IER-induced weight loss are inconsistent, possibly due to a reliance on lab-based environments and retrospective measures of appetite. The investigations in this thesis will attempt to explain inconsistencies in these previous findings by employing EMA and N-of-1 methods to better understand individual differences in appetitive phenomena and how these impact momentary subjective states which act as barriers towards successful dietary adherence under naturalistic settings during IER dieting attempts.

This work aids with the understanding of real-world experiences of dynamic fluctuations in appetitive and affective processes and their implications on momentary subjective states that pose as problems for successful dietary adherence. This work also demonstrates early identification of sensations that may pose as barriers for successful dietary adherence can be predicted at baseline. This work highlights potential differences between retrospective and real-time measures of appetitive which may bias interpretation in investigations of the impact of ER on appetite outcomes. These findings have the potential to inform the development of personalised strategies to cope and manage with strong appetitive and affective sensations during moments of dietary temptation to increase adherence to intermittent ER approaches to weight loss.

1.2 Obesity: definition, prevalence and consequences

Obesity is a chronic disease characterised by abnormal or excess fat that impairs various aspects of health and wellbeing (WHO, 2018). Body mass index (BMI) is based on proportion of weight in kilograms to height in metres (kg/m^2) and is the most common index used to classify weight status. The World Health Organisation (WHO) classifies a BMI of between 25 to 30 kg/m^2 as overweight, 30 to 40 kg/m^2 as obese and 40 kg/m^2 + as severely obese. Whilst BMI is the most convenient measure of the degree of body mass, it only provides a crude estimate of obesity for an individual as it is not a measure of adiposity. This means it cannot differentiate between lean muscle (fat-free mass) and fat mass impacting the sensitivity of this index (WHO, 2018). Other measures exist such as waist circumference, waist-to-hip ratio or body composition analyses (ratio of fat to lean mass based on molecular composition) which may be better measures of adiposy. However, these are less practical for everyday use (Kim, 2016). BMI still has strong correlations with fat mass in adults (Bouchard, 2007), as well as being the most useful population-level measure as it tracks trends over time whilst accounting for individual differences in height, weight, sex and age (WHO, 2018).

The rates of obesity have almost tripled since 1975 placing it as a leading cause of preventable deaths worldwide (Di Angelantonio et al., 2016). In 2016, 39% of adults worldwide (aged 18 or older) were overweight with 13% of these being classified as obese. It was estimated in England alone, 63% of adults were classed as being overweight or obese and is responsible for more than 30,000 deaths each year (PHE, 2017).

Overweight and obesity develops largely due to maintaining behaviours that contribute to a sustained energy surplus leading to increased weight gain constituting as behavioural risk factors for obesity (WHO, 2018). Maintaining a raised BMI in the long-term results in metabolic changes that are associated with increased lifetime risk for developing various non-communicable diseases (NCDs) which are currently the largest risk factors for mortality worldwide according to the most recent Global Burden of Diseases Study (Afshin et al., 2019). These include increased risk for Type-II diabetes, cardiovascular diseases including stroke and hypertension, some types of cancers including breast and prostate cancer. Importantly, the risk for these NCDs increases with raised BMI meaning these diseases are largely preventable through lifestyle modifications to risk factors such as diet (WHO, 2018). Treatment of obesity-related illnesses annually cost the National Health Service (NHS) approximately £6.1 billion 2014-15 with wider societal costs being estimated at £27 billion (PHE, 2017) making the development of effective strategies to tackle the obesity pandemic a global public health priority.

1.3 Drivers of the obesity crisis

1.3.1 Foresight Report: Obesity Systems Map (Fig 1.1)

In the Foresight Tackling Obesities: Future Choices (Butland et al., 2007) a visual representation of the report's findings displayed as a Systems map which describes the sum of all relevant factors and their interactions that determine obesity for individuals and groups of people. The map is a causal loop model that demonstrates the complexity and multifaceted nature of obesity through visualisation of the systemic structure and dynamic relationships between factors.

1.3.2 Energy balance

At the heart of the map is energy balance which characterises the fundamental cause of obesity as a sustained energy imbalance that occurs as a result of a mismatch between calories consumed and expended. Sustaining an energy surplus leads to weight gain whereas an energy deficit leads to weight loss (WHO, 2018). The solution to excess weight is obvious: energy expenditure must exceed intake achieved through a reduction in energy intake and an increase in physical activity. Unfortunately, this solution is not as simplistic as it appears. Energy balance may be better conceptualised as a dynamic regulatory system which integrates current body composition, energy expenditure and metabolic processes with appetitive processes and energy intake. Changes to one of these factors profoundly affect the others which results in a large diversity of eating behaviours and weight change patterns (Casanova et al., 2019). The systems framework illustrates that multiple pathways can contribute towards maintaining a positive energy balance which pose as barriers towards reducing energy intake or increasing energy expenditure impeding successful weight management.

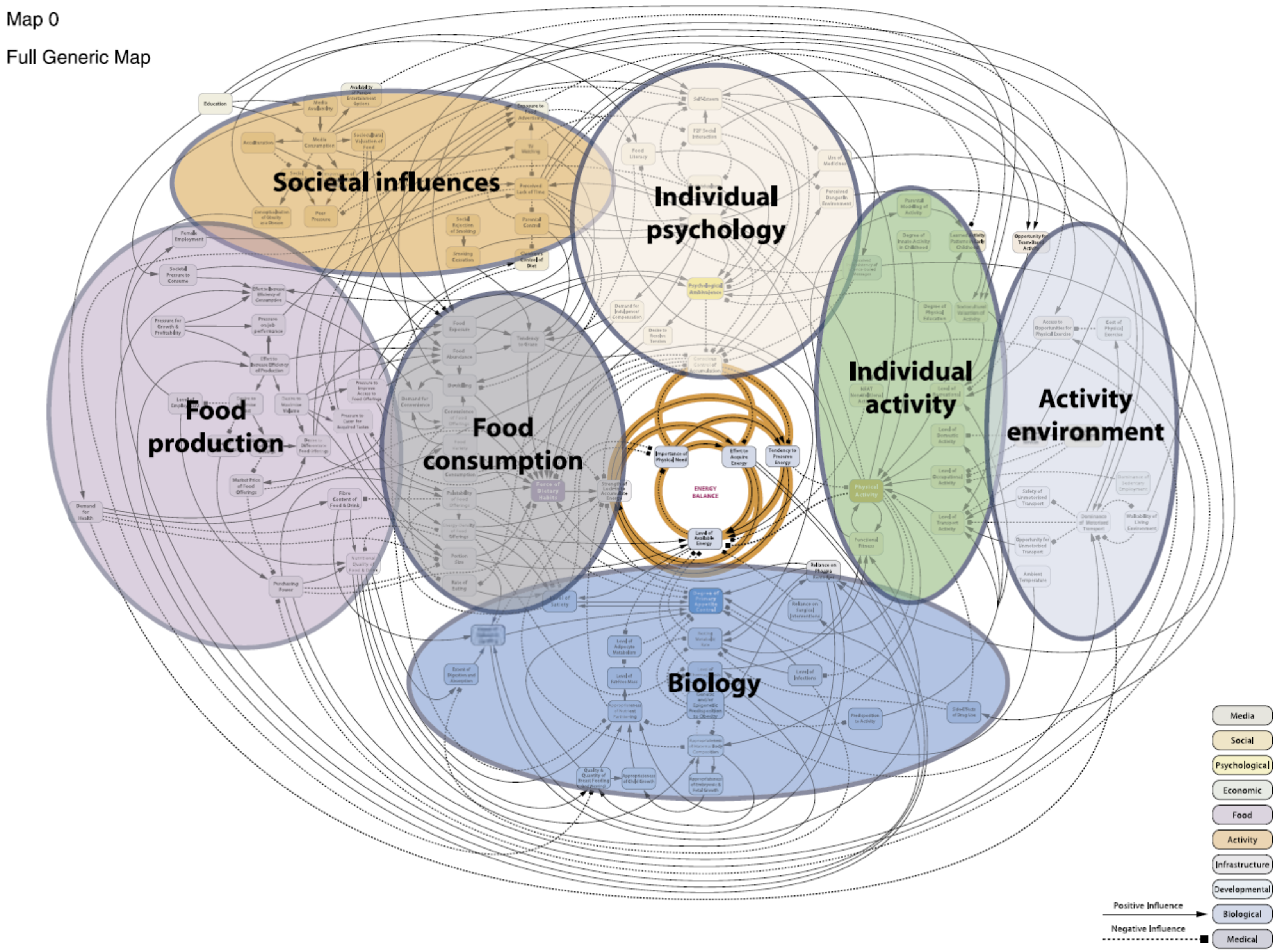

Figure 1.1 – Obesity systems map with thematic clusters. Taken from Tackling Obesities: Future Choices report. Taken from Butland et al. (2007)

1.3.3 The Obesogenic Environment

The largest environmental driver of the obesity crisis is the ‘obesogenic environment’ which is the role that environmental factors have in determining low levels of nutrition and physical activity. This includes an increase in the accessibility of unhealthy foods and prevalence of screen-based sedentary lifestyles, both of which play a major role in maintaining a positive energy balance and subsequent weight gain (Butland et al., 2007).

The rise in the prevalence of obesity rates worldwide since the 1970’s is largely attributable to changes to the physical and technological environment resulting in increased opportunities to consume energy-dense high in fat, salt and sugar (HFSS) foods. This has raised the prevalence of unhealthy ‘obesogenic’ behaviours which increase the risk for weight gain (PHE, 2017). HFSS foods are highly rewarding and pleasurable, and are also aggressively marketed so that cues to their consumption are omni-present (Cairns, Angus & Hastings, 2009). Changes to other physical and sociocultural factors have resulted in more sedentary lifestyles limiting levels of physical activity meaning energy intake does not meet expenditure (Butland et al., 2007). These environmental factors all pose as a significant barrier to healthy dietary choices and contribute to a maintained population-level energy surplus mediated by an increased prevalence of obesogenic behaviours such as unhealthy diet and low physical activity levels (PHE, 2017).

1.3.4 Biology, behaviour and the environment

The food environment provides opportunities and incentives towards achieving a positive energy balance. However, despite the prevalence of obesogenic environments not everyone within a population suffers from obesity meaning there is variability in the effect of obesogenic environments on weight-promoting behaviours (Bouchard, 2007). Even for those who share the same level of excess calorie intake or physical inactivity, weight gain is not identical (Bouchard et al., 1990;1994).

One source of variability in susceptibility to obesity is genetic variance. More than one hundred obesity-associated genetic variants have been identified through genome-wide association studies. However, these heritability estimates drastically range, and the mechanisms behind their causal roles in the development of obesity is still largely unknown (Ghosh & Bouchard, 2017). The interaction between genetic variants and the environment has been stated as to be more important than genetic variants alone in determining weight gain (Llewellyn & Fildes, 2017; Wardle, Sanderson, Guthrie, Rapoport & Plomin, 2002). In a review on the heritability estimates of obesity-related genes from twin studies, heritability estimates tended to be higher in populations living within more ‘obesogenic environments’ characterised by those with a higher than average population level BMI (Poulsen, Vaag, Kyvik, & Beck-Nielsen, 2001).

One hypothesis that explains the differential susceptibility to obesity is that weight gain arises from a gene-environment interaction which is mediated through individual differences in appetitive processes (Carnell & Wardle, 2007). Behavioural susceptibility theory (BST) first developed by Jane Wardle explains how body weight can have genetic and environmental drivers as well as why genetic expression is more prevalent in obesogenic environments (Carnell & Wardle, 2007; Llewellyn & Fildes, 2017; Wardle, 2006).

The role of appetite in obesity has a long history stemming back to 1968 where Stanley Schachter conducted a series of experiments demonstrating adults with obesity compared to normal weight ate more highly palatable foods but showed no difference in intake of bland foods (Schachter, 1968). Individual’s with obesity also did not show a down-regulation of food intake following a high-calorie snack compared to normal weight indicating a blunted satiety (fullness) signalling. BST was built on these observations and states that individuals who inherit a set of genes which predispose them towards greater responsivity towards external food cues or lower sensitivity to sensations of satiety following ingestion are more likely to overeat in obesogenic food environments (Carnell & Wardle, 2007).

John Blundell and colleagues reached similar conclusions in a series of experiments that set out to explain individual variability to weight-gain by characterising susceptible and resistant individuals (Blundell et al., 2005). Blundell and Cooling (2000) investigated variability in body weight in habitual high-fat diets, a behavioural risk factor towards weight gain. They found variability in body weight within habitual high-fat consumers; some lean individuals consumed similar amounts of dietary fat to overweight individuals. Blundell et al. (2005) claimed that this variation reflects biological variability of weight regulation that results from metabolic factors which constitute as risk for weight gain (e.g. low basal metabolic rate, low energy cost of physical activity, low fat oxidation). These biological differences may be expressed through individual differences in obesogenic behaviours such as patterns of eating behaviour, sensory or hedonic events which guide behaviour or sensations which accompany or follow eating. Crucially, these biological dispositions may only become apparent when in obesogenic food environments that provide the omni-present opportunity for overconsumption (Blundell & Cooling, 2000).

1.3.5 Thesis scope

The scope of this thesis in the broader obesity systems framework will focus on the dynamic nature of appetite control and its interactions with dietary habits and environmental influences in determining dietary adherence. This will be in a real-world context during a calorie-reduced diet to achieve a negative energy balance that will allow for the measurement of dietary habits and appetite control during weight loss attempts.

1.4 Appetite regulation and energy intake

Energy intake is an action ultimately under behavioural control, however the motivation to consume or inhibit is primarily a biologically driven process driven by the sociocultural context in which it takes place (MacLean, Blundell, Mennella, & Batterham, 2017). Human eating behaviour is not one uniform response but is characterised by large variability that reflects the degree of biological differences between or within an individual overtime (Dalton et al., 2013).

Eating is characterised as an episodic behaviour as the motivation to consume or inhibit arises from episodic factors of appetite which start, sustain, and stop eating (Gibbons & Blundell, 2019). These signals can also be overridden by food-related environmental cues that increase the hedonic drive or decrease control over eating behaviour (Mela, 2006). In addition, occasions of eating shape individual experiences with food that may reinforce obesogenic patterns of eating behaviours such as increased portion size or frequency of eating as well as food preference which all contribute to overconsumption (Brunstrom, 2007). Physical activity also appears to play an important role in appetite control. There appears to be a J-shaped curve where low levels of activity lead to a dysregulation of appetite and subsequent energy surplus. At higher levels, physical activity appears to influence homeostatic control by an increased drive and enhanced post-meal satiety response allowing for energy intake to better match expenditure (Beaulieu, Hopkins, Blundell, & Finlayson, 2018).

1.4.1 Homeostatic regulation: The satiety cascade (Fig. 1.2)

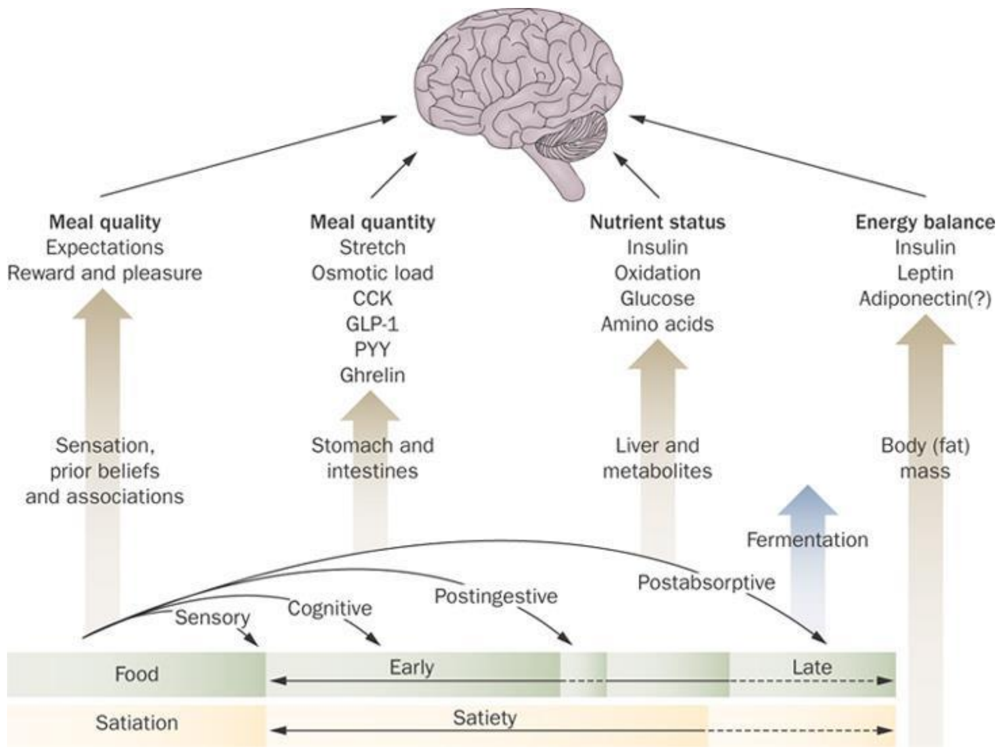

Figure 1.2 – The satiety cascade (originally proposed by Blundell et al. (1987)) demonstrates how sensory, cognitive, post-ingestive and post-absorptive factors fluctuate in response to energy intake which are integrated within the brain to determine the drive and inhibition of further consumption. Figure from Bilman et al. (2017).

Appetite regulation involves a complex network of psychobiological interactions separated into three-levels: i) psychological (e.g. hunger, cravings, and hedonic sensations) and behavioural (e.g. levels of disinhibited or restrained eating), ii) peripheral physiology (e.g. ghrelin and GLP-1) and metabolic events (e.g. insulin release and digestion), and iii) neurotransmitters (e.g. dopamine and cannabinoids) and metabolic interactions within the brain (e.g. leptin) (Blundell, 1991). These interact to influence the cognitive and subjective experiences of appetite that inform patterns of eating behaviour (Halford et al., 2010).

The satiety cascade was conceptualised by John Blundell and colleagues in 1986, and later modified by others (e.g. Mela, 2006). This explains how the physiological processes involved in satiation and satiety control both the size and frequency of eating episodes that forms the structure of eating behaviour (Bellisle & Blundell, 2013). There are two forms of signals that influence appetite regulation which are integrated within a complex brain network that control the overall expression of appetite (Saper, Chou & Elmquist, 2002). *Episodic signals* are mainly inhibitory and fluctuate as a function of eating patterns. *Tonic signals* arise from adipose tissue stores and exert a tonic pressure on the expression of appetite and indicate the level of fat storage (Benelam, 2009).

Episodic signals first inform the brain about the amount of food ingested and its nutritional content via input through the senses. Following ingestion, the *pre-absorptive* phase is where physiological activity is monitored by specialised chemo- and mechano-receptors (e.g. nutrient and stretch receptors) which located within the gastrointestinal tract, and pass information to the brain in the form of gut hormones released in the stomach and intestines (e.g. CCK, GLP-1 and $PPY_{3\text{-}36}$) via afferent projections in the vagus nerve to the hypothalamus. In the *post-absorptive* phase, the nutrients from food have been digested and have crossed the intestinal wall into circulation. These are then metabolised in peripheral tissues or organs which constitute as a class of metabolic satiety signals. In addition, the products of digestion and their respective metabolites reach the brain where they can bind to specific sites of action which influence neurotransmitter synthesis as well as neuronal metabolism which inform the brain about the metabolic state resulting from food consumption (Hopkins et al., 2016). The episodic release and deactivation of these signals underlie fluctuations in subjective feelings of appetite which mediate the termination of an eating episode as well as the strength and duration of inhibition over eating following a meal (Blundell & Naslund, 1999).

Tonic signals serve the function of informing the brain about the current state of adipose tissue stores which are released in proportion to body fat content and current plasma levels in circulation (Schwartz et al., 2000). Leptin and insulin are the most characterised tonic signals of long-term energy stores (Varela & Horvath, 2012). Leptin is secreted directly from adipose tissue in relation current circulation levels, whereas circulating insulin levels increase with peripheral insulin resistance which develops with increased adiposity (Varela & Horvath, 2012).

Leptin and insulin bind to receptors in the brain stem and hypothalamus to inform energy balance by altering food intake and energy expenditure (MacLean et al., 2017). Within these hypothalamic sites, leptin is largely mediated by the melanocortin and neuropeptide Y (NPY) systems (Ellacott & Cone, 2006). The melanocortin system is comprised of pro-opiomelanocortin (POMC) and Cocaine and Amphetamine Related Transcript (CART) anorexigenic peptides which leptin binds to result in reduced food intake. The NPY system is broadly comprised of orexigenic peptides NPY and agouti-related protein (AgRP) which increase food intake, though when leptin levels are high the activity of these neurons is supressed (Oswal & Yeo, 2007). During periods of food deprivation, tonic signalling declines as reduced leptin and insulin signals reach the hypothalamus. This in turn lowers sensitivity to episodic satiety signals (e.g. CCK) causing the normal homeostatic regulation to be off-balanced resulting in greater energy intake needed to generate a sufficient satiation signal to inhibit an eating episode (Woods & D'Alessio, 2008).

Pre-prandial motivation is where diminished satiety signals are detected in the gut by hypothalamic areas which responds by increasing the drive to consume as well as responsivity to environmental food cues (Davidson, Giesbrecht, Thomas, & Kirkham, 2018). The activation in hypothalamic areas result in cephalic phase responses. These are anticipatory responses in the body when exposed to the sensory properties of food (e.g. sight and smell) and serve the purpose of optimising the digestion, absorption, and metabolism of ingested nutrients (Mattes, 1997; Rodin, 1985). The senses provide input via peripheral receptors which project to the primary sensory cortices which are integrated with information about motivational subjective state (e.g. sensations and cognitions of appetite) and information from memory (e.g. learned associations) to influence bodily processes and behaviour (Rolls, 2007). The concept of anticipatory responses was first introduced in Ivan Pavlov's (1902) who demonstrated salivation occurs in response to the anticipation of feeding, though since then these responses now include many other anticipatory gastric secretions (Power & Schulkin, 2008).

1.4.2 Hedonic (reward) regulation

Additionally, hedonic thoughts and sensory appreciation play an important role in the homeostatic response to energy need (Dalton, Finlayson, Esdaile, & King, 2013). Food hedonics (reward) is comprised of distinct affective and motivational components which represent the sensory and cognitive processes involved in the experiences of 'liking' and 'wanting' (Berridge, 2009). 'Liking' is comprised of both an implicit and explicit component, and describes the change in affect observed in hedonic and aversive behavioural patterns associated with taste (implicit) as well as the sensory pleasure that accompanies ingestion of palatable foods (explicit) (Berridge, 2004).

‘Wanting’ is also comprised of both an implicit and explicit component that describes engagement with the environment in pursuit of food. Wanting is thought to arise from the consequence of assigning value to perceptual or cognitive representations of food where sensory and cognitive inputs are transformed into desired outcomes (Berridge & Robinson, 2017). The implicit component of wanting referred to as *incentive salience* is triggered by learned associations between environmental food-related cues or vivid mental imagery and subsequent food intake. The explicit component of wanting is based on explicit representations of the predictive pleasure of an outcome and is based on declarative memories of previous pleasure of that outcome (Berridge, 2013).

The reward system involved in liking and wanting is comprised of glutamate, endocannabinoids, and dopaminergic pathways (Saper et al., 2002). The neural system underlying liking is a network of interactive hotspots nested within limbic structures. These are activated during the pleasure response to palatable food and drugs as well as social and cultural-specific activities (Berridge & Robinson, 2017). These hotspots are found in the limbic prefrontal cortex, orbitofrontal cortex, and insula regions as well as other subcortical areas which are areas thought to be functionally relevant to coding sensory pleasures. (Kringelbach, 2010). These areas are stimulated by opioid and cannabinoid receptors which amplify the ‘liking’ reaction such as making sweetness more enjoyable. These hotspots appear to cooperate to become activated as an integrated circuit with increased intensity of liking requiring more activation of these hotspots in the nucleus accumbens and ventral pallidum (Smith & Berridge, 2005).

The neural components involved in wanting and desire is largely anatomically distinct to liking pathways (Berridge & Kringelbach, 2015) and appear to be more versatile as the neural systems only requiring partial activation of wanting pathways to generate desire. Liking requires activation of the whole network suggesting that wanting has more of an important role in determining behaviour (Berridge, Robinson & Aldridge, 2009). Implicit wanting (incentive salience) occurs in the mesolimbic dopamine system which is comprised of dopaminergic neurons which project from the midbrain towards the nucleus accumbens, striatum, amygdala, and prefrontal cortex (Berridge et al., 2009). Manipulations that increase activation in mesolimbic dopamine areas appear to increase implicit wanting without increasing other reward aspects such as pleasure or cognitive desires (explicit wanting) (Berridge & Robinson, 2017).

These hedonic pathways operate in a dual-systems framework to determine food reward processing. Hedonic and affective components result from incorporating sensory properties with physiological state and associative history (liking), whereas the motivational component is influenced by an underlying implicit drive that orientates current goals towards food-related stimuli (wanting) (Berridge, 1996; Finlayson, King & Blundell, 2007).

The homeostatic and hedonic systems do not operate completely independent from one another as evidence indicates that the endocannabinoid system interacts with the homeostatic system (Stanley, Wynne, McGowan, & Bloom, 2005). Leptin signalling becomes defective when hypothalamic endocannabinoids levels are high (Di Marzo, 2008) through activation of CB1 receptors which prevent the melanocortin system from reducing food intake (Verty, McFarlane, McGregor, & Mallet, 2004). The implication of this is that reward-driven eating can operate independently from biological need (Finlayson, King & Blundell, 2007).

Historically, hedonic processes were seen to arise from a nutritional-need state, though this did not explain the non-homeostatic eating behaviours that cause obesity. This raised the importance of cognitive and hedonic influences on food intake which occur independently from need (Dalton et al., 2013). Erlanson-Albertsson (2005) describes how ingestion of highly palatable foods can offset homeostatic control over eating. The hypothalamus releases hunger signals from peripheral tissue when an energy deficit is registered which increases the drive to engage in consumption. In the case when standard foods are ingested, the brainstem detects information on energy content and taste which is transmitted to the hypothalamus leading to an upregulation of satiety signals causing consumption to eventually cease. However, ingestion of palatable food leads to information regarding taste to be transmitted to reward circuitry. This results in an upregulation of reward neuromodulators (e.g. endocannabinoids) that project to hypothalamic areas causing increases in hunger hormones such as NPY and orexins, and decreases in satiety signals such as insulin, leptin and CCK. Therefore, the drive to eat is maintained during consumption of highly palatable foods as intake is mediated by the reward rather than homeostatic system.

Incentive motivational models of obesity (e.g. Berridge, 2009) state food-cue reactivity is comprised of a series of physiological and psychological responses to environmental cues that are associated with consumption that increases the drive to eat (van den Akker, Stewart, Antoniou, Palmberg, & Jansen, 2014) even in the absence of hunger (Nederkoorn, Guerrieri, Havermans, Roefs, & Jansen, 2009). Automatic psychological and physiological responses to a cue such as the sight and smell of palatable food are developed as a result of repeatedly being paired with subsequent intake. Eventually, the cue becomes conditioned to activate expectancy (reward) effects that increase the extent food is “wanted” driving consumption through neural (e.g. increased activity in dopaminergic areas), physiological (e.g. increased salivation), cognitive (e.g. increased attentional allocation), and affective (e.g. increased subjective food cravings) responses (Berridge & Robinson, 2016). Characteristics of the current food environment responses such as the abundance of highly palatable food items heavily influence the development and maintenance of these associations and can lead to persistent temptations to indulge (Appelhans, French, Pagoto, & Sherwood, 2016).

1.4.3 Sensations of appetite

Appetite refers to the whole field of food intake, selection, motivation and preference. It can also refer specifically to qualitative aspects of eating, sensory aspects or responsiveness to environmental stimulation (Blundell et al., 2010). It is subjectively experienced through the interaction between sensations which increase the drive to eat (e.g. hunger), influence food choice and preference (e.g. desire and cravings), and the inhibition over eating (e.g. satiety). There is a large amount of variation between individuals in the extent they experience these sensations which may account for the diversity in eating behaviours and differing levels of susceptibility to weight gain (Gibbons et al., 2019).

Satiety is a dynamic process typically measured using subjective ratings of hunger and fullness (Gibbons et al., 2019). The hypothalamus registers depletion by releasing hormonal signals (e.g. ghrelin) within the gastrointestinal tract which cues the sensation of hunger (Müller et al., 2015). Hunger is a conscious sensation reflecting a drive to consume which elicits a behavioural response (eating) to a biological need, but also demonstrates a strong situational component such as increased hunger around lunchtime (Finlayson, King & Blundell, 2008).

Satiation (within-meal satiety) is the processes within a meal that generate the negative feedback leading to the termination of eating. It is influenced by components of physical distention and absorption of nutrients, but prior experience has a large contribution to this and can determine meal size (Rolls, Roe, Kral, Meengs, & Wall, 2004). Satiety (post-meal satiety) is the end state of satisfaction which inhibits the drive to consume and is marked by a decline in hunger and increase in sensations of fullness (Blundell et al., 2010). Changes in hunger and fullness during a test meal tend to mirror each other in parallel: as hunger increases, fullness decreases. However, there are subtle differences in the way these ratings change within an eating event suggesting participants can distinguish between sensations arising from the amount of food consumed (fullness) and the desire continue eating (hunger) (Yeomans, 2018).

Though food reward cannot be directly measured, it has a profound impact on food choice, preference and consumption (Oustric, Gibbons, Beaulieu, Blundell & Finlayson, 2018). Their explicit components can be inferred using VAS (e.g. '*how pleasant would the taste of this food be right now?*') which are sensitive to differences in fasted and fed states, and can be used to predict future eating episodes (Cameron, Goldfield, Finlayson, Blundell, & Doucet, 2014). There are various single component measures which can be used to measure food reward including explicit wanting and liking, desire to eat, prospective consumption and cravings. Food cravings are the intense desire to eat a specific food which are difficult to resist and are closely linked with liking since commonly craved foods also tend to be highly palatable (Pelchat, 2002). Food cravings are common experiences among general populations (between 50 – 90%) (Weingarten & Elston, 1991), especially during dieting attempts (Gilhooly et al., 2007) and are found to be more frequent among overweight compared to normal weight in free-living settings (Roefs et al., 2019).

The experience of cravings and desire have been conceptualised in David Kavanagh's Elaborated Intrusion model of desire (Kavanagh, Andrade & May, 2005). Although some differentiate between desires and cravings based on the intensity of experiences, Kavanagh argued for continuum of intensity, with cravings being extreme sensations of desires. Elaborated Intrusion explains that intrusive thoughts are triggered by internal and external events which are followed by cognitive elaboration (i.e. thinking about the enjoyment of eating). Intrusive thoughts happen spontaneously as a result of learned associations between internal and external antecedent events to consumption (e.g. deficit states, negative affect and environmental cues). Elaboration takes place after becoming aware of the initial stimulus and involves controlled processes of searching for relevant information and retaining it within working memory resulting in more cognitive resources being allocated towards information relevant to the desire. Crucially, overconsumption is driven by these processes that occur as a result of learned associations between food-cues and consumption (May, Andrade, Kavanagh, & Hetherington, 2012).

Typically, appetite is measured through multiple subjective ratings on visual analogue scales (VAS) often assessing single components of satiety (e.g. hunger) and reward (e.g. cravings) (Stubbs et al., 2000). Whilst subjective ratings of appetitive sensations have added a great deal to our understanding of appetite regulation, scales used for their measurement should be viewed with some caution. Subjective rating scales of appetite attempt to tap into an individual's self-awareness of sensations relating to motivations to eat or inhibit further consumption which relies on both the accuracy of introspection as well as the honesty of the participant (Yeomans, 2018). Demand characteristics may reduce the likelihood of giving an accurate self-report of their appetite as participants may feel the need to give a more socially desirable response especially in investigations employing dietary manipulations where ratings are obtained within a clinical environment (Anton et al., 2009), though the impact of socially-desirability on subjective appetite ratings has yet to be directly investigated. Furthermore, due to their subjective nature it is hard to draw firm conclusions from studies which compare ratings between groups (e.g. healthy weight vs. overweight).

Nonetheless, these scales can be informative regarding effects of experimental manipulations through the examination of changes in appetite over time within an individual (Yeomans, 2018). Scales have also been shown to be a good predictor of proximal energy intake (Drapeau et al., 2005a; Flint, Raben, Blundell, & Astrup, 2000). Appetite ratings can be implemented in free-living settings with the use of electronic handheld devices to allow for real-time data capture. Electronic appetite rating systems (EARS) are sensitive to experimental manipulations and can detect the impact of a meal on appetite as well as the recovery of sensations throughout the postprandial period (Gibbons, Caudwell, Finlayson, King, & Blundell, 2011; Stubbs et al., 2000). EARS provide the potential to measure the implication of experimental manipulations to energy intake under naturalistic settings as well as to observe a range of other behavioural measures. Electronic rating systems are extensively used for measurement of appetite and eating behaviours throughout this thesis.

1.4.4 Cognitive processes underlying appetite regulation

According to neurocognitive models, decisions to eat are the outcome of a cognitive process which integrates memory, sensory, somatic, affective, and socio-cultural information (Higgs, 2005). These are informed by environmental factors (e.g. food availability) as well as metabolic changes in state (e.g. energy deficit) which motivates behaviour via modulation from changes in cognitive processes (Higgs et al., 2017). Learned associations of a pairing cue with subsequent intake informs habitual behaviours meaning eating can be elicited by the presence of food-cues alone. In contrast, eating can also be informed in a goal-directed manner (e.g. consciously reducing intake) which occurs based on mapping many possibilities of behaviour and expected outcomes including possible health consequences (O'Doherty, Cockburn, & Pauli, 2017). During energy deficit, cognitive processing is biased towards detection of environmental food-cues which becomes more salient with hunger, whereas food-cues become less attractive when energy replete (Higgs & Spetter, 2018).

Memory is fundamental to food-related decisions as representations of food including their remembered enjoyment is stored in memory as well as long-term goals such as health and dietary restriction (Higgs et al., 2017). For example, working memory is the process of holding information in the mind and processing this for goal-directed behaviours which plays a role in food-related decisions. Holding food-related information in working memory increases the attentional allocation to food as attention is drawn to cues paired with representations that are currently being held in working memory (Higgs, Rutters, Thomas, Naish, & Humphreys, 2012). Though desire to eat may also be triggered by remembered experiences of food (Berry, Andrade & May, 2007).

Dual processing accounts conceptualise cognition into two distinct processes: automatic and reflective (Hofmann, Friese, & Strack, 2009), though some argue that these may exist on a continuum of selective processing to exert control over behaviour (Evans & Stanovich, 2013). Automatic processes such as cue reactivity are the outcome of associative pairing of a food-related cue (e.g. sight and smell of food) with the rewarding value of subsequent consumption. These influence eating behaviour automatically through food-related cues capturing attention which may increase the tendency to eat in response to these environmental food cues (Wiers et al., 2010). Reflective processes are 'top down' and are consciously experienced when control is exerted over current behaviour (Verbruggen, 2016). These are closely linked to executive functions which refer to the ability to monitor and update information in working memory, inhibit dominant responses and shift between tasks and mental states (Miyake & Friedman, 2012).

Table 1.1 - Tasks and outcome indexes used to assess constructs of specific domains of cognition

Domain	Task	Construct	Outcome index
Attentional bias	Food Stroop	Attention allocation	RTs for food-related words compared to control words.
	Visual probe task	Attention allocation and maintenance	RT for probes in food compared to neutral.
Behavioural control	Colour Stroop	Cognitive interference	RTs for colour-congruent words compared to colour-incongruent.
	Go/No-go	Automatic inhibition	Initiating a response to no-go cues for food-related trials (commission errors)
	Stop signal	Controlled inhibition	Commission errors and latency for a stop-signal to be processed (stop signal RT)

Attentional biases towards food-cues

Investigations into the attentional processing of food cues assess the extent food grabs and holds the attention and can be measured by a variety of direct and indirect behavioural tasks. The most common indirect tasks used in the measurement of food-related attentional biases is the food-related Stroop and visual probe paradigms (Doolan, Breslin, Hanna, & Gallagher, 2014) (see Table 1.1 for a description of these tasks).

The food-related Stroop task is a modification of the classic colour naming Stroop where words are presented in different coloured inks and the participant has to respond as quickly and accurately as possible by naming the colour of the ink. In the food-related Stroop, participants are presented food-related and control words and are instructed to name the colour and ignore the content of the word. If a bias is present, the content of the food-related word captures the attention more readily and interferes with colour-naming causing a delay in response (Davidson & Wright, 2002). However, it has been suggested that some individuals may have an approach-avoidant pattern of attentional allocation to food which may also result in slower colour naming. This is characterised by diverting attention away from a stimulus following initial orientation to control the onset or increased feelings of cravings which are thought to accompany attentional biases (Doolan et al., 2014).

Another indirect method of attention is the visual probe task (VPT; Posner, Snyder & Davidson, 1980). In the VPT, participants are exposed to a food-related word or image and a matched neutral control which both disappear after a set time and a probe replaces where one of the stimuli was presented. Investigations which use a stimulus onset time ≤ 200ms are considered indications of initial attentional allocation, whereas those which use ≥ 500ms are considered to be maintained attention (Koster, Verschuere, Crombez, & Van Damme, 2005).

Direct measures of attention employ eye tracking which records participant's eye-movement and visual fixations as they complete an attention task such as the VPT. The duration of visual fixations indexes the extent of cognitive processing whereas the point of gaze indicates the initial area of visual interest. Eye tracking overcomes some of the methodological issues encountered with using indirect measures of attention such as providing information on attentional shifts that cannot be measured through indirect measures (Field & Cox, 2008).

Some reviews have found attentional biases on these tasks to be associated with increased subjective experiences of hunger, cravings, and proximal (but not overall) food intake (Hardman, Field, Jones & Werthmann, in prep; Werthmann, Jansen & Roefs, 2011). In addition, attentional biases and cravings are thought to be bidirectionally associated meaning biases towards food may elicit cravings, whilst food cravings may in turn trigger attentional biases for food cues (Field and Cox, 2008; Field et al., 2009). This circular relationship may result in a preoccupation with the desired stimuli increasing the likelihood of subsequent consumption (Franken, 2003). In one review, Werthmann et al. (2011) found some evidence for a positive association between hunger and cravings with early attentional processing of food-related cues; however, associations with maintained attention were less consistent.

The role of food-related attentional biases in development and maintenance of obesity is unclear possibly due to the large amount of heterogeneity in measures, duration times, and populations studied (Field et al., 2016). Castellanos et al. (2009) found faster initial orientation and maintenance of attention to food-related cues using a VPT in populations with overweight and obesity compared to healthy weight, however these differences were not found when measurements were taken during a fasted state. Werthmann et al. (2011) found overweight individuals displayed an approach-avoidant pattern of attentional allocation towards high-fat food. This was observed through faster orientation, but less maintained attention in overweight individuals compared to healthy weight control who had similar levels of hunger and cravings. One review into food-related attentional biases found differences are mostly found in studies employing psychophysiological techniques such as Electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) (Hendrikse et al., 2015). These investigations have found activation in areas involved in initial attentional allocation can distinguish overweight from normal control (Nijs, Muris, Euser, & Franken, 2010) as well as predict future weight gain (Calitri, Pothos, Tapper, Brunstrom, & Rogers, 2010; Yokum, Ng, & Stice, 2011).

Some investigations have attempted to manipulate attention to attempt to evaluate the causal role of biases on subjective states as well as energy intake. Attentional bias modification (ABM) studies primarily employ a modified VPT where the location of the probes is systematically varied so that participants attention is trained to attend towards or to avoid appetitive stimuli (Werthmann, Field, Roefs, Nederkoorn, & Jansen, 2014).

In one review of ABM for alcohol cues, Christiansen et al. (2015) found some investigations reported increases in substance-related cravings following ABM to attend stimuli compared to control. However, it appeared that these were limited to subgroups of participants who was aware of the task contingencies (i.e. knowledge of attention manipulation). Furthermore, no decreases in subjective cravings were found in avoid groups compared to control. Two investigations of ABM for food-cues on subjective sensations of appetite and energy intake found ABM led to reductions in subsequent energy intake in avoid groups; however, no reductions were found in hunger or craving scores (Smith, Treffiletti, Bailey, & Moustafa, 2018; Zhang, Cui, Sun, & Zhang, 2018). These findings seem to contrast those reporting associations between attentional processing and subjective cravings which may suggest there may not be a causal relationship between both variables.

In regards to energy intake, Werthmann, Jansen, & Roefs (2015) reviewed the impact of ABM for food-related cues on subsequent consumption and found higher consumption of foods that were trained in the attend group compared to the avoid groups. However, most studies within this review contrasted avoid and attend groups with omission of a control, therefore it is unclear whether the attend group led to increases or avoid led to decreases in food intake.

Historically, it has been assumed preferential automatic processing of food cues is a characteristic trait of overweight and obesity, and that attentional biases have a causal influence on energy intake and subsequent weight gain (Nijs & Franken, 2012). However, attentional biases are not consistently associated with BMI or overall intake (Field et al., 2016; Hardman et al., in prep) resulting in criticisms of the utility of attentional bias measures (Field & Cox, 2008; Werthmann et al., 2015). Field et al. (2016) stated that attentional biases may be better described as the output of a momentary stimulus evaluation which is determined by the current incentive value of the cue at that moment. Similarly, cravings and energy intake are also outputs of the food's momentary incentive value. This would suggest attentional biases are a state-like dynamic process which fluctuates over time and context (e.g. food availability in current environment). Therefore, the predictive validity of measures may be maximised if measured shortly prior to intake. In support of this, a meta-analysis currently being conducted has reported positive associations between attentional biases and food intake only in studies where measurements occurred shortly before intake (Hardman et al. in prep).

Behavioural control

Inhibitory (behavioural) control refers to the ability to stop, change or delay a response that is not appropriate for the current context (Logan, Zbrodoff, & Williaon, 1984) and is a key element of impulsivity, self-regulation, and restraint (Baumeister, 2014). Behavioural control involves exerting regulatory top-down control over automatic cues to consume, though when control is overwhelmed behaviour can become disinhibited and this can lead to overconsumption and weight gain (Brockmeyer et al., 2016; Hoffman, Friese & Strack, 2009).

Behavioural control can be measured objectively using a variety of reaction time tasks such as the colour Stroop, Go/No-Go task, and Stop signal task which all assess the extent of inhibition over a prepotent motor response when presented with a signal to inhibit (or an incongruent colour in the case of the Stroop task) (Kulendran, Vlaev, Gamboa, & Darzi, 2017) (see Table 1.1 for a description of these methods). These all measure response inhibition which is the ability to deliberately stop a prepotent motor response. This has been conceptualised as a race between competing 'go' and 'stop' signals, whereby if the go signal wins then the pre-potent behaviour will be executed or be successfully inhibited if the stop signal is to win (Band, van der Molen, & Logan, 2003; Jones et al., 2016).

In the Go/No-Go task, participants are presented a series of images with signals imposed over these and have to respond to the appropriate signal (e.g. respond to the letter K and withhold a response to the letter M). This task indexes the probability of executing a response to a No-Go trial. In the Stop signal task, participants perform a choice reaction task on no stop trials (e.g. left arrow for K, right arrow for M) and must withhold a response when stop signals appear. Unlike the Go/No-Go where signals and stimuli are presented concurrently, stop signals are presented after the initial stimuli with a delay which varies from block to block based on the previous block's performance. The stop signal task indexes both the probability of responding to stop signals as well as providing an estimate for the length of time it takes for successful inhibition to be performed.

These tasks measure distinct subcomponents of behavioural control with performance on both tasks being weakly correlated (Reynolds, Ortengren, Richards, & de Wit, 2006). The Go/No-Go task involving restraint of a strong automatic response tendency to a No-Go signal, whereas the stop signal task involves controlling an ongoing motor response when a stop signal is registered (Schachar et al., 2007).

Deficits in behavioural control has been proposed to be a major driver of calorie consumption and obesity (Guerrieri et al., 2007) given that effective control over eating requires suppressing automatic responses that are evoked by external food cues and internal physiological signals (Dalton, Finlayson, Esdaile, & King, 2013). During weight loss attempts, behavioural control is constantly being exerted to inhibit automatic tendencies. When control over eating is compromised, eating may become disinhibited which could lead to overconsumption especially if in the presence of highly palatable energy-dense foods (Polivy, Herman, & Coelho, 2008). One potential explanation for this is that maintenance of a negative energy balance requires the persistent use of cognitive resources to control behaviour leads to ego depletion – a state where control over behaviour is exhausted due to previous exertion (Baumeister, Bratslavsky, Muraven & Tice, 1998).

In support of this, laboratory studies using the Go/No-go task have shown decreased task performance is associated with increased intake of unhealthy foods (Jasinska, Yasuda, Burant, Gregor, Khatri, Sweet & Falk, 2012; Price, Lee, & Higgs, 2016). Some have also found raised levels of hunger to be associated with increased reward-responsivity as well as reduced performance on a Go/No-Go task in healthy weight individuals (Loeber, Grosshans, Herpertz, Kiefer, & Herpertz, 2013). Furthermore lower performance on the stop-signal task is predicted by higher scores on the Food Cravings Questionnaire – State (FCQ-S; Cepeda-Benito, Gleaves, Williams, & Erath, 2000) particularly on its hunger subscale (Meule et al., 2014), strongly implementing increased hunger as a predictor of reductions in behavioural control. Stress and negative affect also are proposed to have detrimental effects on behaviour control, particularly in current dieters and those who exhibit high amount of restraint over their eating behaviours (van Strien, 2018). For example, Rutters, Nieuwenhuizen, Lemmens, Born, & Westerterp-Plantenga (2009) found energy intake for sweet foods was significantly higher in those who were exposure to an acute stressor compared to a control group, and this relationship was stronger for those who reported high levels of disinhibition of eating behaviour.

The association between behavioural control measured on these tasks and overeating or obesity is not completely clear which may be a result of various methodological issues such as differences in measures and populations studied (Price, Lee, & Higgs, 2016). Some studies have found overweight and obesity is associated with poorer performance on behaviour control measures (Nederkoorn, Braet, Van Eijs, Tanghe, & Jansen, 2006; Nederkoorn, Smulders, Havermans, Roefs, & Jansen, 2006), though others have failed to find evidence that task performance is correlated with BMI (Kulendran, Vlaev, Gamboa, & Darzi , 2017). It may be the case that impaired behavioural control predicts energy intake when also paired with high reward reactivity to internal or external cues that evoke automatic appetitive tendencies to consume (van den Akker, Stewart, Antoniou, Palmberg, & Jansen, 2014) (Jones, Christiansen, Nederkoorn, Houben, & Field, 2013). Lawrence, Hinton, Parkinson and Lawrence (2012) found increased activation in the nucleus accumbens predicted BMI, but only in those who scored poor on a food-related Go/No-Go task at baseline. Similarly, Neederkoorn et al. (2010) found that neither objective measures of behavioural control nor implicit preferences for snack foods predicted weight gain over one year. However, there was a significant interaction effect in that weight gain was predicted in individual's with high implicit preference for snack foods as well as low behavioural control.

Current theoretical accounts of behavioural control suggest that whilst individuals display a trait-like capacity for behavioural control, control also functions as a transient state fluctuating in response to both internal and external cues (De Witt, 2009; Jones, Christiansen, Nederkoorn, Houben, & Field, 2013). In support, evidence from free-living investigations have found within-person fluctuations in behavioural control is associated with eating behaviours. Powell, McMinn, & Allan (2017) found that decreased Go/No-Go task performance was associated with increased likelihood of snack consumption being reported in the following hour. Furthermore, others have found increases in negative affect, stress, and current food availability increase the likelihood of unhealthy eating behaviours occurring such as eating high fat and sugary foods (Cleobury & Tapper, 2014; Elliston, Ferguson, Schüz, & Schüz, 2017; Schüz, Bower, & Ferguson, 2015).

Recent accounts suggest that the capacity of behavioural control is amenable to change through repeated practise on cognitive tasks, and improvements may translate to improvements to real-world behavioural restraint over automatic tendencies to consume. This has prompted the development of cognitive training tools that aim to modify unhealthy eating behaviours and aid with weight control (Friese, Hofmann & Wiers, 2011; Stice, Lawrence, Kemps, & Veling, 2015). Inhibitory control training (ICT) make use of tasks such as the Go/No-Go to attempt to train automatic inhibitory responses to food-related cues by consistently pairing food stimuli with no-go trials (Verbruggen & Logan, 2008).

Evidence for the efficacy of these attempts at training inhibitory processes to reduce unhealthy eating behaviours as well as aid with weight control is mixed. One review found consistent reductions in food intake in the laboratory, but associations from free-living investigations were not consistent (Jones, Hardman, Lawrence, & Field, 2018). Jones et al. (2018) reported only free-living investigations which repeatedly implemented ICT across contexts were associated with reductions in energy intake (Lawrence et al., 2015; Veiling, Van Koningsbruggen, Aarts, & Stroebe, 2017). Cognitive processes such as behavioural control are thought to be associatively mediated meaning context may play an important role in determining fluctuations in behavioural control (Rosas, Todd, & Bouton, 2013). Therefore, the efficacy of ICT may be contingent on training automatic inhibitory responses across multiple contexts.

Interim summary: Dynamic fluctuations in cognitive processes

In summary, dual process accounts of appetitive behaviour state overconsumption can result from an increased automatic processing of food-related cues or a decreased capacity of behavioural control over automatic responses. It has previously been assumed that these processes varied between individuals but remained relatively consistent overtime within an individual. However, recent reviews have highlighted a lack of evidence for these claims and suggest these processes may be better conceptualised as transient states which fluctuate over time and context. If the predictive utility of tasks used to measure cognition are to be improved and further developed into tools for cognitive training, a greater focus on understanding the determinants of within person fluctuations is necessary. In addition, future investigations into the role of automatic and reflective systems in overeating and obesity need to take into consideration that cognitive processes may be contextually mediated, meaning more real-world investigations are needed to better understand the contextual effects of cognition and eating behaviour.

1.4.5 Psychological measures of eating behaviours (Table 1.2)

Table 1.2 - Key concepts, measures, and definitions of eating behaviour tendencies

Concepts	Measures	Definitions
Restraint	TFEQ-R; DEBQ-R; Restraint scale	Tendency to exert intentional restriction over intake to influence body weight
Disinhibition	TFEQ-D	Tendency to overeat in response to cues that prompt consumption
Susceptibility to hunger	TFEQ-H	Tendency to eat in response to perceived physiological symptoms that signal the need for food (e.g. hunger pains)
External eating	DEBQ-External eating	Tendency to overeat in response to external (environmental) cues
Emotional eating	DEBQ-Emotional eating	Tendency to overeat in response to internal (emotional) cues

TFEQ – H. Three Factor Eating Questionnaire Susceptibility to Hunger scale; *TFEQ – D.* Three Factor Eating Questionnaire Disinhibition scale; *TFEQ – R.* Three Factor Eating Questionnaire Restraint scale; *PFS.* Power of Food scale; *DEBQ-R.* Dutch Eating Behaviour Questionnaire Restraint scale

Eating behaviours are primarily driven by momentary appetitive processes, however individuals can vary in the extent to which they experience these phenomena which may be displayed through differences in tendencies towards certain styles of eating behaviour. The Three Factor Eating Questionnaire (TFEQ; Stunkard & Messick, 1985) and Dutch Eating Behaviour Questionnaire (DEBQ; van Strien, Frijters, Bergers & Defares, 1986) were among the first inventories created to measure differences between individuals in tendencies towards displaying types of eating behaviours. The TFEQ measures three distinct dimensions of eating behaviour: restrained eating, disinhibition, and susceptibility to hunger, and the DEBQ measures restrained, emotional and external eating. Other measures focus more on specific aspects of eating behaviours associated with overeating and obesity such as inventories which assess the specific experiences of appetite such as cravings and binge eating tendencies.

Paradoxically, high scores on restrained eating measures is associated with increased impulsivity and reward-responsivity to food cues as well as disinhibited eating (Adams, Chambers, & Lawrence, 2019). Therefore, it is unclear whether restrained eating is a cause or consequence of impulsivity or disinhibited eating (Johnson, Pratt, & Wardle, 2012). Restrained eating is also associated with counter-regulation of energy intake whereby more calories will be consumed following ingestion of a standardised palatable food in restrained eaters compared to non-restrained (Herman & Mack, 1975), therefore some suggest this concept essentially measures differences in failing to successfully restrain eating rather than successful restraint over eating. In support of this, some have found individuals who score high on restraint scores consume more forbidden foods especially during experiencing negative emotions, stress or environmental food-cues to consume which leads to a disinhibited effect upon eating behaviour (Guerrieri, Nederkoorn, Schrooten, Martijn, & Jansen, 2009; Guerrieri et al., 2007; Papies, Stroebe, & Aarts, 2008).

However, not all have been able to replicate these findings with some suggesting restraint measured on the TFEQ and DEBQ measure ‘successful’ restraint. Some found that restrained eating in severe obesity is associated with reduction in overall calorie intake as well as intake of high in fat and sugar foods which would suggest restrained eating may actually have a protective factor in severe obesity in that increased restrained eating may be beneficial, especially in response to weight gain (Brogan & Hevey, 2013). Other inventories such as the Restraint Scale (Herman & Polivy, 1978) which was originally an assessment of “chronic dieters” specifically measuring tendencies to experience weight fluctuations and concern for dieting with high scores predicting weight gain (Stice, Cameron, Killen, Hayward, & Taylor, 1999). Generalising findings between measures could potentially explain some of the inconsistencies in previous investigations of restrained eating (Boyce, Gleaves, & Kuijer, 2015).

There is evidence to support the claim that both DEBQ and TFEQ restraint subscales measure successful restraint. High scores on these measures have been associated with reduced calorie intake (Wardle & Beales, 1987) and are also not associated with the effect of a preload on counter regulation (Lowe & Kleifield, 1988). Furthermore, greater increases in restraint scores from pre to post weight loss intervention are associated with increased weight loss. In a 6-month prospective weight loss study, increased TFEQ-R score was associated with greater weight loss (Batra et al., 2013). However, one review on prospective studies of weight change and restraint, scores were found not to consistently predict weight change in any direction (Lowe, Doshi, Katterman, & Feig, 2013). In one prospective investigation of weight loss maintainers using the DEBQ-R, Neumann et al. (2018) found that successful weight loss maintenance was associated with higher scores compared to a sample from the general population. These also investigated weight trajectories over a two-year period in the maintainers group and found that restraint score decreased in both groups, but emotional and external eating increased in the group of weight loss maintainers who gained weight over a 2-year period. These suggest a degree of restraint over eating behaviour is required, but the influence of other eating behaviours styles may counteract this effect.

Some have attempted to further break down the concept of restrained eating to identify features of positive and negative outcomes. Westenhoefer (1991) distinguished items on the TFEQ-R which were positively and negatively associated with disinhibition to produced ‘flexible’ and ‘rigid’ subscales. The rigid subscale is an all-or-none approach to dieting, whereas the flexible subscale in contrast allows for fattening foods to be eaten in small quantities. In one 6-month weight loss investigation, Westenhoefer et al. (2013) showed that flexible restraint is associated with better weight loss and weight loss maintenance, whereas rigid was associated with less weight loss. In addition, flexible restraint was associated with poorer performance on a working memory task, whereas ridged restraint was associated with greater attentional biases towards food cues. Further investigations that identify the underlying appetitive mechanisms responsible for restraint over eating such as cognitive measures of behavioural control may help explain differences in restraint tendencies.

Disinhibition has been shown to distinguish between obesity and healthy weight (Hays et al., 2002; Provencher, Drapeau, Tremblay, Després, & Lemieux, 2003). More recently it has been proposed that disinhibition could be further refined into more specific constructs assessing both internal and external influences such as eating to regulate with internal factors such as mood, stress and hunger or external factors such as environmental cues (Bond, McDowell, & Wilkinson, 2001; Karlsson, Persson, Sjöström, & Sullivan, 2000). Higher trait disinhibition has been associated with greater attentional biases towards food cues (Hege, Stingl, Veit, & Preissl, 2017) as well as predict greater intake following stress manipulations which was moderated by restraint scores, with greater intake being found in individuals with high disinhibition and low restraint scores (Haynes, Lee, & Yeomans, 2003). Disinhibition scores are a strong predictor of food consumption in laboratory studies which find increased energy intake for high calorie foods (Van Strien, Cleven, & Schippers, 2000; Westenhoefer, Broeckmann, Münch, & Pudel, 1994). Furthermore, one review found that disinhibition scores showed positive associations with BMI and weight gain in both cross sectional as well as prospective studies (French, Epstein, Jeffery, Blundell, & Wardle, 2012). There is a paucity of research relating disinhibition scores to motivations to eat such as internal signals of hunger as well as high reward responsiveness which may be correlated with TFEQ-D scores (French et al., 2012).

The DEBQ acknowledges disinhibited effects can be result from cues to consume that can arise from internal affective states as well as external environmental cues through the emotional and external eating subscales respectively. These overlap with TFEQ disinhibition subscale in that they measure the tendency to experience a disinhibited effect over eating behaviour resulting in more calories consumed than intended (van Strien et al., 1986).

Emotional eating is the extent eating occurs in response to intense emotions such as stress, positive or negative affect (Greeno & Wing, 1994). Over half of overweight adults report frequent episodes of emotional eating (Péneau, Ménard, Méjean, Bellisle, & Hercberg, 2013), and scores are positively associated with greater frequency of snacking (O'Connor, Jones, Conner, McMillan, & Ferguson, 2008) as well as greater intake of energy dense foods (Oliver, Wardle, & Gibson, 2000). Greater weight loss success has been also been associated with decreased emotional eating score from pre to post during a behavioural weight loss intervention (Braden et al., 2016).

External eating has been found to predict greater automatic attentional processing of food-related stimuli in overweight individuals on both the Food Stroop as well as neurophysiological measures (Nijs & Franken, 2012). High scores on external eating has been associated with greater intake of crisps whilst watching a food-related commercial compared to a neutral commercial control (Van Strien, Peter Herman, & Anschutz, 2012). Finally, Burton & Lightowler (2007) found that external eating score has been positively associate with BMI in women with total amount of cravings mediating this relationship.

Other measures focus more specifically on specific aspects of eating behaviours or the extent to which individuals may experience common appetitive phenomena such as food cravings or hunger. The Power of Food Scale (PFS; Lowe et al., 2009) takes a detailed focus on the psychological impact of living in food-abundant environments. The authors of this inventory reported the scale moderately correlated with Disinhibition and susceptibility to hunger scores on the TFEQ and the emotional and external eating subscales on the DEBQ. Burger, Sanders, & Gilbert (2016) conducted multiple cross-sectional studies and found baseline PFS score was associated with increased activation in neural regions involved in cue-induced anticipation of food intake, hedonic ratings of palatable foods and binge eating score, but not BMI. Rejeski et al. (2012) found that increased cravings as well as perceived lack of control over eating behaviour was significantly higher in groups fed with water compared to an energy drink, and PFS moderated this relationship with increased score being associated with increased risk of experiencing these effects.

Overweight compared to healthy weighted males have displayed higher susceptibility to hunger scores (Harden, Corfe, Richardson, Dettmar, & Paxman, 2009). In addition, many weight loss studies reporting reductions in susceptibility to hunger scores from pre to post intervention (Bas & Donmez, 2009; Batra et al., 2013; Gilhooly et al., 2007) with the greatest decreases in scores being found in those that lost the most weight (Gilhooly et al., 2007). TFEQ-H is the only factor which was a predictor of weight change after 20 weeks of continual calorie restriction (Batra et al., 2013). However, some have found evidence of a state-dependent effect of current hunger score on responses to the TFEQ-H (Yeomans & McCrickerd, 2017) and others found that susceptibility to hunger score did not associate with appetite sensations measured during test meals (Drapeau et al., 2005b) raising concerns of the utility of this factor in accurately predicting between person differences in experienced sensations of hunger.

Interim summary: Inconsistencies of findings surrounding eating behaviour measures

In summary, there are many inventories that assess differences in tendencies towards specific patterns of eating behaviours that may be problematic for successful weight control. However, inconsistencies in the interpretation of findings add to confusion over what some subscales specifically measure (e.g. restraint), and whether these can reliably predict differences in energy intake or weight outcome during intervention. Furthermore, many of the underlying appetitive mechanisms behind individual differences in measures of trait eating behaviours are currently unknown. Further investigations are required to see whether individual differences in these measures can predict real-world experiences of appetite and eating behaviours. This will confirm the ecological validity of measures as well as provide an understanding of how baseline differences in trait eating behavioural measures could be used to predict individual differences in manipulations of energy balance.

1.4.6 Dual systems framework (Fig. 1.3)

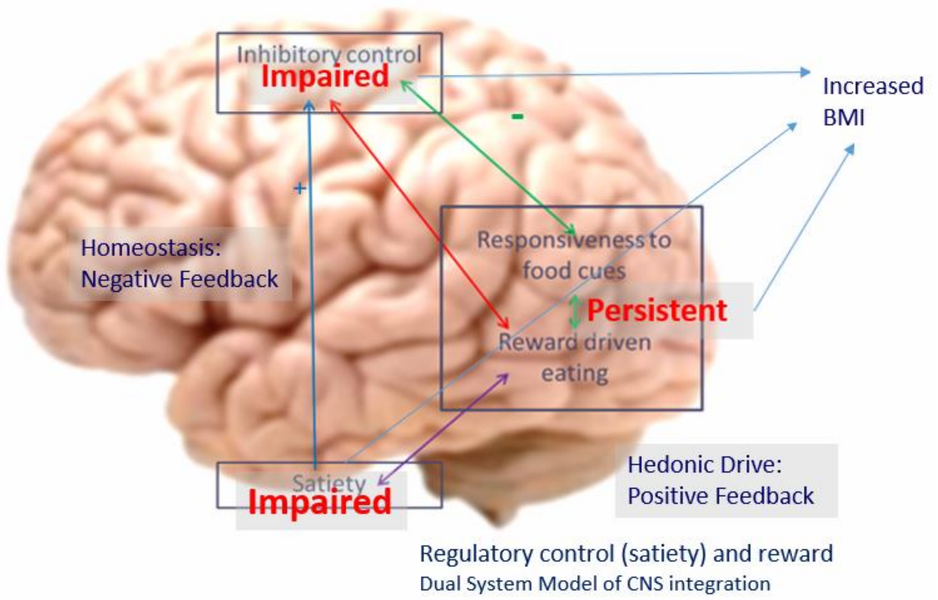

Figure 1.3 – Increased satiety will reduce reward-driven behaviour and boost inhibitory (behavioural) control. Dampened reward-responding will impact satiety and increase behavioural control. Increased behavioural control reduced responsivity to food-cues and reward driven eating. These factors are impacted by increased BMI. Taken from Roberts et al. (2017)

Roberts, Christiansen, & Halford (2017) set out a framework which encompasses homeostatic and hedonic regulation of eating behaviour as well as how this is impacted in obesity. Energy intake is determined by the interplay between satiety, reward-processing and behavioural control. Regulatory control over eating behaviour is undermined by reduced satiety and increased responsivity to food-cues which increases the likelihood of eating in response to food-related cues.

Obesity is caused by a biological vulnerability to weight gain expressed through eating behaviours that lead to overconsumption (Blundell et al., 2005) which include behaviours relating to satiety (e.g. weakened satiety response), reward (e.g. strong hedonic attraction to palatable food) and behavioural control (e.g. disinhibited eating). Individuals with obesity face unique behavioural issues which lead to overconsumption and contribute to maintaining a positive energy balance. Therefore, understanding these issues is crucial for efforts to increase regulatory control over eating behaviour to aid with successful weight control.

1.5 Appetite regulation and weight management

1.5.1 Impact of energy restriction on appetite regulation

Dieting is an approach to weight loss that involves self-imposed restriction over eating behaviour in order to achieve an energy deficit and is considered the most important factor for initial weight loss (Stubbs et al., 2011). A reduction in energy intake producing modest losses of between 5 – 10 % of initial body weight maintained for over a year has been associated with improved metabolic outcomes such as insulin sensitivity (Magkos, 2016) and decreased risk of mortality from all obesity-related comorbidities (Ma et al., 2017) as well as reduced risk of developing diabetes (Hamman et al., 2006) and some forms of cancer (Byers & Sedjo, 2009).

However, most weight loss attempts are unsuccessful in both the short and long-term; many are unable to achieve and maintain modest losses, and the majority of those who do regain this within 3 – 5 years (Maclean, Higgins, Giles, Sherk, & Jackman, 2015). One major problem dieters face is that appetite regulation appears to be asymmetric (Blundell & King, 1996). Maintaining a negative energy balance results in compensatory metabolic and behavioural responses that defend against energy deprivation (regardless of current level of adiposy) whereas systems to defend against weight gain are permissive of excess energy and are easily overridden by the hedonic and sensory aspects of food (Hopkins, Beaulieu, Myers, Gibbons, & Blundell, 2017; King et al., 2007). Maintenance of a negative energy balance also compromises appetite regulation through increased sensations of appetite and reward responsivity to food cues which challenge consumption (Roberts et al., 2017), though the extent to which individuals experience these effects vary between individuals (Gibbons, Hopkins, Beaulieu, Oustric, & Blundell, 2019).

The homeostatic system monitors blood-glucose level and responds to depletion by releasing various hormonal signals (e.g. ghrelin) within the gastrointestinal tract that are integrated within hypothalamic areas which cue the sensation of hunger (Müller et al., 2015) – a strong motivational state that drives behaviour towards restoring a state of energy balance (King et al., 2007). Greater levels of hunger at baseline has been associated with poorer weight loss outcome during behavioural intervention (Sayer, Peters, Pan, Wyatt, & Hill, 2018). In addition, some weight loss studies have reported reductions in susceptibility to hunger scores on the TFEQ from pre to post intervention (Bas & Donmez, 2009; Batra et al., 2013;

Gilhooly et al., 2007) with the greater decreases in scores being associated with increased weight loss (Gilhooly et al., 2007).

Regarding food-cue responsivity, increases in food cravings have been associated with increased intake of the desired food (Chao, Grilo, White, & Sinha, 2014). Compromises to reward-responsivity following ER can be also observed on objective measures of attentional allocation, particularly for the initial orientation of attention. Mogg, Bradley & Lee (1998) found that individuals with high levels of hunger demonstrated greater attentional biases towards food cues on a VPT using a stimulus onset of 500ms compared to those with low levels of hunger. Nijs, Muris, Euser, & Franken (2010) also reported that automatic attentional allocation (but not maintained) was observed in hungry compared to satiated groups. There are also considerable differences between-individuals in the extent of susceptibility to the rewarding effect of food-related cues (Tetley, Brunstrom, & Griffiths, 2009). For example, more intense and frequent cravings have been associated with poor long-term weight management (Franken & Muris, 2005). Additionally, Nijs et al. (2010) reported faster initial orientation of attention towards food cues in individuals with overweight and obesity compared to normal weighted controls.

Successful dietary adherence requires coping with these heightened appetitive responses to a negative energy balance, though affective processes are also impacted during ER. For example, weight loss has also been associated with greater levels of negative mood (Jackson, Steptoe, Beeken, Kivimaki, & Wardle, 2014). Negative mood can induce emotional eating and increased intake of unhealthy foods (Jasinska et al., 2012) as well as binge eating episodes (Stice, Akutagawa, Gaggar, & Agras, 2000). These imply that control is constantly being exerted to inhibit behavioural responses to internal and external cues to consume which challenge successful control over eating behaviour (Roberts et al., 2017). Persistent use of cognitive resources to control behaviour leads to ego depletion – a state where control over behaviour is exhausted due to previous exertion (Baumeister, Bratslavsky, Muraven & Tice, 1998).When control over eating is compromised, eating may become disinhibited which could lead to overconsumption especially if in the presence of highly palatable energy-dense foods (Polivy, Herman, & Coelho, 2008). Taken together, an increased drive to eat as well as a persistent low mood can undermine the ability to maintain a diet, meaning those who benefit the most from weight loss also constitute as the least capable of coping with the consequences of sustained negative energy balance.

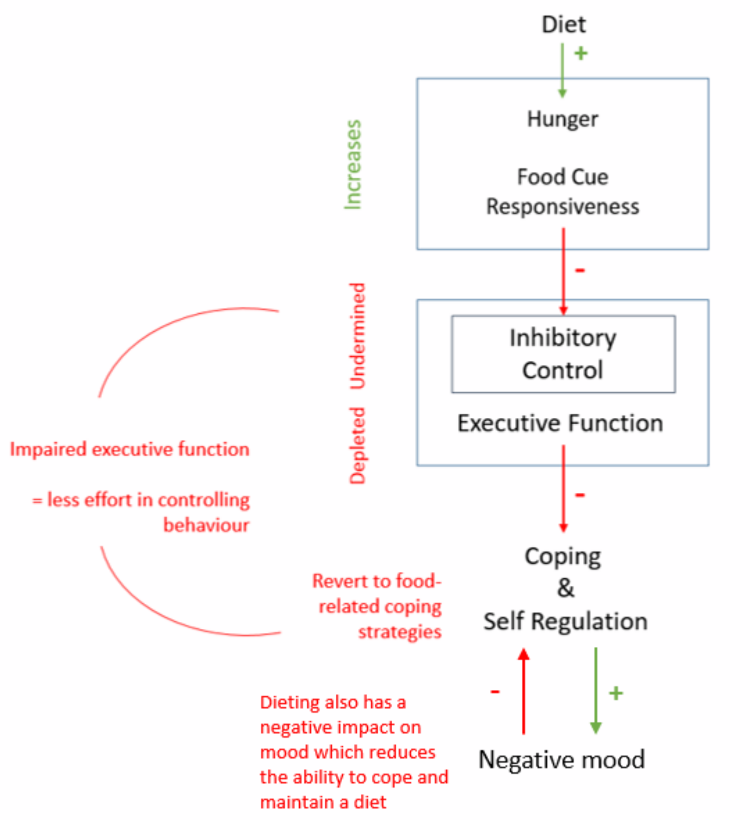

Figure 1.4 - Dieting increases hunger and food-cue reactivity which undermines executive functions such as inhibitory control and impacts the ability to cope and maintain a diet. Dieting also increases negative mood which also reduces the ability to control behaviour and cope with dieting. Adapted from Roberts et al. (2017)

1.5.2 Weight loss and dietary adherence

Appetitive responses to maintaining a negative energy balance contribute to the low rate of compliance in weight loss, particularly in the short-term with managing sensations such as hunger being one of the major factors given for unsuccessful dieting attempts (Drapeau et al., 2007; Gibson et al., 2014; Stubbs et al., 2011). Higher levels of adherence to a diet is important for weight loss regardless of diet type (Alhassan et al., 2008), therefore strategies to improve dietary adherence is essential to aid with successful weight control.

Specific moments of dietary inadherence (i.e. lapses) potentially play an important role in weight control, however very little is known about them (Forman et al., 2017). Most dietary lapses are precipitated by temptations though this is not always the case (Appelhans, French, Pagoto, & Sherwood, 2016). Temptations or desires are an important predictor of effective regulation over eating behaviour (Hofmann, Vohs & Baumeister, 2012) with temptation strength being the most common reasons for eating unhealthy snacks (Cleobury & Tapper, 2013) mediating the relationship between implicit evaluations of unhealthy snack food and subsequent intake (Haynes, Kemps, Moffitt & Mohr, 2014). Temptations thought to be the output of a momentary reward-based evaluation of an environmental food-related stimuli which activates reward-circuitry, and triggers appetitive motivational processes which challenge control over eating behaviour (Appelhans et al., 2016).

Historically, investigations in this area have relied on structured interviews following weight loss or focus on a specific moment of temptation or lapse. These studies reported high levels hunger, cravings, negative affect as well as being in the presence of food-related cues and being in social situations as factors which were responsible for dietary lapses (Grilo, Shiffman & Wing., 1989; Rosenthal & Marx, 1981). However, these accounts may not be representative of all specific moments of temptation and lapses and may be confounded by a reliance on self-reported retrospective reports that may introduce recall bias in these measures (Shiffman & Hufford, 2011). Recent methodological advancements have allowed these issues to be addressed and are a major focus of this thesis. A systematic review of previous investigations employing real-time methods to examine momentary dietary adherence is detailed in Chapter Three.

An increased drive to consume may contribute to high levels of inadherence to weight loss regimens as well as the inability to maintain losses (Doucet, St-Pierre, Alméras, & Tremblay, 2003; Drapeau et al., 2007), therefore adherence to dietary interventions could be improved by dietary strategies which help control or supress appetitive drives to eat that occur during ER (Gibson & Sainsbury, 2017).

One such strategy thought to supress the drive to eat whilst simultaneously avoid compensatory increases in hunger that usually occur during ER are very low energy diets (VLEDs) (Gibson et al., 2014). VLEDs employ severe energy restriction (≤800 kcal/day) which induce a metabolic response to a low carbohydrate intake resulting in increased circulation of ketones bodies produced by the liver. In one meta-analyses, Gibson et al. (2014) found that individuals displayed significantly lower levels of hunger and higher levels of fullness following adherence to a VLED diet compared to baseline. The authors reported that though these were small effects, these findings have important implications as they demonstrate that maintenance of a VLED prevents the compensatory increases in appetite which may pose a barrier for successful dietary adherence.

Ketosis is thought to be the underlying biological mechanism for this suppression of appetite given that changes in appetite coincide with changes in concentrations of ketones in circulation (Gibson & Sainsbury, 2017). For example, raises in appetite has been observed in the first few days of a VLED prior to when increases in circulating ketones are to be expected (Astrup, Vrist & Quaade, 1990; Lappalainen et al., 1990; Wadden, Stunkard, Brownell & Day, 1985). However, after a time when elevated circulating ketone levels are observed, subjective appetite ratings as well as circulating levels of ghrelin and CCK were not significantly different from baseline (Chearskul, Delbridge, Shulkes, Proietto & Kriketos, 2008; Sumithran et al., 2013). Additionally, Sumithran et al. (2013) found that concentrations of ghrelin were supressed relative to baseline, but only in participants currently in ketosis. These appear to demonstrate that ketosis supresses the compensatory biological and behavioural appetite responses to maintaining a negative energy balance which be beneficial for dietary adherence (Gibson et al., 2014). However, there are currently no investigations into the role of baseline appetite on adherence to these diets particularly in the short-term. Further investigations would be required to assess whether individuals who struggle to cope with strong sensations of hunger may not be able to maintain sufficient levels of severe ER to experience the beneficial changes in sensations of satiety which may aid with increasing dietary adherence.

1.5.3 Intermittent energy restriction and appetite

Continual energy restriction where energy intake is restricted every day is the most frequently used weight loss strategy (Steyer & Ables, 2009), however for most it is difficult to follow since intake must be limited daily which may negatively impact appetite and adherence (Anderson, Konz, Frederich, & Wood, 2001; Franz et al., 2007). Intermittent energy restriction (IER) is an alternative approach to weight loss thought to be easier to follow due to favourable changes in appetite as a result of shorter spells of intense ER followed by periods of *ad lib* intake (Hoddy et al., 2016; Johnstone, 2015). Intermittent fasting (IF) is a similar approach to weight loss and commonly used interchangeable with IER, however IER consists of intermittent periods of partial intake (IER; between 50 – 75% ER on restricted days) whereas IF consists of no intake on restricted days. There are potential different metabolic, biological, and behavioural responses such as greater metabolic fluctuations and hyperphagic responses on *ad lib* intake days following a complete fast, therefore it is important to distinguish between approaches (Harvie & Howell, 2016).

The most common approach in human models of fasting has been IER that uses either two consecutive or separate days of ER within the week (e.g. 5:2 diet) or alternating days of ER (ADER). These studies have predominantly focused on the short-term impact of IER limiting our understanding of the longer-term health and behavioural implications possibly over concerns that IER could promote problematic eating patterns due to hyperphagic responses to compensate for the previous day of ER which would negate any health benefits. However, more recent investigations have found reductions in binge eating in individuals with overweight and obesity with pre-treatment and non-binge eating disorder (da Luz et al., 2015), and uncontrolled eating with further increases in restrained eating (Bhutani et al., 2013).

In addition, multiple investigations report a 'carry-over' effect of ER through a spontaneous reduction of between 10 – 23% of prescribed energy intake on all five unrestricted days of an IER diet (Harvey, Howell, Morris, & Harvie, 2018; Hutchison et al., 2019). Whilst the underlying behavioural mechanisms responsible for this reduction is currently unknown, anecdotal reports suggest IER makes individuals more aware of food habits and reassures them that they can manage the high levels of appetite on ER days (Harvie et al., 2011). However, caution must be taken when interpreting these studies as intake was measured using food diaries which are known to suffer from degrees of underreporting (Macdiarmid & Blundell, 1998). Despite this, IER was found to produce comparable levels of weight loss and dietary compliance to CER (Beaulieu et al., 2020; Harvie et al., 2013), though IER may have additional health benefits over CER with greater improvements found in those at risk of obesity-related diseases (Wei et al., 2017). These included greater improvements to inflammation, insulin sensitivity, and reductions in hepatic and visceral fat stores which are thought to mediate reduced risk of certain cancers (Harvie & Howell, 2016), however these effects may only be applicable to IER diets which induce a negative energy balance, whereas IER which maintains energy balance has been associated with transient increases in risk markers for type 2 diabetes (Hutchison et al., 2019).

The effect of IER on appetite regulation is not well-defined due to inconsistencies in previous findings which warrants further investigation (Harvey et al., 2018; Hutchison et al., 2019). Some investigations have found increases in hunger during the first week which gradually decreases over time suggesting habituation in both ADER (Bhutani et al, 2013; Klempel, Bhutani, Fitzgibbon, Freels, & Varady, 2010) and 2d/week of ER (Harvie et al., 2013). Some have also found hunger remains increased throughout (Ravussin, Smith, Anton, Martin, & Heilbronn, 2005), and others have found no changes (Coutinho et al., 2018; Hutchison et al., 2019). A similar pattern emerges for fullness, with some finding initial decreases in fullness on fasting days which appear to increase over time (Hoddy et al., 2016; Varady et al., 2013) whilst others have found fullness remains consistently low (Klempel et al., 2010). Even fewer studies have investigated experiences of cravings and these have only been conducted using periods of total fasting or a VLED diet, both of which found reductions in reported cravings over time (Harvey et al., 1993; Lappalainen et al., 1990).

There is current a lack of published data on subjective appetite ratings during *ad libitum* days of interventional studies using IER (Harvey et al., 2018) meaning the impact of IER on appetite on days following ER is unknown. Currently, the only published evidence comes from one laboratory feeding study where participants with overweight and obesity completed two 3-day experimental trials in a randomised crossover design (Clayton, Creese, Skidmore, Stensel, & James, 2016). These trials consisted of a 24h dietary intervention day where they consumed 25% (ER) or 100% (energy balance) of estimated energy requirements followed by two *ad lib* days. They found no elevations in hunger, fullness, desire to eat and prospective consumption or *ad lib* energy intake in the 48h period following ER compared to days following energy balance.

Taken together, these findings suggest there are no compensatory appetitive or eating responses to short-term intense spells of ER on *ad lib* days of IER meaning it may be a viable strategy for increasing dietary adherence. However, given many report strong sensations of hunger as a reason for non-compliance (e.g. Sayer, Peters, Pan, Wyatt, & Hill, 2018), IER may be unsuitable for individuals who are susceptible to the effects of this sensation. Many current interventional studies using IER suggest average levels of hunger diminish over the course of an intervention, though this is still disputed warranting further studies to better understand the role of hunger in IER. Notably, there has yet to be an investigation whether baseline measures of hunger such as the TFEQ-H predict individual differences in the experience of hunger during IER.

1.5.4 Issues in measurement of appetite regulation and eating behaviour

Investigations into appetite regulation and eating behaviour have been conceptualised as a spectrum of approaches ranging from naturalistic to highly controlled (Gibbons, Finlayson, Dalton, Caudwell & Blundell, 2014). Laboratory-based approaches allow for specific factors to be studied in isolation under strictly controlled environments to assess causal mechanisms thought to be associated with eating. This is the most common approach taken as they provide much greater precision and accuracy above free-living approaches. However, this approach trades off ecological validity in that appetite, energy intake, and their underlying cognitive mechanisms are heavily influenced by environmental factors (Jones et al., 2013; Rosa, Todd & Bouton, 2014) that are likely impacted by the lab environment. For example, decreased energy intake can result from increased awareness of observation during laboratory ingestion studies (Robinson, Hardman, Halford, & Jones, 2015). This suggests that the understanding of appetite regulation and energy intake from these investigations may be limited to clinical and research settings as the degree of artificiality imposed by these highly controlled environments may not adequately represent these processes under naturalistic settings.

Free-living approaches are higher regarding ecological validity as measurement takes place within the participant's natural setting, but these have historically suffered from numerous methodological issues impacting their internal validity, meaning outcomes may not accurately be related to the behaviour of interest (Blundell et al., 2010). Self-report methods of food intake such as daily diaries and 7-day recall methods are prone to varying degrees of underreporting (Livingstone & Black, 2003) which may lead to inaccurate associations between dietary behaviour and health outcomes (Lissner & Potischman, 2009). These approaches also make regular use of global retrospective recall methods (e.g. *'How hungry have you felt over the past 7-days?'*). However, these only provide snapshots of appetite, and are known to be biased due to the use of heuristics that occurs when asked to aggregate experiences over a given time. For example, the peak-end rule (Kahneman & Redelmeier, 1996) where judgements of past experiences are based on the most intense point and how the experience ended such as remembered enjoyment of a previous eating episode (Robinson, Blissett, & Higgs, 2011). Reliance on these global retrospective measures also obscure our understanding of dynamic changes in behaviours over time and situation limiting our ability to characterise and understand real-world health behaviours which may impede our ability to effectively promote long-lasting behaviour change (Shiffman, Stone & Hufford, 2008).

Gibbons, Hopkins, Beaulieu, Oustric, & Blundell (2019) stated that a prominent feature of appetite-related processes is the existence of large inter-individual variability in these phenomena. Figure 1.5 shows how appetite responses follow a typical average response pattern to a test meal, however a closer examination of the individual variation reveals large variability in the individual appetite profiles of subjective appetite ratings.

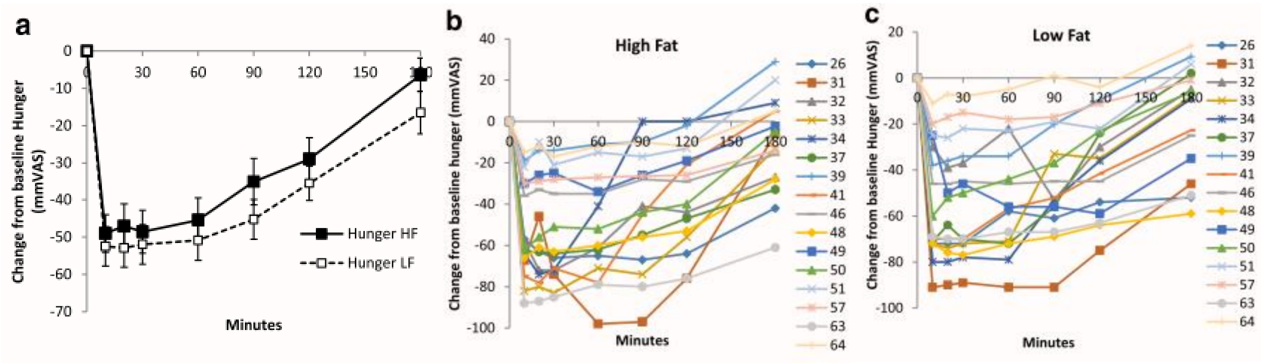

Figure 1.5 - Panel **a** shows average hunger response following a low and high-fat test meal. Panel **b** and **c** show individual profiles of hunger for each participant after both a low- and high-fat test meal. Taken from Gibbons et al. (2019)

Gibbons et al. claimed understanding individual differences in subjective sensations of appetite and cognitive processes that underlie energy intake may help explain the large diversity in eating behaviours and susceptibility for weight gain which is supported by similarly large variability found in body weight responses to weight loss interventions. Many modern behavioural weight loss interventions report clinically significant weight losses of 8-10% of initial body weight, but a closer examination of individual variability shows between 40-60% of individuals achieve this goal (Sherwood et al., 2016). Many have struggled to find robust predictors for variability in treatment outcomes (Rosenbaum et al., 2018) indicating a normative “one size fits all” approach may not be suitable to account given the vast variability in eating behaviours which contribute to weight management problems. This strongly suggests more personalised approaches towards the treatment for overeating and obesity are required.

Interim summary: investigating individualised problems of dieting in the real world

Recent methodological advancements have paved the way towards addressing these issues. Ecological Momentary Assessment (EMA; Shiffman, Stone, & Hufford, 2008) is an emerging methodology which involves repeated measurement within real-world environments that focus on current feelings rather than asking them to recall or summarise over long periods of time making this method perfectly suited for addressing the issues associated with retrospective recall and lab-based environments. Additionally, there is an increasing interest in N-of-1 (single case) methodologies driven by developments in electronic technologies such as smartphones which have enabled the design of studies to investigate individual-level predictors of health behaviours which could provide the basis for development of personalised interventions (Sniehotta, Presseau, Hobbs, & Araújo-Soares, 2012). Chapter Two provides a detailed discussion of both methodologies, and Chapter Three details a systematic review and meta-analyses of previous investigations which employed real-time methodologies during weight loss interventions.

1.6 Thesis aims

The primary aim of this thesis was to compare fluctuations of appetitive processes between energy-restricted and non-restricted days of intermittent energy restriction as well as between momentary states during ER days which pose as barriers for successful dietary adherence in naturalistic settings using Ecological Momentary Assessment. The decision to focus on IER was two-fold: i) IER employs very low energy on ER days which may have added health benefits above continual ER as well as beneficial implications for sensations of appetite if maintained. However, intense momentary appetite responses to ER in the initial stages of weight loss may be problematic for those who struggle to cope with these sensations; ii) alternating days allows for contrasts of variables between nER and ER days so that within-person changes can be statistically modelled, and between-person moderators of these relationships can be investigated. The studies detailed in this thesis are among the first to employ real-time measures of appetite during IER to increase our understanding of real-world dietary adherence in samples of individuals with overweight and obesity. The experimental chapters made use of methodologies which allowed for a better understanding of individual variation, and findings could help pave the way for the development of personalised weight loss plans that aid in coping with appetitive responses to ER in naturalistic settings when and where these problems are encountered.

The secondary aim of this thesis was to examine whether baseline measures of appetite and eating behaviours could be used to explain individual differences in subjective sensations of appetite or cognitive processes underlying eating behaviours. This thesis made use of trait eating behaviour inventories as well as baseline measures of appetite sensations to better understanding how these measures explain differences in real world experiences. Findings could help in early identification of individuals who may benefit from support with coping with specific appetitive phenomenon during weight loss.

Finally, this thesis aimed to examine whether differences are observable between retrospective and real-time measures of appetite responses. Both real-time and retrospective measures of appetite were used in the experimental chapters detailed in this thesis so that differences in responses could be directly investigated. These findings have methodological implications for future investigations into appetitive responses to dietary interventions.

In Chapter Three, a systematic review and meta-analyses was conducted to synthesise existing evidence on appetitive and affective processes that were measured during ER within naturalistic settings using real-time methods. Chapter Three aimed to assess appetitive, affective, and cognitive outcomes between assessments of dietary temptation, dietary lapse, and assessments which randomly take place throughout the day to better understand how fluctuations in these outcomes determine momentary subjective states which are problematic for successful dietary adherence. An additional aim of this investigation was to better understand the antecedents of temptations and lapses as well as between-person differences in appetitive and affective outcomes.

Chapter Four aimed to investigate the impact of IER on dynamic fluctuations of subjective sensations of appetite, food-cue responsiveness, and behavioural control on both ER and nER days in a sample of individuals with overweight and obesity engaging in a non-consecutive 2 d/week IER diet. A secondary aim was to investigate whether baseline measures of eating behaviours could explain individual differences in outcome measures. This study also aimed to examine differences in outcomes when measured proximal to the initiation of an eating event. Finally, this study aimed to investigate change in hunger ratings from pre to post investigation using a 7-day retrospective measure.

Chapter Five aimed to investigate the impact of a 4-week ADER intervention on dynamic fluctuations in appetite, stress, and behavioural control to understand how these outcomes differ between momentary subjective states which pose a problem for successful dietary adherence in sample of individuals with overweight and obesity. Additionally, the investigation aimed to investigate whether baseline measures of eating behaviours and appetite measures could explain individual differences in appetite responses to ER. Finally, the study aimed to examine the association between retrospective and real-time measures of appetite.

Chapter Six provides an in-depth discussion of how the investigations detailed within this thesis address the overarching aims set out within this current chapter. This discussion provides an overview of findings which were synthesised within several themes to allow for a detailed explanation of how utilising EMA addressed the issues that were previously present within literature surrounding appetitive processes and dietary adherence during ER. This chapter also discusses the several methodological limitations which were common among the investigations in this thesis. Finally, this chapter discusses the implications of these results for future investigations of appetitive processes during ER and details some potential directions for future research.

Chapter Two

General Methods

2.1 Ecological Momentary Assessment (EMA)

As previously mentioned, investigations into appetite and ER have relied heavily on laboratory-based settings and retrospective recall of experiences (e.g. '*rate your hunger over the past 7 days*') both of which may be limited by various methodological biases.

Patterns of eating are lifelong learned and reinforced with every meal we eat (Scalfani, 1997). The cognitive processes which guide consumption such as attention and behavioural control are associatively mediated by both internal and external cues (Jones et al., 2013; Rosa, Todd & Bouton, 2014). This means that the degree of artificiality imposed by controlled environments limits our understanding of appetite to clinical and research settings which only provide a snapshot of appetitive processes whilst under conditions not representative of daily life (Robinson, Hardman, Halford, & Jones, 2015).

In addition, retrospective recall is known to be biased due to the use of heuristics that occur when we are asked to aggregate experiences over a given time. One example of this is *the peak-end rule* (Kahneman & Redelmeier, 1996) where judgements of a past experience are based on the most intense point and how the experience ended, this has been shown to affect remembered enjoyment of a previous eating episode (Robinson, Blissett, & Higgs, 2011). Furthermore, lab-based approaches and retrospective recall are incapable of studying dynamic changes in responses over time and in different situations. This limits our ability to accurately characterise and understand behaviours within the real world and how these dynamically fluctuate from day-to-day and moment-to-moment (Shiffman, Stone & Hufford, 2008).

2.1.1 EMA: Principles and historical roots

Ecological Momentary Assessment (EMA; Shiffman et al., 2008) is an emerging methodology involving repeated measurement within real-world environments. EMA focuses on current feelings rather than asking participants to recall or summarise over long periods of time making this method perfectly suited for overcoming the limitations of those approaches. Assessment times are strategically selected based on the feature of interest (e.g. using event-assessments for discrete behaviours such as lapsing whilst on a diet) or random sampling to characterise experiences through representative sampling of moments throughout the day to observe how behaviours vary across time and contexts. EMA can also be used for prospective analyses of processes that lead to behaviours that have been historically hard to capture such as fluctuations in stress and affect preceding a lapse during smoking cessation (Shiffman & Waters, 2004).

The term *"Ecological Momentary Assessment"* first used by Arthur Stone and Saul Shiffman in 1994 to describe the principles and rationale for a methodological approach toward assessing behavioural and cognitive processes in their natural setting (Stone & Shiffman, 1994). In a later methodology paper outlining its development, Shiffman et al. (2008) explained that EMA was influenced by several historic roots that included traditional pen-and-paper diaries, self-monitoring, ambulatory monitoring, and experience sampling procedures. The stated objective of developing the EMA methodology was to encompass the broad range of disciplines which all take a different approach towards sampling behaviours under a unifying methodological framework.

Diaries and self-monitoring techniques have largely been utilised in clinical research to examine target behaviours and experiences (Schlundt, Johnson & Jarrell, 1985). These use event-based sampling techniques which are comprised of counts of relevant events as well as information regarding antecedents and context, but do not focus on experiences outside these target events. Ambulatory monitoring of cardiovascular function influenced the development of time-based sampling techniques used in EMA. For example, one early study required participants to wear an ambulatory blood pressure monitor which signalled participants every 15 minutes to rate subjective mood, allowing for associations between mood and blood pressure to be explored (Schwartz, Warren & Pickering, 1994). The development of the experience sampling methodology (Csikszentmihalyi, 2014) was also an important milestone for the development of real-time assessment of behaviours. This allowed the application of random sampling to daily experiences within the moment allowing for observation of momentary subjective states and how these fluctuate throughout the day.

EMA has also been referred to as intensive longitudinal design due to assessments being made at multiple time points (common to longitudinal designs) though the distinction with EMA is that assessments are conducted frequently with relatively short time period in between measurements (Bolger & Laurenceau, 2013). Historically, participants were given pagers and prompted to complete paper assessments, though more recent technological developments allow for measurements to be made on electronic devices (e.g. smartphones) allowing for more complex EMA designs (e.g. implementing objective measures of cognition) as well as better compliance to assessment protocols compared to the traditional pen-and-paper protocols due to digital timestamping (Stone, Shiffman, Schwartz, Broderick, & Hufford, 2003).

2.1.2 EMA testing application (APPetite)

In the experimental chapters of this thesis, EMA was used to collect data in real-world environments as participants go about their daily lives whilst engaging in IER. The assessments were strategically chosen based on features of interest such as event assessments for occasions like experiencing a temptation (TA) or lapse (LA), and random assessments (RA) for characterising experiences through representative sampling of moments throughout the day.

APPetite is a novel testing smartphone application that was developed for the purpose of this thesis to assess momentary fluctuations in sensations of appetite and affect, cognitive processes, and the context in which assessments took place. A brief description and schematic diagram (see Figure 2.1) of the app is provided below.

APPetite was programmed with OpenSesame version 3.2.4 (Mathôt, Schreij & Theeuwes, 2012), a Python-based programme capable of accurately measuring reaction time responses which is essential for cognitive testing. APPetite was imported to Android-based smartphones (Doogee X10; Android 6.0) that were loaned to participants for the duration of each study and run using OpenSesame runtime for Android application. An autorun file was also installed on phones which bypassed OpenSesame's experiment selection and imputation of subject number pages (computed manually in each case during initial set up of the smartphone before being loaned) which took the user directly to the start-up page of APPetite.

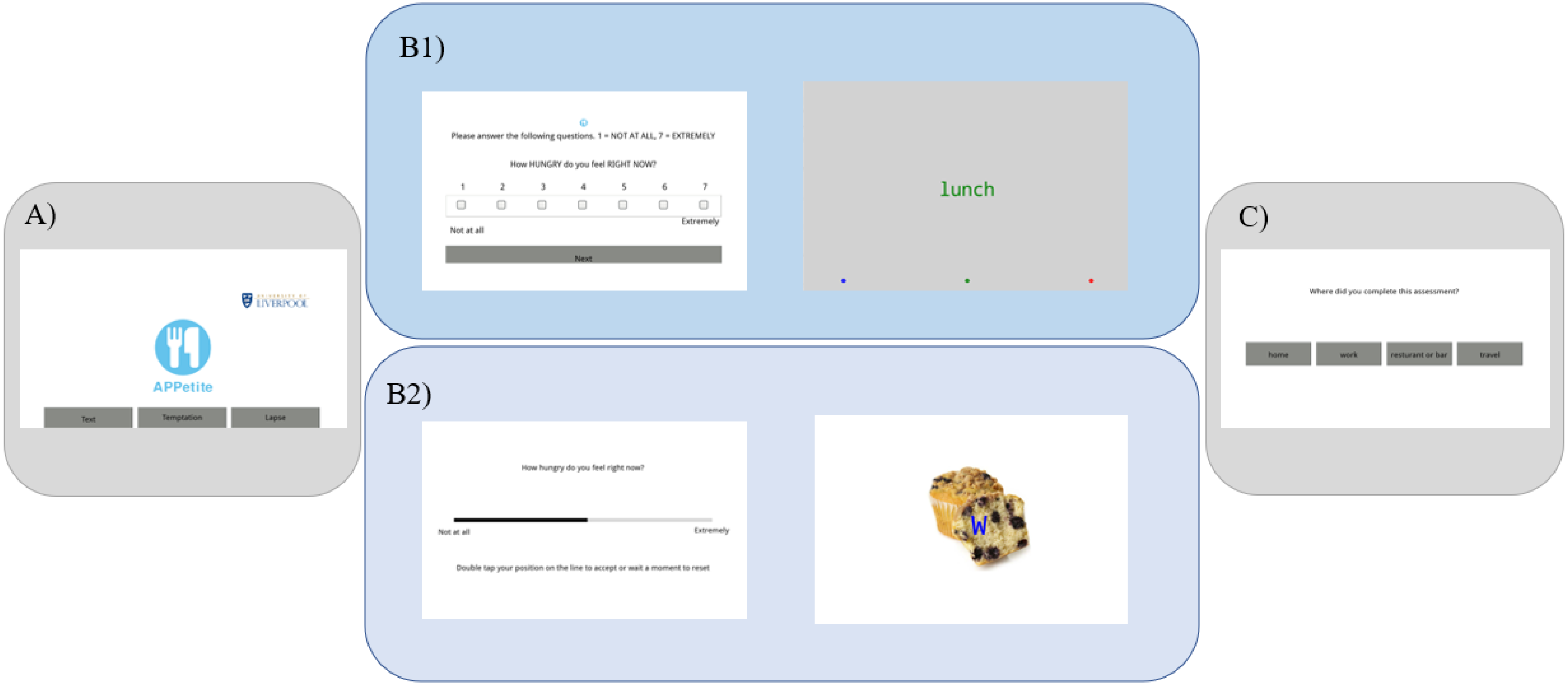

Figure 2.1 - Schematic diagram illustrating the main task formats for APPetite separated by Chapter. Panel A shows the start-up page. Panel B1 shows tasks specific to Chapter Four (Likert scales and Stroop task). Panel B2 shows tasks specific to Chapter Five (VAS and Go/No-go). Panel C shows the format of contextual questions which took place at the end of each assessment.

The start-up page consisted of a logo in the middle and a ‘start’ button at the bottom of the screen. Once pressed, there was an instruction page informing the participant to find a safe place to perform an assessment free from distractions. Assessment procedures for each chapter are discussed below. All assessments ended by asking various contextual close-ended questions relating to where the assessment took place (home, work, restaurant or bar, travel, other) and if caffeine, cigarettes or alcohol had been consumed in the past hour (yes or no) followed by a page stating that the assessment had finished with an ‘end’ button at the bottom of the screen.

Chapter Four: Measuring daily fluctuations of hunger, reward-responsivity, and behavioural control

The assessment began with two 7-point Likert scales asking, ‘how hungry are you right now?’ and ‘how intense are any cravings for food right now?’ which were end anchored ‘not at all’ to ‘extremely’. These rating scales were presented in a randomised order for every assessment. They were followed by a screen of instructions detailing the food Stroop task and order of response buttons with a ‘start’ button at the bottom of the screen. A colour Stroop was also presented in the same format following completion of the food Stroop (see Chapter Four for details on the Stroop tasks).

Chapter Five: Measuring fluctuations of satiety, reward-responsivity and behavioural control during temptations, lapses, and random moments throughout the day

The assessment began with three buttons labelled ‘Text’, ‘Temptation’, and ‘Lapse’ presented at the bottom of the screen. During RAs (Text), the assessments began with four 100-point VAS asking ‘how hungry do you feel right now?’, ‘How full do you feel right now?’, ‘How much are you craving food right now?’, and ‘How stressed do you feel right now?’. Participants would drag a visual slider across a line which was end anchored ‘not at all’ to ‘extremely’ to respond. VAS were presented in a randomised order every assessment. This was followed by a page of instructions detailing the food-specific Go/No-Go task (see Chapter Five for details on the Go/No-Go task).

During TA and LAs, participants were presented with four 100-point VAS assessing appetite and stress in the same format detailed above, with the exception of lapse assessments which asked how they felt *right before* lapsing. Following this, fourteen VAS assessing the use of coping strategies during temptations or lapses (Carels, Douglass, Cacciapaglia, & O’Brien, 2004) were presented in a randomised order. These asked participants to rate the extent to which they engaged in various activities which were: “removed myself from the situation,” “distracted myself,” “talked to someone for advice or comfort,”, “encouraged myself,” “meditated/relaxed,” “exercised,”, “thought about the benefits associated with dieting and/or being healthy,” “thought about the negatives associated with not dieting and/or being unhealthy,” and “other.” These were end anchored ‘not at all’ to ‘I did this a lot’ and responses were summed to compute a total coping score for the temptation or lapse event. Finally, to reduce participant burden, there was a 25% chance that a food-specific Go/No-go task was administered.

For all RAs, an automatic text messaging service (Scheduled; Utrecht, Netherlands) was used which sent a text to participants personal mobile phones prompting them to complete an assessment within 45 minutes of receiving the text and to text back ‘done’ once completed. Compliance was checked during lab visits. Assessment timings were made using a random number generator in Microsoft Excel. Time schedules were based on random time intervals detailed in Section 4.3.2 (P. 119) and Section 5.3.2 (P. 150)

2.2 N-of-1 design

Between-person designs such as cohort studies and randomised control trials aim to assess the effect of an intervention in a study population, though average responses do not apply to the individual as some may gain greater benefit from a treatment whilst others do not see any benefit (Kravitz, Duan, & Braslow, 2004). Statistically, these designs treat individual differences as *error* (see Figure 2.3), though in reality these differences relate to the extent to which an intervention benefits the individual compared to the average response. In Section 1.5.4, it was mentioned that a prominent feature of appetite, eating behaviours, and weight loss is the existence of large inter-individual variability (see Figure 1.5 on P. 39). Personalised approaches towards the treatment of obesity may thus prove more effective.

N-of-1 (single-case) methods examine how behaviours change within an individual over time. They provide an opportunity to explore inter-individual variation which can be used for testing hypotheses or assessing responses to personalised interventions making findings highly applicable to the individual (Vieira, McDonald, Araújo-Soares, Sniehotta, & Henderson, 2017).

In a systematic review, McDonald et al. (2017) examined previous investigations of health behaviours employing N-of-1 methods, broadly characterising them as either observational or interventional. Observational N-of-1 designs involve use of repeated measurement of an outcome to investigate temporal patterns in a target behaviour. These involve no experimental manipulation therefore lack the ability to draw causal conclusions, though contextual predictors (e.g. time and location) can be measured to examine associations at the individual level (Hobbs, Dixon, Johnston & Howie, 2013). Interventional N-of-1 designs assess the effect of an intervention on behaviour and are comprised of phases (i.e. 'A' baseline, 'B' intervention) which can also be combined and randomised into a sequence (e.g. 'ABAB') (Shamseer et al., 2016). Interventional designs have also been suggested for understanding causal determinants of behaviour by testing theories and their predictive validity (Medical Research Council, 2008).

N-of-1 protocols applied to more than one individual can be combined into a case-series allowing for analyses to be made on aggregate responses with multilevel modelling to determine how generalisable findings are between cases as well as to examine potential between-person moderators of within-person processes (Araujo, Julious & Senn, 2010; Sniehotta, Presseau, Hobbs & Araujo-Soares, 2012).

In Chapter Five, an N-of-1 approach was taken to investigate the impact of alternate day energy restriction (ADER) on appetite-related processes, energy intake and dietary adherence. This study used an interventional AB design consisting of 1-week of *ad libitum* energy intake (A phase) and 4-week ADER (B phase) (see Section 5.3.2 on P. 150) for details on study design). Cases were combined into a series and analyses were conducted on aggregate responses.

For exploratory analyses, outcome measures taken using EMA during the baseline phase of the investigation were averaged to calculate participant-level scores which were imputed into models to assess whether baseline ratings could explain appetitive measures during the interventional phase. For further details of analytic procedures, see Section 5.3.5 (P. 156).

2.3 Measures of energy intake

In Chapter Four, a photographic food diary was employed to record precise timing of consumption using the loaned smartphone camera. Participants were instructed to take a photo of anything they ate or drank (excluding coffee and tea without milk or water) immediately prior to consumption. Digital photographs are time and date stamped so timings of consumption could be estimated. During data tabulation, RAs that took place within two hours of an eating event being subsequentially logged were identified and dummy coded allowing for comparison with RAs where an eating event was not logged (detailed in Section 4.3.4 on P. 122).

In Chapter Five, an app-based calorie counter (MyNetDiary) was used to record daily calorie intake. MyNetDiary is comprised of an extensive database of food products which requires users to input what was eaten as well as the weight or amount to provide an estimated calorie content. Ingredients can also be combined to create recipes if homemade meals were consumed. A user profile was created for the purpose of the study and the app was installed on the loaned smartphone or their own personal phone depending on preference, and participants were instructed to log everything they ate and drank on that day throughout the study period.

2.4 Measures of height and weight

In both Chapters 4 and 5, height was measured using a Seca 222 telescopic measuring rod (Chino, USA) and weight was recorded using a Seca 888 compact digital floor scale (Hamburg, Germany). These were used to accurately calculate body mass index (BMI) using the equation: Weight (Kg) / Height $(m)^2$.

2.5 Statistical analyses

2.5.1 Hierarchical data structures in repeated measure designs

Repeated measure designs which were used extensively throughout this thesis are comprised of multiple observations made within the same individual which result in nested hierarchical data structures (see Figure 2.2). These structures produce clustering of datapoints as observations that are made within the same individual are likely to demonstrate high levels of dependency (e.g. an individual’s responses may fluctuate over time, but these should be highly correlated with their previous responses).

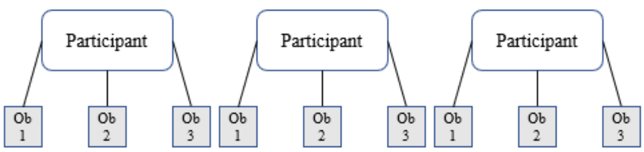

Figure 2.2 - Unit diagram illustrating a hierarchical data structure of repeated measurements where observations are nested within individuals

2.5.2 Issues with ordinary least squares (OLS) regression in repeated measure designs

In linear regression models, a straight line is fitted to a scatterplot of a predictor (*x*) against an outcome (*y*) which describes the strength and direction of the relationship between both variables. The basic equation of a basic regression with one predictor variable is given as:

$$y_i = \beta_0 + \beta_1 + e_i$$

Where y_i is a given response ($i = 1\ldots\text{N}$), β_0 represents the intercept (overall average in response for the sample), β_1 represents a predictor (independent variable) that modifies the slope of the line equating to the amount of change in *y* for 1-unit change in *x*. e_i (residual error) is the difference between an actual response and the expected value predicted from the regression line (see Figure 2.3).

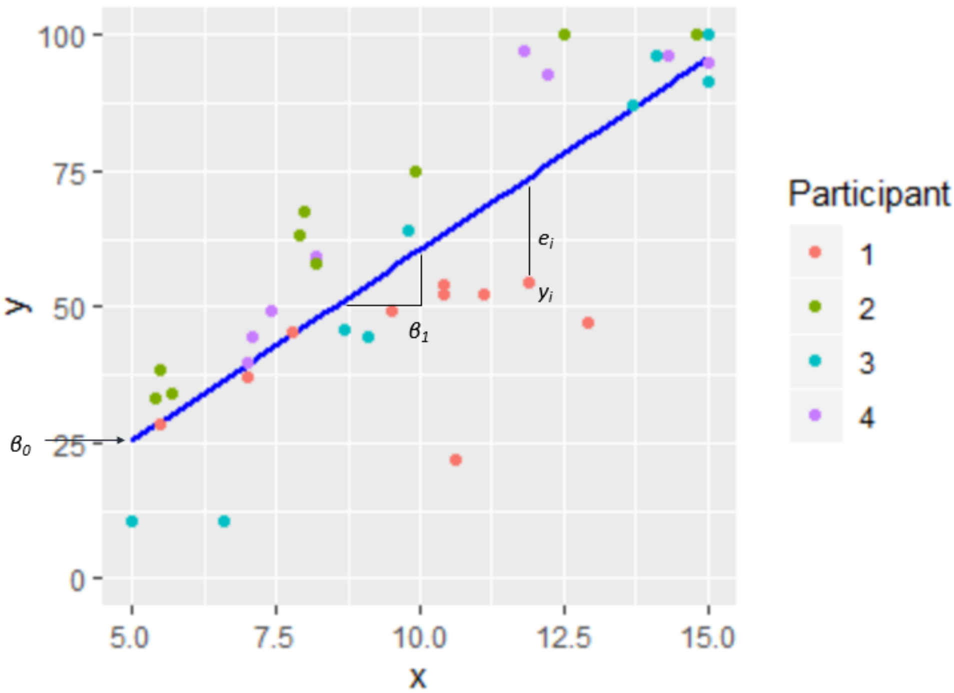

Figure 2.3 - Scatterplot illustrating the features of interest relating to the formulaic expression of a single-level regression

In linear models, β_0 and β_1 are population parameters drawn from the sample using an estimation method called ordinary least squares (OLS). This involves finding a line which best fits the observed data by minimising the sum of squared differences between all residual errors and the expected value given by the plotted line.

OLS makes the following assumptions regarding these residual errors:

1. They have zero mean and a variance (σ^2) that is equally distributed around the mean (normality of errors).
2. The variance is constant regardless of the value of *x*, so that *y* values have approximately the same variance at any value of *x* (homoscedastic).
3. The residuals are not correlated with each other. This may arise if observations are clustered somehow such as if an individual contributes more than one observation (independence).

The assumption of independence is likely to be violated in the case of repeated measurements due to the high levels of correlation between datapoints. The oft-stated 'ANOVA is a robust test' does not apply as readily to violations of the assumption of independence, regardless of the variant used (Hartmann, 1974). For example, in the case that datapoints are positively correlated, standard errors will be lowered, and test-statistics will be heightened inflating the risk of Type I errors (Steenbergen & Jones, 2002).

There are two broad statistical approaches for accounting for dependency in hierarchical datasets (Jones, 1997). Marginal approaches estimate the correlation between each residual; however, they treat clustering as a nuisance rather than an additional source of variance that could be used to explain differences in outcomes. The multilevel approach allows for this dependency to be investigated and is discussed in detail in the next section.

2.5.3 Multilevel modelling

Multilevel modelling is an approach towards analysing hierarchical data structures which explicitly models clustering by partitioning the overall variance into separate levels allowing for predictors of both within and between processes as well as their interactions to be modelled (Szmaragdand & Leckie, 2013). The simplest form of multilevel model is a 2-level random intercept model where observations are nested within participants which is achieved by adding a random effect of participant allowing for between-person differences in the mean response of *y* (see Figure 2.4).

The formula for a 2-level structure is:

$$y_{ij} = \beta_0 + u_j + e_{ij}$$

y_{ij} is a given response (i = 1…n) for a given participant (j = 1…N). u_j is the difference between a participant's mean response and the overall mean for the sample (β_0). e_{ij} is the difference between an individual observation and the deviation from the participant's mean from which the response was given. The interpretation of β_1 as a slope modifier (strength of relationship) does not change for random intercept models.

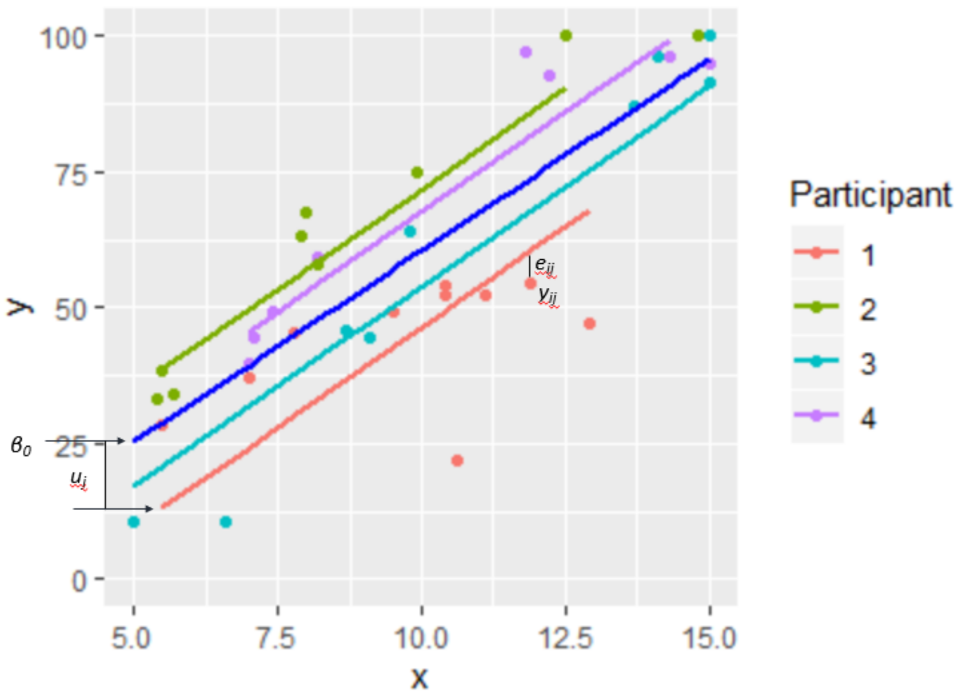

Figure 2.4 - Scatterplot illustrating the features of interest relating to the formulaic expression of a two-level random intercept model

Variance in this model is partitioned into two random components: a between (u_j) and within (e_{ij}) person effect. A null model with no predictors, also referred to as a variance component model (VCM) is used to categorise the proportion of variance that can be attributed to the addition of a random component and can be assessed using the variance partition coefficient (VPC):

$$\sigma^2_u / \sigma^2_u + \sigma^2_e$$

The VPC ranges from 0 to 1 and describes the percentage of variance that can be attributed to each level of analyses. For example, if the VPC is 0.4, that means that 40% of variance can be attributed to between participant differences. The magnitude of clustering can be examined with the intraclass correlation coefficient (ICC) which is the correlation between two y values of randomly selected observations within the same cluster. For 2-level models, the ICC is the same as the VPC.

To test the significance of including a random effect of participant, the 2-level model can be compared to a single level model using a likelihood ratio (LR) test. The test statistic can then be compared to a X^2 distribution with a degree of freedom (*df*) equal to the number of additional parameters of the multilevel model (i.e. $df = 1$ for the addition of u_j).

To create a conditional model, predictor variables can be input at each level of analyses to simultaneously estimate both within- and between-person effects which are significance-tested by computing Z-scores.

All between person variation is treated as a random effect by the inclusion of the random intercept which provides more precise estimates of the within-person variance (Enders & Tofighi, 2007) as well as grand-mean centring all between-person variables (Kreft, de Leeuw & Aiken, 1995).

To assess model fit, the conditional model can be compared to the null model using an LR test and compared to a X^2 distribution with a *df* equal to the number of additional predictors included in the model.

2.5.4 Calculating VPCs for variants of multilevel models

3-level multilevel model

In Chapters 4 & 5, EMA designs were used which produce multiple observations that are made on each study day for each participant producing a 3-level hierarchical structure. 3-level random intercept models were used which consisted of observations (level 1) nested within study days (level 2) nested within participants (level 3). Model specification for a 3-level structure is identical to the process detailed above with the addition of a random component of study day. The formula for a multilevel model is given as:

$$y_{ijk} = \beta_0 + v_k + u_{jk} + e_{ijk}$$

y_{ijk} is a given response (i = 1…n) on a given day (j = 1…n) for a given participant (k = 1…N). v_k is the deviation of a participant's mean response from the overall mean for the sample (β_0). u_{jk} is the deviation of a study day's mean (j) from the participants mean response (k). e_{ijk} is the deviation of a given response (i) from the mean value of a study day (j) that are from the same participant (k).

Variance in this model is partitioned into three random components: between-participants (v_k), between-days within participants (u_{jk}), and between-observations within the same day and participant (e_{ijk}). There are three VPCs for a 3-level model which explain the amount of variance at each level of analyses:

The participant level VPC is the ratio of participant variance to total variance:

$$\sigma^2_v \ / \ \sigma^2_v + \sigma^2_u + \sigma^2_e$$

The day level VPC is the ratio of participant variance to total variance:

$$\sigma^2_u \ / \ \sigma^2_v + \sigma^2_u + \sigma^2_e$$

The observation VPC is the ratio of participant variance to total variance:

$$\sigma^2_e \ / \ \sigma^2_v + \sigma^2_u + \sigma^2_e$$

As mentioned in Section 2.4.2, the ICC can also be calculated to describe the magnitude of clustering for each level by assessing the correlation between two randomly selected observations within the same cluster. The participant level ICC is the same as the participant level VPC. The day level ICC can be calculated using:

$$\sigma^2_v + \sigma^2_u \ / \ \sigma^2_v + \sigma^2_u + \sigma^2_e$$

Multilevel ordinal models (Steele, 2011)

In Chapter Four, ordinal responses were collected in the format of 7-point Likert scale responses. As is common in psychological research, these responses were treated as linear to aid with interpretation of the model parameters. However, to confirm this assumption, ordinal models were also created to confirm there was no substantive differences in findings between models.

The approach taken towards analysing ordinal responses was to fit a cumulative logit model with proportional odds. A 2-level example is described here, however this was extended to fit the three-level structure:

$$\text{logit}(y_{kij}) = \alpha_k + \beta x_{ij} + u_j$$

$$K = 1 \ldots \text{C-1}$$

This model is based on a cumulative response probability (y_{kij}) which indicates the probability of being in category (k) or lower with C being the maximum category (i.e. Likert rating of 7).

α_k is the threshold parameter which is interpreted as intercept terms. The interpretation of the threshold parameter is the log-odds that a response will be in category k or lower (e.g. α_2 is the log-odds of being in category 1 or 2 rather than > 3). There is a different intercept for each category except for the last category (C). u_j allows for these category thresholds to vary between-individuals which also allows for the cumulative response probability to vary between-individuals. βx_{ij} is the regression coefficient of a predictor and the effect of these are assumed to be constant between response categories (proportional odds assumption).

A cumulative logit model can be expressed as a linear model which assumes there is a continuous latent (unobserved) variable (y*) that underlies the observed responses.

$$y_{ij}^* = \beta x + u_j + e_i^*$$

y_{ij}^* represents an individual's propensity to have a given observed value. Above a certain value of y_{ij}^*, a threshold is crossed meaning there is an increase of 1-unit on the Likert scale response. e_i^* is a residual error term. As y^* is an unobserved value, a predetermined set value for e_i^* which is given as standard logistic distribution ($e_i^* = 3.29$). For logit models, the VPC can be estimated as:

$$\sigma^2_u \;/\; \sigma^2_u + 3.29$$

The VPC for a 2-level model represents the proportion of total residual variance in a propensity to have a high observed value of y that is due to differences between groups.

Multilevel Poisson and negative binomial (NB) models (Leckie, Browne & Goldstein 2019)

In Chapter Five, a count variable of the amount of commission errors towards food-related Go/No-Go task was used as the dependent variable in the model. 2-level models are described here, however these were extended to 3-level models in analyses where the data permitted (see Section 5.4.3 on P. 159). The first step to modelling count data was to build VCM for both Poisson and NB models to assess the degree of clustering as well as overdispersion before entering predictors.

A VCM 2-level Poisson conditional (clustered) expectation model is expressed as:

$$\mathrm{Ln}(\mu^{c}_{ij}) = \beta_0 + u_j$$

μ^{c}_{ij} is the conditional (c) expected count. β_0 is the intercept, and u_j is the group-level variance. The conditional variance is assumed to be the same as the conditional expectation following the assumption of a Poisson distribution (variation equals the mean).

To work out the conditional model, a marginal (participant-averaged) expectancy model needs to be constructed which averages expected count over u_j. This is given as:

$$\mu^{m}_{ij} = \exp(\beta_0 + \sigma^2_u/2)$$

The marginal variance (w^{m}_{ij}) is averaged over u_j which is a quadratic function of the marginal expectancy (μ^{m}_{ij}). w^{m}_{ij} is larger than 0 if clustering is present. The formula is given as:

$$w^{m}_{ij} = \mu^{m}_{ij} + (\mu^{m}_{ij}{}^2)\,\{\exp \sigma^2_u - 1\}$$

These expressions can be used to work out the VPC for multilevel Poisson models which represents the proportion of marginal response variance which lies between people. The calculation of this is given in Figure 2.5. To work out the proportion of variance which is attributed to within-person (level-1) differences, it is one minus the Level-2 VPC.

$$\mathrm{VPC}_{ij} = \frac{\overbrace{\left(\mu^{M}_{ij}\right)^2\{\exp(\sigma^2_u)-1\}}^{\text{level}-2\text{ variance}}}{\underbrace{\left(\mu^{M}_{ij}\right)^2\{\exp(\sigma^2_u)-1\}}_{\text{level}-2\text{ variance}} + \underbrace{\mu^{M}_{ij}}_{\text{level}-1\text{ variance}}}$$

Figure 2.5 - Formula for calculating the Level-2 VPC of a multilevel Poisson model. Level-1 variance captures within-person variance in the actual observed counts around the expected counts (μ^{c}_{ij}). Level-2 variance captures between-person variance around the expected counts which can be attributed to the inclusion of a random effect for participant (u_j). Taken from Leckie et al. (2019).

A NB model is a special form of Poisson model which allows for overdispersion (where the conditional variance is greater than the conditional expected count). A VCM 2-level NB conditional (clustered) expectation model is identical to a 2-level Poisson model with the inclusion of an overdispersion random effect (e_{ij}) which can be checked with a X^2 goodness of fit test. A 2-level NB model is expressed as:

$$\mathrm{Ln}(\mu^{c}_{ij}) = \beta_0 + u_j + e_{ij}$$

The calculation of the VPC for a 2-level NB model is given in Figure 2.6. To work out the proportion of variance which is attributed to within-person (level-1) differences, it is one minus the Level-2 VPC.

$$\mathrm{VPC}_{ij} = \frac{\overbrace{\left(\mu_{ij}^{M}\right)^{2}\{\exp(\sigma_{u}^{2})-1\}}^{\text{level}-2\text{ variance}}}{\underbrace{\left(\mu_{ij}^{M}\right)^{2}\{\exp(\sigma_{u}^{2})-1\}}_{\text{level}-2\text{ variance}}+\underbrace{\mu_{ij}^{M}+\left(\mu_{ij}^{M}\right)^{2}\exp(\sigma_{u}^{2})\alpha}_{\text{level}-1\text{ variance}}}$$

Figure 2.6 - Formula for calculating the Level-2 VPC of a multilevel negative binomial model. Level-1 variance captures within-person variance in the actual observed counts around the expected counts (μ^{c}_{ij}). However, this now includes an overdispersion parameter (α). Level-2 variance captures between-person variance around the expected counts which can be attributed to the inclusion of a random effect for participant (u_j). Taken from Leckie et al. (2019).

2.5.5 Sample sizes and missing data in multilevel designs

One key issue in multilevel model is what constitutes a sufficient sample size for accurate estimates with the major restriction for multilevel modelling being the sample size at the highest (group) level. Maas & Hox (2015) conducted a simulation study to investigate the effect of different sample sizes at the group-level on the accuracy of estimates and standard errors. They reported that only a small sample (N < 50) at the group level lead to biased estimates which is now regarded as the rule of thumb for sample sizes in multilevel designs.

Rasbash (2008) stated an important consideration for determining a sufficient sample size is the target of inference of the study. For example, if inferences are only to be made about a specific group unit rather than treating the group level as a representative sample (e.g. N-of-1 designs) then a greater number of Level-1 observations will be required to gain a representative sample of within-person fluctuations in the outcome of interest. However, these inferences cannot be generalised to a wider-population of group-level units.

Multilevel designs also allow for unequal amount of assessments across participants that arises from missing data (Rasbash, 2008). Incompleteness can be assumed to be missing at random (MAR) if missingness of data is beyond the researchers' control (Schafer & Graham,

2002) such as data collection taking place in naturalistic settings as is the case in EMA designs.

The assumption of data being MAR permits Iterative Generalized Least Squares (IGLS) estimations to be used to determine parameters by transforming residuals to remove covariance between observations (Hox, 2010). IGLS approximate Maximum Likelihood methods of estimating parameters which involve estimating a likelihood function (i.e. goodness of fit) for each participant (case) based on all the observations in a case so that the likelihood of obtaining the observed value is maximised. For cases which have missing data present, likelihood estimates are computed separately to cases which have complete data and are then fitted together to provide estimates of the model parameters (Enders, 2001).

2.5.6 Sensitivity analyses

One of the main weaknesses of EMA approaches is the potential for data contamination due to the lack of experimental control. In the real-world, measures can be influenced by many extraneous factors, therefore it is important to control for those known to have a potential impact on outcomes. Sensations of appetite and behavioural response times can be influenced by recent consumption of caffeine, alcohol, and nicotine or if any distractions were experienced during reaction-time tasks. In both experimental chapters, at the end of each assessment participants were asked to report recent consumption and distractions. Datapoints that may have been contaminated by these factors were excluded and analyses were reperformed to assess whether findings were robust to these sensitivity analyses (see Table 4.S.1 and Table 5.S.3 on P. 138 and P. 181 respectively).

2.6 Questionnaires

Psychological measures of eating behaviours were taken in Chapters 4 & 5 which were consistent across both studies. These were used for sample descriptives and to investigate between-person differences in appetitive outcomes. All questionnaires were taken at baseline. Internal reliability of these scales in the samples within this thesis were also examined using McDonald's ω which is reported here. A description of these measures and their psychometric properties is detailed below.

2.6.1 Three Factor Eating Questionnaire (TFEQ; Stunkard & Messick, 1985)

The TFEQ is a 51-item tool measuring the tendency towards three dimensions of eating behaviour: cognitive restraint (TFEQ-R), disinhibition (TFEQ-D), and susceptibility to hunger (TFEQ-H). It consists of 36 statements which are scored as a ‘true’ or ‘false’, 15 statements in a Likert scale format scored from 1 – 4 that used a different range of anchors for each item e.g. ‘never’, ‘rarely’, ‘often’ and ‘always’, and 1 statement scored from 0 – 5 anchored ‘eat whatever you want, whenever you want’ to ‘constantly limiting food intake, never giving in’.

The tool was initially validated in a sample of dieters and non-dieters which revealed Cronbach’s alpha for TFEQ-R, TFEQ-D, and TFEQ-H of .93, .91 and .85 respectively. McDonald’s ω in the thesis sample for TFEQ-R, TFEQ-D, and TFEQ-H of .81, .74 and .89 respectively.

In a community sample, energy intake assessed through 24h dietary recall was positively associated with TFEQ-D and TFEQ-H accounting for 1.96% and 11.56% of variance respectively. However, TFEQ-R was not found to be associated with energy intake (French, Mitchell, Finlayson, Blundell, & Jeffery, 2014).

2.6.2 Power of Food Scale (PFS; Lowe et al., 2009)

The PFS is a 15-item tool that assesses the psychological impact of living in a food-abundant environment, and measures appetite for palatable foods, rather than their consumption. It measures 3 levels of food proximity: food available, food present, and food tasted. Each item is scored from 1 – 5 anchored ‘don’t agree at all’, ‘agree a little’, ‘agree somewhat’, ‘agree’ and ‘strongly agree’.

A PFS total score can be computed by adding scores of the three subscales together to give an overall measure of the hedonic impact of being in the presence of highly palatable foods. Scores have been shown to be independent of state hunger suggesting this measure is specific to hedonic hunger independent of physiological need (Witt, Raggio, Butryn, & Lowe, 2014). The tool was validated in two samples of mostly normal weight university students which demonstrated adequate test-retest reliability (r = .77) and a Cronbach’s alpha of .91 indicating good internal consistency of the tool, and is consistent with McDonalds ω in the thesis sample (.92).

2.6.3 Addiction-like Eating Behaviour Scale (AEBs; Ruddock, Christiansen, Halford & Hardman, 2017)

The AEBs is a 15-item tool to assess behaviours that contribute to addiction-like patterns of eating and is comprised of a two-factor structure: appetitive drive and dietary control.

Responses were in a Likert format scored from 1 – 5 anchored ‘never’, ‘rarely’, ‘sometimes’, ‘most of the time’ and ’always’.

The two-factor structure of this tool is consistent with dual process accounts of eating behaviour, specifically enhanced reward responsivity and top-down control over eating behaviour. Internal consistency was high for both appetitive drive ($\alpha = .90$) and dietary control ($\alpha = .85$). Similarly, drive ($\omega = .78$) and control ($\omega = .77$) were found to have good internal consistency in the thesis sample.

The scale also demonstrated good test-retest reliability for both appetitive drive ($r = .74$) and dietary control ($r = .74$). Additionally, the scale predicted an increased likelihood of overweight or obesity, with one-unit increase in AEBs score increasing the odds of a classification of overweight or obesity by 1.03.

2.7 Preregistration and data access

Study protocols for Chapters 3 and 5 were preregistered, and data and analyses for all studies have been made publicly accessible on Open Science Framework. The systematic review and meta-analysis in Chapter Three was preregistered on PROSPERO (CRD42018115796). Data from Chapter Four can be accessed on osf.io/qctph/, and the protocol for Chapter Five was registered on Aspredicted.org (registration number: 25906) and data can be accessed on osf.io/hrjkp/.

Chapter Three

Systematic Review and Exploratory Meta-analyses: Appetitive and Affective Processes during Moments of Temptation and Lapses under Energy Restriction in Naturalistic Settings

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This systematic review and meta-analyses investigated appetitive and affective processes during moments of temptation and lapses during dieting attempts measured with Ecological Momentary Assessment. The manuscript for this paper is currently being prepared to submit for publication in *Annals of Behavioural Medicine*.

The roles of the co-authors are summarised below:

I designed the study in collaboration with Jason Halford, Paul Christiansen, Amy Ahern, Emma Boyland, and Carl Roberts. I performed literature searches, data extraction, quality assessment with the aid of Jack Stevenson-Smith. I analysed the data and wrote the manuscript. Carl Roberts assisted in the design of the meta-analyses. Amy Ahern, Emma Boyland, Carl Roberts contributed useful comments whilst preparing the manuscript.

3.1 Abstract

Rationale: Heightened appetitive and affective responses to maintaining a negative energy balance contribute to the low rates of compliance in weight loss attempts. However, the influence of momentary changes in these on specific moments that are problematic for successful dietary adherence has yet to be established.

Objective: The aim of this study was to synthesise the current empirical evidence of the impact of ER on appetitive and affective processes in individuals with overweight and obesity that were measured using EMA.

Methods: Appetitive and affective outcomes were contrasted between assessments of dietary temptation, dietary lapse, and random assessments. 3 meta-analyses were performed using subgroup analyses by appetitive (hunger, fullness, satisfaction), affective (positive mood, negative mood, abstinence-violation effects) and engagement in coping strategies outcome measures. There were 14 studies identified overall. 4 studies were included in meta-analyses; 2 studies for temptation Vs. random assessment; 3 studies for lapse Vs. random assessment; 3 studies for temptation Vs. lapse assessments. A narrative synthesis was undertaken on outcomes which could not be included in meta-analyses.

Results: Heightened appetitive (hunger and satisfaction) and affective responses (negative mood) were found during temptation assessments compared to random assessments. Heightened appetitive and affective responses were found during lapse assessments relative to random assessments. There was no overall effect of lapses compared to temptation. However, there was evidence of a subgroup effect. Greater negative abstinence-violation effects were found during lapses relative to temptations. The narrative synthesis identified between and within-person differences in outcome measures predict likelihood of lapse occurrences. Associates of outcome measures with weight loss as well as contextual descriptives of temptations and lapses is also described.

Conclusion: These findings indicate momentary changes in appetitive and affective processes during ER accompany subjective states which pose as a barrier for successful dietary adherence. Establishing predictors of individual differences in these processes could aid with identifying those who may struggle to cope during moments of heightened effects during ER. Additional support strategies may be tailored based on the unique problem’s individuals will face during weight loss attempts.

3.2 Introduction

Dieting is an approach to weight loss that involves self-imposed restriction over eating behaviour in order to achieve an energy deficit and is considered the most important factor for initial weight loss (Stubbs et al., 2011). Unfortunately, most weight loss attempts are unsuccessful in both the short and long-term; many individuals are unable to achieve and maintain modest losses, and the majority of those who do regain this within 3 – 5 years (Maclean, Higgins, Giles, Sherk, & Jackman, 2015). One major challenge dieters face is that appetite regulation appears to be asymmetric (Blundell & King, 1996) meaning strong regulatory systems within the body defend against energy deprivation (regardless of current weight status or fat stores). Although, systems to defend against weight gain are permissive of excess energy and are easily overridden by the hedonic and sensory aspects of food (Erlanson-Albertsson, 2005).

During a negative energy deficit, there are increases in subjective sensations of appetite and reward responsivity to food cues; an effect which is greater in individuals with overweight and obesity (Nijs et al., 2010). In addition, energy restriction (ER) has also been associated with greater negative mood (Jackson et al., 2014) which can induce emotional eating leading to increased intake of unhealthy foods (Jasinska et al., 2012) and binge eating episodes (Stice et al., 2000). Though, positive mood can also induce overconsumption (Cardi, Leppanen & Treasure, 2015) particularly those who score high on emotional eating inventories (Bongers & Jansen, 2016).

These appetitive and affective responses to maintaining a negative energy balance overwhelm regulatory control over eating behaviour and contribute to the low rate of compliance in ER for weight loss, particularly in the short-term, with managing strong sensations of hunger and negative mood being one of the major factors given for unsuccessful dieting attempts (Drapeau et al., 2007; Gibson et al., 2014; Roberts et al., 2017). Higher levels of adherence to a dietary intervention is important for weight loss (Alhassan et al., 2008). However, very little is known about specific momentary subjective states which pose as barriers for successful dietary adherence (i.e. temptations and lapses) (Forman et al., 2017). Dietary temptations are defined as "a sudden urge to eat in which you had come close to the brink of breaking your diet" whilst lapses are "an incident where you felt that you broke your diet (e.g. overate, ate a forbidden food, etc)" or "eating or drinking likely to cause weight gain, and/or put weight loss/ maintenance at risk" (Forman et al., 2017).

Temptations or desires are an important predictor of effective regulation over eating behaviour (Hofmann, Vohs & Baumeister, 2012). Temptation strength is a common reason provided for eating unhealthy snacks (Cleobury & Tapper, 2013), and has been found to mediate the relationship between implicit evaluations of unhealthy snack food and subsequent intake (Haynes, Kemps, Moffitt & Mohr, 2014). Temptations have been characterised as the output of a momentary reward-based evaluation of a previously associated environmental food-related stimuli with consumption that activates reward-circuitry, and triggers appetitive motivational processes which challenge control over eating behaviour (Appelhans et al., 2016). Given the omnipresence of food-cues within a modern-day context, the development and maintenance of these associations and can lead to persistent temptations to indulge.

Previous investigations into the factors associated with dietary lapses have often relied on structured interviews following weight loss or have focussed on recalling a specific moment of lapsing. These studies have identified high levels of hunger, cravings, negative affect as well as being in the presence of food-related cues and being in social situations as factors which were responsible for lapsing (Grilo, Shiffman & Wing., 1989; Rosenthal & Marx, 1981). Most lapses are precipitated by temptations though this is not always the case (Appelhans et al., 2016). Those who are unsuccessful at achieving and maintaining weight loss have demonstrated a poor range of coping strategies and self-regulatory abilities to deal with temptations (Johnson, Pratt & Wardle, 2012; McKee & Ntoumanis, 2014) and have been shown to respond more negatively to lapses with increased negative abstinence-violation effects such as lower self-efficacy and beliefs that their dieting attempt will be a success following a lapse occurrence (Dohm, Beattie, Aibel & Stregel-Moore, 2001).

Taken together, these studies demonstrate that temptations and lapses are problematic momentary subjective states that pose as barriers towards successful dietary adherence and weight loss. What remains unclear is the dynamic relationship underlying these experiences. A better understanding of the factors which characterise temptations and lapses, as well those which distinguish these experiences from one another, is required so that strategies can be developed to aid in coping with strong sensations during experiences of temptations to reduce the likelihood of lapse occurrences.

Investigations into appetite regulation and eating behaviour have been conceptualised as a spectrum of approaches ranging from naturalistic to highly controlled (Gibbons, Finlayson, Dalton, Caudwell & Blundell, 2014). Laboratory-based approaches allow for specific factors to be studied in isolation in strictly controlled environments to assess causal mechanisms that drive overconsumption. They are perhaps the most common approach taken as they provide much greater precision and accuracy above free-living approaches. However, this approach has a trade off with ecological validity given that appetite, energy intake, and their underlying cognitive mechanisms are heavily influenced by environmental factors (Jones et al., 2013; Rosa, Todd & Bouton, 2014) that are likely impacted by the lab environment. One example of this is decreased energy intake in adults due to increased awareness of observation during laboratory ingestion studies (Robinson, Hardman, Halford, & Jones, 2015). This suggests that our understanding of appetite regulation and energy intake may be limited by the degree of artificiality imposed by these highly controlled environments.

Free-living approaches benefit from greater ecological validity as measurement takes place within the participant's natural setting. However, they also suffer from numerous methodological issues impacting their internal validity, meaning outcomes may not accurately be related to the behaviour of interest (Blundell et al., 2010). Self-report methods of food intake such as daily diaries and 7-day recall methods are prone to varying degrees of underreporting, particularly in those with overweight and obesity (Livingstone & Black, 2003) which may lead to inaccurate associations between dietary behaviour and health outcomes (Lissner & Potischman, 2009).

These approaches make regular use of global retrospective recall methods (e.g. *'How hungry have you felt over the past 7-days?'*). However, these are known to be biased due to the use of heuristics that occur when asked to aggregate experiences over a given time. One example of such bias is the peak-end rule (Kahneman & Redelmeier, 1996), where judgements of past experiences are based on the most intense point and how the experience ended such as remembered enjoyment of a previous eating episode (Robinson, Blissett, & Higgs, 2011). A reliance on global retrospective measures mean that there are few accounts of dynamic changes in behaviours over time and situations. This limits the ability to characterise and understand real-world health behaviours and to develop strategies to effectively promote long-lasting behaviour change (Shiffman, Stone & Hufford, 2008).

The availability of smartphone devices has paved the way for more valid real-time measurement of appetite and eating behaviours with devices and applications serving as a platform that can be used as a mobile lab. Electronic time and date stamps of entries increase internal validity by ensuring correct compliance with assessment protocol (Stone et al., 2003). Cognitive tasks are increasingly being implemented on devices allowing for objective measures of real-world fluctuations in these processes and their determining effect on eating behaviour (e.g. Powell, McMinn & Allan, 2017). The ubiquity of smartphone use makes these devices a promising avenue for use in naturalistic investigations.

Ecological momentary assessment (EMA) is an emerging methodology which capitalises on these developments and involves repeated measurement within real-world environments. This focus on current feelings in the natural environment in which they are experienced makes this method perfectly suited for addressing the issues associated with retrospective recall and lab-based environments. EMA is also referred to as intensive longitudinal design due to multiple assessments being made in a relatively short time period (Bolger et al., 2013) or experience sampling methodology as it involves randomly sampling experiences throughout daily lives (Csikszentmihalyi, 2014). EMA uses repeated measurements to capture how experiences and behaviours fluctuate across time and situation which provide information on when and where experiences took place or if experiences are associated with increases in momentary sensations and cognitions. Assessment times are strategically selected based on the feature of interest, e.g. using event-assessments for discrete behaviours such as lapsing whilst on a diet, or random sampling to characterise daily experiences through representative capture of moments throughout the day. These allow to contrast outcomes which have been taken during experiencing different moments in the real-world, e.g. how subjective sensations of cravings are different when experiencing a temptation compared to a random moment where no temptation or lapse has recently taken place (Shiffman et al., 2008).

EMA has already demonstrated its usefulness in evaluating predictors of real-world problematic eating behaviours. For example, it has been used to i) show momentary fluctuations in behavioural control drive snacking behaviour (Powell et al., 2017), ii) identify internal and external factors associated with increased likelihood of eating (Elliston, Ferguson, Schüz & Schüz, 2017), and iii) show that high momentary food cravings are associated with greater consumption of snacks, particularly in high scorers on a food craving questionnaire (Richard, Meule, Reichenberger & Blechert, 2017). Therefore, EMA may be an effective approach towards understanding momentary fluctuations in appetitive and affective processes and their impact on momentary experiences that pose as problems for successful dietary adherence.

Currently, there has yet to be a systematic review that synthesises the current evidence base on the impact of ER on appetitive and affective processes using EMA methods. EMA in this area is of interest as sensations of appetite and affect are processes which fluctuate over time and heavily context dependent. The benefit of using EMA in investigations of these processes during ER is that frequently assessing sensations within their natural environment can generate insight into the temporal dynamics of sensations during dieting attempts and their associations with eating behaviours, contextual variables, and dietary adherence. There have been systematic reviews of EMA studies in other domains such as anxiety which claim the insights provided from these investigations could not have been obtained using more traditional retrospective recall methods (Walz, Nauta & aan het Rot, 2014).

This indicates that there is a clear need to develop our understanding of the real-world dynamic experiences of appetite regulation and affect in those engaging in ER in order to highlight any potential mechanisms that may pose as significant barriers towards successful dietary adherence within naturalistic settings. A better understanding of how fluctuations in appetitive and affective processes during ER determine moments of dietary adherence within the real-world would aid in the development of strategies that provide support in coping with problematic appetitive responses to maintaining a negative energy balance. To this end, a systematic review and meta-analyses was conducted of studies that used EMA to assess subjective sensations of appetite, affect, and cognitive processes in adults with overweight or obesity engaging in ER for weight loss.

The aim of this study was to synthesise the current empirical evidence of the impact of ER on appetitive and affective processes that were measured within naturalistic settings using real-time methods. Specifically, this study aims to contrast appetite, affective, and cognitive outcomes between assessments of dietary temptation, dietary lapse, and assessments which randomly take place throughout the day. This will enable a better understanding of how fluctuations in these factors determine momentary experiences which are problematic for successful dietary adherence. Engagement with coping strategies between temptations and lapses were also included in a contrast to assess whether coping distinguished temptations from lapses.

Information that could not be included in contrasts were summarised in the form of a narrative synthesis. This was due to identified papers taking an analytical approach which could not be integrated into the format of the current meta-analyses. A narrative synthesis was taken on the antecedents and consequences as well as between-person differences of temptations and lapse assessments. A description of the context in which these assessments took place (e.g. timing and location) was also provided. In addition, any reported associations between EMA assessments and weight loss was reported in the narrative synthesis.

3.3 Method

3.3.1 Information sources and search strategy

The current systematic review is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) and was preregistered on PROSPERO (CRD42018115796). Three electronic databases: Scopus, MEDLINE, and PsycInfo were searched in September 2019 using the following string: (Obes* OR Overweight) AND (“Ecological momentary” OR “Experience sampling” OR “Intensive longitudinal” OR “Daily diary”) AND (Diet* OR Weight OR Energy OR Calorie) with no date limitations.

Formal database searches were performed and supplemented by manual searches of reference sections of included articles and which yielded additional four papers.

3.3.2 Eligibility criteria

To be eligible for inclusion, studies had to meet the following criteria:

Participants

Studies that investigated human participants between the ages of 18 – 65 years with overweight or obesity (BMI $\geq$25 kg/m^2). Investigations that exclusively recruited populations with diagnosed diseases, conditions or disorders that may impact appetite or eating behaviour (e.g. diabetes) were excluded. Investigations that included patients of bariatric surgery or with history of any eating disorders were also excluded.

Interventions

Included studies were required to employ any form of ER for any period of time.

Outcome measures

Included studies were required to have an outcome measure of subjective ratings scales of appetitive and affective measures or objective tasks which measure cognitive processes relating to eating behaviours and were measured within naturalistic settings using EMA methods. Outcome measures were not included in search strings to avoid omission of any relevant studies through differences in terminology but were screened during full text review. Unfortunately, no ER studies utilising EMA to measure real-time cognitive processes were identified, therefore these are absent from analyses. Some outcome measures were categorised into a broader domain (e.g. negative mood) to aid with analyses which described in Table 3.1 (P. 99).

Appetitive outcome measures included hunger, fullness, and satisfaction with last meal. Affective outcomes included positive mood, negative mood, positive abstinence-violation effects, and negative abstinence violation effects. Engagement with coping strategies was also included as an outcome measure. All outcome measures were end-anchored *not at all* to *extremely* (see Table 3.3 on P. 101 for description of all identified outcome measures).

3.3.3 Data search and extraction

Article selection and data extraction

One author (MR) performed the formal database searches and supplementary searches. Two authors (MR and JSS) were responsible for assessing articles for inclusion, and decisions over article selection were confirmed through discussion. Data were extracted by two coders independently and cross-checked. One corresponding author was contacted via email and provided data where the study met the inclusion criteria but did not report necessary information to compute effect sizes (Forman et al., 2017). Another paper identified in the manual searches (Massey & Hill, 2012) did not explicitly use an EMA approach; however, this study was included in the narrative syntheses for two reasons: i) it shares similar methodological components with EMA such as examining sensations prior to, during and after an target event (i.e. experiencing a food craving); ii) No other investigation that was identified examined subjective cravings during dieting, therefore it was deemed important to include for a description of the experience under naturalistic settings.

The following data were extracted for each study: number of participants, average number of within person assessments, sex (% female), age, BMI, duration of EMA procedure, and a description of the type of ER used. Type of EMA sampling contingency (temptation assessment; TA, lapse assessment; LA or random assessment; RA). Means and SDs for outcome measures were also extracted from studies which employed multiple EMA contingencies to be used for statistical comparison.

3.3.4 Quality assessment

Originally, The Guide to Community Preventative Services data extraction form (Briss et al., 2000) was selected to assess the quality of included studies which assesses the quality of interventional components. However, during data extraction it was found that whilst papers identified were EMA investigations during some form of ER, most EMA investigations are conducted alongside other structured weight loss interventions and are primarily conducted for observational purposes to complement findings of a larger weight loss intervention.

Currently, there is no validated quality assessment scale for investigations using EMA resulting in previous systematic reviews and meta-analyses of EMA conducted in other areas to omit any form of quality assessment (e.g. Aan het Rot, Hogenelst, & Schoevers, 2012; Keel, 2012; Maugeri & Barchitta, 2019; Walz, Nauta, & aan het Rot, 2014). A quality assessment more appropriate for observational designs was chosen and questions were adapted to better assess quality of EMA design.

Newcastle-Ottawa scales

The tools chosen to assess the quality of included studies was the Newcastle-Ottawa cohort scale adapted for cross sectional studies (NOS for cross-sectional scale; Modesti et al., 2016) and the Newcastle-Ottawa scale for case-control studies (NOS for case studies scale; Stang, 2010). Both scales were modified to assess the qualities of EMA observational investigations (see descriptions below for details on modifications). Results are shown in Table 3.2 (P. 100).

Newcastle-Ottawa cross-sectional scale

The NOS for cross sectional studies rates quality of selection, comparability, and outcome.

Selection is comprised of four items with a maximum score of five. These items assess sample representativeness, sample size, non-respondents and ascertainment of the exposure, all with a score of one except the latter item which has a maximum score of two. Items on sample representativeness were modified to assess representativeness of within-person assessments as these are the target of inference in EMA. A point was awarded for representativeness if RAs were utilised in the study design, and the time scheduling used for these assessments were either completely random times throughout the day (e.g. notified to perform an assessment at four random points throughout the day at any given time) or random timeframes (e.g. notified to complete between the hours of 8-10am, 10-12pm, and

12-4pm). A point was not awarded if RAs were not utilised or the time scheduling used for assessments were at fixed times (e.g. complete an assessment at 8am, 4pm, and 6pm).

Comparability is measured using two items with a maximum score of two. These items assess the most important factor for comparability (i.e. statistical analyses to account for clustering such as mixed models) as well as other important factors for comparability (i.e. controlling for differences in compliance and response rate during analyses, providing appropriate instructions to participants regarding assessment procedure and definitions of temptations and lapses).

Outcome has a maximum score of three and is measured by two items which assessed the type of assessment for the outcome used (maximum score of two) and appropriateness/description of statistical tests used (maximum score of one).

Newcastle-Ottawa case-control study scale

The NOS for case control studies rates quality of selection, comparability and exposure. As Kwasnicka et al. (2017) was an observational within-person investigation, the scale was modified by omitting any questions relating to controls (selection and definition of control).

Selection is rated using two items assessing adequacy of case definition and case representativeness with a maximum score of two.

The comparability item is rated with two items assessing the most important factor for comparability (i.e. controlling for non-compliance such as removing cases which suffered from substantial amounts of missing data) as well as other important factors (i.e. selecting participants matched on previous weight loss) with a maximum score of two.

The exposure item is rated with three items assessing adequate assessment of the outcome, appropriateness and description of statistical test used, and reporting of nonresponse rate with a maximum score of three.

3.3.5 Meta-analyses

Contrasts

In the meta analyses, three contrasts for outcomes that were measured under different momentary states were conducted. Outcomes were included in contrasts only if studies measured the outcome during two or more momentary states. A narrative synthesis was taken on outcomes that could not be included in contrasts.

RA (Random assessment) v TA (Temptation assessment) and *RA v LA (Lapse assessment)* assessed how appetite, and affect were different during temptations and lapses compared to random moments throughout the day. This provides information on how appetitive and affective outcomes are different between momentary states (e.g. from random moment to experiencing a temptation).

The contrast *TA v LA* assessed how appetite, affect, and engagement with coping strategies were different during temptations compared to lapses. This allowed for a better understanding of whether outcomes such as raised hunger or engagement with coping strategies could distinguish a lapse from a temptation.

Statistical and subgroup analyses

Standardised Mean Difference (SMD) and SEs were calculated for each outcome measure included in the contrasts (RA v. TA, RA v. LA, TA v. LA). SMD provides an estimate of the strength of difference between conditions on a given outcome measure and controls for variation that may result from between-study differences in outcome measures included in the analyses (e.g. $RA_{mean} – TA_{mean}$/within-group SD_{pooled}) (Durlak, 2009).

Outcome measures that were included in the meta-analyses were reviewed by the authors so that the direction of differences in subjective ratings on the various outcome measures were consistent with the interpretation of greater sensations of appetite or negative affect during condition 2 compared to condition 1. For example, if hunger is raised during TAs compared to RAs this would indicate greater appetitive affects during temptations relative to random moments which would result in a positive SMD in the meta-analysis. Similarly, if fullness is lower during TAs compared to RAs, this would indicate greater appetitive effects during TA compared to RA, however this would result in a negative SMD prior to recoding for interpretation consistency. Fullness, satisfaction, positive mood, and positive AV effects were therefore negatively coded so that positive SMDs represented greater appetitive (e.g. more hungry, less full) or negative affective effects (e.g. increased negative mood, decreased positive mood) in condition 2 relative to condition 1, whereas a negative SMD represented greater effects in condition 1 relative to condition 2.

Contrasts were performed for each study that reported data on assessments that took place i) whilst experiencing a temptation (temptation assessments; TA), ii) shortly after a dietary lapse had occurred (lapse assessments; LA) or iii) following random prompts throughout the day to capture an average level of measures when no temptation or lapse has occurred (random assessments; RA). Some outcome measures were categorised into a broader domain to aid with analyses (described in Table 3.1 on P. 99).

Statistical analyses were carried out using Review Manager 5.3 (Cochrane Informatics & Knowledge Management Department, UK, 2014). Each meta-analysis was conducted by grouping effect sizes from individual outcome measures reported in relevant studies into distinct appetitive (e.g. hunger) or affective (e.g. negative affect) domains whereby each domain was considered a subgroup.

SMD magnitude can be interpreted as 0.2 = small, 0.5 = moderate, and 0.8+ = large effect (Higgins & Green, 2011). Following recommendations by Elbourne et al. (2002) regarding within-group contrasts, within-subject correlations were accounted for when calculating the standard error of the SMD. No within-group correlations were reported in included papers, so a conservative estimate was used (r=.70) as recommended by Rosenthal (1991). A random effects models for meta-analyses was used due to high levels of heterogeneity across studies. Studies were considered outliers if their contributing SMD had a Z-score > 3.30 (Roberts et al., 2020) or if confidence intervals did not overlap with any other contributing study in that outcome.

Currently, there is no conventional approach towards the meta-analyses of EMA data. The number of assessments can differ greatly between participants depending on individual differences in compliance and reporting (e.g. individuals will complete different numbers of random prompts or experience different amounts of temptations and lapses during a study period). As an attempt to account for this, the average number of assessments from a given contingency was used for the individual study sample sizes when calculating SMD (for a similar procedure, see Haedt-Matt & Keel, 2012) or where average number of assessments were not reported we calculated this by dividing the total amount of assessments by the total amount of participants in the study.

3.4 Results

3.4.1 Study selection (Fig. 3.1)

The search strategy identified 36 studies using Medline, 56 using PsycInfo, and 78 using Scopus. An additional 4 papers were included from supplementary searches. 76 duplicates were removed leaving 98 papers for initial review. After screening titles and abstracts, 39 articles remained for full text review. A further 26 were excluded following full text review (See Figure 3.1 for reasons of exclusion) leaving a total of 13 papers for analyses.

3.4.2 Characteristics of included studies

Information from all included studies are displayed in Table 3.3. The mean age and BMI of participants from included studies was 42.08 years and 31.01 kg/m^2 respectively, and the mean proportion of females was 85.14%.

Of the thirteen included studies, six were secondary analyses, of which five were of Forman et al. (2017) and one was of Carels et al. (2004a). Four primary studies employed 1 week long EMA testing procedures. One primary study employed an 8-week testing procedure, and another employed 6 months of continual EMA. One primary study took place over a 12-month period and conducted 2 weeks of EMA in the first 2 weeks, 1 week at 6-month and 1 week at 12-month of the intervention.

Three studies were conducted during a structured weight loss intervention, two sampled participants from local community weight loss groups, one of which had both dieters and weight maintainers. Two studies examined self-guided dieting attempts, one of which had both dieting for weight loss and for weight loss maintenance. One study used a combined N-of-1 and EMA approach in weight loss maintainers who intentionally lost 5% of body weight in the previous 6 months.

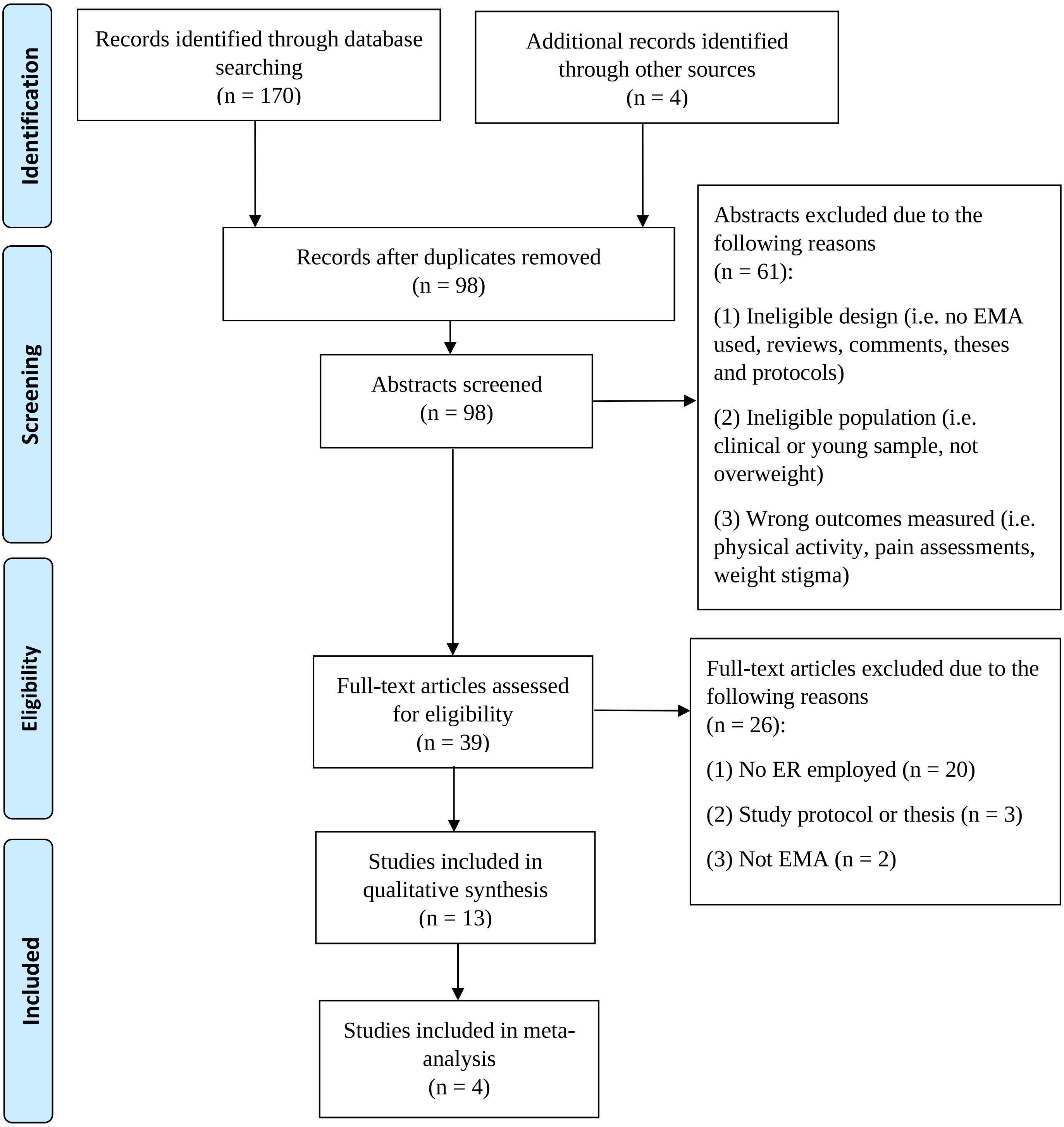

Figure 3.1 - PRISMA flow diagram for study identification and inclusion

3.4.3 Meta analyses

Appetite and affect during random assessments compared to temptation assessments (Fig. 3.2)

Data from two published articles contributing seven effect sizes were included in the RA v. TA contrast (see Table 3.3 on P. 101 for descriptive information), the sample consisted of 66 participants. The analyses indicated that there was evidence of a small overall effect of RA vs TA [SMD = 0.37, 95% confidence interval (CI) 0.13 to 0.60, Z = 3.04, p<.001, I^2 = 80%]. There was no evidence of a subgroup effect (χ^2(df)= 3.77(6), p =.71, I^2 = 0%). Individual analyses are reported below.

Appetite

Hunger: Two studies contributing a total of two effect sizes were included, data showed that hunger was elevated in TAs compared to RAs, with a large effect. (SMD = 0.93, 95% CI 0.01 to 1.86, Z = 1.99, p = 0.05, I^2 = 91%).

Fullness: Two studies contributing a total of two effect sizes were included, data showed no evidence of a difference in fullness between conditions (SMD = 0.36, 95% CI -0.34 to 1.06, Z = 1.02, p = 0.31, I^2 = 84%).

Satisfaction: Two studies contributing a total of two effect sizes were included, data showed that satisfaction was lower during TA compared to RA, with a small to medium effect (SMD = 0.40, 95% CI 0.12 to 0.67, Z = 2.82, p < 0.01, I^2 = 0%).

Affect

Positive mood: Two studies contributing a total of two effect sizes were included, data showed no evidence of a difference in positive mood between conditions (SMD = -0.05, 95% CI -1.22 to 1.13, Z = 0.08, p = 0.94, I^2 = 94%).

Negative mood: Two studies contributing a total of two effect sizes were included, data showed that negative mood was elevated during TA compared to RA, with a medium effect (SMD = 0.45, 95% CI 0.18 to 0.73, Z = 3.23, p < 0.01, I^2 = 0%).

Positive abstinence-violation: Two studies contributing a total of two effect sizes were included, data showed no evidence of a difference in positive AV effects between conditions (SMD = 0.17, 95% CI -0.18 to 0.52, Z = 1.62, p = 0.10, I^2 = 35%).

Negative abstinence-violation: Two studies contributing a total of two effect sizes were included, data showed no evidence of a difference in negative AV effects between conditions (SMD = 0.28, 95% CI -0.06 to 0.63, Z = 0.95, p = 0.34, I^2 = 89%).

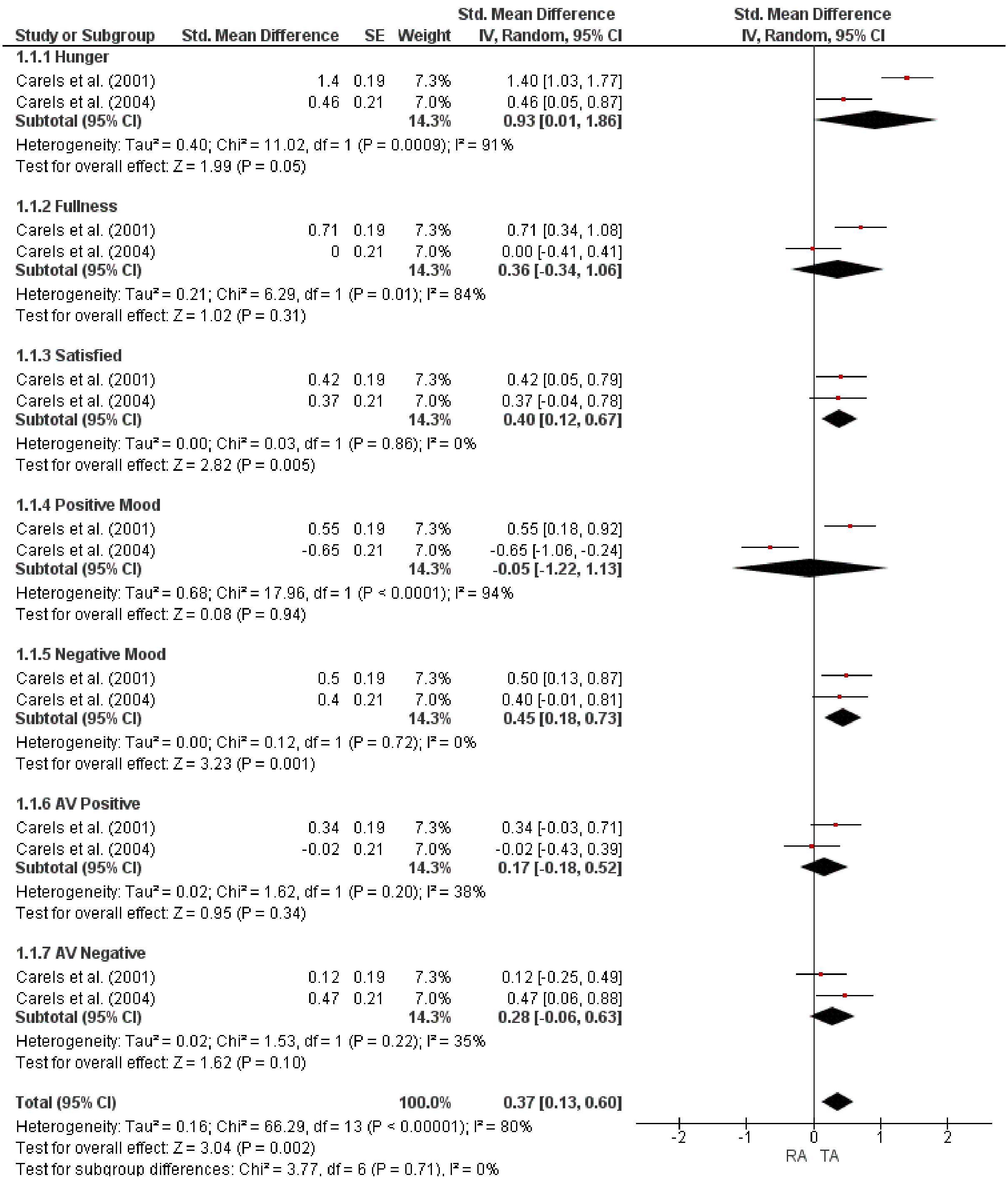

Figure 3.2 - Effect of temptation on appetitive and affective domains. Pooled effects for differences in domains shown for studies that compared measures during random assessments (RA) compared to temptation assessments (TA). Data are expressed as SMD (95% Confidence Interval) using generic inverse variance models with random effects

Appetite and affect during random assessments compared to lapse assessments (Fig. 3.3)

Data from three published articles contributing seven effect sizes were included in the RA v. LA contrast (see Table 3.3 on P. 101 for descriptive information), the sample consisted of 255 participants. Analyses indicated that there was evidence of a small overall effect of RA vs LA [SMD = 0.26, 95% CI 0.06 to 0.47, Z = 2.51, p= 0.01, I^2 = 83%]. There was no evidence of a subgroup effect (χ^2(df)= 9.19(6), p = .16, I^2 = 34.7%). Individual analyses are reported below.

Appetite

Hunger: Three studies contributing a total of three effect sizes were included, data showed no evidence of a difference in hunger between conditions (SMD = 0.30, 95% CI -0.49 to 1.09, Z = 0.74, p = 0.46, I^2 = 95%).

Fullness: Two studies contributing a total of two effect sizes were included. There was no evidence of a difference in fullness between conditions (SMD = 0.01, 95% CI -0.27 to 0.29, Z = 0.08, p = 0.94, I^2 = 0%).

Satisfaction: Two studies contributing a total of two effect sizes were included, data showed no evidence of a difference in satisfaction between conditions (SMD = 0.25, 95% CI -0.03 to 0.53, Z = 1.77, p < 0.08, I^2 = 0%).

Affect

Positive mood: Two studies contributing a total of two effect sizes were included, data showed there was no evidence of a difference in positive mood between conditions (SMD = -0.22, 95% CI -1.12 to 0.69, Z = 0.47, p = 0.64, I^2 = 91%).

Negative mood: Three studies contributing a total of three effect sizes were included. There was statistical evidence that negative mood was elevated during LA compared to RA which was a small to medium effect (SMD = 0.42, 95% CI 0.24 to 0.61, Z = 4.49, p < 0.01, I^2 = 20%).

Positive abstinence-violation: Two studies contributing a total of two effect sizes were included, data showed there was no evidence of a difference in positive AV effects between conditions (SMD = 0.16, 95% CI -0.48 to 0.81, Z = 0.49, p = 0.62, I^2 = 80%).

Negative abstinence-violation: Two studies contributing a total of two effect sizes were included, data showed evidence that negative abstinence-violation effects were elevated during LA compared to RA, with a strong effect (SMD = 0.71, 95% CI 0.11 to 1.32, Z = 2.30, p = 0.02, I^2 = 79%).

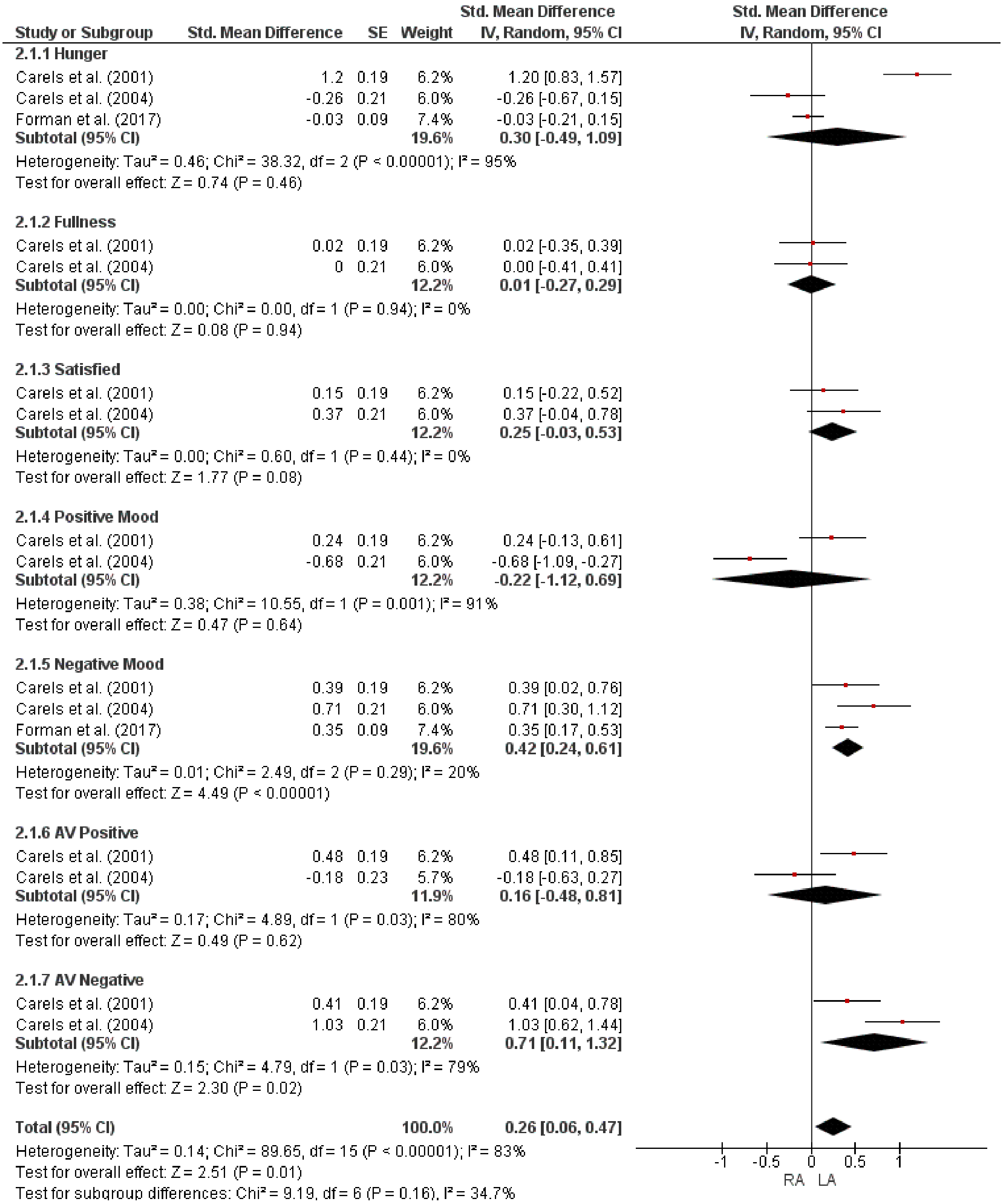

Figure 3.3 - Effect of lapsing on appetitive and affective domains. Pooled effects for differences in domains shown for studies that compared measures during random assessments (RA) compared to lapse assessments (LA). Data are expressed as SMD (95% Confidence Interval) using generic inverse variance models with random effects.

Appetite and affect during lapse assessments compared to temptation assessments (Fig. 3.4)

Data from three published articles contributing eight effect sizes were included in the LA v. TA contrast (see Table 3.3 on P. 101 for descriptive information), the sample consisted of 144 participants. There was no evidence of an overall effect of RA vs LA [SMD = 0.16, 95% CI -0.28 to 0.13, Z = 0.76, p= 0.45, I^2 = 78%], however there was evidence of subgroup effect indicating differences between some of the conditions included in the contrast (χ^2(df)= 14.64 (7), p = 0.04, I^2 = 52.2%).

Appetite

Hunger: Three studies contributing a total of three effect sizes were included, data showed no evidence of a difference in hunger between conditions (SMD = -0.29, 95% CI -0.78 to 0.20, Z = 1.15, p = 0.25, I^2 = 85%).

Fullness: Two studies contributing a total of two effect sizes were included. There was no evidence of a difference in fullness between conditions (SMD = -0.37, 95% CI -1.07 to 0.34, Z = 1.02, p = 0.31, I^2 = 85%).

Satisfaction: Two studies contributing a total of two effect sizes were included, data showed no evidence of a difference in satisfaction between conditions (SMD = -0.16, 95% CI -0.44 to 0.12, Z = 1.10, p < 0.27, I^2 = 5%).

Affect

Positive mood: Two studies contributing a total of two effect sizes were included, data showed there was no evidence of a difference in positive mood between conditions (SMD = -0.07, 95% CI -0.45 to 0.32, Z = 0.34, p = 0.74, I^2 = 47%).

Negative mood: Three studies contributing a total of three effect sizes were included, data showed there was no evidence of a difference in negative mood between LA compared to RA (SMD = 0.16, 95% CI -0.09 to 0.41, Z = 1.23, p = 0.63, I^2 = 0%).

Positive abstinence-violation: Three studies contributing a total of three effect sizes were included, data showed there was no evidence of a difference in positive AV effects between conditions (SMD = 0.15, 95% CI -0.24 to 0.55, Z = 0.75, p = 0.45, I^2 = 57%).

Negative abstinence-violation: Two studies contributing a total of two effect sizes were included, data showed evidence that negative abstinence-violation effects were elevated during LA compared to TA, with a small effect (SMD = 0.42, 95% CI 0.14 to 0.69, Z = 2.97, $p < .01$, $I^2 = 0\%$).

Coping strategies

Two studies contributing a total of two effect sizes were included, data showed there was no evidence of a difference in engagement with coping strategies between conditions (SMD = -0.08, 95% CI -0.28 to 0.13, Z = 0.76, $p = 0.45$, $I^2 = 78\%$).

Study or Subgroup	Std. Mean Difference	SE	Weight	Std. Mean Difference IV, Random, 95% CI
3.1.1 Hunger				
Carels et al. (2001)	0.08	0.19	5.6%	0.08 [-0.29, 0.45]
Carels et al. (2004)	-0.68	0.21	5.4%	-0.68 [-1.09, -0.27]
McKee et al. (2014)	-0.28	0.3	4.4%	-0.28 [-0.87, 0.31]
Subtotal (95% CI)			**15.4%**	**-0.29 [-0.78, 0.20]**
Heterogeneity: $Tau^2 = 0.13$; $Chi^2 = 7.20$, df = 2 (P = 0.03); $I^2 = 72\%$				
Test for overall effect: Z = 1.15 (P = 0.25)				
3.1.2 Fullness				
Carels et al. (2001)	-0.72	0.19	5.6%	-0.72 [-1.09, -0.35]
Carels et al. (2004)	0	0.21	5.4%	0.00 [-0.41, 0.41]
Subtotal (95% CI)			**11.0%**	**-0.37 [-1.07, 0.34]**
Heterogeneity: $Tau^2 = 0.22$; $Chi^2 = 6.46$, df = 1 (P = 0.01); $I^2 = 85\%$				
Test for overall effect: Z = 1.02 (P = 0.31)				
3.1.3 Satisfied				
Carels et al. (2001)	-0.29	0.19	5.6%	-0.29 [-0.66, 0.08]
Carels et al. (2004)	0	0.21	5.4%	0.00 [-0.41, 0.41]
Subtotal (95% CI)			**11.0%**	**-0.16 [-0.44, 0.12]**
Heterogeneity: $Tau^2 = 0.00$; $Chi^2 = 1.05$, df = 1 (P = 0.31); $I^2 = 5\%$				
Test for overall effect: Z = 1.10 (P = 0.27)				
3.1.4 Positive Mood				
Carels et al. (2001)	-0.25	0.19	5.6%	-0.25 [-0.62, 0.12]
Carels et al. (2004)	0.14	0.21	5.4%	0.14 [-0.27, 0.55]
Subtotal (95% CI)			**11.0%**	**-0.07 [-0.45, 0.32]**
Heterogeneity: $Tau^2 = 0.04$; $Chi^2 = 1.90$, df = 1 (P = 0.17); $I^2 = 47\%$				
Test for overall effect: Z = 0.34 (P = 0.74)				
3.1.5 Negative Mood				
Carels et al. (2001)	0.03	0.19	5.6%	0.03 [-0.34, 0.40]
Carels et al. (2004)	0.3	0.21	5.4%	0.30 [-0.11, 0.71]
McKee et al. (2014)	0.18	0.3	4.4%	0.18 [-0.41, 0.77]
Subtotal (95% CI)			**15.4%**	**0.16 [-0.09, 0.41]**
Heterogeneity: $Tau^2 = 0.00$; $Chi^2 = 0.92$, df = 2 (P = 0.63); $I^2 = 0\%$				
Test for overall effect: Z = 1.23 (P = 0.22)				
3.1.6 AV Positive				
Carels et al. (2001)	0.14	0.19	5.6%	0.14 [-0.23, 0.51]
Carels et al. (2004)	-0.17	0.21	5.4%	-0.17 [-0.58, 0.24]
McKee et al. (2014)	0.62	0.3	4.4%	0.62 [0.03, 1.21]
Subtotal (95% CI)			**15.4%**	**0.15 [-0.24, 0.55]**
Heterogeneity: $Tau^2 = 0.07$; $Chi^2 = 4.69$, df = 2 (P = 0.10); $I^2 = 57\%$				
Test for overall effect: Z = 0.75 (P = 0.45)				
3.1.7 AV Negative				
Carels et al. (2001)	0.31	0.19	5.6%	0.31 [-0.06, 0.68]
Carels et al. (2004)	0.55	0.21	5.4%	0.55 [0.14, 0.96]
Subtotal (95% CI)			**11.0%**	**0.42 [0.14, 0.69]**
Heterogeneity: $Tau^2 = 0.00$; $Chi^2 = 0.72$, df = 1 (P = 0.40); $I^2 = 0\%$				
Test for overall effect: Z = 2.97 (P = 0.003)				
3.1.8 Coping				
Carels et al. (2004)	-1.28	0.21	5.4%	-1.28 [-1.69, -0.87]
McKee et al. (2014)	-0.03	0.3	4.4%	-0.03 [-0.62, 0.56]
Subtotal (95% CI)			**9.8%**	**-0.67 [-1.90, 0.55]**
Heterogeneity: $Tau^2 = 0.71$; $Chi^2 = 11.65$, df = 1 (P = 0.0006); $I^2 = 91\%$				
Test for overall effect: Z = 1.08 (P = 0.28)				
Total (95% CI)			**100.0%**	**-0.08 [-0.28, 0.13]**
Heterogeneity: $Tau^2 = 0.16$; $Chi^2 = 81.20$, df = 18 (P < 0.00001); $I^2 = 78\%$				
Test for overall effect: Z = 0.76 (P = 0.45)				
Test for subgroup differences: $Chi^2 = 14.64$, df = 7 (P = 0.04), $I^2 = 52.2\%$				

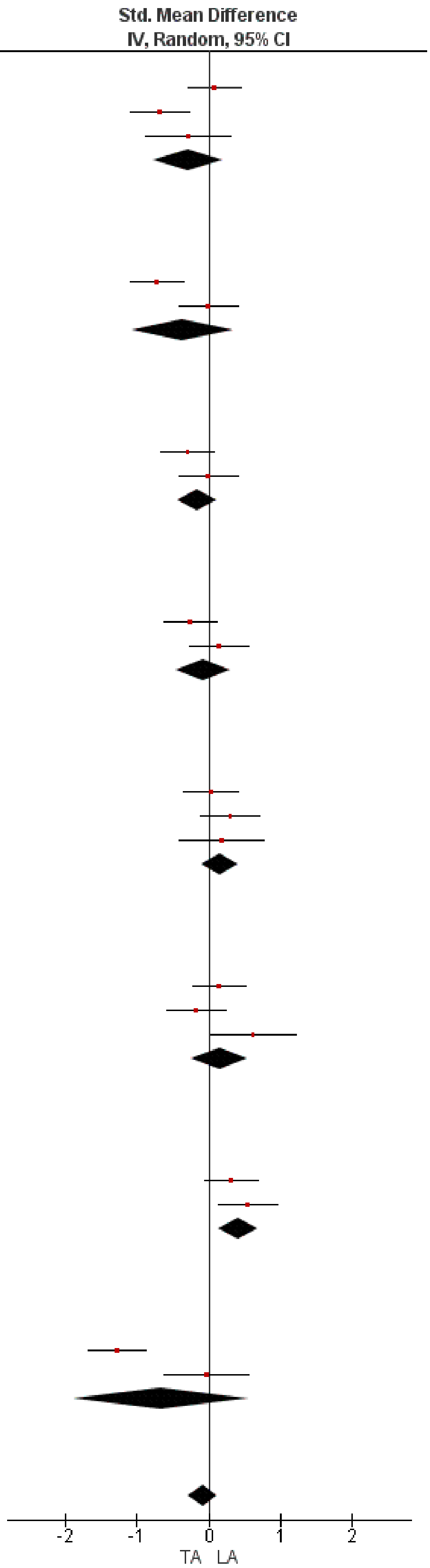

Figure 3.4 - Effect of lapsing compared to temptation on appetitive and affective domains. Pooled effects for differences in domains shown for studies that compared measures during lapse assessments (LA) compared to temptation assessments (TA). Data are expressed as SMD (95% Confidence Interval) using generic inverse variance models with random effects

3.4.4 Narrative synthesis

Antecedents, consequences, and between-person predictors of experiences

Two studies assessed various factors associated with temptations and lapses, and one study examined experiences of cravings during dieting.

Goldstein et al. (2018b) investigated appetitive and affective factors associated with different types of lapses and found that eating an unintended food was associated with higher than average between-person levels of stress, irritability, and fatigue as well as within-person increases in hunger and deprivation and decreases in irritability. Eating at an unplanned time was associated with higher between-person levels in stress, boredom, loneliness, and deprivation as well as within person increases in stress and boredom. Eating a larger portion size than intended was associated with higher between person levels in stress, boredom, irritability, loneliness, fatigue as well as within person increases in hunger and deprivation. These findings support findings from the meta-analyses that increased within-person levels of hunger and negative affect are associated with experiencing a dietary lapse. This study additionally provides evidence that between-person differences in these outcomes can also play a major role in determining a lapse.

Schumacher et al. (2018) investigated self-attitudes following lapses and found that lower between-person levels of self-efficacy and self-regard predicted greater overall lapse frequency. They also found that both low and high between-person levels of self-regard as well as within-person decreases in self-criticism also predicted greater likelihood of another lapse on the same day. These complement the findings that lapsing is associated with greater negative abstinence-violation effects, however these also indicate that greater positive abstinence violation effects (e.g. higher levels of self-attitudes) following a lapse increases the chance of a subsequent lapse on the same day.

Massey and Hill (2012) conducted a descriptive quasi-prospective study on the experiences of cravings in current dieters, people watching their weight, and non-dieters. Using pre and post craving records that assessed hunger, craving, and mood intensity they found that dieters had stronger and less resistible cravings compared to non-dieters and watchers in the context of lower hunger. Watchers experienced weaker craving intensity compared to dieters in the context of greater hunger. In the current meta-analyses, temptations were found to occur in the context of greater hunger. Whilst conceptually different, temptations and cravings are broadly the output of reward-based processes. This may imply that hunger has different effects for different components of reward-based processing. However, caution with this interpretation must be advised as Massey and Hill compared cravings between groups based on dieting status, whereas the currently meta-analyses employed within-person contrasts.

In addition, there was a decrease in hedonic tone (i.e. feelings of pleasure) from pre to post craving experience, but cravings were not found to occur in the context of an overall low mood in dieters supporting the meta-analytic finding that ER is not accompanied by a persistent negative mood. Dieters also rated their cravings as being slower to disappear compared to both groups with post craving hunger remaining low and did not differ from pre to post craving.

Studies of EMA outcome measures and baseline differences

Three studies investigated the impact of baseline differences in measures relating to executive function or control over eating behaviour on EMA outcome measures. These were all secondary analyses of Forman et al. (2016).

Crochiere et al. (2019) used the achievement score on the Delis-Kaplan Executive Function System Tower Task (D-KEFS; Delis, Kaplan & Kramer, 2001) to assess executive function at baseline. This is the number of moves required to complete a trial which indexes the executive function skills needed to complete this task inclusive of cognitive flexibility, planning, and inhibitory control. They found that within-person increases in tiredness, deprivation and boredom were associated with an increased likelihood of lapsing, and individuals who scored high on the D-KEFS (indexing lower executive function skills) experienced a greater likelihood of experiencing a lapse in response to increased tiredness and deprivation, whereas individuals who score low on the D-KEFS (indexing higher executive function skills) experienced a greater likelihood of experiencing a lapse in response to increased boredom.

Manasse et al. (2018a) conducted a multimodal investigation of executive function on risk of lapsing. They found that higher baseline levels of negative urgency on the UPPS impulsive behaviour scale (Whiteside & Lynham, 2001) predicted greater frequency of lapses reported, and this moderated the effect of hunger and loneliness on risk of lapsing with higher loneliness scores predicting more lapse occurrences in those with high negative urgency, and higher levels of hunger predicting lapse occurrences in those with low negative urgency. A moderating effect of stop signal reaction time (SSRT) on the relationship between stress and lapsing was also reported. Higher within-person levels of stress predicted greater likelihood of reporting a lapse, and this relationship was greater for individuals who performed poorer on the stop signal task at baseline (indexing lower levels of behavioural control).

Manasse et al. (2018b) investigated whether loss-of-control over eating behaviour measured on the overeating section of the Eating Disorder Examination (Mond, Hay, Rodgers, Owen, Beaumont, 2004) was associated with lapse triggers. They found that higher scores on the loss-of-control over eating subscale predicted greater lapse likelihood, and this effect was greater in individuals who displayed higher between-person levels of loneliness, boredom, anger, hunger and deprivation.

These findings complement those in the meta-analyses by demonstrating that individual differences in the relationship between outcome measures and momentary subjective states such as lapses may be able to be predicted at baseline prior to engagement with an intervention.

Studies assessing EMA measures and associations with weight loss

Four studies investigated whether individual differences in EMA outcomes were associated with weight loss.

Carels et al. (2004b) found mood, coping strategies or the frequency of temptations and lapses were not associated with weight loss during the end of a structured weight loss intervention. Self-reported greater feelings of failure during a lapse was the only negative abstinence-violation effect outcome measure associated with lower percentage of weight loss during post-study follow-up.

Forman et al. (2016) found that greater frequency of lapsing during the initial weeks of a structured weight loss intervention was associated with less weight loss at 12-month follow-up. Forman et al. (2018) found no associated between the frequency of planned and unplanned lapses with weight loss throughout an 8-week weight loss intervention. Goldstein et al. (2018b) found lapses characterised as eating at an unplanned time predicted worse weight loss outcome at both 4-week and 12-month follow up.

Kwasnicka et al. (2018) examined predictors of weight loss maintenance plan adherence using a combined N-of-1 and EMA approach and found factors such as motives, self-regulatory capacity (e.g. hunger, temptations, obstacles for adherence) habits (e.g. routines), personal resources (e.g. stress, energetic, happiness) and environmental influence all predicted plan adherence across all cases, however the strength and significance of predictors differed between individual cases suggesting that it is important to consider that individual variation will impact the relative importance of predictors which relate to weight loss.

Studies assessing contextual characteristics of temptations and lapses

Four studies investigated the timing and location of temptation and lapses, and one looked at timing and locations of experiences of cravings.

In Carels et al. (2001) investigation of self-dieting attempts, lapses were found to be more likely to occur at home, but no location distinguished between temptations and lapses. In contrast, Carels et al. (2004a) investigation of the final week of a weight loss intervention found no location increased the likelihood of a temptation or lapse occurrence. In another investigation of individuals from local weight loss groups and self-dieting attempts, the strength of temptations did not differ as a result of the time of day, but lapses were found to be equally likely to occur on the weekends and weekdays, and were more likely to occur in the evenings (McKee et al., 2014). This study also found that the strength of a temptation, the presence of others, and the environment (whether a temptation was un expected or sought out) predicted whether a temptation led to a lapse. In another that took place over the course of a 12-month weight loss intervention, it was found that lapses were more likely to occur in the evenings, at home, and on the weekends (Forman et al., 2016). Similarly, Massey & Hill (2012) found that cravings were most frequently experienced at home, in the presence of others, and in the afternoon and evenings.

Two studies investigated changes in lapse frequency throughout the course of weight loss interventions. Forman et al. (2018) found a decrease in the frequency of lapses from week 1 to 8 of a prescribed Weight Watchers diet, whereas Forman et al. (2016) found that the frequency of lapses decreased from the first weeks to 6-months, then increased again at 12-months. These studies also characterised lapses into either eating an unintended food, unplanned eating or larger portion size than intended and found eating an unintended food was the most common type of lapse across the intervention.

3.4.5 Quality assessment (Table 3.2)

Most studies were of reasonable quality as assessed by the NOS. However, they uniformly performed poorly on sample size. No studies mentioned how sample sizes were determined or if power analyses were performed. If appropriate multilevel forms of analyses are employed to account for repeated measurements, then large sample sizes are less of a problem than other statistical approaches as units of analyses are the within-person assessments and these are usually sufficiently powered. However, in multilevel analyses the major restricting factor is usually the group (between-subject) level sample size as these are usually lower than the number of within-person assessments, contain a greater amount of variation than within-person assessments, and have been shown to produce biased group-level estimates in smaller sample sizes (McNeish & Stapleton, 2016). Future investigations in this area would benefit from citing guidelines that describes appropriate group-level sample sizes for multilevel modelling (e.g. Maas and Hox, 2005) to avoid scepticism surrounding sample sizes.

Most investigations used appropriate mixed method analyses to account for both within and between person effects. Accounting for nesting of datapoints is important in repeated measures design as within person assessments are likely to be highly correlated which violates the assumption of independence of errors as datapoints. Ordinary least squares analyses such as ANOVA are highly susceptible to violations of this assumption which can produce biased estimates if not properly accounted for in analyses (Hayes, 2006). Most studies also reported appropriate statistics though there were few that failed to report confidence intervals for their associated *p*-values.

Reporting of differences between respondents and non-respondents or controlling for these in analyses was generally good in identified studies, and most reported average compliance rates of EMA assessment protocol. Compliance with assessment protocol is a limitation of EMA as rates can have an impact on statistical power of the study, particularly if data is missing not at random and is systematic (e.g. missing prompts due to working hours) (Graham, 2009). There is currently no 'gold-standard' rate of compliance, though a rule of thumb is that compliance rates of at least 80% are considered acceptable (Jones et al., 2019). Providing descriptive information on compliance rates is essential as it may indicate whether a particular EMA assessment procedure may be too burdensome and allows for reviews to be conducted that examine overall compliance rates across studies as well as predictors that may influence compliance that could be used to facilitate higher rates (see Jones et al., 2019).

All studies used subjective measures and self-report which are associated with information bias such as socially desirability and demand characteristics. Furthermore, one problem of EMA investigations relate to reactivity to experimental procedure (see Rowan et al., 2007) which could also introduce bias into measures. However, given the subjective nature of appetite ratings these experiences would be difficult to measure otherwise. Future investigations could combine both free-living and laboratory-based approaches to validate changes in average levels of real-world subjective appetite ratings such as hunger and fullness throughout weight loss with physiological markers such as plasma ghrelin levels.

3.5 Discussion

Summary of meta-analytic findings

This systematic review and meta-analyses was conducted to evaluate the current empirical evidence of the impact of ER on appetitive and affective processes measured within naturalistic settings using EMA to better understand how fluctuations in these outcomes determine momentary states which are problematic for successful dietary adherence. This study aimed to contrast appetite, affective, and cognitive outcomes between assessments of dietary temptation, dietary lapse, and assessments which randomly take place throughout the day. Engagement with coping strategies between temptations and lapses were also contrasted to assess whether coping distinguished temptations from lapses.

Regarding overall main effects of the range of appetitive and affective measures, greater appetitive and negative affective effects were found during temptations assessments relative to random assessments. Greater effects were also found during lapse assessments relative to random assessments. There were no differences in overall effects between temptations and lapse assessments. These findings indicate that dynamic fluctuations in appetitive and affective sensations during ER result in experiencing momentary subjective states which pose as barriers for successful dietary adherence. This is opposed to persistent and static-like changes in appetite and affect which occur in response to ER. However, it appears further dynamic changes in appetitive and affective measures do not distinguish a temptation from a lapse. Shedding light onto the distinguishing characteristics of temptations and lapses may help with the development of strategies to aid with dietary adherence during weight loss.

Evidence was found for increased hunger on temptations relative to random assessments, but no differences in hunger were found between lapses and random assessments or between temptations and lapse assessments. Hunger has previously been stated as one of the main factors influencing dietary adherence (Drapeau et al., 2007; Gibson et al., 2014; Roberts et al., 2017), though the present results suggest that it is momentary increases in the sensation of hunger during ER that influence state experiences of temptations rather than persistently increased hunger. Further, increases in hunger sensations do not distinguish a temptation from a lapse suggesting lapsing does not occur as a result of unmanageable levels of hunger. McKee et al. (2014) found temptation strength was a predictor of whether a temptation led to a lapse, and demonstrated that temptation is influenced by hunger, however other factors can influence the strength of a temptation such as reward-based evaluations (Haynes et al., 2014).

Interestingly, hunger was not different between lapses and random assessments which contrasts previous accounts that increased hunger precipitate a lapse episode (Grilo, Shiffman & Wing, 1989; Rosenthal & Marx, 1981). Two studies appeared to show no difference in hunger on lapses compared to random assessments which influenced the pooled estimates. Forman et al (2017) asked how hungry they felt in the moment, rather than preceding the lapse. Given eating had recently taken place, it seems reasonable that this would have an impact on hunger ratings. Furthermore, Carels et al. (2004a) took place at the end of a structured 12-month weight loss intervention. It is possible that over the course of an intervention, management of hunger became easier which means that the sensation has less of an impact on lapsing. This might suggest that lapses may be better associated with increases in other appetitive (reward-based) or affective processes. In support, Massey and Hill (2012) found dieters experienced stronger cravings which were less resistible and occurred in the context of lower hunger compared to non-dieters and individuals watching their weight.

Evidence was found that satisfaction with a prior eating episode was lower on temptations compared to random assessments, but not for any other contrasts. As previous accounts suggest temptations are reward-based evaluations of environmental stimuli (Appelhans et al., 2016), if satisfaction with previous eating events is low then appetitive-based processes may still have an active effect on behaviour and momentary states. Satisfaction was no different between lapses and random moments or lapses and temptation assessments. Given that a lapse is a moment where dietary adherence was violated it may be unsurprising that ratings of satisfaction would be affected as lapses result in reduced self-efficacy and increased feelings of failure (Carels et al., 2004a; Schumacher et al., 2018) which would likely impact evaluations of satisfaction.

No evidence was found that fullness was different on any of the contrasts. A potential explanation is that all the studies within this review employed continual forms of ER, fullness ratings were persistently low therefore there was no difference between random moments, temptations, and lapses. Another potential reason is that sensations of fullness result from physiological signalling which indicate current short-term energy stores rather than acting as a motivational drive to direct behaviour towards energy intake such as hunger and cravings. As temptations are the output of a reward-based evaluation process (Appelhans et al., 2016), it could be the case that fluctuations in sensations which act as drivers of eating behaviour such as hunger and cravings are more prominent during states of temptations and lapses during dieting.

Evidence was found for increased negative mood on temptations relative to random assessments, and on lapses compared to random assessments, but no difference between temptations and lapse assessments. Negative mood has been previously linked as a consequence of maintaining a negative energy balance required for weight loss (Roberts et al., 2017) and has been provided as a major reason for lapsing (Grilo, Shiffman & Wing., 1989; Rosenthal & Marx, 1981). Theoretical accounts suggest persistent negative mood impacts the ability to cope and maintain ER, however the current study indicates that it is momentary fluctuations in negative affect that influences dietary adherence rather than a persistent low mood. In support, dieters showed similar levels of end of day negative mood to non-dieters and watchers overall, though dieters did show small increases in low mood on craving days compared to watchers which may reflect differences in perceptions of success or failure to resist cravings (Massey & Hill, 2012). Similar to hunger, it appears that even greater sensations of negative affect did not distinguish temptations from lapses meaning coping with increased sensations during temptations may influence whether these lead to a lapse rather than greater increased sensations between the two states.

No evidence was found that positive mood was different on any of the contrasts in the analyses suggesting that positive mood is consistent across moments of temptation, lapse and random moments throughout the day. Though negative mood is more of a consistent predictor of overeating, particularly during ER (Roberts et al, 2017), some previous accounts shown that increased positive mood can increase intake of high energy foods (Cardi et al., 2015), but this may be greater for individuals who score high in measures of emotional eating (Bongers et al., 2016). Future investigations could attempt to understand the role of fluctuations in positive affect and its impact on eating behaviour in those who score high on measures of emotional eating.

Regarding abstinence-violation effects, evidence was found that negative AV effects (e.g. desire to give up the diet) were raised during lapse assessments compared to random assessments as well as being raised during lapses compared to temptations. As lapsing involves breaking a diet, negative effects which relate to the violation of abstinence-goals may be unsurprising. No differences were found in positive abstinence-violation effects (e.g. feelings that the diet will be a success) suggesting self-beliefs are more impacted by breaking a diet than successfully resisting a temptation. The effect of violating abstinence goals has previously been stated to have a negative impact on weight loss. Individuals who respond more negatively to lapses are more likely to regain weight following weight loss resulting from the impact of the lapse on attitudes relating to self-efficacy and self-regard (Dohm et al., 2001). Coping strategies to manage the negative abstinence-violation effects following a dietary lapse may be an effective approach at preventing weight gain and dietary relapse (Johnson, Pratt & Wardle, 2012; McKee & Ntoumanis, 2014).

No evidence was found for a pooled effect of engagement with coping strategies between temptations and lapses. However, independently, both studies which employed measures of coping strategies found an effect. A potential reason for this is that there was considerable heterogeneity in coping measures included in the analyses. In Carels et al. (2001), a summed response was created from 14-items which was more comprehensive of strategies that the participant could have engaged in to cope with a temptation, whereas McKee et al. (2014) measured only two responses which both related to thinking about weight loss goals. Given that previous accounts suggest most lapses are preceded by a temptation (Appelhans et al., 2016), further investigations should employ more comprehensive measures of coping strategy engagement to better understand how coping can distinguish temptations from lapses. As individuals who struggle at achieving and maintaining weight loss are thought to have a poor range of coping strategies to deal with temptations (Johnson, Pratt & Wardle, 2012; McKee & Ntoumanis, 2014), this could potentially inform the development of real-time interventions to aid with engagement of strategies which are personalised to suit the style of coping that works best for the individual.

Summary of narrative synthesis

Information that could not be included in contrasts were summarised in the form of a narrative synthesis. This was due to identified papers taking an analytical approach which could not be integrated into the format of the current meta-analyses. A narrative synthesis was taken on the antecedents, consequences, and between-person differences lapse assessments as well as a description of the context in which these assessments took place (e.g. timing and location). In addition, any reported associations between EMA assessments and weight loss were reported in this narrative synthesis.

The studies outlined in this synthesis demonstrate the wide-reaching potential of utilising EMA in the investigation of the real-world experiences associated with dieting to aid with our understanding of real-world appetitive and affective processes and how these may impact adherence in different populations of dieters. Some of the studies identified within this review examined the antecedents of events to shed light onto the dynamic relationship of momentary fluctuations in sensations and their impact on the likelihood of lapse occurrences (e.g. Goldstein et al., 2018b). These accounts complement the findings of the current meta-analytic investigation by providing a more detailed description of the between- and within-person differences of appetitive and affective outcomes and their potential implications on lapse experiences.

Other studies examined the role of between-person differences in average levels of EMA outcomes or on baseline measures such as performance on an executive function task (Crochiere et al., 2019) to examine how these differences can moderate the relationship between fluctuations in momentary sensations and risk of lapse likelihood. These findings suggest it may be beneficial to investigate baseline differences in appetitive processes and eating behaviours as these may predict individual differences in sensations experienced in the real-world which could pose a problem for dietary adherence. A better understanding of how between-person differences could be used to predict real-world outcomes would aid in the understanding of how individuals experience different barriers towards successful weight loss during ER, and how these could possibly be detected at baseline prior to engagement with an ER intervention.

In regards to the association of EMA measures and weight loss, decreases in overall lapse frequency had no association with weight loss (Forman et al., 2018). Though the frequency of lapses during the initial weeks of interventions was associated with greater weight loss (Forman et al., 2017; Goldstein et al., 2018). In addition, greater feelings of failure during a lapse assessment predicted less weight loss (Carels et al.; 2004b) supporting previous account that abstinence-violation effects that relate to self-attitudes and self-efficacy impact weight outcome (Dohm et al., 2001). Taken together, these suggest that lapsing, particularly in the early stages of weight loss is associated with worse overall weight loss. Improving self-attitudes, specifically reducing feelings of failure following a lapse that occurs in the later stages of an intervention may aid with weight loss.

In regards to contextual descriptives of temptations and lapses, investigations that focused on individuals undergoing self-dieting attempts or from community weight loss groups reported lapses were more likely to occur at home compared to work and school (Carels et al., 2001), in the evenings compared to any other time of day. There was also no difference in likelihood of temptations and lapses between weekend and weekdays (McKee et al., 2014). McKee et al. also found temptation strength was not affected by the time of day, though the strength of the temptation and whether others were present influenced whether a temptation led to a lapse. Similarly, cravings were more likely to occur at home, in the evenings, and in the presence of others (Massey & Hill, 2012).

In investigations of structured weight loss programmes, the associations between context and likelihood of temptations and lapses are less clear. At the end of a 12-month behaviour weight loss programme, no location was associated with a greater likelihood of temptations or lapsing (Carels et al., 2004), whereas in an EMA panel design over a 12-month period, lapses were more likely to occur at home, in the evening, and on the weekends (Forman et al., 2017). One potential explanation for this was that as the investigation was conducted near the end of a weight loss programme, participants may have successfully limited the availability of tempting snacks and foods at home. Contextual effects in Forman et al. (2017) were averaged over the 12-month period which limits the ability to see changes in these variables over the course of weight loss.

Taken together, these suggest that lapses are more likely to occur at home, in the evenings, and on the weekends, but these may be affected by interventional factors, particularly those which attain to stimulus control and meal-time planning (Carels et al., 2004b). Further investigations are required to better understand change in contextual effect of temptations and lapses over the course of weight loss.

It is noteworthy that Kwasnicka et al (2018) used a combined EMA and N-of-1 approach to investigate predictors of fluctuations in weight loss maintenance plan adherence over a 6-month period. N-of-1 or single-case studies involve repeated measurement of one or several individuals over time to gain a detailed understanding of predictors of within-person change. Findings are highly applicable to that case with greater precision gained through increased repeated measurements. In Kwasnicka et al. predictors of weight maintenance plan adherence were identified, however the strength and significance of these differed from case to case. For example, they found higher hunger during the day was associated with less plan adherence in five out of the eight of the cases with four participants showing a medium correlation, and one participant showing a high correlation. Though this approach is still in its infancy, there is great potential for combining N-of-1 and EMA methods in investigations of ER for use in identifying the problems that pose as the biggest barrier towards successful dietary adherence for a specific individual. This approach may help pave the way for personalised interventions to aid in coping with appetitive and affective processes which pose as problems for weight loss.

These suggest there is potential in using EMA to understand individual variability in the real world and help inform personalised strategies to cope with strong sensations of appetite and affect that may lead to dietary lapse and negative implications for overall weight loss. More investigations into how appetite fluctuates over the course of a day during ER and the impact of these fluctuations on eating behaviour, daily calorie intake or weight outcome are required. This would provide more detailed accounts of both within and between-person predictors of fluctuations in appetite and affect would lead to a better understanding of the factors that lead to real-time dietary lapse and overall weight loss.

A number of studies were identified as using EMA methods and machine learning algorithms to predict high-risk moments of lapses but were excluded as these limited to machine model prediction and feasibility (e.g. Forman et al., 2018; Goldstein et al., 2018). Currently, very little is known about the real-time relationships of appetitive and affective processes on eating behaviour, and machine learning models may obscure our understanding through producing unreproducible models (Olorisade, Brereton, Andras, 2017). This limits the ability to understand causal mechanisms and inter-relationships between associates of real-world behaviours. Future investigations of ER using EMA should focus on determining the predictive validity of baseline and real-world predictors of fluctuations in appetite, affect, cognition, and eating behaviour to validate previous lab-based findings and provide dynamic and contextually driven accounts.

In addition, currently no study to date has employed a real-time cognitive task as an objective measure of fluctuations in cognitive domains such as attentional allocation and behavioural control during ER. Understanding the causes of fluctuations in cognitive processes and their influence on experienced temptations and lapses would further our understanding of the role of attention and behavioural control in real-world energy intake as well as the impact of ER and the environment on these measures. This could be used to inform real-world cognitive bias modification studies which aim at reducing problematic cognitive processes in those who may experience problems with increased reward-processing of food-related environmental cues or have impaired control over impulsive behavioural responses to food as a personalised strategy to aid with problematic appetitive processes during weight loss.

Strengths and limitations

A strength of this systematic review and meta-analysis is that it is the first comprehensive account of the current evidence from real-world investigations of the impact of ER on within person changes in appetite and affect in adults under different momentary states common of the experience of dieting in adults with overweight and obesity. It also the first to provide a contextually descriptive account of experiencing a dietary temptation or lapse from both self-guided as well as structured weight loss attempts. These findings complement those from previous lab-based approaches by demonstrating the dynamic within-person nature of appetite and affect during experiences of temptations and lapses, and how these are impacted by contextually driven factors emphasising the importance of measuring within the moment to capture these effects.

One major limitation of this study is that very few papers were identified could be meta-analysed and just under half of the identified studies were secondary analyses of two papers, which limits the reliability of this evidence base. More primary investigations are needed to be conducted in different samples to ensure the consistency of these findings as well as provide data which would result in greater power for meta-analyses.

In addition, the sample size used to calculate SMDs in the current meta-analyses were derived from the average number of reported assessments per EMA contingency rather than overall sample size of the study which is likely to have impacted estimations of standard errors. In experience sampling methodologies, repeated observations are the unit of analyses meaning inferences are made about the momentary state in which these observations were recorded. However, the amount of assessments that are completed by an individual depends on compliance with completing random prompts and self-reporting of temptations and lapses, which results in unequal amounts of observations between individuals. In light of these limitations, it was determined that tests for heterogeneity and publication biases would be too underpowered.

Another limitation of the meta-analyses is that some of the included studies employed paper-and-pencil diary methods of EMA (Carels et al., 2001; 2004a; 2004b). This method is subject to bias through backfilling or hording of assessments given that time/date of completed entries cannot be verified and demonstrates substantially lower levels of compliance than electronic assessments (Jones et al., 2018). These biases could have an impact on the effect sizes yielded in the current analyses as compliance for assessment procedure (e.g. completing an assessment within 30 minutes of being prompted) could not be independently verified. Given the reliance on these investigations for all contrasts that were performed, this constitutes a major limitation of the current investigation. Future EMA investigations of appetite and ER should attempt to replicate findings using electronic methods to ensure these findings are reliable and future meta-analyses may benefit from either excluding studies using paper-and-pencil methods or test for potential differences in these methods of assessments in subgroup analyses.

Regarding the quality assessment that was performed, the NOS for cross-sectional studies may not be appropriate for assessment of EMA investigations. This is because the assessment of the qualities of within-person units of analyses may not be the same as between-group units. Future reviews would benefit from a validated quality assessment checklist for investigations that use EMA. In addition, the current sample size of papers in this review impacted the ability to perform sensitivity analyses by removal of poor-quality studies. Nevertheless, it was deemed important to attempt a quality assessment for descriptive purposes to highlight potential methodological limitations of current ER investigations using EMA. Future updates of this review should seek to perform sensitivity analyses to ensure robustness of these findings.

Conclusion

These findings indicate appetitive and affective effects are heightened when experiencing a momentary subjective state and therefore pose barriers for successful dietary adherence. Dynamic fluctuations in appetite which act as motivational drivers such as hunger appear to relate to experiences of temptation, though these may not have a direct impact on lapsing. More evidence is required to understand the role of appetite, particularly reward-based processes, in determining dietary adherence. Negative affect is increased during experiences of temptation and lapsing suggesting momentary fluctuations in affect which play a role in determining dietary adherence rather than a persistent low mood. No sensations are increased during lapses compared to temptations. What distinguishes these is the use of coping strategies to deal with problematic sensations. Increasing engagement with coping strategies whilst experiencing a temptation may be an effective strategy to reduce the chances of control over eating behaviour becoming overwhelmed which will aid with dietary adherence.

Between-person differences in average levels of appetitive and affective sensations, as well as baseline measures relating to eating behaviour can predict individual differences in real-world sensations which can influence the likelihood of experiencing a lapse. A better understanding of how measures can be used to predict individual differences at baseline could serve use in identifying those who may struggle to cope with appetitive and affective sensations that arise during ER so that strategies can be tailored to address problems on a case by case basis.

3.6 Supplementary materials

Table 3.1 - Classification of subgroup domains that were summed from multiple outcomes

Domain	Author	Outcome	Measure
Negative mood	Carels et al. (2001)	Bored, stressed, angry, frustrated, lonely, nervous, deprived, restless, sad, tired	5-point Likert scales
	Carels et al. (2004)	See Carels et al. (2001)	5-point Likert scales
	McKee et al. (2014)	Depletion, stress	7-point Likert scales
	Forman et al. (2017)	Loneliness, boredom, anger/irritation, stress, deprivation, fatigue	5-point Likert scales
Positive mood	Carels et al. (2001)	Content, in control, happy, relaxed, carefree	5-point Likert scales
	Carels et al. (2004)	See Carels et al. (2001)	5-point Likert scales
Positive abstinence-violation effects	Carels et al. (2001)	Resist temptation, not likely to be tempted, ability to maintain diet, feeling diet will be a success, control future eating, willpower	5-point Likert scales
	Carels et al. (2004)	Unlikely to be tempted, diet will be a success, willpower, control future eating	5-point Likert scales
Negative abstinence-violation effects	Carels et al. (2001)	Worried about maintaining diet, desire to give up, feelings of failing the diet	5-point Likert scales
	Carels et al. (2004)	Worried about maintaining diet, feelings of failing the diet, feeling guilty about temptation or lapse, feelings of responsibility for lapse	5-point Likert scales
Coping strategies	Carels et al. (2004)	Removed myself from situation, distraction, talked to a group member/family/friend, encouraged myself, medicated/relaxed, engaged in spiritual activities, exercised, thought about benefits of dieting, thought about benefits of being healthy.	5-point Likert scales
	McKee et al. (2014)	Long-term thinking of weight loss goal, importance of weight loss goal	7-point Likert scales

Table 3.2 - Quality assessment of studies using modified Newcastle-Ottawa scales for assessing included studies of appetite measures with EMA during ER

Study*	**Selection**				**Comparability**	**Outcome**		**Total (max 9●)**
	Representiveness of sample (●)	Sample size (●)	Non-respondents (●)	Ascertainment of the exposure (●●)	(●●)	Assessment of the outcome (●)	Statistical test (●)	
Carels 2001	●	-	-	●●	●●	●	-	●●●●●● (6)
Carels 2004a	●	-	-	●●	●●	●	-	●●●●●● (6)
Carels 2004b	-	-	●	●●	-●	●	-	●●●● (4)
Crochiere 2019	●	-	●	●●	●●	●	●	●●●●●●●● (8)
Forman 2016	●	-	●	●●	●●	●	●	●●●●●●●● (8)
Forman 2018	●	-	●	●●	●-	●	-	●●●●●● (6)
Goldstein 2018	●	-	●	●●	●●	●	●	●●●●●●●● (8)
Manasse 2018a	-	-	-	●●	●●	●	●	●●●●●● (6)
Manasse 2018b	-	-	●	●●	●●	●	●	●●●●●●● (7)
Massey & Hill 2012**	●	-	●	●●	-●	●	-	●●●●●● (6)
McKee 2014	●	-	-	●●	●-	●	-	●●●●● (5)
Schumacher 2018	●	-	●	●●	●●	●	●	●●●●●●●● (8)

* Lettering subscript adapted for current paper and do not represent subscript in published literature
**Assessed with usual criteria for NOS cross sectional studied applied

Study	**Selection**		**Comparability**	**Exposure**			**Total (max 8●)**
	Case definition adequate (●)	representativeness of cases (●)	Based on design and analyses (●●)	Assessment of the outcome (●●)	Statistical test (●)	Non-respondents (●)	
Kwasnicka 2018	-	●	●●	●	-	-	●●●● (4)

Table 3.3 – Summary table of characteristics and findings of all included studies in the systematic review and meta-analyses

Author	Design	Domain	Outcome measures	EMA Assessment	Result
Carels et al. (2001)	*N* = 30 (73% F, mean age (SD) = 19.88 (4.4), mean BMI (SD) = 29.2(3.9)). 1 week of EMA	Appetite and affect	5-point Likert Scale (not at all to extremely) assessing hunger, fullness, satisfied, positive and negative mood	RA, TA and LA	Greater hunger and negative mood on TA and LA. Less fullness on TA and less satisfied on LA
	Self-guided dieting attempts (12% weight loss maintenance; 88% weight loss)	Abstinence-violation effects	Responses from four 5-point Likert scales (not at all to extremely) summed to produce separate negative and positive AV effects (see Table 3.1)	RA, TA and LA	Greater negative AV on TA and LA. TA greater positive AV compared to LA.
		Location	Entries taking place at home, work/school (%)	RA, TA and LA	LA more likely to occur at home. No location differences between LA and TA
Carels et al. (2004a)	*N* = 37 (100% F, mean age (SD) = 55.4 (7.9), mean BMI (SD) = 29.2(5.5)). 1 week of EMA	Appetite and affect	5-point Likert Scale (not at all to extremely) assessing hunger, fullness, satisfied, positive and negative mood	RA, TA and LA	Greater positive and negative mood on LA compared to RA

	Final week of weight loss intervention (LEARN programme; Brownell, 2000)	Abstinence-violation effects	Responses from four 5-point Likert scales (not at all to extremely) summed to produce separate negative and positive AV effects (see Table 3.1)	RA, TA and LA	Greater negative AV effects on LA
		Location	Entries taking place at home, work/school (%)	RA, TA and LA	No location increased likelihood of LA or TA
		Coping strategies	Response from 14 5-point Likert scales (not at all to extremely) summed to produce coping strategies score	TA and LA	Coping more strongly associated with TA than LA
Carels et al. (2004b)	Secondary analyses of Carels et al (2004)	Associations with weight loss (%)	Mood, AV effects, coping strategies, frequency of temptations and lapses, Weight change (%)	-	Feelings of failure during lapse associated with less weight loss (%). No other associations with weight loss
Crochiere et al. (2019)	Secondary analyses of Forman et al. (2016)	Associations with baseline differences	Mood, frequency of LA, achievement score on the Delis-Kaplan Executive Function System Tower Task (D-KEFS; Delis, Kaplan & Kramer, 2001).	-	Less EF moderated increases in tiredness, deprivation and boredom, and subsequent likelihood of lapsing.

Forman et al. (2017)	*N* = 189 (82% F, mean age (SD) = 51.81 (9.76), mean BMI (SD) = 36.93(5.8)).	Appetite and affect	5-point Likert Scale (not at all to extremely) measuring hunger, and summed responses from 7 scales to produce negative mood	RA and LA	Hunger and feelings of deprivation associated with LA
	2 weeks in first 2 weeks, 1 week at 6 months, and 1 week at 12 months of EMA	Lapse type	Entries which were described as unintended food eaten, unplanned time or larger portion size than intended (%)	LA	Eating an unintended type of food most common lapse across all assessment periods
	12-month behavioural weight loss programme	Location and time	Entries taking place at home, work/school, taking place in the morning, afternoon or evening, and (%)	LA	Lapses occurred most in the evenings, at home, on the weekends.
		Association with weight loss (%)	Lapse frequency and weight loss (%)	-	Greater lapses during first EMA week associated with less weight loss
		Change in lapse frequency	Lapse frequency at week 1 & 2, 6-month and 12-month	-	Lapses decreases from week 1 & 2 to 6 month and then increased at 12-month

Forman et al. (2018)	*N* = 44 (86% F, mean age (SD) = 50.98 (12.72), mean BMI (SD) = 35.6 (5.88)).	Associations with weight loss (%)	Lapse frequency (planned and unplanned) and weight change (%)	-	No associations between weight change and both types of lapses
	8-week of EMA 8-week Weight Watchers intervention	Change in lapse frequency	Lapse frequency (planned and unplanned) at Week1 and 8	-	The frequency of unplanned lapses decreased from week 1 to 8
Goldstein et al. (2018b)	Secondary analysis of Forman et al. (2016)	Contextual associates of lapses	Lapse type (eating an unintended food, eating at an unplanned time, eating a larger portion than intended) and appetite	LA	Higher between-person levels of stress, irritability, fatigue, exposure to delicious foods, and within-person increases in hunger and deprivation, and decreases in irritability associated with eating an unintended food Higher between-person levels of stress, boredom, loneliness, deprivation and exposure to delicious foods and within person increases in stress and boredom associated with eating at an unplanned time Higher between-person levels of stress,

		Associations with weight change (%)	Lapse frequency and weight loss (%)	-	boredom, irritability, loneliness, fatigue and exposure to delicious foods and within person increases in deprivation and hunger associated with eating a larger portion Eating at an unplanned time predicted overall weight loss (%)
Kwasnicka et al. (2018)	*N* = 8 (75% F, mean age = 54, mean BMI = 31.09) 6-month N-of-1 and EMA of 2 RAs per day Weight loss maintenance of individuals who intentionally lost 5% of body weight in the previous 6 months	Predictors of weight loss plan adherence	Self-reported weight loss plan adherence predictors	-	Weight loss maintenance motives, self-regulation, habit, personal resources, and environment all predicted plan adherence. Strength and significance of predictors differed between each case.
Manasse et al. (2018a)	Secondary data analysis of Forman et al (2016)	Baseline predictors of lapse triggers	Assessments of impulsivity (Stop signal task; Manasse et al., 2016, Delayed discounting task; Robles & Vargas, 2007, and self-reported measure of negative urgency (UPPS; Whiteside & Lynham, 2001)	-	Main effect of negative urgency on increased risk of lapse. Negative urgency moderated the effect of hunger and loneliness on risk of lapse. Loneliness more strongly predicted lapse in those with high

					negative urgency. Hunger more strongly predicted lapses in those with low negative urgency Moderating effect of stop signal reaction time on momentary changes in stress and subsequent lapse, however this was conducted in the absence of a main effect of SST.
Manasse et al. (2018b)	Secondary data analysis of Forman et al. (2016)	Baseline predictors of lapse triggers	Overeating section of the Eating Disorder Examination (Mond, Hay, Rodgers, Owen, Beaumont, 2004) to assess loss-of-control eating	-	Main effect of LOC on dietary lapse. There was a moderating effect of LOC on between-person differences in average levels of loneliness, boredom, anger, hunger and deprivation.
Massey & Hill (2012)	*N* = 92 female current dieters (n = 40 weight watchers (mean age (SD) = 44.2 (1.7), mean BMI (SD) = 24.3 (0.4). n = 52 dieters (mean age (SD) = 40.70 (1.6), mean BMI (SD) = 29.10 (0.8)) 1 week of pre- and post-craving records	Pre and post craving associates	Craving record assessing context of craving (location, social context, triggers) and food craved. Craving and hunger intensity (100mm VAS), and mood state (12-item version of the UWIST Mood Adjective Checklist, Matthews, Jones & Chamberlain, 1990)	-	Majority of cravings experienced at home, in the presence of others, and in the afternoon or evening. Dieters had stronger and less resistible cravings in the context of lower hunger without a pervasive low mood.

	Three commercial weight loss clubs as well as self-dieters from the community				Watchers cravings were less strong and occurred in the context of greater hunger compared to dieters. Post craving hunger remained low and did not decrease in dieters. Hedonic tone decreased from pre to post craving in dieters. End of day mood ratings showed low levels of negative affect in all groups. Small increases in negative mood were found in dieters and non-dieters, but not watchers on craving days.
McKee et al. (2014)	*N* = 80 (80% F, mean age (SD) = 41.21 (15.60), mean BMI (SD) = 30.78 (7.26)). 1 week of EMA Recruited from local weight loss groups (45%) and self-attempted dieting (55%)	Appetite and affect	6 7-point Likert scales (not at all to very much) assessing hunger, temptation strength, 2 separate summed responses from 2 scales to produce negative mood and coping	TA and LA	Hunger, stress, the environment, and presence of others positively predicted, whereas coping responses negatively predicted temptation strength.
		Environment and presence of others	Binary response (yes, no)		Presence of others and the environment positively predicted temptation strength.

		Time of temptations and lapses	Entries taking place in the morning, afternoon or evening and on weekdays/weekends		No differences in strength of temptation at any time. Lapses equally likely to take place on the weekends and weekdays, but more likely to occur in the evenings.
Schumacher et al. (2018)	Secondary analysis of Forman et al. (2016)	Self-attitudes and lapse frequency	4-point Likert Scales (not at all critical to extremely critical) assessing self-criticism, self-forgiveness, self-regard and self-efficacy	LA	Lower between-person levels of self-efficacy and self-regard predicted greater lapse frequency Between-person differences in self-regard predicted same-day lapse. Lower momentary self-criticism predicted same-day lapse.

Chapter Four

Appetite, Reward, and Behavioural Control during Intermittent Energy Restriction in Overweight and Obesity: An Ecological Momentary Assessment Study

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This investigation examined appetite, reward-responsivity, and behavioural control during intermittent energy restriction. It contrasts these variables between ER and non-ER days and examines potential baseline predictors of individual differences in the effect of ER on outcome measures. This study also examines how these variables are different in the moments prior to eating occurrences. Finally, this study examines changes in pre and post hunger using a 7-day retrospective measure. The manuscript for this paper is currently being prepared to submit for publication in *Appetite*.

The roles of the co-authors are summarised below:

I designed the study in collaboration with Jason Halford, Paul Christiansen, Amy Ahern, and Emma Boyland. I collected and analysed the data and wrote the manuscript. Amy Ahern, Emma Boyland, Paul Christiansen, and Carl Roberts contributed useful comments whilst preparing the manuscript.

4.1 Abstract

Rationale: Appetite regulation involves the interplay between satiety, reward-processing, and behavioural control. During ER, these orientate behaviour towards restoring a state of energy balance posing a problem for dietary adherence. However, the influence of momentary shifts in these processes on energy intake in naturalistic settings has yet to be established. IER is an increasingly common approach to weight loss, though currently little is known about the role of appetite regulation in determining adherence to this strategy. Large individual differences exist in appetitive responses to manipulations of energy intake, therefore establishing predictors of these differences may help identify those who may struggle to cope with heightened appetitive effects during ER days.

Objective: This study investigated the impact of IER on fluctuations of subjective sensations of appetite, food-cue responsiveness, and behavioural control on both ER and nER days in a sample of individuals with overweight and obesity engaging in a non-consecutive 2 d/week IER diet. A secondary aim was to investigate whether baseline measures of eating behaviours could explain individual differences in outcomes. This study also aimed to examine differences in outcomes prior to the initiation of eating. Finally, this study investigated change in hunger from pre to post investigation on a 7-day retrospective measure.

Methods: Sixty-four individuals with overweight and obesity engaged in a 1-week 2 day/week non-consecutive IER diet. They completed three RAs per day assessing current intensity of hunger and food cravings as well as a food-related Stroop task and a colour Stroop task. Participants also kept a photographic food-log which was used to identify RAs which took place in the 2 hours prior to an eating event. They also completed a battery of questionnaires at baseline as well as a pre and post 7-day retrospective measure of hunger.

Results: Increases in hunger and craving intensity were found on ER days compared to nER days. Individuals who scored higher on TFEQ-H experienced greater increases in hunger on ER days. PFS predicted individual differences in average levels of craving intensity. Hunger and cravings were raised in the moments leading up to eating. A comparison of pre and post retrospective measure of hunger indicates that hunger decreased over the study week.

Conclusion: Baseline measures may be used to identify individuals who struggle to cope with heightened momentary appetite responses to IER. There may be discrepancies between real-time and retrospective measures of appetite.

4.2 Introduction

Appetite can be understood as a biologically driven process which expresses itself through eating behaviours which take place within a sociocultural context (MacLean, Blundell, Mennella, & Batterham, 2017). Eating is regulated by the interplay between satiety, reward responsivity, and behavioural (inhibitory) control which interact to drive or inhibit consumption (Roberts, Christiansen, & Halford, 2017). Both homeostatic (e.g. satiety) and hedonic (e.g. reward responsivity) drives interact within a complex gut-brain axis of neuronal and hormonal signals which form the biological-basis for motivation to consume or inhibit eating (Timper & Brüning, 2017; Volkow, Wang, & Baler, 2012).

The homeostatic system monitors blood-glucose level and responds to depletion by releasing various hormonal signals (e.g. ghrelin) within the gastrointestinal tract that are integrated within hypothalamic areas which cue the sensation of hunger (Müller et al., 2015) – a strong motivational state that drives behaviour towards restoring a state of energy balance (King et al., 2007). The hedonic system is comprised of a series of physiological and psychological responses to food-related environmental cues that have previously been associated with consumption which increase the drive to eat (van den Akker, Stewart, Antoniou, Palmberg, & Jansen, 2014) and can occur even in the absence of hunger (Nederkoorn, Guerrieri, Havermans, Roefs, & Jansen, 2009).

Dual-processing accounts conceptualise cognition into two distinct processes: automatic and reflective (Hofmann et al., 2009). Automatic processes guide consumption through reward-processing of environmental food-related cues which capture attention and result in automatic approach responses to food-cues (Wiers et al., 2010). Reflective processes are ‘top down’ and are consciously experienced when control is exerted over current behaviour (Verbruggen, 2016). Consumption may be influenced by individual differences in behaviours relating to both the appetitive drive as well as dietary control over eating behaviours which may be measured using inventories such as the Addiction-Like Eating Behaviour Scale (AEBS; Ruddock, Christiansen, Halford, & Hardman, 2017).

During energy restriction (ER), appetite regulation is compromised so that hunger and reward-based processing of food cues are both increased which challenge successful control over eating behaviour (Roberts et al., 2017). These appetitive responses to maintaining a negative energy balance contribute to the low rate of compliance in weight loss, particularly in the short-term with managing sensations of hunger being one of the major factors given for unsuccessful dieting attempts (Drapeau et al., 2007; Gibson et al., 2014; Stubbs et al., 2011). Additionally, large amounts of individual variability exist in these appetite responses to manipulations of energy balance which may give birth to the diversity in eating behaviours and susceptibility to weight gain. Recognition that individuals will not respond in the same way to the same treatment therefore is essential for the development of more effective obesity treatments (Gibbons, Hopkins, Beaulieu, Oustric & Blundell, 2019).

Greater baseline hunger has been associated with poorer weight loss outcome during behavioural intervention (Sayer, Peters, Pan, Wyatt, & Hill, 2018). In addition, some weight loss studies have reported reductions in susceptibility to hunger scores on the Three Factor Eating Questionnaire (TFEQ-H; Stunkard & Messick, 1985) from pre to post intervention (Bas & Donmez, 2009; Batra et al., 2013; Gilhooly et al., 2007) with the greater decreases in scores being associated with increased weight loss (Gilhooly et al., 2007). TFEQ-H is the only factor which was a predictor of weight change after 20 weeks of continual calorie restriction (Batra et al., 2013). These suggest individuals who display high levels of baseline hunger scores may experience the greatest problems with this sensation during ER and subsequently may experience lower levels of weight loss.

There are considerable differences in the extent individuals are susceptible to the rewarding effect of food-related cues evident in the large amount of variability found in food-cue responsivity (Tetley, Brunstrom, & Griffiths, 2009). This variability may be explained by individual differences in eating behaviours which are impacted by external factors including restraint, binge eating and disinhibition (Fedoroff, Polivy, & Herman, 1997; Fedoroff, Polivy, & Herman, 2003; Meule, Lutz, Vögele, & Kübler, 2014). For example, Burger, Sanders and Gilbert (2016) conducted multiple cross-sectional studies and found baseline PFS scores predicted increased activation in neural regions involved in cue-induced anticipation of food intake, as well as increased hedonic ratings of palatable foods and binge eating score.

Food cravings are intense desires to eat a particular food which challenge control over eating (Hill, 2007). Cravings are the output of reward-based evaluations which relate to the expectation of rewarding effects of intake which result from exposure to a cue that has previously been paired with subsequent consumption (May et al., 2012). Higher trait-level food cravings are associated with higher levels of hunger, restraint, and disinhibition (Batra et al., 2013b; Polivy et al., 2008). Early reductions in the intensity of cravings during weight loss have been associated with long-term weight loss success (Batra et al., 2013; Dalton et al.,

2017) and the management of food cravings is an essential component of maintaining weight loss (Elfhag & Rössner, 2005; Ferguson, Brink, Wood & Koop, 1992).

Increases in state cravings have been associated with increased intake of the desired food (Chao, Grilo, White, & Sinha, 2014), and more intense and frequent cravings are associated with poor long-term weight management (Franken & Muris, 2005). Additionally, Rejeski et al. (2012) found that increased intensity of cravings were significantly higher in groups fed with water compared to an energy drink. PFS moderated this relationship with increased PFS score being associated with increased intensity of cravings. In one free-living investigation, higher craving intensity was associated with consumption of the food which was being craved and this relationship was higher in individuals who scored high on a trait-craving inventory (Richard, Meule, Reichenberger, & Blechert, 2017). Given cravings are a frequent reason for failing to adhere to a diet (Hall & Chow, 2011), these findings suggest accounting for trait and state cravings may be important to target during dietary interventions.

Food-related attentional biases have been associated with greater activation in areas involved in attentional processing (Nijs, Muris, Euser, & Franken, 2010) which has predicted future weight gain (Yokum, Ng, & Stice, 2011). Attentional biases may also be more pronounced in individuals high in disinhibition (Hege, Stingl, Veit, & Preissl, 2017). There are a variety of tasks that can be used to measure attentional processing of rewarding stimuli (see Table 1.1 on P. 18). One of the most common methods used to assess attentional biases towards food-cues is the food-related Stroop task (Doolan et al., 2015) which indexes food-related attentional biases by computing a mean difference score between reaction times to food-related words and control words. A slower reaction time towards food-related words relative to control words is thought to be indicative of the presence of an attentional bias towards food-related cues. This is thought to occur as the food content of the stimuli words interferes with the colour-naming performance of the task. However, evidence for the predictive utility of attentional biases in obesity has been mixed. Increased attentional biases have not been consistently associated with BMI or energy intake (Field et al., 2016). Field et al. stated that instead of a being a trait-like feature of obesity, biases may be the output of stimulus evaluation that is determined by the current incentive value of the cue at that moment in time meaning the predictive validity of measures should be maximised when measured soon before intake takes place whilst in the same context. In support of this, Hardman, Field, Jones & Werthmann (in prep) found attentional biases are associated with food intake, but only if measured proximal to the task.

Behavioural control is characterised as both a trait-like capacity for tendencies towards impulsive behaviours as well as a dynamic process which fluctuates in response to environmental and internal signals (De Witt, 2009; Jones, Christiansen, Nederkoorn, Houben, & Field, 2013). Behavioural control is measured with a variety of tasks which all measure different components of inhibition (see Table 1.1 on P. 18). For example, the colour Stroop task measures the ability to inhibit cognitive interference that occurs when automatic processing of a specific feature of a stimulus (e.g. written word) impedes the processing of another attribute of the stimulus required for the current goal (e.g. naming the colour of the font). Higher scores on this task indicate less ability to inhibit this interference (Scarpina & Tagini, 2017). Effective control of eating requires suppressing momentary automatic responses that are evoked by external food cues and internal physiological signals (Dalton, Finlayson, Esdaile, & King, 2013). When control over eating is compromised, eating may become disinhibited which could lead to overconsumption especially if in the presence of highly palatable energy-dense foods (Polivy, Herman, & Coelho, 2008). One possible underlying psychological mechanism for this is that persistent use of cognitive resources to control behaviour leads to ego depletion – a state where control over behaviour is exhausted due to previous exertion (Baumeister, Bratslavsky, Muraven & Tice, 1998). In support of this, studies using the Go/No-Go task show decreased performance is associated with increased intake of unhealthy foods (Jasinska, Yasuda, Burant, Gregor, Khatri, Sweet, 2013; Price, Lee, & Higgs, 2016).

Deficits in behavioural control has been proposed to be a major driver of calorie consumption and obesity (Guerrieri et al., 2007). Lower between-person levels of behavioural control poses as a problem for dietary adherence and future weight gain (Allan, Johnston, & Campbell, 2011; Chantal Nederkoorn, Houben, Hofmann, Roefs, & Jansen, 2010; Hofmann, Friese & Wiers, 2008; Wiers, Gladwin, Hofmann, Salemink, & Ridderinkhof, 2013). There have been some attempted at increasing an individual's capacity for behavioural control to reduce overconsumption (Stice, Lawrence, Kemps, & Veling, 2015). Studies of inhibitory control training (ICT) which makes use of tasks such as the Go/No-Go to train automatic inhibitory responses to food-related cues by consistently pairing them with trials that require a behavioural response (Verbruggen & Logan, 2008). However, findings for the efficacy of these approaches have been mixed (Jones, Hardman, Lawrence, & Field, 2018). Given the transient nature of behavioural control, it may be important that theoretical models also take into consideration the role of context in determining fluctuations (Rosa, Todd, & Bouton, 2014).

A concept which relates to control over eating behaviour is restrained eating (Herman & Mack, 1975). However, high restrained eating may be detrimental to weight control as it may result in disinhibited eating and overconsumption following exposure to food-cues, though this may only be the case when restrained eaters are demonstrate low levels of behavioural control. For example, Jansen et al. (2009) found evidence that individuals who scored high on the Restraint Scale (RS; Herman & Polivy, 1987) ate more than individuals with low scores on the RS, but only when they also performed poorer on the Stop-signal behavioural task. Some argue that the RS measures unsuccessful restraint over eating behaviour, whereas other measures of restraint such as the TFEQ measures successful restraint (Wardle & Beales, 1987). To support this claim, increased TFEQ-R scores during weight loss intervention being associated with increased weight loss (Batra et al., 2013).

Continual ER (CER) is the most frequently used weight loss strategy (Steyer & Ables, 2009); however, for most it is difficult to follow since intake must be limited daily which may negatively impact appetite and long-term dietary adherence (Franz et al., 2007). Intermittent energy restriction (IER) is an alternative approach thought to be easier to follow due to shorter spells of intense ER followed by periods of *ad lib* intake (Batra et al., 2013; Hoddy et al., 2016; Johnstone, 2015). There were early concerns regarding the potential of a compensatory hyperphagic response on nER days of IER, however many IER investigations actually report a 'carry-over' effect of ER through a spontaneous reduction of between 10 – 23% of prescribed energy intake on all 5 unrestricted days of an IER diet (Harvey, Howell, Morris, & Harvie, 2018; Hutchison et al., 2019). Whilst the underlying behavioural mechanisms responsible for this reduction is currently unknown, anecdotal reports suggest IER makes individuals more aware of food habits and reassures them that they can manage the high levels of appetite on ER days (Harvie et al., 2011). However, the role of appetite in IER currently is understudied and warrants further investigation (Harvey et al., 2018).

Previous investigations of ER on appetite regulation and energy intake have relied heavily on laboratory-based environments and retrospective recall of past experiences (e.g. '*how hungry have you felt today?*') both of which may introduce a level of bias within the data. EMA addresses these by using repeated measurements to capture how experiences and behaviours fluctuate across time and situation (See Section 2.1 on P. 43 for a detailed description of

EMA). However, there has yet to be an investigation employing both retrospective and real-time measures of appetite to allow for a comparison of findings between both approaches.

EMA can also be used for prospective analyses of the processes which lead to behaviours. These have been historically hard to capture such as fluctuations in stress and affect preceding a lapse during smoking cessation (Shiffman & Waters, 2004). The current study uses time and date stamps of food diaries to assess whether assessments taking place in the moments leading up to the initiation of energy intake differ to assessments where no intake was logged.

To date, very few studies have employed EMA to investigate appetite regulation whilst engaging in ER in populations with overweight and obesity. These have primarily focused on experiences of dietary temptations and lapses (see Chapter Three for a review of previous literature). This is an important approach given that characteristics of the current food environment responses such as the abundance of highly palatable food items heavily influence reward-based eating and can result in persistent temptations to indulge, particularly when energy is being restricted (Appelhans, French, Pagoto, & Sherwood, 2016).

These have demonstrated that momentary states of temptation and lapses are associated with increased levels of hunger, stress, negative and positive mood compared to assessments where no temptation or lapses were recently recorded (Carels et al., 2001; Carels, Douglass, Cacciapaglia, & O'Brien, 2004; McKee, Ntoumanis, & Taylor, 2014). In a sample of dieters attending a formal weight loss program, Mckee et al. (2014) found approximately 50% of temptations led to a dietary lapse which was mediated by hunger, stress, and the strength of the temptation. These indicate dynamic fluctuations in sensations of appetite and affect during ER influence the likelihood of experiencing a momentary subjective state which pose as a barrier towards successful dietary adherence such as a dietary temptation or lapse.

Whilst these investigations have shed light onto the differences in appetite sensations between momentary states during continual ER, there is currently a lack of systematic investigations which take a primary focus on appetite regulation throughout the day during IER. The benefit of focusing on IER is two-fold: i) IER employs very low energy on ER days which may have added health benefits above continual ER (Wei et al., 2017), though this may result in more intense momentary appetite responses ER which may be problematic for those who struggle to cope with strong sensations of appetite; ii) alternating days allows for contrasts of variables between nER and ER days so that increases can be modelled, and moderators of these relationships can be investigated.

Investigating how appetite changes from moment to moment as individuals go about their daily lives is essential for developing our understanding of the effect of IER on appetite regulation and would provide the basis for a more detailed explanation of dynamic fluctuations in appetite processes determine energy intake and dietary adherence. Additionally, a better understanding of the predictors of individual differences in these processes may aid with identification of those who may struggle to cope with particular appetitive responses to ER.

To this end, the current study aimed to investigate the impact of IER on dynamic fluctuations of subjective sensations of appetite, food-cue responsiveness, and behavioural control on both ER and nER days in a sample of individuals with overweight and obesity engaging in a non-consecutive 2 d/week IER diet. A secondary aim was to investigate whether baseline measures of eating behaviours could explain individual differences in outcomes. This study also aimed to examine differences in outcomes prior to the initiation of eating. Finally, this study aimed to investigate change in hunger from pre to post investigation using a 7-day retrospective measure of hunger.

Participants underwent a 1-week IER (5:2) diet which allowed for comparison of appetite measures between ER and nER days. A testing application was created (*APPetite*) which was installed on loaned smartphones and consisted of two subjective 7-point Likert scales assessing intensity of hunger and cravings, a colour Stroop to assess behavioural control, a food Stroop to assess attentional bias toward food-cues, and contextual questions such as the location of the assessment and recent consumption which may influence appetite (e.g. caffeine). A battery of questionnaires was administered consisting of the TFEQ, PFS, and AEBs to measures individual differences in eating behaviours. Finally, a pre and post 7-day retrospective measures of hunger were also implemented.

It was hypothesised that intensity of hunger will be significantly higher on ER days compared to nER, and this relationship will be greater for individuals who score high on the TFEQ-H. Intensity of craving and food-related attentional biases will also be significantly higher on ER days compared to nER and this relationship will be greater for individuals who score high on TFEQ disinhibition subscale (TFEQ-D), PFS, and AEBs-Drive. Finally, colour Stroop interference score will be significantly higher on ER days compared to nER, and this relationship will be greater for individuals who score high on the TFEQ-D, whereas the relationship will be lower for individuals who score high on the TFEQ restraint subscale (TFEQ-R) and AEBs-Control.

Additionally, it was predicted that the intensity of hunger and cravings as well as Food and Colour Stroop score will be significantly higher on assessments taking place 2 hours prior to an eating event being logged compared to assessments where no eating event was logged.

Finally, it was hypothesised that responses on a 7-day retrospective measure of hunger will be significantly higher on post measures compared to pre-measures.

4.3 Methods

4.3.1 Participants

Sixty-four individuals (49 females, 77%) were recruited for the study. Participants were eligible for the study if they were aged between 18 – 65 years (mean 34.77 ± 12.62), had a BMI categorised as with overweight or obesity (25 – 40kg/m^2; mean 30.02 ± 3.93), were fluent English speaking, and were willing to engage in an intermittent energy-restricted (2d non-consecutive/week) diet for a week. Participants were not eligible to take part if they were currently engaging in a dieting attempt, displayed any indications of ill health (e.g. asthma, diabetes, digestive problems, epilepsy, or suffering from a cold or flu), were taking prescription medication that affects appetite, were pregnant or breastfeeding, or suffered from colour blindness.

The study was advertised around the University of Liverpool campus and the wider Merseyside area via online paper and radio advertisements. The study was approved by the University of Liverpool ethics committee (Reference number: 2181).

4.3.2 Procedure and measures

Procedure (Figure 4.1)

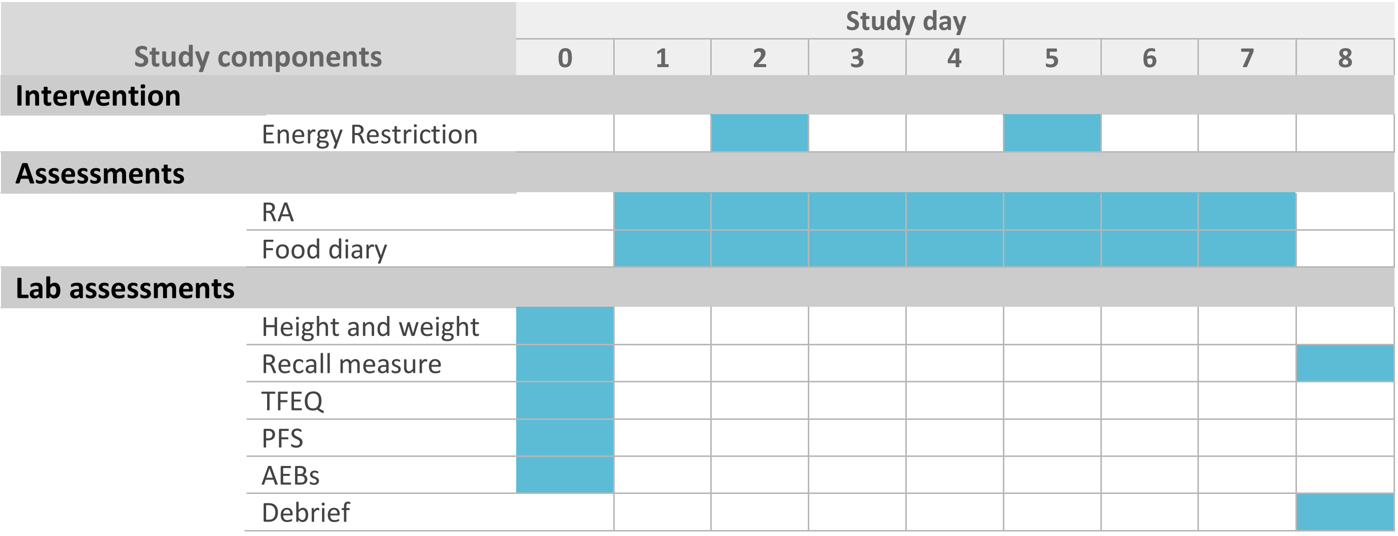

Figure 4.1 - Gantt chart showing an overview of the 1-week study procedure. Study components are listed on the left and blue blocks indicate when these were implemented throughout the course of the investigation. Blocks relating to ER are an example as these were dependent on participant choice of ER days. *RA.* Random assessment; *TFEQ* Three Factor Eating Questionnaire; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

Participants were screened via email prior to attendance and eligible participants were invited to attend an initial appointment at the university where they provided informed consent. Height and weight were measured to accurately calculate BMI (see Section 2.4 on P. 50) and a battery of baseline measurements of eating behaviours was administered (see Section 2.6 on P. 59 for a detailed description) as well as a 7-day retrospective measure of hunger.

Participants were loaned a smartphone (Doogee X10: 12.7cm screen size) preloaded with the testing application (detailed in Section 2.1.2 on P. 45). They were taught how to navigate the application and complete the task whilst supervised until they felt comfortable with using the application. They received information on the IER (5:2) dietary intervention they would be taking for the following week (detailed below).

Participants were instructed to keep a photographic food diary for the duration of the study which was logged via the camera on the loaned smartphone and were instructed to take a photo of any food consumed throughout the study just before eating (see Section 2.3 on P. 49 for a detailed description).

They were instructed that they would receive three random assessments (RAs) per day which would occur every morning (8 a.m. – 12 p.m.), afternoon (12 p.m. – 4 p.m.) and evening (4 p.m. – 8 p.m.). RAs were sent via text prompts to their personal mobile device which instructed participants to initiate an assessment within 45 minutes of receiving the text message and respond ‘done’ once the task was completed. Participants were instructed to miss the assessment if it had been 45 minutes since the notification text.

They returned to the university after a week to return the phone and complete another 7-day retrospective measure of hunger. EMA compliance was checked by comparing assessment completion times with the RA schedule. Finally, participants were thanked, debriefed, and reimbursed up to £25 in high street vouchers (love2shop) for their participation. A structured reimbursement scheme common to EMA studies was implemented whereby payment was contingent on the number of RAs completed.

Dietary intervention

The diet consisted of five days of *ad lib* intake (nER) days and two (ER) days of reducing intake to 25% of the recommended daily calorie allowance (500 Kcal/day for males; 600Kcal/day for males).

Participants chose which days they wished to restrict their calorie intake. Two conditions were given for deciding ER days: i) they could not begin the study on a restriction day to allow for any unforeseen problems that may arise due to technical issues or confusion to be dealt with; ii) restriction days could not be consecutive. They received guidance to aid them in choosing restriction days and were informed they could contact the researcher to request to change these if the restriction day had not begun. Participants also received two text reminders to their personal mobile phones regarding their ER day on the night before (8 p.m.) and again at the start of the morning period (8 a.m.).

They received a dietary guidance booklet to aid them through restriction days that was adapted from Carbsandcals.com – a website endorsed by Diabetes UK which consists of meal plans, recipes, portion size guide for common foods, and general dietary guidance for IER such as strategies for counting calories on restriction days.

4.3.3 Measures

Subjective appetite ratings (7-point Likert scales) and contextual questions

Participants responded to subjective appetite ratings on 7-point Likert scales that were presented in a randomised order each assessment which assessed momentary subjective sensations of appetite (e.g. '*How intense are any cravings for food right now?'*).

Participants then completed the food and colour Stroop which were followed by contextual questions about where the assessment took place (see Section 2.1.2 on P. 45 for a detailed description of self-reported measures).

Photographic food diary

Participants were required to keep a photographic food diary for the duration of the study which was logged via the camera on the loaned smartphone which was used to measure precise timings of eating events throughout the course of the intervention (see Section 2.3 on P. 49).

Food and colour Stroop tasks (see Figure 4.2)

The tasks were programmed using OpenSesame software (version 3.2; Mathôt, Schreij, & Theeuwes, 2012). The food Stroop tasks were based on a task used by Davidson and Wright (2002). The task consisted of 12 food-related words (e.g. chocolate) and 12 neutral words (environment-related, e.g. chair) which were matched in terms of word length and frequency. Each word was presented in three colours (red, blue or green) in a randomised order with the constraints that no colour or word were presented consecutively. Food and neutral words were presented in a separate block design consisting of 36 trials each with the presentation of blocks being randomised. Two food Stroop tasks were utilised throughout the experiment which used different word stimuli and order of response buttons to limit the learning effects associated with Stroop tasks (Logan et al., 1984). The version of task was randomly assigned upon opening the application.

The colour Stroop consisted of three colours (red, blue or green) presented in a mixed-block design consisting 18 colour-congruent (e.g. "red" in red font) and 24 colour-incongruent (e.g. "red" in blue font) trials giving a total of 42 trials per assessment.

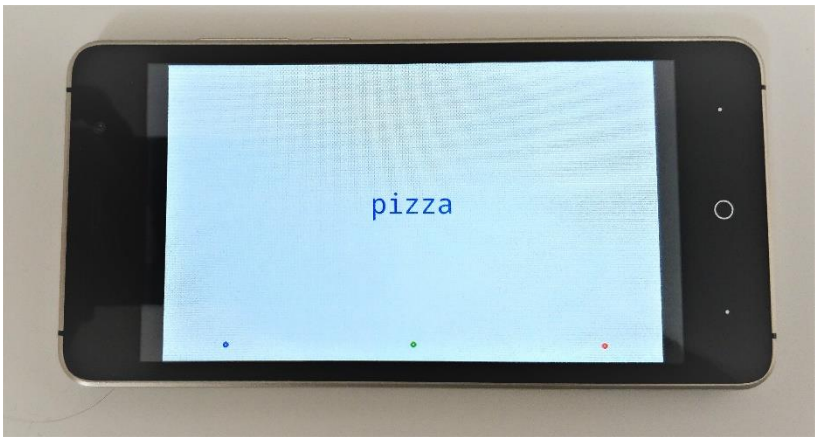

Figure 4.2 - Image of food Stroop task on a smartphone device. Responses were recorded by tapping one of the three buttons presented at the bottom of the display

Each trial started with a black fixation point on a grey background that was presented for 500ms followed by a word presented in the centre of the display in either a red, blue or green font. Participants had to name the font colour by tapping one of the three options presented at the bottom of the screen as fast and as accurately as possible (see Figure 4.2). The word stimulus remained on the screen until a response was given or for a maximum of 2000ms. If a response was wrong or slower than 2000ms, a red fixation point appeared on the screen for 500ms (or green if correct) and the task moved onto the next trial.

7-day retrospective recall hunger measure

During each lab visit, participants responded to one 100mm VAS assessing intensity of hunger over the past 7-days (e.g. '*How hungry did you feel over the past 7 days?*') which was end anchored '*not at all'* to *'extremely'*.

4.3.4 Data Reduction

Responses on the Stroop tasks that were incorrect, faster than 200ms, slower than 2000ms or three standard deviations above the mean for an individual's response time was discarded (Schoenmakers, Wiers, & Field, 2008). A total of 3154 trials (3.84% of total trials) were discarded on the food Stroop task, and 2126 trials (4.67%) were discarded on the colour Stroop task.

For the food Stroop task, mean reaction times for food words were subtracted from mean reaction times for neutral words producing a food bias score for each assessment. A positive score indicates the presence of an attentional bias (AB) towards food cues.

For the colour Stroop task, mean reaction times for colour congruent trials were subtracted from mean reaction times for colour incongruent trials producing a colour Stroop interference score for each assessment. A positive score indicates greater interference meaning more time required to inhibit a prepotent response.

A Spearman's correlation between individuals' colour Stroop and food Stroop performance was run which indicated there was little correlation between the two tasks ($r_s = .02$).

To examine the internal reliability of the food Stroop tasks administered on a mobile device, Cronbach's α was calculated where $\alpha \geq .70$ was considered acceptable (Kline, 1999). Reaction times for all word stimuli across colour presentation on the first usage of each task were calculated. Food and neutral words were matched based on word length and frequency of use, and neutral words were subtracted from food words to create twelve word pairs for each task. Cronbach's α reflected the internal consistency among these pairs on first usage of the given task and both showed excellent levels of reliability ($\alpha = 0.93$ and 0.94).

To investigate whether there were any differences in appetite outcomes on RAs that were more proximal to the initiation of an eating event, time and date stamps from food diary logs were compared to completed assessment files. This produced a time difference that was used to categorise whether an assessment took place within the two hours preceding an eating event.

4.3.5 Statistical analyses

Analyses were conducted using Iterative Generalized Least Squares (IGLS) bootstrapped (500 samples) multilevel modelling approach in MLwiN (Rasbash, Steele, Browne, Goldstein, & Charlton, 2012). Assessment of model fit and significance testing for multilevel models is detailed in Section 2.5.2 (P. 52).

The study sample size was large enough ($N > 50$) to be appropriate for multilevel modelling (Maas, & Hox, 2005).

Sample sizes are reported separately in analyses. The α level was set as $< .05$.

Data and analyses are available on osf.io/qctph/.

Primary analyses

Primary analyses assessed the hypotheses that EMA outcome measures would be significantly different on ER days compared to nER days, and baseline measures would predict individual differences.

The hierarchical dataset was structured so that session (*morning, early afternoon, late afternoon, and evening*) was nested within days, within participants resulting in a 3-level structure. In all models, a dummy variable was used to identify ER days with nER as the reference category. Furthermore, a dummy variable was used to identify assessments which took place in the 2h proceeding an eating event being logged, with no eating event logged as the reference category.

No significant variation was found at the highest level of analysis (no between-person differences) for food Stroop score, therefore multilevel modelling was inappropriate (Peugh et al, 2010). Ridge regression was used as an alternative as it allows for a degree of bias in estimation that accounts for multicollinearity due to repeated measurement (Cule & De Iorio, 2013).

For the hypothesis that retrospective hunger scores will be significantly higher on post-study ratings compared to pre-study ratings, a dependent T-test was used to investigate differences in pre and post retrospective recall hunger scores.

Exploratory analyses

To test whether baseline 7-day retrospective hunger scores could predict between-person differences in hunger scores during the interventional phase, the hierarchical dataset was structured so that session was nested within days within participants resulting in a 3-level structure.

4.4 Results

4.4.1 Participant characteristics

Baseline descriptives and measurements of the sample are reported in Table 4.1.

There were a total of 1141 photographic food diary logs in total. Fifty-one participants provided at least one photographic food diary log during the 7-day study period. The number of logs per participant ranged from 1 – 18 (mean = 9 logs ± 4.45).

Table 4.1 - Participant characteristics at baseline. Values are means (standard deviations)

Baseline characteristic	
Age (years)	34.77 (12.62)
F (%)	72.58
BMI	30.02 (3.93)
TFEQ - H	6.42 (3.44)
TFEQ - D	9.17 (3.57)
TFEQ - R	10.20 (4.24)
PFS	44.83 (12.99)
AEBs Drive	25.28 (4.11)
AEBS Control	18.77 (2.53)

TFEQ – H. Three Factor Eating Questionnaire Susceptibility to Hunger scale; *TFEQ – D.* Three Factor Eating Questionnaire Disinhibition scale; *TFEQ – R.* Three Factor Eating Questionnaire Restraint scale; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

4.4.2 Compliance

In total, four participants withdrew from the study (6.25 %). Two had difficulty adhering with the EMA schedule and a further two dropped out due to technical issues with the loaned smartphone. The total sample for all analyses was sixty participants.

Completion rates for RAs ranged from 42% – 100%. There were fifty-five participants who completed at least one RA on each day. Four participants completed less than 50% of RAs, however these data were retailed for analyses. Overall, participants completed 1042 (82.69%) out of a possible 1260 assessments. 351 (83.57%) morning assessments; 339 (80.71%) afternoon assessments; 352 (83.81%) evening assessments) were completed.

630 (60.46%) assessments took place at home, 288 (27.64%) at work, 36 (3.45%) in a restaurant or bar, and 76 during transit (7.29%). 92 (8.83%) assessments took place in the presence of others.

After data reduction, there was a total of 361 photographic food logs (132 morning logs, 113 afternoon logs, 116 evening logs) which took place within the 2-hour period following an RA taking place (average time = 47 mins).

To examine whether findings were robust, primary analyses were repeated after excluding assessments that may have been confounded by alcohol intoxication, smoking or caffeine (N

$_{session}$ = 350, 33.59% overall; 131 morning RAs, 109 afternoon RAs, 110 evening RAs). Sensitivity analyses (see Table 4.S.1 in supplementary materials on P. 138) revealed some differences relating to between-person predictors which most likely resulted from a loss of power. Results from primary analyses are presented and differences are discussed later.

4.4.3 Primary analyses

Means (SDs) for EMA measures can be found in Table 4.S.2 in supplementary materials (P. 139). Hunger and craving outcomes were ordinal data but treated as linear to aid with interpretation. Analyses were rerun using ordinal regressions to confirm findings from linear models (see Table 4.S.3 in supplementary materials P. 140). This identified some small differences in predictors; however, although these crossed the predefined significance level, changes in effect sizes were minimal. Findings from the linear models are presented as main analyses and potential explanations for differences between models are discussed later.

Hunger intensity

Mean hunger score for the final model was β_0 = 2.23 (SE = 0.11).

Variance componence models were created to assess the effect of stratifying hunger score into levels. The two-level model was a better fit to the data then the single level model (χ^2 (1) = 115.23, p < .001). Additionally, the three-level model was a better fit to the data than the two-level model (χ^2 (1) = 10.65, p < .001). The intra-class coefficient (ICC) of the null model ($n_{session}$ = 1042, n_{day} = 416, $n_{participant}$ = 60) revealed 25.51% (ICC_{within} = .255) of variance was within day, 16.23% ($ICC_{between}$ = .162) was between-person.

To test the hypotheses that hunger scores would be significantly higher on ER compared to nER days, and that baseline measures of TFEQ-H interact with ER to produce increased scores, ER was included as a day level variable. TFEQ-H was included as a participant level variable as well as its interaction term with ER. To assess the hypothesis that hunger will be significantly higher on assessments which took place proximal to an eating event being logged, eating within the next 2h was included as a session-level variable.

Compared to the null three-level model, adjusting for predictors was a better fit to the data (χ^2 (4) = 161.81, p < .001). A comparison of the variance partition coefficients (VPCs) show the model predicted 4% variance in hunger scores at the participant level, 87.76% at the day level, and 12.31% at the session level.

Results are reported in Table 4.2. Hunger scores were significantly higher on ER days compared to nER days. TFEQ-H scores were found to be a significant predictor of hunger scores, and a significant interaction between ER and TFEQ-H scores was found. Hunger was higher on ER days and higher TFEQ-H scores predicted greater hunger scores. Hunger scores were also found to be significantly higher on assessments which took place in the 2h prior to initiation of an eating event compared to assessments that were not.

Craving intensity

Mean craving intensity score for the final model was $\beta_0 = 1.99$ (0.11).

The two-level model was a better fit to the data then the single level model (χ^2 (1) = 147.10, p < .001). Additionally, the three-level model was a better fit to the data than the two-level model (χ^2 (1) = 13.95, p < .001). According to the ICC of the null model ($n_{session}$ = 1042, n_{day} = 416, $n_{participant}$ = 60), 30.16% (ICC_{within} = .302) of variance was within-day, 19.72% ($ICC_{Between}$ = .197) was between-person.

To test the hypotheses that intensity of craving scores would significantly increase as a result of ER, and that baseline measures of TFEQ-D, PFS, and AEBs-drive scores would interact with ER to produce increased scores, ER was included as a day-level variable, and TFEQ-D, PFS, and AEBs-drive score as participant-level variables. Interaction terms were included if participant-level variables were identified as significant.

To assess the hypothesis that intensity of cravings will be significantly higher on assessments which took place proximal to an eating event being logged, eating within the next 2h was included as a session-level variable.

Compared to the null three-level model, adjusting for predictors was a better fit to the data (χ^2 (5) = 124.84, p < .001). The model predicted 3.26% variance in craving intensity scores at the participant level, 71.15% at the day level, and 9.24% at the session level.

Results are shown in Table 4.2. Craving intensity scores were significantly higher on ER days. PFS significantly predicted craving intensity scores, whereas TFEQ-D or AEBS appetitive drive did not. No significant interactions among variables were found. Intensity of cravings were also found to be significantly higher on assessments which took place within 2 hours of eating compared to assessments that were not followed by an eating event.

Behavioural control

Mean Stroop interference score for the final model was $\beta_0 = 35.88$ (SE = 5.67).

The two-level model was a better fit to the data then the single level model (χ^2 (1) = 236.55, $p < .001$). Additionally, the three-level model was a better fit to the data than the two-level model (χ^2 (1) = 4.13, $p < .05$). According to the ICC of the null model ($n_{session} = 784$, $n_{day} = 359$, $n_{participant} = 59$), 30.92% ($ICC_{within} = .302$) of variance was within-day, 23.66% ($ICC_{between} = .236$) was between-person differences.

To test the primary hypotheses that Stroop scores would be significantly increased as a result of ER, and that baseline TFEQ-D score would interact to produce decreased Colour Stroop interference score, whereas TFEQ-R, and AEBs-control scores would interact with ER to produce increased Colour Stroop interference scores, ER was included as a day-level variable, and TFEQ-D, TFEQ-R, and AEBs-control score as participant-level variables. Interaction terms were included if participant-level variables were identified as significant.

To assess the hypothesis that colour Stroop interference score will be significantly higher on assessments which took place proximal to an eating event being logged, eating within the next 2h was included as a session-level variable.

Compared to the null three-level model, adjusting for predictors was a better fit to the data (χ^2 (5) = 38.65, $p < 0.01$), however no predictors were found to be significant (see Table 4.2 for results).

Table 4.2 - Multilevel models examining participant and daily level predictors of fluctuations of appetitive outcomes

	β (SDs)	LB-CI	UB-CI	*p*
	Hunger intensity			
Participant level				
TFEQ - H	.079 (.01)	.008	.112	.03
Daily level				
ER	1.17 (0.12)	.943	1.39	<.001
Session level				
Eating in 2h	0.79 (0.01)	.599	.979	<.001
Interactions				
ER x TFEQ-H	0.06 (0.03)	.001	.115	.05
	Craving intensity			
Participant level				
TFEQ - D	-.05 (.06)	-.155	.059	.38
PFS	.02 (.01)	.001	.045	.04
AEBs- Drive	.03 (.03)	-.036	.096	.38
Daily level				
ER	1.00 (.10)	.807	1.20	<.001
Session level				
Eating in 2h	.37 (.03)	.201	.537	<.001

	β (SDs)	LB-CI	UB-CI	*p*
	Colour Stroop interference score			
Participant level				
TFEQ - D	-.799 (1.04)	-2.73	.82	.24
TFEQ - R	-1.65 (1.11)	-3.55	-0.04	.10
AEBs- Dietary control	.93 (1.52)	-1.53	3.08	.28
Daily level				
ER	-7.41 (4.21)	-14.66	-1.00	.07
Session level				
Eating in 2h	3.81 (4.41)	-2.86	10.84	.20

UB-CI. Lower-bound 95% confidence interval; *LB-CI.* Lower-bound 95% confidence interval; *TFEQ – H.* Three Factor Eating Questionnaire Susceptibility to Hunger scale; *TFEQ – D.* Three Factor Eating Questionnaire Disinhibition scale; *TFEQ – R.* Three Factor Eating Questionnaire Restraint scale; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

Food-related Attentional Bias

Multilevel analysis was not appropriate for food bias score as no significant variance was found among participants (χ^2 (2) = 0, p = 1), therefore a ridge regression was used as opposed to standard OLS regression.

To test the hypotheses that attentional bias towards food cues would significantly increase as a result of ER, and baseline measures of TFEQ-D, PFS, and AEBs-drive scores would interact with ER to produce increased scores, food bias scores was input at the outcome variable and, ER, TFEQ-D, PFS, and AEBs drive score were predictors. Interaction terms were included if between-person predictors were significant.

To assess the hypothesis that food bias scores will be significantly lower on assessments which took place proximal to an eating event being logged, eating within the next 2h was also included.

The model was revealed to be non-significant (F (6, 1117) = 0.33, multiple $R^2 < 0.01$, p = 0.92).

Comparison of pre and post 7-day retrospective recall of hunger

To assess the hypotheses that hunger ratings would be significantly higher on post measures compared to pre measures, responses from both time points were compared using paired sample t-tests.

Contrary to expectations, retrospective hunger scores were significantly lower on post scores (M = 47.15, SD = 20.41) compared to pre scores (M = 54.34, SD = 19.48) , (t (59) = 2.93, 95% CI = 2.27 to 12.07, p = .005, d = .36).

4.3.4 Exploratory analyses

Baseline hunger and interventional hunger scores

To assess whether a baseline retrospective measure of hunger would predict individual differences in appetite responses throughout the study period. Pre-hunger score was entered into a three-level model with ER as a day level variable as well as their interaction term.

Compared to the null model three-level model adjusting for predictors was a better fit to the data (χ^2 (3) = 95.387, p < .001). Pre-hunger was significantly associated with hunger score (β= 0.01 (0.01), 95% CI = .435 to .833, p = .04). The interaction between Pre-hunger and ER was also significant (β= 0.01 (0.01), 95% CI = .974 to .994, p = .04). Hunger score was increased on ER days compared to nER with higher Pre-hunger predicting greater scores.

4.5 Discussion

The present study aimed to investigate the impact of IER (2 non-consecutive days over 1 week) on dynamic fluctuations of hunger, reward responsivity and behavioural control. It also examined whether baseline measures of eating behaviour could predict individual differences in appetitive responses during the study period in a sample of individuals with overweight and obesity. An additional aim to this study was to investigate whether appetite responses were raised in the moments leading up to an eating event. Finally, this study aimed to investigate the impact of IER on hunger using a 7-day retrospective recall measure.

Mixed support was found for the primary hypotheses that ER would increase hunger and reward-responsivity, and lower behavioural control. Hunger and craving intensity scores were significantly higher on ER compared to nER days. However, no evidence was found that ER influenced performance on either the Food-related Stroop or colour Stroop. Partial support was also found for the hypotheses that baseline measures of eating behaviour could predict individual differences in appetite responses to ER. Finally, contrary to expectations, hunger appeared to decrease from pre to post using a 7-day retrospective measure of hunger.

Regarding hunger, scores were higher on ER days compared to nER days and TFEQ-H scores moderated the relationship between ER and hunger intensity scores which was also replicated using baseline 7-day retrospective hunger scores. Intensity of hunger scores were higher during ER and greater increases were found for those who scored high on baseline measures of hunger. Previous investigations have found that greater baseline hunger is associated with poorer weight loss outcome (Sayer et al., 2018) and early reductions in hunger scores have predicted greater weight loss (Batra et al., 2013a). Taken together, these findings indicate that using baseline measures of hunger may be a useful approach towards early identification of individuals who will experience the greatest levels of hunger during ER so that additional support can be tailored for these individuals to manage their sensations of hunger during ER, particularly during the initial weeks of weight loss.

Evidence was found that hunger intensity was increased on RAs which took place within two hours of an eating event being logged. This provides evidence that real-time measures are sensitive towards detecting the relationship between physiological signalling which determine the motivation to consume and energy intake (Roberts et al., 2017; van den Akker et al., 2014). Whilst this provides evidence that dynamic fluctuations in hunger precedes an eating episode, the measure of energy intake employed did not distinguish between intentional and unintentional eating. In Chapter 3, the meta-analyses found greater levels of hunger during moments of temptations, but not lapses suggesting dynamic changes in hunger can lead to experiencing a temptation to break a diet, but increased hunger is not associated with lapsing. Further investigations are required to better understand how dynamic fluctuations in appetite determine energy intake and whether there are differences in these relationships whilst under conditions of ER.

Interestingly, a comparison of pre- and post-responses on a 7-day retrospective measure of hunger revealed that despite raised hunger on two of the seven days, participants reported lower hunger during the intervention week compared to the week preceding the intervention week. One potential explanation for this is that coping with strong sensations of hunger on ER days could reveal to participants that they can successfully manage increased sensations (Harvie et al., 2011) and this may impact the recall of hunger during the intervention period. The present study is the first to employ real-time measures of appetite in IER, and the discrepancy with retrospective measures may be explained by a biased recall that is influenced by engagement with IER. Whilst this may provide some benefit, it limits our ability to understand the real-time experiences of appetite during IER, and subsequently the ability to observe how fluctuations influence moments which pose problems for successful dietary adherence. However, there is one large caveat to this explanation: whilst the difference between mean pre and post values was statistically significant, the values were similar meaning that this finding may not be functionally relevant. Nonetheless, this finding warrants further investigation to better understand the associations between real-time and retrospective recall methods of experiences of appetite.

In regards to intensity of cravings, scores were higher on ER days compared to nER days, and higher PFS scores predicted higher between-person levels in craving intensity score. However, PFS score did not moderate the relationship between ER and intensity of craving score suggesting individuals scoring high on PFS experience greater levels of cravings in general, but do not experience greater increases during ER.

The PFS measures the psychological impact of being in food-rich environments and has previously predicted increased neural activation in areas associated with the anticipation of reward (Burger et al., 2016). Given that cravings are the output of reward-related processes that occur as a result of processing environmental cues previously been paired with consumption (May et al., 2012), these current findings support the ecological validity of the PFS. The finding that PFS score did not moderate the relationship between ER and intensity of craving score is somewhat surprising. Rejeski et al. (2012) found that increased intensity of craving scores were significantly higher in a group given water compared to a group given an energy drink. PFS moderated this relationship between energy content of the drink and increased intensity of craving score with higher PFS score predicting greater intensity of cravings.

Nonetheless, these findings indicate that individuals who score high on the PFS experience greater intensity of cravings in general which could mean they may struggle with controlling their intake when in the presence of cues to consume. Evidence was found that intensity of craving score was raised in the moments leading up to the initiation of eating. This supports findings from a previous free-living study which identified that higher momentary intensity of food cravings predicts snack consumption (Richard et al., 2017). The authors also found this relationship was higher in individuals who scored high on a trait craving inventory.

Taken together, these suggest targeting cravings early in weight loss which important to aid with weight loss (Batra et al., 2013a; Dalton et al., 2017) may help reduce consumption of unhealthy foods, particularly those who are high in trait-craving.

Regarding behavioural control, no evidence was found that colour Stroop interference scores were significantly higher on ER days compared to nER, or that TFEQ-R, TFEQ-D, or AEBs-DC scores predicted between-person differences. Stroop interference scores displayed a three-level structure indicating behavioural control varies throughout the day as well between individuals, however no consistent predictors of these sources of variation were found. One potential reason for this is that the colour Stroop task used to measure behavioural control is a measure of cognitive interference rather than restraint over automatic tendencies meaning it may lack sensitivity towards fluctuations in behavioural control towards food-specific cues. A food-specific task such as the food-related Go/No-Go task may be a better suited task towards the measurement of behavioural control over eating behaviour. Given not everyone is tempted by the same stimuli (Hofmann, Friese & Wiers, 2008), a measure which uses food-stimuli may be more sensitive to fluctuations in control over eating behaviour.

Regarding food-related attentional bias, after following the suggestions of Field et al. (2016) which set out to maximise the predictive validity of attentional bias measures such as the food-related Stroop task through measurement within the moment, no evidence was found that attentional-bias towards food-related cues was predicted by ER or that biases displayed any variation between-day or between-person. In addition, whilst Hardman et al. (in prep) identified attentional biases are predictive of intake if measured proximal to eating, the present study found no evidence that fluctuations in attentional bias score predicted intake within a two-hour period. These findings replicate those from a study using a similar design to investigate alcohol consumption where attentional bias towards alcohol-related word cues was not predictive of alcohol intake (Spanakis et al., in prep).

These findings suggest that reward-related Stroop tasks employed with EMA may not be appropriate for measuring the effect of attentional biases on behaviour as these may not be representative of reward processing of visual environmental cues or provide any information on the pattern of attentional processing of cues (Doolan et al., 2017). It remains unclear as to the role of attentional processes in determining consumptive behaviour, however it could be the case that these processes occur rapidly and if measurement does not take place between registering an environmental cue and subsequent behaviour, then attentional bias measures will not be predictive. For example, the experience of food cravings in individuals with overweight has previously been associated with the initial orientation of attention towards food-cues (Werthmann et al., 2011) which was measured using eye-tracking. Future investigations of attentional processing of food cues using EMA could utilise a food visual probe task as these are more ecologically valid compared to the food Stroop given that visual stimuli are used, and the stimuli presentation onset can be manipulated to assess the initial allocation of attentional processing. However, the most consistent indices of attentional biases are obtained by monitoring eye movements (Field et al., 2016), therefore it may be currently unfeasible to shed light onto the role of attentional processing and eating behaviour within naturalistic settings.

No evidence was found for between-person differences in behavioural control or attentional biases towards food cues. The colour Stroop is a measure of cognitive interference rather than inhibition over food-related impulses, therefore food-related measures may be unsuitable to detect individual differences in this task. No variation was found at the participant level for the food-related Stroop, therefore it is unsurprising no significant predictors were found. In addition, no evidence that disinhibition or AEBs drive predicted individual differences in craving scores, which is surprising given disinhibition has previously been associated with cravings (Batra et al., 2013b; Polivy et al., 2008). One potential explanation for these are that 7-point Likert scales used for the measurement of sensations of appetite in the present study may not be sensitive enough to detect these between-person effects. However, given other between-person effects were detected using Likert scales, this seems unlikely. Another explanation could be that there could be a self-selection bias due to the study being advertised as an IER diet. Individuals who are aware that they suffer from levels of disinhibited eating may be less likely to volunteer for a study which employs intense levels of ER over fears that they will not be able to adhere to the dietary regimen. Though this explanation may also be unlikely given the mean of TFEQ-D indicates the sample scored medium in disinhibition with a range from low to high (range = 1 – 20).

Sensitivity analyses were performed to ensure the robustness of findings which identified some significant deviations from the main analyses. Notably, when trials which may have been contaminated by recent consumption were excluded, the effect of PFS on craving intensity was no longer significant. Reperforming primary analyses of subjective sensations with ordinal models also revealed that that the interaction between TFEQ-H score and ER was no longer significant. Differences in these findings may be attributable to a loss of power to detect between-person differences. Statistical differences were small and effect sizes between models did not drastically change. Nonetheless these findings should be treated with caution. Further replication of these results is required in order to demonstrate their robustness.

The current study had several limitations. Firstly, there was no measure of dietary compliance, therefore it is impossible to validate whether participants engaged in ER. As increased sensations of appetite on ER days is expected, demand characteristics could have been present. This would also mean that the impact of ER on the cognitive tasks employed would have been reduced meaning erroneous conclusions could have been reached regarding their insensitivity towards detecting these differences. Physiological indices such as monitoring fasting insulin levels could confirm dietary compliance. Monitoring weight change throughout the course of the intervention is another approach which could indicate dietary compliance. Whilst this approach does not objectively validate whether weight loss was achieved through ER such as other physiological indices, it serves as a proxy for compliance as it demonstrates that behavioural changes which impact energy balance has taken place.

Secondly, the measure of energy intake employed was used to identify when eating began, therefore there is no way of knowing the amount that individuals consumed or whether they kept within the daily calorie goal. Future investigations should employ measures such as daily food diaries so that daily energy intake can be estimated.

Thirdly, most studies employing 2d/week IER use consecutive days of ER, whereas the form of IER was non-consecutive. Differences in biological and behaviour responses between different forms of IER have been found (Harvie & Howell, 2016). Future research utilising IER should seek to be as consistent as possible with previous attempts to avoid dilution of the literature due to a large heterogeneity of dietary approaches used.

Finally, 7-point Likert scales may suffer from similar problems surrounding sensitivity to detect changes as there is less potential for variation in responses. Due to technical limitations, it was unfeasible to employ standardised 100mm visual analogue scales (VAS) which are the gold-standard for measuring appetite responses to manipulations of dietary intake. Future investigations should seek to employ these as measures of changes in appetite responses over time.

The current findings have potential implications for aiding in the development of more personalised approaches for behavioural weight loss intervention. Due to the intensity of restriction needed for IER diets, sensations are likely to be a significant challenge during ER days. Early identification of individuals who struggle to cope with strong sensations during ER may be an important step for developing effective personalised strategies to aid with managing with these sensations during dieting to help aid in dietary adherence.

In summary, this study found evidence that individual differences in appetite responses to ER that are measured in naturalistic settings using EMA can be predicted by baseline measures of eating behaviours. Baseline measures of TFEQ-H and PFS identified increased between-person levels of hunger and cravings. Furthermore, individuals with higher TFEQ-H score experienced greater hunger on ER days. Additionally, this study found evidence for increased sensations of hunger and cravings can be observed in the moments leading up to an eating episode. The study also found retrospective and real-time measures of hunger may display some differences. Caution should be taken when employing retrospective measures of appetite in future dietary interventional studies. These findings indicate momentary increases in appetitive sensations precede an eating episode, therefore individuals who display greater levels of sensations may struggle to cope with these experiences during ER. Identifying those at baseline who would benefit from additional support with strong sensations of appetite may aid with increasing dietary adherence during weight loss attempts.

4.6 Supplementary materials

Table 4.S.1 - Multilevel models excluding assessments that were possibly contaminated by recent smoking, caffeine or alcohol consumption

	β (SDs)	LB-CI	UB-CI	*p*
	Hunger intensity			
Participant level				
TFEQ - H	.061 (.031)	.008	.013	.05
Daily level				
ER	.984 (.132)	.726	1.24	<.001
Session level				
Eating in 2h	.634 (.127)	.385	.883	<.001
Interactions				
Restriction x TFEQ-H	.073 (.034)	.006	.14	.03
	Craving intensity			
Participant level				
TFEQ - D	-.054 (.048)	-.148	.20	.11
PFS	.019 (.013)	-.007	.045	.14
AEBs- Drive	.047 (.041)	.033	.127	.14
Daily level				
ER	.894 (.121)	.657	1.13	<.001
Session level				
Eating in 2h	.361 (.114)	.138	.584	<.001

UB-CI. Lower-bound 95% confidence interval; *LB-CI.* Lower-bound 95% confidence interval; *TFEQ – H.* Three Factor Eating Questionnaire Susceptibility to Hunger scale; *TFEQ – D.* Three Factor Eating Questionnaire Disinhibition scale; *TFEQ – R.* Three Factor Eating Questionnaire Restraint scale; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

Table 4.S.2 - Means (SDs) of outcomes for each session on both nER and ER days

Measure	Morning		Afternoon		Evening	
	nER	ER	nER	ER	nER	ER
Hunger intensity	2.81 (1.68)	3.20 (1.79)	2.71 (1.63)	3.64 (1.82)	2.66 (1.73)	3.85 (1.96)
Craving intensity	2.31 (1.50)	2.55 (1.57)	2.03 (1.27)	3.02 (1.65)	2.23 (1.53)	3.50 (1.81)
Food AB	5.61 (48.60)	5.15 (39.90)	5.29 (50.30)	5.04 (46.30)	2.47 (39.90)	12.60 (45.40)
Behavioural control	34.30 (61.40)	30.50 (60.50)	37.70 (59.30)	22.20 (51.70)	33.50 (60.40)	28.80 (61.00)

Table 4.S.3 - Multilevel ordinal model for intensity of hunger and cravings

	β (SDs)	eβ (OR)	LB-CI	UB-CI	*p*
	Hunger intensity				
Participant level					
TFEQ - H	.079 (.034)	1.08	.013	.145	.02
Daily level					
ER	.834 (.252)	2.30	.013	1.33	<.001
Session level					
Eating in 2h	.871 (.126)	2.39	.623	1.12	<.001
Interactions					
Restriction x TFEQ-H	.063 (.034)	1.06	-.003	.129	.06
	Craving intensity				
Participant level					
TFEQ - D	.090 (.056)	1.09	-.020	.20	.11
PFS	.028 (.015)	1.03	-.058	.002	.06
AEBs- Drive	.067 (.048)	1.07	-.016	.028	.16
Daily level					
ER	1.20 (.132)	3.32	. 942	1.46	<.001
Session level					
Eating in 2h	.472 (.128)	1.60	.022	.724	<.01

eβ. Exponent beta value; *OR.* Odds ratio; *UB-CI.* Lower-bound 95% confidence interval; *LB-CI.* Lower-bound 95% confidence interval; *TFEQ – H.* Three Factor Eating Questionnaire Susceptibility to Hunger scale; *TFEQ – D.* Three Factor Eating Questionnaire Disinhibition scale; *TFEQ – R.* Three Factor Eating Questionnaire Restraint scale; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

Chapter Five

The Impact of Fluctuations in Appetite, Stress, and Behavioural Control on Dietary Adherence during Alternate Day Energy Restriction: A combined N-of-1 and EMA series

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This investigation examined appetite, stress, and behavioural control during intermittent energy restriction. It contrasts these variables between ER and non-ER days and examines potential baseline predictors of individual differences in the effect of ER on outcome measures. It also contrasts outcome measures between temptation, lapse, and random assessments on ER days. Finally, this study examines the correlation between real-time and retrospective measures. The manuscript for this paper is currently being prepared to submit for publication in *Appetite*.

The roles of the co-authors are summarised below:

I designed the study in collaboration with Jason Halford, Paul Christiansen, Amy Ahern, and Emma Boyland. I collected and analysed the data and wrote the manuscript. Amy Ahern, Emma Boyland, and Paul Christiansen contributed useful comments whilst preparing the manuscript.

5.1 Abstract

Rationale: Changes in appetitive processes during ER pose problems for dietary adherence, but the extent of these changes is characterised by large amounts of individual differences. Affective processes, such as perceived stress, are also problematic potentially through diminishing ability to control eating behaviour. Chapter Three indicated momentary changes in both appetitive and affective processes influence the likelihood of experiencing a temptation and lapse, but engagement with coping strategies may prevent lapses for occurring. Establishing predictors of individual differences may aid in identifying those who would benefit from additional coping support during ER days. Furthermore, Chapter Four indicated there may be discrepancies between real-time and retrospective recall measures of appetite. However, the association between these approaches has yet to be directly investigated.

Objective: This study investigated the impact of IER on fluctuations in appetite, stress, and behavioural control and how these outcomes differ between subjective momentary states which pose a problem for successful dietary adherence. Secondly, this study aimed to investigate whether individual differences in appetitive responses to ER could be predicted using baseline measures as well aggregated scores from a baseline study phase. Finally, this study aimed to investigate the association between retrospective and real-time measures of appetite. An exploratory aim was to examine the moderating role of stress on the relationship between behavioural control and energy intake.

Methods: Thirteen individuals with overweight and obesity engaged in 1-week of no intervention and 4-weeks of ADER. They completed four RAs per day assessing current intensity of hunger, food cravings, fullness, and stress as well as a food-related Go/No-Go task. They completed EAs when experiencing a temptation or lapse which assessed subjective sensations as well as engagement with coping strategies. Additional measures included: a food diary for the 5-week duration, a battery of questionnaires at baseline and weekly 7-day retrospective measures of appetite and stress.

Results: Increased sensations of appetite, but not stress, were found on ER days compared to nER days. On ER days, increased sensations of appetite and stress were found on TAs and LAs compared to RAs. Engagement in coping strategies were higher on TAs compared to LAs. Predictors of individual differences of the effect of ER on appetite sensations were

identified. There were modest correlations between real-time and retrospective measures of appetite and stress, particularly for measures of satiety.

Conclusion: Results indicate monitoring appetite at baseline could help identify individuals who may experience even greater appetitive effects on ER days which may be problematic, particularly during moments of temptation. Personalised coping strategies can be developed to avoid dietary lapses based on baseline appetitive profiles. Additionally, future weight loss interventions assessing appetite should exercise caution when using retrospective measures as these may not relate to real-time experiences.

5.2 Introduction

Successful weight loss primarily relies on adherence to energy-restricted diets (Stubbs et al., 2011). However, many dieters struggle to cope with increased sensations of appetite and affect in both the short- and long-term, posing an issue for successful dietary adherence and weight control (Drapeau et al., 2007; Gibson et al., 2014). Appetite regulation involves the interplay between physiological signals of satiety, reward-processing of food-related cues and behavioural control. Hunger directs behaviour towards restoring a state of energy balance and is usually accompanied by the feeling of diminished fullness – a sensation which signals the state of short-term energy reserves (Müller et al., 2015). Food cravings are the output of reward-based processes where the expectation of eating is triggered by internal (mood) or external (environmental) cues to consume (May, Andrade, Kavanagh & Hetherington, 2012). Behavioural control is the extent that regulatory top-down control is exerted over these cues to consume. When control becomes overwhelmed, consumption can become disinhibited which can eventually lead to weight gain (Brockmeyer et al., 2016; Hoffman, Friese & Strack, 2009). These appetitive processes all interact within the gut-brain axis to ultimately inform energy intake (Roberts et al., 2017).

Engaging in energy restriction (ER) increases hunger and reward-related processes which both undermine behavioural control over eating behaviour – effects which are more pronounced in individuals with overweight and obesity (Blundell, Stubbs, & Golding, 2005). During dieting, coping with these heightened appetitive responses to a negative energy balance means that control is constantly being exerted to inhibit behavioural responses to both these internal and external cues to consume. When behavioural control is overwhelmed, cues to consume can result in overconsumption. One possible mechanism for this is that persistent use of the cognitive resources required to control behavioural responses throughout the day can result in ego depletion – a state where control over behaviour is exhausted due to previous exertion (Baumeister, Bratslavsky, Muraven & Tice, 1998). In support, one previous investigation has reported that reductions in performance on a Go/No-Go task predicts snack consumption in the following hour (Powell, McMinn & Allan, 2017). Crucially, these appetitive responses to achieving and maintaining a negative energy balance pose as barriers towards successful weight control, and those who are in the most need of weight loss are also the least capable of successfully achieving this (Roberts et al., 2017).

ER also results in increased negative mood (Ogden, 1995; Jackson et al., 2014; Smoller, Wadden & Stunkard, 1987) which also has a detrimental impact on behavioural control over energy intake (Stice, Akutagawa, Gaggar & Agras, 2000). For example, evidence obtained from laboratory-based investigations demonstrate that there is an increase in energy intake on bogus taste tests following stress manipulation tasks (Mann & Ward, 2004; Royal & Kurtz, 2010). Furthermore, investigations using EMA have found an interactive effect of stress on performance tasks used to measure behavioural control (see Table 1.1 on P. 18) and unhealthy eating behaviours. Manasse et al. (2018a) reported an increased perceived stress and likelihood of reporting a lapse was greater in individuals with lower behavioural control (indexed by a larger between-person difference on the stop-signal task). Smith et al. (2020) found that in participants self-reporting anorexia nervosa and bulimia nervosa symptoms, the relationship between negative affect and the likelihood of reporting a binge eating episode was greater when behavioural control was lower (indexed by greater within-person commission errors on a food-related Go/No-Go task).

Investigations using real-time measures such as EMA have demonstrated that these appetitive and affective responses to ER dynamically fluctuate from moment-to-moment which may pose a greater problem for dietary adherence rather than persistent raises in these sensations. For example, one previous EMA investigation identified that increased momentary intensity of cravings precipitated snack intake (Richard et al., 2017). Chapter Four reported that intensity of current hunger and cravings was significantly higher on assessments which took place two hours preceding an eating event compared to assessments where no eating event was logged in this period. However, this analysis could not distinguish between intentional and unintentional (e.g. lapsing) intake.

The meta analyses conducted in Chapter Three focused on specific momentary states which pose as problems for successful dietary adherence. These were dietary temptations which are moments of sudden urge to eat where the individual had come close to breaking their diet, and lapses which are incidents where the individual felt they broke their diet (e.g. overate, ate a forbidden food etc.). Most dietary lapses are preceded by moments of temptations implicating these subjective states as significant barriers towards successful dietary adherence (Appelhans et al., 2016). The meta-analyses identified that hunger was raised during temptations, but not lapses compared to random moments throughout the day. However, this is thought to be a result of differences between studies in the instructions given to participant as to when to complete a lapse assessment. For example, some investigations require participants to report how they felt immediately prior to experiencing a lapse (e.g. Carels et al., 2001) whereas others required participants to report on current sensations in the moment following a lapse (e.g. Forman et al., 2017). The current investigation seeks to investigate sensations in the moments preceding a lapse occurrence.

The meta analyses in Chapter Three also revealed that negative mood was raised on both temptations and lapse episodes compared to random assessments. However, no appetitive or affective sensation distinguished temptations from lapses suggesting that sensations do not continually increase until they become unmanageable which eventually leads to a dietary lapse. Some studies have found the factor which distinguishes a temptation from a lapse is engagement with coping strategies (Carels et al., 2004; McKee et al., 2014). However, the meta analyses found no overall evidence that engagement with coping strategies was greater during temptations compared to lapses. This could have been largely driven by heterogeneity in coping measures which were included in the subgroup analyses. Both of the studies independently found that engagement with coping strategies distinguished temptations from lapses. The outcome measure used in Carels et al. (2004) was a comprehensive 14-item measure of various strategies that individuals could engaged in, whereas McKee et al. (2014) used a 2-item measure which only assessed strategies relating to thoughts about weight-loss goals. The current study seeks to replicate these findings by using the measure employed in Carels et al. to provide additional support that strategies to aid in engagement in coping with momentary temptations would be beneficial for increasing dietary adherence.

Importantly, whilst appetitive processes demonstrate both a capacity to fluctuate from moment to moment, they also demonstrate large amounts of individual variation which could influence the large diversity in eating behaviours and weight responses to manipulations of energy balance (Gibbons, Hopkins, Beaulieu, Oustric & Blundell, 2019). In Chapter Four, evidence was found that measures of baseline hunger moderated the increases in hunger on ER days compared to non-energy restricted (nER) days. Individuals with higher scores on the TFEQ-H and a baseline 7-day retrospective recall measure of hunger experienced greater levels of hunger on ER days. PFS score was found to predict individual differences in the average levels of cravings experienced during the investigation but did not moderate the relationship between ER and craving score. Behavioural control also demonstrates a trait-like capacity as some individuals display a greater capacity for delaying short-term rewards to prioritise long-term goals (Baumeister, Bratslavsky, Muraven, & Tice, 1998). The Addiction-like Eating Behaviour Scale Dietary Control subfactor (AEBS-DC; Ruddock, Christiansen, Halford & Hardman, 2017) focuses on dimensions of observable behaviours relating to behavioural control over dietary practices, and from a dual-systems perspective this subfactor measures diminished top-down control over eating behaviour. Understanding how ER impacts these appetitive processes and how these relationships differ between individuals could help identify those who may benefit from additional support in coping with heightened appetitive processes during ER.

Modern behavioural weight loss interventions report clinically significant weight losses of 8-10% of initial body weight, though a closer examination of individual variability shows between 40-60% of individuals achieve this goal (Sherwood et al., 2016). Furthermore, appetitive processes are characterised by large amounts of individual variability in eating behaviours and susceptibility for weight gain (Gibbons et al., 2019). Taken together, these indicate a one-size-fits-all approach towards weight loss may not be suitable to account for the vast amount of variability in eating behaviours which contribute to weight management problems. N-of-1 methods allow for individual variation to be extensively explored which can be used to assess responses to interventions so that treatments can be personalised (Vieira et al., 2017). The current study makes use of a combined EMA and N-of-1 series methodology to explore whether appetite sensations observed during the baseline phase could be aggregated and used to predict individual differences in appetite responses to ER during the interventional phase.

Intermittent energy restriction (IER) is an approach to weight loss which is thought may be easier to follow compared to continual ER due to shorter spells of intense ER followed by periods of *ad libitum* intake (Johnstone, 2015). IER is also thought to result in favourable reductions in appetite throughout the course of weight loss, though the effect of sustained IER on appetite currently remains ill-defined and warrants further investigation (Harvey et al., 2018; Hutchison et al., 2019). Some have found hunger gradually decreases over time suggesting habituation in both 10-week (Bhutani et al, 2013) and 8-week (Klempel, Bhutani, Fitzgibbon, Freels, & Varady, 2010) ADER intervention as well as a 3 month 2d/week IER (Harvie et al., 2013). Others have found hunger remains persistently high throughout 3-weeks of ADER (Ravussin, Smith, Anton, Martin, & Heilbronn, 2005), 12-weeks (Coutinho et al., 2018) and 8-weeks (Hutchison et al., 2019) of 3d/week of IER. A similar pattern has also been found for fullness, with some finding initial decreases in fullness on fasting days with gradual increases over 8-weeks (Hoddy et al., 2016) and 12-weeks (Varady et al., 2013) of ADER, whilst others have found fullness remains consistently low (Klempel et al., 2010).

Even fewer studies have investigated experiences of cravings. In a 3-week period of total fasting (Lappalainen et al., 1990) and 12-weeks of a very low energy diet (Harvey et al., 1993), both found reductions in reported cravings over time.

Previous IER investigations have relied on retrospective measures of appetite which may be affected by various recall biases that could impact the internal validity of these measures (Kahneman & Redelmeier, 1996). In previous investigations of IER, four assessed appetite at the end of fast days just before going to bed (Bhutani et al., 2013; Harvie et al., 2013; Klempel et al., 2010; Kroeger et al., 2013) or during a weekly visit to the clinic (Hoddy et al., 2016; Hutchison et al., 2019; Ravussin et al., 2005). Harvie et al. (2011) stated that anecdotal reports suggest IER makes individuals more aware of food habits and reassures them that they can manage the high levels of appetite on ER days. Whilst this may seem beneficial, it could also potentially affect retrospective recall of participants experiences of appetite during ER days which would impact the understanding of appetite control during IER. For example, in Chapter Four a 7-day retrospective measure of hunger was significantly lower following the 1-week study period compared to baseline, though significant increases in hunger were found using real-time measures. An aim of the current study aims to examine the extent that 7-day retrospective measures associate with real-time measures of appetite and affect during IER.

The primary purpose of this study was to investigate the impact of a 4-week ADER intervention on dynamic fluctuations in appetite, stress, and behavioural control to understand how these outcomes differ between subjective momentary subjective states which pose a problem for successful dietary adherence in sample of individuals with overweight and obesity. Secondly, this study aimed to investigate whether individual differences in appetitive responses to ER could be predicted using baseline measures. Finally, this study aimed to investigate the association between retrospective and real-time measures of appetite. An exploratory aim of this investigation was to examine the moderating role of stress on the relationship between behavioural control and energy intake. Additionally, this investigation explored whether responses obtained during the baseline measurement could be used to create an appetite profile to predict individual differences in appetitive responses to ER.

ADER was chosen as the dietary intervention opposed to the 2-day/week non-consecutive IER that was used in Chapter Four for multiple reasons. Firstly, most studies employing 2d/week IER use consecutive days of ER, whereas the form of IER used in Chapter Four was non-consecutive. Harvie and Howell (2016) reported there are potential differences in biological and behaviour responses between different forms of IER and future research of IER should seek to be as consistent as possible with previous attempts to avoid dilution of the literature due to a large heterogeneity of dietary approaches used.

Secondly, given the lower sample size employed in the current investigation, two days of ER per week may lower the statistical power to detect the effect of ER, particularly for the Go/No-Go task. In addition, previous accounts of IER report a 'carryover effect' of reduced energy intake on nER days of IER diets (Harvey, Howell, Morris, & Harvie, 2018; Hutchison et al., 2019). A supplementary analysis was planned to assess the presence of this effect (see Section 5.6). Similarly, given the small sample size recruited ADER would provide more power to detect significant effects given more ER days are employed compared to a 2-day/week IER approach.

A testing application (*APPetite*) was installed on loaned smartphones where participants completed random, temptation, and lapse assessments, and an app-based food diary (*MyNetDiary*) was used to measure daily caloric intake. A battery of questionnaires consisting of the TFEQ, PFS, and AEBs was also used to measures individual differences in eating behaviours. Weekly lab-visits were arranged where weight was recorded, and retrospective measures of appetite and affect were taken.

The first set of hypotheses is that the intensity of hunger will be higher on ER days compared to nER days and this relationship will be greater for individuals who score high on the TFEQ-H. Intensity of craving will be higher on ER days compared to nER days and this relationship will be greater for individuals who score high on the PFS. Commission errors to food-related cues will be higher on ER days compared to nER days and this relationship will be greater for individuals who score high on AEBS dietary control subsection (AEBS-DC). Finally, fullness will be lower and stress will be higher on ER days compared to nER days.

The second set of hypotheses is that intensity of hunger, cravings, stress, and commission errors will be higher, whereas fullness will be lower, on event assessments (temptations and lapses) compared to random assessments. It is also hypothesised that intensity of hunger, cravings, stress, and commission errors will be higher, whereas fullness and engagement with coping strategies will be lower, on lapse assessments compared to temptation assessments.

The third set of hypotheses is that 7-day retrospective measures of hunger, cravings, fullness and stress will not correlate with real-time measures of appetite that are aggregated over the same period of time.

An exploratory hypothesis was that commission errors on the food-related Go/No-Go task will positively predict increased daily energy intake, and this will be moderated by perceived stress with increased stress predicting greater daily energy intake. Additionally, it was predicted that ER will interact with baseline phase hunger measurements to predict greater hunger scores during intervention. It was also hypothesised that ER will interact with baseline phase craving measurements to predict greater craving scores during intervention.

5.3 Methods

5.3.1 Participants

Thirteen individuals (11 Female, 85%) were recruited for the study. Participants were eligible if they were aged between 18 – 65 years (mean 38.31 ± 11.25), had a BMI categorised as with overweight and obesity (25 – 40kg/m^2; mean 31.37 ± 4.81 at baseline), were fluent English speaking, and were willing to engage in a 5-week study consisting of 1-week of no dieting, 4-weeks of an ADER diet which consists of alternate days of energy restriction (~25% of BMR for 24h) and no energy restriction (*ad lib* food consumption for 24h). Participants were not eligible to take part if they were currently engaging in a dieting attempt, displayed any indications of ill health (e.g. asthma, diabetes, digestive problems, epilepsy, or suffering from a cold or flu), were taking prescription medication that affects appetite, or were pregnant or breastfeeding.

The study was advertised around the University of Liverpool campus and the wider Merseyside area via online and paper advertisements. The study was approved by the University of Liverpool ethics committee (Reference number: 5349).

5.3.2 Design and Procedure

Design

The present investigation consisted of two experimental phases. The baseline phase consisted of 1-week of no restriction on eating behaviour. The interventional phase consisted of a 4-week ADER intervention which was comprised of alternating days of nER and ER days.

Three EMA sampling strategies were utilised. Random assessments (RAs) which occurred four times a day throughout the study period as well as temptation assessments (TAs) and lapse assessments (LAs) which were user-initiated any time an event was experienced during ER days. TAs and LAs are both types of Event Assessments (EAs).

Procedure (Figure 5.1)

Participants were screened via email prior to attendance and those eligible were invited to an initial lab session at the university where they provided consent. Height and weight were measured to calculate BMI (see Section 2.4 on P. 50). A battery of baseline measurements of eating behaviours was also administered (detailed in Section 2.6 on P. 59).

Participants were loaned a smartphone (Doogee X10: 12.7cm screen size) preloaded with the testing application (detailed in Section 2.1.2 on P. 45) and were instructed to keep a food diary for the duration of the study which was logged via the application '*MyNetDiary'* (detailed in Section 2.3 on P. 49). They were taught how to navigate the applications whilst supervised until they felt comfortable.

There were four random assessments per day which occurred every morning (8 a.m. – 11:30 a.m.), early afternoon (11:30 a.m. – 3 p.m.), late afternoon (3 p.m. – 6:30 p.m.) and evening (6:30p.m. – 10pm). Random assessments were sent via text prompts to their personal mobile device which instructed participants to initiate an assessment within 45 minutes of receiving the text message and respond 'done' once the task was completed. Participants were instructed to miss the assessment if it had been 45 minutes since the notification text.

Weekly lab-visits were arranged where weight was measured, compliance with random assessments was checked by comparing assessment completion times with RA protocol, and 7-day retrospective measures of appetite and affect were administered. For the baseline phase, participants were informed there were no restrictions over their energy intake and not to alter their eating behaviour. At baseline phase follow-up, participants were prescribed the ADER diet and informed about completing event assessments within 15 minutes of experiencing a dietary temptation or lapse during ER days. Temptations were defined as 'a sudden urge to eat in which you had come close to the brink of breaking your diet' and lapses were defined as 'an incident where you felt that you broke your diet (e.g. overate, ate a forbidden food etc.)' Definitions were used from previous investigations using EMA during ER (Carels et al., 2001).

The total length of the study was 35 days. The baseline phase lasted for 7 days and the interventional phase lasted for 28 days which consisted of 14 ER and 14 nER days.

During Week 5 follow-up, participants were debriefed and reimbursed up to £150 in high street vouchers (Love2Shop) for their participation upon return of the loaned smartphones. Reimbursement was determined using a structured reimbursement scheme common to EMA studies whereby payment was contingent on the number of random assessments completed.

Dietary intervention

The prescribed ADER diet involved alternating between ER days (25% of energy needs consumed for a period of 24h) and nER days (food is consumed *ad libitum* over a period of 24h). Energy requirements were calculated using the Mifflin–St. Jeor equation which involves calculating the minimum caloric requirements based off their basal metabolic requirements (e.g. energy needs to support vital functions) (Mifflin et al., 1990) which ranged from 5455 to 8122 KJ/day for the study sample.

Participants were provided a booklet containing dietary advice and were encouraged to ask any questions regarding the dietary plan. Dietary information was adapted from Carbsandcals.com which contained advice on meal planning and recipes for ER days with information on calorie and macronutrient content. It also included general dietary advice such as eating a healthy balanced diet, guidance on snacking and grazing as well as visual aids and calorie content for portion sizes of commonly consumed foods. Participants were told that there was no restriction over their energy intake during nER days and to eat as they wish.

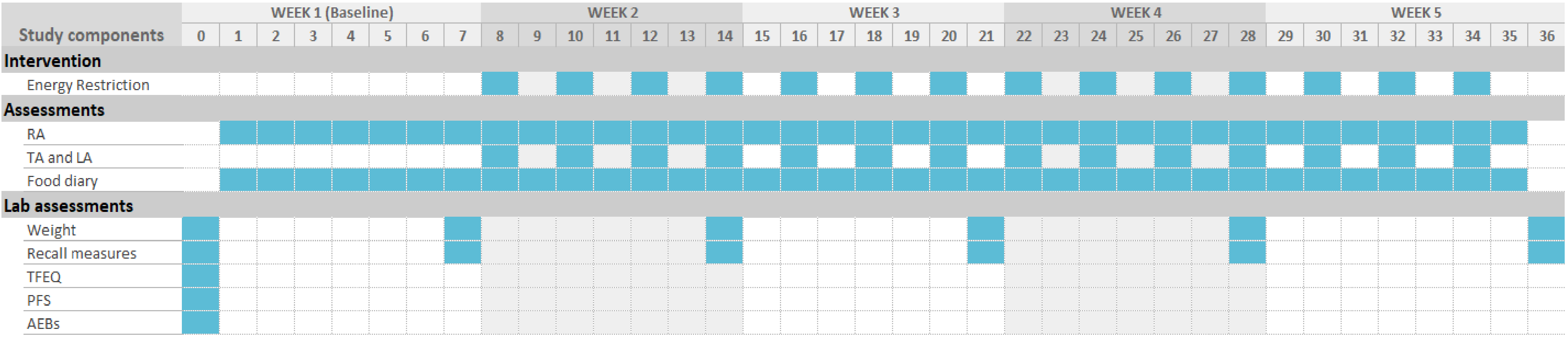

Figure 5.1 - Gantt chart showing an overview of the 5-week study procedure. Study components are listed on the left and blue blocks indicate when these were implemented throughout the course of the investigation. *RA.* Random assessment; *TA.* Temptation assessment; *LA.* Lapse assessment; *TFEQ.* Three Factor Eating Questionnaire; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

5.3.3 Measures

100-point Visual analogue scales (VAS) and contextual questions

During all assessments, participants responded to four 100-point VAS which assessed momentary sensations (e.g. '*How hungry do you feel right now?*') of hunger, cravings, fullness and stress. During lapse assessments, questions related to the period immediately prior to lapsing (e.g. '*How hungry did you feel right before lapsing?*'). In addition, during temptation and lapse assessments, participants responded to fourteen 100-point VAS assessing the use of coping strategies during temptation and lapse episodes. At the end of each assessment, participants reported various aspects of contextual associates of the assessment (see Section 2.1.2 on P. 45 for a detailed description of self-reported measures).

Food diary

Participants were required to record energy intake via an app-based food diary (*Mynetdiary*) which was used to measure daily caloric intake throughout the course of the investigation (described in Section 2.3 on P. 49).

Go/No-go Task (Figure 5.2)

The task was programmed using OpenSesame software (version 3.2; Mathôt, Schreij, & Theeuwes, 2012) consisting of three blocks of 64 trials comprised of 48 'go' (75%) and 16 'no-go' (25%) letters (total of 192 trials, 48 of which were 'no-go' trials) which were displayed in a pseudorandom order to avoid consecutive presentation of two 'no-go' trials. The task was weighted towards 'go' trials in order to build up a prepotent tendency to respond, increasing inhibitory effort necessary to successfully withhold responding to a 'no-go' trial (Simmonds, Pekar & Mostofsky, 2008). There was a total of 32 images that consisted of 16 unhealthy foods (e.g. chocolate) and 16 neutral (e.g. common household items) images that were matched for visual complexity and colour and presented in a mixed-block design. Each image was presented twice within a block in a pseudorandomised order so that no image was presented consecutively. The 16 no-go trials consisted of 8 trials for unhealthy foods and 8 trials for neutral stimuli on each block. This equated to a maximum of 24 potential commission errors for each stimuli group in one assessment.

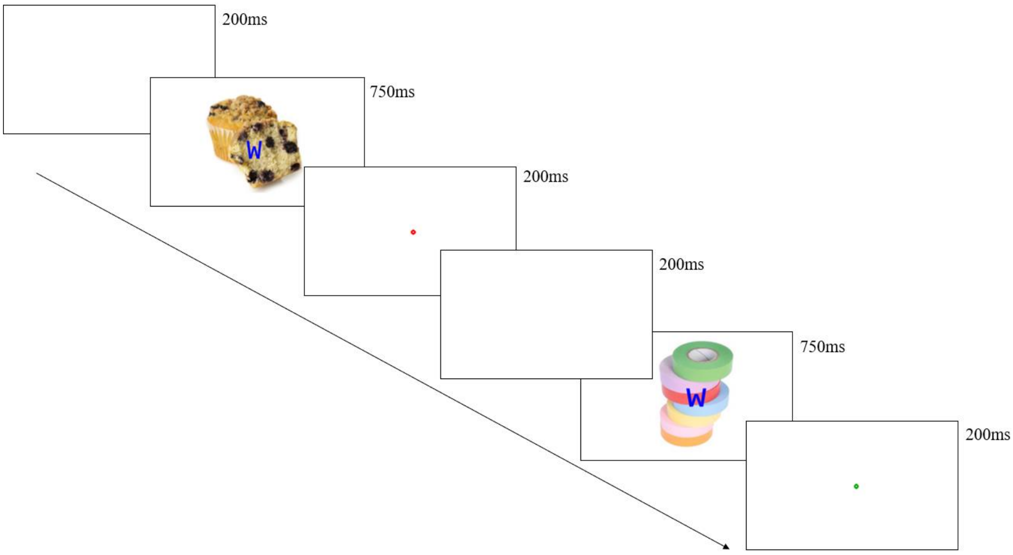

Figure 5.2 – Schematic diagram of the Go/No-go task. Responses were recorded by tapping the screen.

Each assessment began with instructions to tap the screen in response to 'go' trials and withhold any response to 'no-go' trials. 'go' trials were identified by a blue "W" presented in the middle of the screen, whereas 'no-go' trials were presented by a blue "Z". Each trial started with a white background for 200ms which was followed by an image (food or neutral) as well as the letter "W" or "Z" which appeared in the middle of the screen for a maximum of 750ms where the response was registered. Following this, either a green (correct) or red (incorrect) fixation point was presented on a white background for 200ms and then the task commenced onto the next trial.

7-day retrospective recall measures

During lab visits, participants responded to four 100mm VAS assessing intensity of hunger, cravings, fullness and stress over the past 7-days (e.g. '*How hungry did you feel over the past 7 days?*') which were end anchored '*not at all*' to *'extremely'*.

5.3.4 Data Reduction

The outcome of interest for the Go/no-go task was commission errors (incorrectly responding go to a no-go trial) when in the presence of food-cues with a greater score indicating less behaviour control towards food-related cues. Assessments which were <2.5 s.ds (Price, Lee & Higgs, 2016) above the participant mean or where a distraction was experienced during completion of the task were discarded.

5.3.5 Statistical analyses

All analyses were conducted in R-Studio using R version 1.2.1. Multilevel models were created using an Iterative Generalized Least Squares (IGLS) bootstrapped (500 samples) design using the package "lme4". Assessment of model fit and significance testing for multilevel models is described in Section 2.5.2 (P. 52).

The sample size was under the recommended amount (N > 50) recommended for multilevel modelling (Maas, & Hox, 2005) meaning replication would be required to ensure generalisability of findings.

Sample sizes are reported separately in analyses. The α level was set at < .05.

Data and analyses scripts are available on osf.io/hrjkp/

Primary analyses

For the first set of hypotheses which was that EMA outcome measures would be significantly different on ER days compared to nER days, and baseline measures of eating behaviours would predict individual differences in EMA outcome measures. The hierarchical dataset was structured so that session (*morning, early afternoon, late afternoon, and evening*) was nested within days within participants resulting in a 3-level structure. Only outcomes from the interventional phase were included in these analyses.

For the second set of hypotheses which was that EMA outcomes will be significantly different on during temptations and lapses (event assessments) compared to random assessments, the hierarchical dataset was structured so that session was nested within participants resulting in a 2-level model. Temptations and lapses only occurred during ER days, therefore only random assessments on ER days were used for comparison. In addition, it was revealed that too few Go/No-Go task were completed on EAs, therefore this outcome was not included in analyses.

For the third set of hypotheses which was there will be no correlation between retrospective and EMA measures of appetite, scores from random assessments for each outcome and were averaged over a 7-day period and Pearson's correlations were performed to assess the association between these measures.

Exploratory analyses

To test the moderating role of stress on the relationship between behavioural control and energy intake, analyses were performed on the entire dataset (baseline and interventional phases) with daily energy intake as the dependent variable. The data was structured so that day was nested within participant resulting in a 2-level structure.

To test whether responses from the baseline phase could predict between-person differences during the interventional phase, the hierarchical dataset was structured so that session was nested within days within participants resulting in a 3-level structure. Only outcomes from the interventional phase were included in these analyses.

5.4 Results

5.4.1 Participant characteristics

Baseline descriptives and measurements of the sample are reported in Table 5.1 and follow-up measurements are reported in Table 5.S.1 in supplementary materials (P. 179). Participants lost an average of 3.86% (±2.25%) of their initial body weight throughout the investigation.

Table 5.1 - Participant characteristics at baseline. Values are means (SDs)

Baseline measures	
Age (years)	38.31 (11.25)
F (%)	84.61
Height (cm)	168.83 (9.99)
Weight (kg)	82.27
BMI	31.37 (4.81)
TFEQ - H	7.67 (2.84)
TFEQ - D	9.50 (3.04)
TFEQ - R	8.83 (3.56)
PFS	47.75 (9.78)
AEBs - Drive	28.42 (3.71)
AEBS – Dietary Control	19.83 (2.48)

TFEQ – H. Three Factor Eating Questionnaire Susceptibility to Hunger scale; *TFEQ – D.* Three Factor Eating Questionnaire Disinhibition scale; *TFEQ – R.* Three Factor Eating Questionnaire Restraint scale; *PFS.* Power of Food scale; *AEBS.* Addiction-like Eating Behaviour scale.

Participants reported consuming an average of 1736 (±1269.72) kcal on baseline days and 1790 (±662.08) kcal on nER days of the intervention. They met the GDA for caloric intake on 70.24% of baseline days and on 80.46% of nER days.

Participants also reported consuming 500.62 (±284.17) kcal on ER days. They met their personal energy goal on 49.09% of ER days and reported an average surplus of 208.17 (±283.23) kcal on days where they exceeded the calorie limit.

5.4.2 Compliance

One participant was withdrawn from the study (7.69 %) due to failure to comply with EMA protocol and data was discarded from analyses. The total sample for all analyses was twelve participants.

Completion rates for random assessments (RAs) ranged from 53.57% – 97.28%. Nine participants completed at least one RA on each day. Overall, participants reported 73 event assessments (34 temptations; 39 lapses) throughout the intervention phase. All participants reported at least one event assessment with one participant reporting no temptations and one reporting no lapses. Completion rates and contextual descriptives of all EMA assessments are reported in Table 5.2.

Participants reported consuming alcohol, nicotine, caffeine or experiencing a distraction on 504 assessments (30% of completed assessments; 117 or 33.33% of morning RAs; 114 or 32.47 % early afternoon RAs, 127 or 35.47 % of late afternoon RAs; 146 or 40.78% of evening RAs). Sensitivity analyses (see Table 5.S.3 in supplementary materials, P. 181) revealed some significant differences. However, although these crossed the predefined significance level, changes in effect sizes were minimal. Findings from the linear models are presented as main analyses and potential explanations for differences between models are discussed later.

Table 5.2 - Completion rates and contextual descriptives all EMA assessments

	Random assessments	Temptations	Lapses
Completion rates			
Total	1409/1680 (83.86%)	34	39
Morning	342/420 (81.42%)	1 (2.95%)	2 (5.13%)
Early afternoon	351/420 (83.57%)	8 (23.53%)	5 (12.82%)
Late afternoon	358/420 (91.66%)	9 (26.47%)	6 (15.38%)
Evening	358/420 (91.66%)	16 (47.06%)	26 (66.66%)
Contextual descriptives			
Location			
Home	576 (40.88%)	21 (61.75%)	24 (61.53%)
Work	496 (35.20%)	19 (55.88%)	11 (28.21%)
Restaurant or bar	224 (15.90%)	1 (2.94%)	4 (10.26%)
Transit	82 (5.82%)	2 (5.88%)	0 (0%)
Others present	564 (40.28%)	16 (47.06%)	11 (28.21%)

5.4.3 Confirmatory analyses

Hypotheses Set 1

Hypotheses set 1 predicted EMA outcome measures would be significantly different on ER days compared to nER days, and baseline measures of eating behaviours would predict individual differences in EMA outcome measures. Descriptive statistics for outcomes in hypotheses 1 are reported in Table 5.S.2 in supplementary materials (P. 180).

Hunger

Mean hunger score for the final model was $\beta_0 = 30.35$ (SE = 3.75).

Variance componence models were created to assess the effect of stratifying hunger score into levels. The two-level model was a better fit to the data than the single level model (χ^2 (1) = 194.80, $p < .001$). Additionally, the three-level model was a better fit than the two-level model (χ^2 (2) = 125.89, $p < .001$). The intra-class coefficient (ICC) of the three-level null model ($n_{session} = 1105$, $n_{day} = 334$, $n_{participant} = 12$) revealed 3.36% ($ICC_{within} = .034$) of variance was within-day, 18.02% ($ICC_{between} = .180$) was between-person.

To test the hypotheses that hunger scores would be significantly higher on ER compared to nER days, and that baseline measures of TFEQ-H would predict individual differences, ER was included as a day level variable and TFEQ-H was included as a participant level variable as well as the interaction term.

Compared to the null three-level model, adjusting for predictors was a better fit to the data (χ^2 (3) = 104.98, $p < .001$). A comparison of the variance partition coefficients (VPCs) show the model predicted 9.91% variance in scores at the participant level, 81.15% at the day level, and 9.70% at the session level.

Results are reported in Table 5.3. In summary, hunger was significantly higher on ER days compared to nER days. TFEQ-H scores were not found to be a significant predictor of hunger scores. The interaction between ER and TFEQ-H scores was also non-significant.

Fullness

Mean fullness score for the final model was $\beta_0 = 40.10$ (SE = 2.85).

The two-level model was a better fit to the data than the single level model (χ^2 (1) = 94.79, $p < .001$). Additionally, the three-level model was a better fit than the two-level model (χ^2 (1) = 12.88, $p < .001$). The ICC of the three-level null model ($n_{session} = 1105$, $n_{day} = 334$, $n_{participant} = 12$) revealed 2.60% ($ICC_{within} = .026$) of variance was within-day, 8.92% ($ICC_{between} = .089$) was between-person.

To test the hypotheses that fullness scores would be significantly lower on ER days compared to nER days, ER was included as a day level variable with nER as the reference category.

Compared to the null three-level model, adjusting for predictors was a better fit to the data (χ^2 (1) = 109.51, $p < .001$). A comparison of the VPCs show the model predicted 36.16% variance in scores at the participant level, 100% at the day level, and 9.29% at the session level.

Results are reported in Table 5.3. In summary, fullness was significantly lower on ER days compared to nER days.

Cravings

Mean craving score for the final model was $\beta_0 = 27.25$ (SE = 4.17).

The two-level model was a better fit to the data than the single level model (χ^2 (1) = 274.86, p < .001). Additionally, the three-level model was a better fit than the two-level model (χ^2 (1) = 19.10, p < .001). The ICC of the three-level null model (n $_{session}$ = 1105, n $_{day}$ = 334, n $_{participant}$ = 12) 4.18% (ICC $_{within}$ = .042) of variance was within-day, 24.05% (ICC $_{within}$ = .240) was between-person.

To test the hypotheses that craving scores would be significantly higher on ER compared to nER days, and that baseline measures of PFS would predict individual differences, ER was included as a day level variable with nER as the reference category, and PFS as a participant level variable as well as their interaction term.

Compared to the null three-level model, adjusting for predictors was a better fit to the data (χ^2 (3) = 88.56, p < .001). A comparison of the VPCs show the model predicted 8.87% variance in scores at the participant level, 70.73% at the day level, and 6.70% at the session level.

Results are reported in Table 5.3. In summary, Craving score was significantly lower on ER days compared to nER days. PFS did not predict craving score, however a significant interaction between ER and PFS was found. Individuals who scored higher on the PFS experienced greater cravings on ER days.

Behavioural control

Mean commission error score for the final model was β_0 = 1.85 (SE = 0.25).

The two-level model was a better fit to the data than the single level model (χ^2 (1) = 955.36, p < .001). Additionally, the three-level model was a better fit than the two-level model (χ^2 (1) = 47.96, p < .001).

To test the hypotheses that error scores would be significantly higher on ER compared to nER days, and that baseline measures of AEBs-DC would predict individual differences, ER was included as a day level variable with nER as the reference category, and AEBs-DC as a participant level variable as well as their interaction term. Reaction time to food No-Go trials was also included in the model to control for differences in commission errors that could be attributable to reaction timing.

Compared to the null three-level model, adjusting for predictors resulted in a better fit to the data (χ^2 (4) = 76.08, p <.001). The ICC of the three-level conditional model (n $_{session}$ = 814, n

$_{day}$ = 305, n $_{participant}$ = 12) revealed 16.21% (ICC $_{between}$ = .162) was between-person, 4.95% (ICC $_{within}$ = .050) of variance was within-day.

Results are reported in Table 5.3. In summary, greater reaction time to food No/Go trials predicted lower commission errors. No other predictors were found to be significant.

Change in behavioural control over IER

To explore whether behavioural control changed over the course of the intervention, Week was included as a series of dummy variables into the null three-level model with Week 1 as the reference category. Reaction time to food No-Go trials was also included in the model to control for differences in commission errors that could be attributable to reaction timing.

Compared to the null three-level model, adjusting for predictors resulted in a better fit to the data (χ^2 (2) = 60.35, p <.001).

It was revealed that higher reaction time to food-cues predicted lower commission errors (β = -.003 (.001), 95% CI = - .004 to -.002, p <.001). There were no significant differences in commission errors on Week 2 (β= -.09 (.06), 95% CI = -.21 to .03, p = .15) or Week 3 (β= .10 (.06), 95% CI = -.02 to .21, p = .09) relative to Week 1. However, commission errors on Week 4 were found to be significantly higher relative to Week 1 (β = .14 (.06), 95% CI = .03 to .25, p <.001).

To explore whether the difference in behavioural control between Week 1 and Week 4 could be attributable to differences in the impact of ER on commission errors, separate models were created for both weeks.

A three-level structure were inappropriate for both models (ps >.05). A two-level null model for Week 1 (n $_{session}$ = 287, n $_{participant}$ = 12) was a better fit to the data than the single level model (χ^2 (1) = 285.81, p < .001). A two-level model for Week 4 (n $_{session}$ = 253, n $_{participant}$ = 12) was also a better fit to the data than the single level model (χ^2 (1) = 283.49, p < .001).

ER was included as a predictor in both models with nER day as the reference category. Reaction time to food No-Go trials were also controlled for in the models.

For Week 1, it was revealed that higher reaction time to food-cues predicted lower commission errors (β = -.005 (.001), 95% CI = -.006 to -.003, p <.001). It was also found that commission errors were significantly lower on ER days compared to nER days (β= -.16 (.08), 95% CI = -.325 to -.003, p = .05).

For Week 4, it was revealed that higher reaction time to food-cues predicted lower commission errors (β = -.002 (.001), 95% CI = -.004 to -.001, p =.03). However, there were no significant differences in commission errors on ER days compared to nER days (β= .02 (.001), 95% CI = -.134 to -.176, p = .79).

A comparison of slopes was then conducted by computing a Z-score of the difference in ER β values and their SEs between the Week 1 and Week 4 model in order to assess whether there was the strength of ER on behavioural control was significantly different. A comparison of slopes for reaction time to food No-Go trials was also conducted to assess whether the effect of reaction times on commission errors was significantly different between models.

This revealed that there was a significant decrease in the effect of ER on commission errors between Week 1 and Week 4 (Z = -2.25, p = .03). There was also a significant decrease in the effect of reaction time on commission errors between Week 1 and Week 4 (Z = -2.12, p = .04).

Table 5.3 - Multilevel models examining participant and daily level predictors of fluctuations of appetitive outcomes

	β (SEs)	LB-CI	UB-CI	*p*
	Hunger intensity			
Participant level				
Hunger cons.	30.35 (3.75)	23.29	38.16	<.001
TFEQ - H	.44 (1.32)	-2.17	2.90	.74
Daily level				
ER	17.23 (1.55)	14.11	20.32	<.001
Interactions				
ER x TFEQ-H	.82 (0.54)	-.27	1.82	.13
	Fullness intensity			
Participant level				
Fullness cons.	48.10 (2.85)	41.57	53.40	<.001
Daily level				
ER	-16.80 (1.48)	-19.80	-13.95	<.001
	Craving intensity			
Participant level				
Craving cons.	27.25 (4.17)	19.64	35.66	<.001
PFS	-.07 (.427)	-.933	.753	.87
Daily level				
ER	14.47 (1.48)	11.60	17.29	<.001
Interactions				
ER x PFS	.38 (.151)	.088	.689	.01
	Behavioural control			
Participant level				
Errors cons.	1.90 (.24)	1.44	2.36	<.001
Reaction time	-.003 (.001)	-.004	-.002	<.001
AEBS-DC	.04 (.06)	-.086	.160	.56
Daily level				
ER	-.04 (.04)	-.126	.039	.30
Interactions				
ER x AEBS-DC	.02 (.02)	-.019	.050	.39

UB-CI. Lower-bound 95% confidence interval; *LB-CI.* Lower-bound 95% confidence interval*; TFEQ – H.* Three Factor Eating Questionnaire Susceptibility to Hunger scale; *PFS.* Power of Food scale; *AEBS-DC.* Addiction-like Eating Behaviour scale Dietary Control; *ER.* Energy restriction.

Hypotheses Set 2

Hypotheses set 2 was that hunger, cravings and stress will be higher, whereas fullness and behavioural control will be lower on event assessments (EAs; temptations and lapses) compared to random assessments (RAs). It is also hypothesised that intensity of hunger, cravings and stress will be higher, whereas fullness, behavioural control, and engaging in coping strategies will be lower on lapse assessments compared to temptation assessments.

Descriptive statistics for outcomes are reported in Table 5.S.2 (P. 180) in supplementary materials).

Random assessments vs event assessments

To test the hypothesis that outcomes were significantly different on event assessments compared to random assessments, a two-level model ($n_{session} = 629$, $n_{participant} = 12$) was fitted to the dataset. Type of assessment was included as a session-level variable with random assessment being the reference category.

Adjusting for predictors was a better fit to the data than the null models for hunger (χ^2 (1) = 25.28, p < .001), fullness (χ^2 (1) = 4.96, p =.03), craving (χ^2 (1) = 312.92, p < .001), and stress (χ^2 (1) = 15.40, p < .001).

When hunger was the outcome, mean score was 47.38 (SE = 4.11) and was significantly higher on event assessments compared to random assessments (β= 16.96 (3.34), 95% CI = 10.68 to 23.23, p < .001).

Fullness had a mean score of 31.74 (SE = 2.87) and was significantly lower on event assessments compared to random assessments (β= -6.70 (3.00), 95% CI = -12.61 to -1.05, p = .03).

Craving had a mean score was 42.22 (SE = 4.55) and was significantly higher on event assessments compared to random assessments (β= 28.79 (3.17), 95% CI = 23.21 to 35.67, p < .001).

When stress was the outcome, mean score was 21.94 (SE = 9.66) and was significantly higher on EAs compared to RAs (β= 9.66 (2.44), 95% CI = 4.77 to 15.06, p < .001).

Temptation assessments vs lapse assessments

To test the hypothesis that appetite outcomes and engagement with coping strategies outcomes were significantly different during lapses compared to temptations, a two-level model was fitted to a dataset which contained all event assessments. Type of assessment was input as a session-level variable with temptations being the reference category.

No significant differences were found for hunger (p = .06), fullness (p = .22), cravings (p = .40) or stress (p = .56).

When use of coping strategies was the outcome, mean score was 45.19 (SE = 3.40), and adjusting was a better fit to the data than the null model (χ^2 (1) = 14.42, p < .001). Coping score was significantly lower on LAs compared to TAs (β= -15.41 (3.85), 95% CI = -23.43 to -7.04, p < .001).

Hypotheses Set 3

Hypotheses set 3 was that there will be no correlations between EMA and retrospective measures of appetite and affect. Descriptive statistics for outcomes are reported in Table 5.S.1 (P. 179 in supplementary materials).

There was a strong positive correlation found for cravings (r (58) = .74, p < .001). Retrospective measures explained 55% of variance in EMA measures. There was also a moderate positive correlation between retrospective and EMA measures of hunger (r (58) = .61, p < .001) as well as stress (r (58) = .69, p < .001). Retrospective measures explained 37% of variance in EMA measures of hunger and 45% in stress. Finally, there was a weak positive correlation found for fullness (r (58) = .37, p < .001) with retrospective measures explaining 14% of variance in EMA measures.

5.4.4 Exploratory analyses

Moderating role of stress on behavioural control to inform energy intake

To explore whether the interaction between stress and behavioural control significantly increased daily energy intake, a two-level model was fitted to the dataset with daily calorie intake as the dependent variable.

The two-level model (n_{day} = 249, $n_{participant}$ = 12) was a better fit to the data than the single level model (χ^2 (1) = 13.05, p < .001). However, adjusting for predictors did not result in a better fit to the data than the null model (χ^2 (3) = 3.25, p = .35).

Baseline appetite measurements as between-person predictors

To investigate whether measurements taken during the baseline phase could be used to predict individual in appetitive sensations during the interventional phase, three-level models for hunger and craving were created.

There were two separate models for both hunger and cravings to assess both baseline retrospective and EMA measures as predictor variables. These predictors were included in the models as participant-level variables as well as their interaction with ER.

Baseline EMA measures as between-person predictors

When hunger was the outcome, mean score was 30.48 (SE =2.37). Compared to the null three-level model, adjusting for predictors explained 20.65% of total variance and was a better fit to the data (χ^2 (3) = 112.87, $p < .001$).

A comparison of the VPCs show the model predicted 57.24% variance in scores at the participant level, 73.61% at the day level, and 25.56% at the session level. There was a significant positive association with baseline EMA hunger score (β= 0.99 (0.27), 95% CI = 0.50 to 1.55, $p < .001$), however the interaction between ER and baseline EMA hunger score was not significant (β= 0.30 (0.18), 95% CI = -0.001 to 0.64, p = 0.10).

When craving was the outcome, mean score was 27.35 (SE =2.15). Compared to the null three-level model, adjusting for predictors explained 25.80% of total variance and was a better fit to the data (χ^2 (3) = 102.62, $p < .001$).

A comparison of the VPCs show the model predicted 70.96% variance in scores at the participant level, 58.76% at the day level, and 34.07% at the session level. There was a significant positive association with baseline EMA craving score (β= 1.11 (0.23), 95% CI = 0.70 to 1.58, $p < .001$), and the interaction between ER and baseline EMA craving score was significant (β= 0.42 (0.16), 95% CI = 0.10 to 0.74, $p < .01$). Individuals with who had higher levels of real-time cravings during the baseline phase experienced a greater increase in cravings on ER days.

Baseline retrospective measures as between-person predictors

When hunger was the outcome, there was no significant association were found with baseline retrospective hunger score (β= 0.09 (0.22), 95% CI = -.366 to .533 p = .68), and no significant interaction with ER (β= -0.06 (0.09), 95% CI = -.259 to .114, p =.50).

When craving was the outcome, there was no significant association with baseline retrospective craving score (β= 0.40 (0.21), 95% CI = -0.02 to 0.84, p = .06), nor was the interaction between ER and baseline EMA craving score (β= 0.17 (0.09), 95% CI = -0.02 to 0.34, p = .06).

5.5 Discussion

The present study aimed to investigate the impact of a 4-week ADER intervention on dynamic fluctuations in appetite, stress, and behavioural control to understand how these outcomes differ between momentary subjective states which pose a problem for successful dietary adherence in sample of individuals with overweight and obesity. Additionally, this study aimed to investigate whether baseline measures of appetite and eating behaviours could explain individual differences in appetite responses to ER. A final aim of this study was to examine the association between retrospective and real-time measures of appetite.

Regarding hunger, evidence was found that intensity of hunger was increased on ER days compared to nER days. Evidence was also found that hunger was higher on EAs compared to RAs on ER days. These support the findings in Chapter Four and suggest that intensity of hunger is persistently higher on ER days of an IER diet, but it is further momentary increases during ER days which are associated with experiencing a momentary subjective state which pose a problem for dietary adherence.

No support was found that TFEQ-H score interacted with ER to produce increased hunger scores. It would be expected that a dietary intervention which employs a very low energy requirements on ER days to see those susceptible to the effects of hunger to experience greater increases in this sensation. Given the intensity of ER employed in this study (~25% of BMR), it is surprising a differential effect of TFEQ-H score was absent. One explanation is that the study suffered from a low sample size which impacted the ability to draw firm conclusions regarding between person differences. The investigation could have also suffered from a self-selecting bias. Those who are knowledgeable of their management with hunger may have been more hesitant to volunteer for a study with frequent bouts of low energy intake.

Fullness was lower on ER days compared to nER days, and scores were even lower on EAs compared to RAs on ER days. The finding that fullness was significantly decreased during EAs compared to RAs contrasted Chapter Three where no effect of EA on fullness score was identified in the meta-analyses. One potential explanation for this could be as the intensity of ER employed in the current study was more than previous investigations which employed continual but more modest intensities of ER. Interestingly, whilst a large amount of day-level variance was explained in all outcomes after the inclusion of the ER contrast, day-level variance in fullness was fully explained. This suggests that the level at which fullness differs from day-to-day was completely due to engagement with an alternate day ER diet.

Regarding cravings, intensity was higher on ER days compared to nER days, and who scored high on PFS score experienced greater increases in cravings on ER days. Intensity of cravings were also higher on EAs compared to RAs on ER days. Previous investigations have seldom measured cravings during temptations and lapses using EMA, therefore the dynamic relationship between cravings and dietary adherence has largely been understudied. Temptations and cravings are the output of reward-based processing which is triggered by exposure to palatable foods (Appelhans et al., 2016) meaning previous associations between cues and subsequent consumption are required. Given EMA takes place within naturalistic settings where these associations have already been formed, this methodology is perfectly suited for studying the effects of reward-based processing of environmental cues. These findings demonstrate momentary increases in the intensity of cravings that accompanies the experience of a temptation may be a large driver of dietary inadherence.

Additionally, this relationship may differ based on individual differences in trait food cravings and food-reward responsivity. One previous free-living found that increases in momentary sensations of cravings predicted snack consumption, and this effect was greater in individuals who scored higher on a baseline measure of trait cravings (Richard et al., 2017). This finding is in alignment with the current findings a higher baseline PFS scores predicted greater increases in cravings during ER days. However, it is important to note that this relationship was no longer significant following the sensitivity analyses which removed any assessments which were contaminated by recent consumption of caffeine, nicotine or alcohol. Similar to the results of the sensitivity analyses in Chapter Four, given that the effect sizes do not greatly differ, it is likely that this results from a loss of power to detect a significant between-person effect. Nonetheless, these findings highlight the potential usefulness of the PFS in identifying those at baseline who may struggle with high levels of cravings during ER days of IER which may pose as a barrier to successful dietary adherence.

Regarding stress, no evidence was found for increased sensations on ER days compared to nER days. However, stress was higher during EAs compared to RAs on ER days. Perceived stress was included as a measure of negative affect due to its implications with behavioural control and energy intake (Mann & Ward, 2004). Negative mood is thought to be increased during ER (Roberts et al., 2017) posing a problem for dietary adherence, particularly for those who display tendencies towards eating in response to strong emotions (Royal & Kurtz, 2010). However, the concept of negative mood encompasses many sensations such as depression, anxiety, low energy, and distress (Jackson et al., 2014; Ogden, 1995) which could be an explanation as to why perceived stress was not higher on ER days compared to nER days. Assuming a single item measure of negative affect would be impacted by ER similar to multivariate measures of negative affect could have been inappropriate. For example, Smoller et al. (1987) reported that differences between studies of the mood measures employed predicted the direction of changes in affect during dieting.

Perceived stress may occur more momentarily in response to immediate external influences such as work and life pressures that could pose as issues to dietary adherence which is supported by the finding that perceived stress was raised on EAs compared to RAs on ER days. However, previous EMA evidence suggests that negative mood may also influence adherence through momentary rather than persistent increases. Goldstein et al. (2018b) found between and within-person differences in various affective measures including stress increased the likelihood of reporting a lapse. McKee et al. (2014) found within person increases in stress predicted greater temptation strength. Manasse et al. (2018a) also found negative urgency increased the likelihood of reporting a lapse. Finally, Carels et al. (2001; 2004) both found TAs and LAs were accompanied by increased within-person levels of negative mood compared to RAs. These suggest that negative affect including stress influences adherence through momentary processes, though further investigations which employ a more comprehensive measure of negative affect is required to shed light onto whether negative affect demonstrates persistent increases on ER days of IER diets.

Regarding behavioural control, the task employed indexed deficits in control through increased commission errors towards food-cues on the Go/No-Go task. Findings in this investigation are similar to those found in Chapter Four. Evidence was found of both within and between-person variation in performance on the behavioural task, however there were no consistent predictors of this variation in the overall interventional period.

One explanation could be that ER does not directly impact behavioural control as is the case with appetitive sensations. Cognitive processes such as behavioural control may play a mediating role between sensations and behaviour. Fluctuations in task performance may impact behaviour only when coping with dynamic increases in appetitive sensations, rather than being persistently changed during ER days. In support of this, Powell et al. (2017) employed a Go/No-Go task hourly and found momentary decreases in performance predicted snacking at the next assessment. This could also explain why the current investigation found no interactive effect between task performance and stress on daily caloric intake. Commission errors as well as stress were averaged at the day level due to energy intake being measured at this level. Future investigations should investigate whether fluctuations in behavioural control predict an eating episode occurring shortly after the measurement was taken and examine whether this relationship is mediated by increases in sensations of appetite and affect.

Interestingly, in follow-up analyses it was found that there were significantly more commission errors towards food-cues made during Week 4 compared to Week 1. Further analyses revealed that there were less commission errors on ER days compared to nER days during Week 1 of the interventional period, but this effect was not present at Week 4. A comparison of slopes analysis revealed that the difference between commission errors on nER and ER days was significantly lower on Week 4 relative to Week 1 indicating the impact of ER on behavioural control decreased over the course of the intervention. Taken together, these suggest that during the initial week of IER behavioural control was raised during ER days as control was successfully being exerted over automatic responses towards cues to consume which resulted in weight loss. However, as weight loss occurred throughout the intervention, changes to appetite regulation caused by maintaining a negative energy balance (Roberts et al., 2017) could have resulted in individuals finding it harder to inhibit automatic responses towards food cues during ER days of the final week of the intervention. One possible underlying cognitive mechanism for this is ego depletion (Baumeister, Bratslavsky, Muraven & Tice, 1998). Persistent use of cognitive resources to control automatic behavioural responses to increasing appetitive and affective responses resulting from maintaining a negative energy balance over the 4 weeks may have exhausted the ability to control behaviour on ER days later in the intervention.

However, another potential explanation is that findings could have been impacted by methodological limitations of the task. There was a potential of twenty-four commission errors towards food-cues for each assessment, though the low intercept of commission errors (intercept = 1.85) indicates that this task could have suffered from a ceiling effect. Given the ease of the task, this may also have produced fatigue or boredom effects by Week 4 of the intervention which resulted the increase of errors found relative to Week 1. Additionally, the task employed could also have been unsuitable for repeat assessment in the timeframe employed in the current study. The task consisted of 32 images presented multiple times in one assessment which was completed four times a day over a 5-week period meaning practise effects could have occurred. In support of this, during Week 1 and Week 4 slower reaction times to food No-Go trials predicted less commission errors, and a comparison of slopes revealed that this effect was lower on Week 4 relative to Week 1 indicating less time was required to decrease the likelihood of commission errors occurring during Week 4. Alternatively, as there was an increase in errors during Week 4, the decrease in reaction time may have resulted from boredom effects. Following four weeks of repeated implementation of the Go/No-Go task, participant engagement may have decreased resulting in the change in errors and reaction time. In order to reduce the limitations associated with repeated implementation of cognitive tasks, future investigations would benefit from implementation of design traits which increase participant engagement such as personalised stimuli or gamifying tasks (Forman et al., 2018).

No evidence was found that AEBs-DC predicted individual differences in performance. It may be the case that performance on behavioural measures is conceptually different to behavioural control as measured by trait questionnaires. AEBs-DC measures control over general dietary behaviours such as making healthy purchasing choices and beliefs surrounding the health status of diet (Ruddock et al., 2017). Go/No-Go performance on the other hand is an index of current inhibition over pre-potent automatic motor responses towards food-related cues. Whilst these both relate to behavioural control, they are undoubtably distinct factors. Therefore, AEBs and other trait questionnaires relating to control over behaviour may be unsuitable for predicting individual differences in motor control capacity.

Regarding differences in appetitive and affective responses between EAs and RAs, support was found for the hypothesis that appetitive and affective measures were significantly different during moments of temptations and lapses compared to random moments throughout the day. Specifically, intensity of hunger, cravings, and perceived stress were higher, whereas fullness was lower during temptation and lapses. Interestingly, whilst appetite sensations were all impacted by ER, it was even greater increases in these effects during ER days which posed as barriers to successful dietary adherence. Additionally, stress was not increased on ER days overall, but was raised during EAs compared to RAs on ER days. These suggest that dynamic increases in appetitive and affective responses which occur during engagement with ER influence subjective momentary states which pose as a problem for dietary adherence.

No differences were found in appetite and affect measures between temptations and lapses, however engagement with coping strategies was found to be higher during temptations compared to lapses. The measure of coping strategies was a comprehensive 14-item measure of various strategies that individuals could engage in such as removing oneself from the environment, engaging in relaxation and seeking support from peers. This identifies that a characteristic which distinguishes a temptation from lapse was the extent of engaging in coping strategies, therefore engagement may be effective towards preventing a lapse occurrence. Given the outcome measure indexed multiple strategies, it is unclear which strategy is the most effective, though the efficacy of specific strategies is likely to differ between individuals (Appelhans et al., 2016). Future investigations could examine the effectiveness of creating personalised coping strategy plans which aim to aid individuals through experiencing a temptation as an attempt to reduce lapse frequency during ER.

The contextual descriptives of reported temptations and lapses are also in agreement with previous investigations (Carels et al., 2001; 2004; Forman et al., 2017; McKee et al., 2014). Both temptations and lapses were reported most frequently at home followed by at work. The frequency of both events increased throughout the day, with evening being the most prevalent time for an event to be reported. It is important to note that the current study reported substantially lower EAs compared to previous investigations. Furthermore, as an attempt to reduce participant burden, Go/No-Go tasks were programmed to have a 25% chance of taking place upon logging an EA. Unfortunately, this resulted in insufficient amount of assessments where a task was performed, therefore this hypothesis could not be tested. Whilst lower reporting rates were affected by a small sample, it is possible that due to the primary focus of completing RAs (e.g. text prompts, checking compliance during lab-visits, etc.), reporting EAs may have been viewed as less important to the study. Future investigations may benefit from prompting participants at the beginning of ER days to remember to log any EAs.

Regarding the association between real-time and retrospective measures, whilst the hypothesis that there will be no correlation between these measures proved overly ambitious, interestingly, most correlations were found to be of a modest strength. Retrospective measures of cravings and perceived stress had high and modest correlations respectively, whilst hunger measures displayed a modest correlations and fullness displayed a weak correlation.

In the exploratory analyses conducted, between-person predictors of appetitive sensations were better predicted by aggregated real-time measures of hunger and cravings compared to retrospective measures of these sensations which spanned the same period of time. These indicate that future dietary interventional studies should exercise caution when employing retrospective measures of appetite, particularly for measures of satiety as these may under- or overstate the actual experienced levels of appetite during ER which could lead to erroneous conclusions of the impact of interventions on changes in appetitive outcomes. The current study only assessed retrospective measures spanning a period of 7-days, though longer periods could display even weaker correlations. Some interventional studies employ long timeframes such as 1-month for retrospective accounts, therefore a better understanding of the correlation between retrospective and real-time measures of appetite over varying lengths of time could further inform future interventional studies that make inferences regarding appetite outcomes.

The exploratory analyses undertook regarding a baseline measurement phase to identify individual differences in appetitive responses to ER demonstrated the potential of this novel N-of-1 approach. An aggregate score of the real-time measurements of hunger and cravings taking during the baseline phase was used as an appetite profile which was found to predict large amounts of variance at the participant level for these appetite outcomes during the interventional phase. Additionally, the interaction between real-time baseline ratings and ER was significant for both hunger and cravings implying this approach is effective at identifying individual differences in appetitive responses to ER. EMA platforms for the real-time measurement of appetite measures such as 'APPetite' are easily deployed through smartphone devices. Completing one week of VAS measures of appetite during a baseline phase is relatively non-intrusive and has the potential to provide greater predictive utility of individual differences above the use of retrospective appetite measures or baseline measures of eating behaviours. Future investigations should assess whether appetite responses recorded during a baseline phase to create an appetitive profile could be used to develop effective personalised strategies to aid in coping with strong sensations that may pose a problem for successful dietary adherence during weight loss.

Limitations

The major limitation of this investigation was the small sample size recruited. This investigation took an intensive longitudinal approach to follow experiences of appetite and energy intake over a 5-week period, therefore a small sample was recruited due to financial constraints of the design. This greatly limited the ability to draw firm conclusions about many hypotheses relating to individual differences. In multilevel model, power is determined by the higher units (i.e. participant level) as lower sample sizes at this level have been shown to produce unreliable estimates, particularly for predictors of between-person differences (Mass & Hox, 2005). This limitation could have greatly affected the ability to detect individual differences which could potentially explain many of the null findings present, but also could have led to some spurious findings, therefore caution must be taken in interpretation of these results. Replication of these results in encouraged in investigations with larger sample sizes.

Another limitation of this study is its heavy reliance on self-reported measures. As this investigation focused on appetitive sensations during ER, responses may have been influenced by demand characteristics as participant know increased sensations would be a product of intense ER. Furthermore, self-reported calorie intake suffers from varying degrees of underreporting, particularly in the study population of interest. This may have also impacted the reporting of temptations and lapses. Participants may be apprehensive to report these moments of dietary inadherence, particularly if multiple lapses occurred successively.

Summary

In summary, this investigation found evidence that appetitive sensations were heightened during ER compared to nER days. However, further increases in these sensations as well as sensations of perceived stress which occur momentarily during ER days are what pose the greatest barrier to successful dietary adherence. The extent to which an individual engages with coping strategies during experiencing a temptation may determine whether this leads to experiencing a lapse episode. Additionally, 7-day retrospective measure of appetite modestly correlate with real-time measures of appetite, particularly for measures of satiety, and these may not reliably predict individual differences in appetitive sensations experienced in real-time. Future interventions should be cautious when employing recall measures as these may lead to erroneous conclusions regarding appetite. Finally, evidence was found for individual differences in average levels of hunger and cravings. Individual differences in craving responses to ER could be predicted by PFS score, highlighting the potential of this measure to be used to identify individuals at baseline who may benefit from additional support in coping with sensations of cravings during IER. Furthermore, utilising a baseline measurement phase where appetite is monitored prior to engagement with an intervention to create a personalised appetitive profile may also be beneficial in early identification of individuals who may experience high levels of appetitive sensations during ER.

The implication of these is that the early identification of appetitive responses which may be heightened during ER may aid in the development of personalised coping strategies through appetitive profiling to manage these problems during engaging in a weight loss attempt. This may prove to be an effective approach for increasing dietary adherence through reducing dietary lapses which could cause problems for successful weight management.

5.6 Supplementary analyses: 'Carry-over' effect of ER

Rationale

Multiple investigations of IER have reported a 'carry-over' effect of ER through a spontaneous reduction of between 10 – 23% of prescribed energy intake on unrestricted days of an IER diet (Harvey, Howell, Morris, & Harvie, 2018; Hutchison et al., 2019). The underlying mechanisms responsible for this reduction is currently unknown. Many of these previous investigations have provided dietary advice for nER days such as keeping within the recommended daily calorie limit and providing advice on maximal portions of foods to ensure participants did not overconsume (Harvey et al., 2018). Providing guidance on consumption for nER days could have introduced an interventional effect that could have influenced energy intake on these days. The current study placed no restriction on energy intake or provided any advice for eating on nER days to examine whether the presence of a 'carry-over' effect of reduced energy intake could be attributed to interventional attributes.

The supplementary hypothesis is that reported daily caloric intake will be lower on nER days compared to baseline days intake data.

Results

A hierarchical dataset was structured so that day was nested within days within participants resulting in a 2-level structure. The two-level model was fitted to a dataset, and phase was included as a day level variable with baseline days being the reference category.

Mean daily caloric intake for the final model was $\beta_0 = 1790.12$ (SE = 68.37). The two-level model ($n_{day} = 249$, $n_{participant} = 12$) was a better fit to the data than the single level model (χ^2 (1) = 61.91, $p < .001$).

Adjusting for predictors was a better fit to the data than the null model (χ^2 (1) = 8.76, $p < .01$). Caloric intake score was significantly lower on nER days of the intervention compared to baseline days (β= -203.84 (68.37), 95% CI = -336.56 to -79.20, $p < .01$).

Discussion

Support was found for the hypothesis that energy intake on nER days would be significantly reduced compared to baseline days. Furthermore, average daily caloric intake suggest that this was less than caloric GDA for both baseline and nER days.

The current investigation differed from previous studies into IER by providing no guidelines for energy intake on nER days other than to eat as they wish. This still produced a reduction in reported energy intake which suggest reductions found in previous investigations are not a result of providing dietary guidance for nER days. As previously suggested, it is possible that this reduction could be a direct result of ER. For example, after engaging in ER, participants may become more aware of their eating habits and reaffirm that they can manage with strong appetitive sensations (Harvie et al., 2011).

However, these reductions could also be explained by reactivity and engagement with the experimental intervention. The study was advertised as an alternate day fasting diet, therefore participants were motivated to engage in a weight loss attempt which is supported by the observation that reported caloric intake was less than the GDA even during the baseline week. Furthermore, daily calorie intake was significantly lower on nER days compared to baseline days which could suggest increased engagement with protocol when the intervention was implemented.

Another explanation for reported reductions could be a result of observation of eating and weight. Dietary investigations require self-monitoring of calorie intake and weight which are well-known behaviour change techniques that can increase awareness of unhealthy eating habits and lead to behaviour modification (Peterson et al., 2014). Furthermore, a Hawthorne effect could also be present as the knowledge that increased energy intake would impact weekly weight measurements. In support of these observations, small amounts of weight loss were observed for most participants during the baseline week.

Self-reported calorie intake suffers from varying degrees of underreporting which could have a profound impact on some of the findings within this supplementary analysis. For example, a reported reduction in energy intake on nER days could simply be due to underreporting. Nonetheless, caution was taken in the interpretation of these findings. Regardless of whether a reduction of energy intake on these days occur, the results still indicate that a counteractive effect of hyperphagia was not present, as if this was the case weight loss would have been minimal.

Regardless of the explanation, these findings provide further evidence that IER does not produce a hyperphagic response on nER days which counteract weight loss benefits gained from ER days during formal weight loss interventions. Future investigations could utilise a panel design to examine whether individuals who engage in self-guided IER diets experience similar weight loss found in structured regimens which could confirm the effectiveness of this dietary approach in community samples. If a hyperphagic response is present in these samples, then weight loss would be expected to be minimal, or the study would suffer from substantial drop-out rates as many give up on maintaining the diet due to poor outcomes.

5.7 Supplementary materials

Table 5.S.1 - Participant characteristics during follow-ups during intervention phase. Values are means (SDs)

Measures		End of baseline	Week 1	Week 2	Week 3	Week 4
Weight (Kg)		82.02 (28.16)	80.68 (27.74)	79.88 (27.50)	79.45 (27.48)	79.05 (27.43)
BMI		28.81 (9.79)	28.34 (9.62)	28.06 (9.56)	27.92 (9.56)	27.78 (9.53)
Retrospective	Hunger	40.08 (18.30)	51.92 (20.33)	56.33 (20.32)	51.75 (22.74)	54.00 (19.43)
	Fullness	65.67 (15.08)	47.25 (11.96)	52.33 (21.22)	52.42 (18.17)	49.33 (13.93)
	Craving	42.00 (17.31)	54.03 (20.14)	53.25 (29.64)	45.33 (29.13)	52.33 (25.14)
	Stress	41.83 (26.13)	31.17 (19.46)	36.33 (26.51)	32.25 (26.31)	38.83 (27.29)
Realtime	Hunger	30.77 (26.84)	39.53 (29.14)	38.23 (28.54)	39.74 (29.45)	39.36 (30.61)
	Fullness	46.97 (31.01)	38.43 (26.70)	43.09 (28.64)	37.77 (26.76)	39.98 (27.53)
	Craving	27.05 (25.24)	36.92 (28.37)	33.40 (27.91)	33.44 (28.00)	35.22 (29.60)
	Stress	19.29 (21.36)	18.79 (22.52)	18.14 (21.11)	20.10 (22.61)	18.24 (21.34)

Table 5.S.2 - Measurements for all EMA assessments across the study period. Values are means (SDs)

Measure		Total	Morning	Early afternoon	Late afternoon	Evening
Hunger	Baseline	30.77 (26.82)	37.72 (28.56)	29.32 (25.49)	27.64 (26.06)	28.43 (26.37)
	nER	31.08 (26.70)	36.45 (27.30)	30.98 (26.59)	33.77 (27.34)	23.74 (24.09)
	ER	47.71 (29.68)	47.20 (29.06)	45.80 (29.41)	54.51 (29.20)	43.03 (30.10)
	TA	61.73 (25.49)	-	-	-	-
	LA	69.88 (22.64)	-	-	-	-
Fullness	Baseline	46.97 (31.01)	37.11 (28.08)	46.72 (32.11)	50.87 (30.46)	53.14 (31.42)
	nER	48.04 (27.23)	40.40 (29.99)	46.58 (26.89)	47.24 (24.54)	57.16 (27.96)
	ER	31.81 (25.29)	27.76 (23.78)	35.75 (26.01)	25.48 (21.97)	38.45 (27.10)
	TA	26.30 (23.96)	-	-	-	-
	LA	21.40 (23.64)	-	-	-	-
Craving	Baseline	27.06 (25.24)	29.23 (26.80)	25.22 (25.36)	26.26 (23.92)	27.51 (25.13)
	nER	27.81 (25.25)	30.37 (26.99)	25.80 (23.19)	31.94 (26.21)	23.48 (23.96)
	ER	41.94 (29.86)	39.66 (28.50)	41.33 (29.09)	46.81 (30.29)	39.69 (31.13)
	TA	73.14 (21.78)	-	-	-	-
	LA	74.21 (22.29)	-	-	-	-
Stress	Baseline	19.29 (21.36)	22.31 (22.00)	18.81 (21.59)	20.86 (22.71)	15.06 (18.62)
	nER	18.38 (21.28)	17.64 (20.72)	19.87 (21.95)	21.22 (23.12)	14.74 (18.75)
	ER	20.06 (23.17)	18.96 (21.19)	23.50 (26.22)	20.71 (22.30)	17.10 (22.47)
	TA	29.66 (26.50)	-	-	-	-
	LA	37.82 (32.03)	-	-	-	-
Behavioural control	Baseline	1.66 (1.90)	1.46 (1.67)	1.59 (1.82)	1.71 (2.15)	1.88 (1.95)
	nER	2.18 (2.19)	2.00 (1.94)	1.99 (2.19)	2.49 (2.26)	2.21 (2.31)
	ER	2.07 (2.34)	1.83 (2.34)	2.28 (2.38)	2.16 (2.30)	1.99 (2.34)
	TA	-	-	-	-	-
	LA	-	-	-	-	-

nER. Non-Energy-restricted day; *ER.* Energy-restricted day*; TA.* Temptation assessment; *LA.* Lapse assessment

Table 5.S.3 - Multilevel models excluding assessments that were possibly contaminated by recent smoking, caffeine or alcohol consumption

	β (SEs)	LB-CI	UB-CI	*p*
	Hunger intensity			
Participant level				
Hunger cons.	30.86 (3.83)	24.02	38.90	<.001
TFEQ - H	.31 (1.34)	-2.56	3.02	.94
Daily level				
ER	16.71 (2.26)	12.59	21.64	<.001
Interactions				
ER x TFEQ-H	.99 (0.82)	-.58	2.90	.23
	Fullness intensity			
Participant level				
Fullness cons.	46.76 (3.26)	40.33	53.34	<.001
Daily level				
ER	-17.62 (2.17)	-2.19	-12.91	<.001
	Craving intensity			
Participant level				
Craving cons.	28.48 (4.29)	20.92	37.23	<.001
PFS	-.06 (.44)	-.86	.87	.17
Daily level				
ER	13.03 (2.12)	8.81	17.84	<.001
Interactions				
ER x PFS	.32 (.24)	.10	.82	.18
	Behavioural control			
Participant level				
Errors cons.	2.08 (.29)	1.53	2.65	<.001
Reaction time	-.004 (.001)	-.005	-.002	<.001
AEBS-DC	.001 (.06)	-.12	.12	.98
Daily level				
ER	-.05 (.06)	-.17	.06	.37
Interactions				
ER x AEBS-DC	.05 (.03)	-.003	.10	.07

UB-CI. Lower-bound 95% confidence interval; *LB-CI.* Lower-bound 95% confidence interval*; TFEQ – H.* Three Factor Eating Questionnaire Susceptibility to Hunger scale; *PFS.* Power of Food scale; *AEBS-DC.* Addiction-like Eating Behaviour scale Dietary Control; *ER.* Energy restriction.

Chapter Six

General Discussion

In Chapter One, it was established that appetite regulation involves the interplay between satiety, reward-related processes and behavioural control which are heavily influenced by internal and environmental factors. Maintenance of a negative energy balance compromises the control of appetite and these changes pose a problem for successful dietary adherence. However, the extensive use of laboratory-based testing and retrospective recall reduce our understanding of appetitive processes to lab-based environments or as snapshots at specific timepoints throughout investigations thus limiting the ability to understand how momentary changes can impact dietary adherence. Considering this, the primary aim of this thesis was to provide real-world dynamic accounts of appetitive processes during intermittent ER to study the how fluctuations in outcome measures differ between momentary subjective states which may pose as barriers towards successful dietary adherence. In addition, whilst appetite varies from moment-to-moment, is also characterised by a substantive amount of individual variation which could explain the wide diversity in eating behaviours and body weight responses to dietary interventions. The secondary aim was to examine whether baseline measures of appetite and eating behaviours could be used to explain individual differences in appetitive responses to ER. Finally, this thesis also investigated associations between retrospective and real-time measures of appetite to provide primary evidence for the claims made regarding the limitations of using recall methods compared to real time measures.

These research questions were investigated in adults with overweight and obesity who were otherwise healthy (not suffering from illness such as diabetes) and were willing to engage in IER dietary interventions. These individuals are at risk of developing co-morbidities associated with increased weight status and may also experience difficulty maintaining control over strong appetitive processes whilst maintaining a negative energy balance.

6.1 Summary of main findings

- The findings establish the capability of utilising EMA to measure daily fluctuations in appetite responses during ER and their impact on momentary subjective states which pose a problem for successful dietary adherence.

- The findings demonstrate the usefulness of employing multilevel modelling to simultaneously explain both within- and between-person variation in appetitive processes as well as their interactions.

- Dynamic fluctuations in responses and momentary states:
    - Fluctuations in sensations of hunger and cravings are observed in the two-hour period which precipitates the initiation of eating behaviour.
    - Whilst sensations of hunger and cravings are more intense overall on ER days compared to nER days, it is dynamic changes in these sensations as well as negative affect during ER days which are associated with experiencing momentary subjective states that pose as a barrier towards successful dietary adherence (i.e. dietary temptations and lapses).
    - Increases in sensations of hunger, cravings and negative affect do not differ between the moments leading up to a lapse compared to when experiencing a temptation. What appears to distinguish these states is the extent to an individual engages with coping strategies to manage the temptation.

- Individual differences in appetitive responses to ER:
    - TFEQ-H score and baseline 7-day retrospective measure of hunger predict individual differences in intensity of hunger score and interacts with ER to predict greater hunger scores on ER days of a 5:2 dietary intervention. However, these findings were not replicated during an ADER intervention.
    - PFS score predicts individual differences in intensity of craving score on a 5:2 dietary intervention. On an ADER intervention, PFS score interacts with ER to predict greater cravings on ER days.
    - Real-time measurements of hunger and cravings which were recorded during a baseline study phase prior to engagement with an intervention are strong

predictors of individual differences in appetitive responses and interact with ER to predict greater scores on ER days during intervention.

- Inconsistencies in retrospective and real-time accounts of appetite regulation:
    - A pre and post comparison of hunger suggested decreases over 1-week, though raised sensations were experienced during 2-days of the study week.
    - Retrospective and real-time measures of appetite responses demonstrate varying levels of correlation. It appears measures relating to satiety demonstrate the weakest correlations, particularly for measures of fullness.
    - Real-time measures of appetite during a baseline phase prior to engagement with an ADER intervention predicted individual differences in responses during the intervention, whereas retrospective measures did not.

6.2 Themes

This thesis addressed several issues relating to the measurement and analysis of appetite responses to ER. Firstly, appetite is a biologically driven process which expresses itself through eating behaviours which take place within a socio-cultural context (MacLean et al., 2017). However, these processes are seldom measured within the context where they take place. Secondly, whilst appetitive responses to manipulations of energy intake display large levels of within-person variation, these processes also exhibit significant levels of individual differences. This variation could be a major driver of the large diversity in eating behaviours and responses to interventions (Gibbons et al., 2019). Several themes emerged throughout the investigations detailed in this thesis. The primary finding was that dynamic fluctuations in appetitive and affective responses during ER influence changes in momentary subjective states which pose as significant barriers toward successful dietary adherence. Additionally, individual differences in levels of appetitive sensations during ER can be identified at baseline. Finally, retrospective and real-time measures of appetite appear to demonstrate some inconsistencies which may influence appetite-related conclusions that are drawn from interventional studies.

6.2.1 Measurement of appetite responses within naturalistic settings

The measurement of interventional effects on appetite responses have previously relied on laboratory-based environments or use of retrospective recall. These approaches are limited as appetitive processes and eating behaviours are heavily influenced by environmental factors

(Mela, 2006). Additionally, retrospective accounts of past experiences are known to be associated with several biases which can impact recall (Kahneman & Redelmeier, 1996). These accounts reduce our understanding of appetite to processes which were observed under highly controlled settings or as biased static snapshots throughout the course of an intervention. Naturalistic investigations are higher in external validity as measures are being taken where behaviours take place. However, these are characterised by a lack of experimental control which limits the internal validity of these approaches (Blundell et al., 2010). Nonetheless, it is still important to conduct investigations within naturalistic settings to complement and validate theoretical accounts obtained from laboratory-based investigations. Repeated measurement of appetitive and affective processes as participants go about their daily lives provides a better understanding of the real-world dynamic experiences of appetite regulation during ER where the barriers to dieting are encountered. These barriers can take the form of momentary changes in subjective states such as temptations where individuals are on the brink of breaking their diet, or lapses where something has been consumed which was not intended. These momentary states are important to measure as they are common real-world experiences that pose problems for successful weight loss but are notoriously hard to capture using lab-based and retrospective methods.

The measurement of dynamic fluctuations in appetitive responses to ER in naturalistic settings was accomplished by capitalising on advances in smartphone technology which increased the potential for real-time data capture. A testing application was developed and installed on loaned smartphones which allowed for real-time assessment of appetitive and affective processes during engagement with an IER dietary intervention using EMA. Real-time data capture was achieved by two methods of EMA in the studies detailed in this thesis: i) text-prompts to initiate a random assessment to achieve random sampling of moments throughout the day; ii) participant-initiated event-based assessments of dietary temptations and lapses to allow for measurements of appetite and affect during or shortly after experiencing a specific subjective momentary state.

Random assessments provide information on how appetite responses vary from moment to moment throughout the course of a day. Given the interventions in this study utilised both ER and nER days, it was also possible to assess how random moments also differ between type of days. Additionally, in Chapter Five utilising event-based assessments provided information on appetite responses whilst experiencing specific events such as a dietary temptation or lapse. These assessments could be contrasted to random assessments to provide information on how appetite responses are different in momentary states which pose as barriers towards successful dietary adherence. Furthermore, in Chapter Four, multiple data sources were integrated using time and date stamps which identified random assessments that took place proximal to an eating event so that appetite responses could be investigated in the moments leading up to energy intake. Shiffman & Waters (2004) took a similar approach to investigate negative affect during cigarette abstinence in smokers in the moments leading up to a lapse. As the authors noted, assessments which are identified using this type of approach provide further information above lapse assessments alone given lapse assessments still require some degree of retrospection as these assessments usually ask to recall experiences immediately prior to lapsing. Taken together, these demonstrate the utility of EMA for the assessment of real-time appetite responses to ER in naturalistic settings where the barriers to dieting are encountered. The methods and analysis techniques used in this thesis have helped provide a better understanding the dynamic relationship between heightened appetitive and affective processes and their impact on momentary subjective states which pose a problem for dietary adherence in the real-world.

In both Chapters Four and Five, evidence suggests that retrospective and real-time measures of appetite are, to some degree, inconsistent. Chapter Four demonstrated that a pre and post comparison of a 7-day retrospective recall of hunger indicated that this sensation decreased over the course of a 1-week 2d/week IER intervention. However, results obtained with EMA indicated hunger was significantly raised on two of the seven days. One possible explanation for this is that IER is assumed to aid individuals in recognising that they can cope with high levels of hunger (Harvie et al., 2011). Whilst this may appear to be a beneficial process as it demonstrates that when recalling appetite, individuals may remember their experiences as less intense than what they experienced in the moment. This obscures our understanding of the appetitive processes which actually take place throughout engagement with IER. Dynamic fluctuations in appetitive processes are what determine moments of dietary (in)adherence, therefore real-time measures are required if the role of appetite during IER is to be accurately understood.

The mean values of pre and post hunger scores in Chapter Four were similar raising questions of whether the statistically significant differences were of functional relevance. Given sensations have been found to be described as more frequent and intense on recall compared to real-time measures in other domains (Shiffman, Stone & Hufford, 2008), it was deemed important to investigate discrepancies between these approaches in appetite during IER.

Therefore, in Chapter Five, the associations between 7-day retrospective accounts of appetite with their real-time counterparts were investigated. It was found that these approaches demonstrated varying degrees of correction. Measures of satiety demonstrated the lowest levels of correlation: i) hunger demonstrated a modest correlation; ii) fullness demonstrated a weak correlation. These findings are theoretically important as hunger and fullness are among the most studied sensations during IER (Bhutani et al, 2013; Hoddy et al., 2016; Klempel et al., 2010), and could possibly be a reason as to why there is no current consensus on how these change throughout the course of IER-induced weight loss (Harvey et al., 2018). Intense ER common to very low energy diets is thought to result in favourable changes to appetite, notably reductions in hunger levels (Gibson et al., 2014). However, as the results in this thesis demonstrate, caution must be taken when interpreting retrospective accounts of appetite as these may be influenced by recall biases.

For example, in Chapter Five discrepancies were found between retrospective and real-time measures of appetite when these outcomes were utilised as between-person (baseline) predictors. Retrospective account of baseline hunger and cravings did not predict individual differences in appetite responses to ER, whereas aggregate scores from real-time measures which spanned the same period were predictive. Whilst a 7-day retrospective account of hunger was predictive of individual differences in hunger responses to ER in Chapter Four, there are multiple factors relating to differences in sample sizes and experimental design that could explain this which are discussed later. Nonetheless, these findings demonstrate that there is a potential for different effects to be produced based on the method of measurement employed which can potentially lead to different conclusions.

6.2.2 Multilevel modelling of appetitive responses

In Chapter One, it was established that appetitive responses demonstrate both a substantial amount of both within- and between-person variation which explains the large diversity in eating behaviours and weight-related changes to manipulations of energy intake (Gibbons et al., 2019). Recognition that individuals will not respond in the same way to the same treatment is essential for the development of more effective obesity treatments, therefore it is important to employ statistical models that account for both within and between sources of variation.

The findings in this thesis demonstrate the effectiveness of using multilevel modelling to understand predictors of both within-person fluctuations and between-person differences in appetitive processes. The statistical models employed throughout the experimental chapters demonstrate that accounting for hierarchical structures which arise in repeated measures design allows for within- and between-person predictors to be included as well as cross-level interaction terms. This allows to simultaneously identify an interventional effect of ER on within-person changes in appetitive measures (e.g. is hunger is raised during ER days compared to nER days?) as well as to identify how individual differences moderate these relationships (e.g. do individuals who experience greater levels of baseline hunger also experience a greater interventional effect of ER on hunger responses?).

The multilevel models created within this thesis mostly consisted of three random factors: i) level 1 (session) within-day; ii) level 2 (day) between-day; iii) level 3 (participant) between-person. These factors are treated as random samples from a wider population (e.g. random sample of within-day moments from a wider population of moments throughout the day) allowing for differences to be explained at each of these levels.

Regarding the session level, predictors explained what caused dynamic fluctuations in measurements from moment to moment. For example, in Chapter Four, eating in two hours was input as a session level variable which allowed to assess differences in appetite ratings on assessments which took place proximal to eating, and Chapter Five allowed to assess differences in moments of temptation and lapses by imputing these as session level variables. This level consistently demonstrated the largest amounts of variance which is unsurprising given sensations vary considerably from moment-to-moment. The findings within this thesis demonstrate that these fluctuations are an important driver of momentary states relating to dietary adherence, therefore approaches to understand and characterise this session-level (individual) variation such as N-of-1 designs may serve as useful approaches for the development personalised treatment plans for obesity (Vieira et al., 2017).

Regarding the day level, predictors explained what caused appetite to differ from day-to-day. This level consistently demonstrated the lowest level of variance which was mostly explained by including the ER contrast to distinguish ER and nER days. This indicates that experiences of appetite do not substantially differ between days other than differences that were caused by engagement with IER. For example, in Chapter Five, 100% of variance in fullness score was explained at the day-level after including ER as a variable meaning differences in the daily-average of fullness could be fully explained by the interventional effect of alternating days of ER.

Regarding the participant level, predictors explained individual differences in average ratings of appetite which relate to trait-like differences that remain relatively stable over time. Evidence was found in the experimental chapters that baseline measurements can be used to explain individual differences in appetitive responses to ER demonstrating that multilevel modelling can explain how individuals respond differently to the same intervention.

The findings within this thesis demonstrate that multilevel modelling is a powerful statistical approach towards a better understanding of appetite responses in repeated measures designs. These models produce less biased estimates compared to traditional ordinary least squares analyses such as ANOVA (Steenbergen & Jones, 2002) which can lead to over or underestimation of effects as a result of not accounting for hierarchical structures in datasets which results from co-dependency in observations (see Section 2.5.2 on P. 51). Accounting for hierarchical structures produces multiple levels of variation which allows for both interventional effects as well as individual differences in responses to be simultaneously explained.

6.2.3 Dynamic fluctuations of sensations as barriers towards dietary adherence

Across the experimental chapters in this thesis, real-time evidence obtained using EMA has highlighted that dynamic fluctuations in appetitive and affective processes which happen momentarily influence subjective states which pose a problem for successful dietary adherence. These heightened sensations are associated with experiencing a dietary temptation and precipitate eating events as well as dietary lapses. Differences in the intensity of sensations of appetite and affect do not distinguish temptations from lapses. It appears that rather than sensations increasing until they are at an unmanageable level; what distinguishes these states is the extent an individual engages in coping strategies to manage a temptation episode.

Previous theoretical accounts of appetite regulation during maintenance of a negative energy balance state decreased satiety and increased reward-processing of food-related cues is a product of maintaining a negative energy balance (Roberts et al., 2017). The findings of the current thesis expand on these by demonstrating that momentary changes to these factors influence subjective states which themselves pose as the barrier to successful dietary adherence. Event-based assessments of temptations and lapses are common in investigations using EMA and have been used to measure adherence to abstaining from alcohol, cigarettes, and illicit drugs (Shiffman & Waters, 2004; Waters, Marhe & Franken, 2012; Waters et al., 2020). These investigations are in alignment with the outcomes detailed in this thesis. These all suggest that dynamic changes in sensations which accompany subjectively experienced states during abstinence influence consummatory behaviour and inadherence in naturalistic settings.

In both Chapters Four and Five, evidence was found that appetite sensations were raised during ER days compared to nER days, but further changes in these sensations within ER days are what pose a greater issue towards successful adherence. Chapter Four demonstrated that hunger and cravings were raised in the moments leading up to an eating event supporting a previous free-living study that demonstrated dynamic increases in the intensity of cravings preceded snack consumption (Richard et al., 2017). However, the assessment method used in Chapter Four could not distinguish between intentional and unintentional eating which is an important factor to take into consideration when assessing dietary adherence. Previous evidence suggests that most dietary lapses are preceded by a temptation that arises from exposure palatable foods (Cleobury & Tapper, 2014). The strength of the temptation which mediated by momentary levels of hunger influence the likelihood of whether it leads to a dietary lapse (McKee et al., 2014). Chapter Five identified that hunger and cravings were higher, whereas fullness was lower during temptation and lapse assessments compared to random moments throughout ER days demonstrating the subjective experiences of dietary temptations and lapses are influenced by the underlying inter-relationship between satiety and reward-related processes. These demonstrate that EMA is well suited for detecting the influence of ER on appetite responses given environmental cues to consume within naturalistic settings which impact the experience of temptations are likely to have a greater effect on eating-related processes compared to standardised stimuli used in laboratory-based settings as not everybody is tempted by the same stimuli (Hofmann, Friese & Wiers, 2008).

Interestingly, in Chapter Five perceived stress did not differ between nER and ER days, though this sensation was found to be raised on event-based assessments compared to random moments on ER days. Goldstein et al. (2018b) reported increases in momentary perceived stress is associated with lapsing, and Mckee et al. (2014) found that the strength of a temptation was mediated by momentary perceived stress. Additionally, the meta-analytic investigation demonstrated that overall negative mood is raised on temptations and lapses compared to random assessments. Taken together, these findings imply that raised negative mood inclusive of perceived stress is not a persistent consequence of maintaining a negative energy balance (Jackson et al., 2014), but rather momentary increases in negative mood influence the likelihood of experiencing subjective states of dietary temptations and lapses. It is possible that increased momentary negative mood during ER results in the increased reward-processing of environmental cues and these lead to experiencing a dietary temptation when a reward has been processes. For example, emotional eating episodes occur due to the disinhibitory effects of experiencing strong emotions such as stress which drives intake of unhealthy high energy foods (Adams & Epel, 2007). This thesis has demonstrated that EMA is an effective methodology for understanding the real-world dynamic relationship between appetite and affect, and their implications for subjective moments of dietary adherence.

The current thesis also identified that coping strategies to manage with problematic momentary states may be a central component towards increasing dietary adherence. Engagement with coping strategies was the only factor which distinguished a temptation from a lapse episode in Chapter Five and other previous EMA investigations (Carels et al., 2004; McKee et al., 2014). Individuals who are unsuccessful at achieving and maintaining weight loss demonstrate a poor range of coping strategies and self-regulatory abilities to manage temptations (Johnson, Pratt & Wardle, 2012; McKee & Ntoumanis, 2014). These suggest that providing support to these individuals to aid with strategies to cope with the momentary states of temptation may be an effective approach towards increasing dietary adherence, particularly if these strategies can be personalised (Appelhans et al., 2016). Additionally, evidence from the meta-analyses suggest that negative abstinence-violation effects were raised following a lapse. Negative abstinence-violation effects such as reduced self-efficacy and feeling that the diet will be a success occur due to a violation to abstinence goals. These effects which follow a lapse may also increase the likelihood of another lapse occurring on the same day (Schumacher et al., 2018). The degree to which an individual can cope with these negative effects may have an impact on long-term weight loss success (Dohm, Beattie, Aibel & Stregel-Moore, 2001), therefore coping strategies to manage with abstinence-violation effects may also be effective for individuals who suffer from lowered self-attitudes following a lapse occurrence.

The meta-analytic investigation identified an important issue for investigations utilising EMA to measure momentary subjective states. Instructions to complete an assessment of a temptation or lapse can differ between investigations which can have a profound impact on findings. For example, some previous EMA investigations instruct participants to complete an assessment shortly following a lapse requiring participants to engage in some form of retrospection to recall how they felt immediately prior to a lapse occurring (e.g. Carels et al., 2001; 2004; McKee et al., 2014) whereas other requested participant to report their sensations in that moment, meaning lapse assessments measured how they felt following a lapse taking place (e.g. Forman et al., 2017). This may have affected the meta-analyses conducted in Chapter Three as there was no overall evidence for raised hunger sensations on lapse assessments compared to random assessments. For this reason, the same instructions that were provided to participants in Carels et al (2004) to complete temptations and lapses were used in Chapter Five as the appetitive and affective processes that precipitated a lapse episode were of interest, and this confirmed that hunger was raised in the moments leading up to lapsing. This highlights the importance of the instructions provided to participants for completing an event-based assessment. If the aim of the investigation is to understand the moments leading up to an event, then some form of retrospective recall will be required (e.g. how did you feel right before lapsing?). However, if the aim is to understand the moments following, then language relating to current sensations would be required.

Multiple cognitive tasks were employed throughout these investigations to investigate how dynamic fluctuations in automatic and reflective processes that underlie appetite can influence real world consumptive behaviour. Previous theoretical accounts suggest that state fluctuations in cognitive processes that are environmentally mediated may have more of an impact on behaviour rather than trait-like differences (Field et al., 2016; Jones et al., 2013a). The failure to detect any predictors of within-person fluctuations in attentional bias towards food-cues and the implications of these findings for the role of attention biases in obesity has been discussed in Section 4.5 (P. 131). The current thesis found evidence that behavioural control is characterised by both a within and between-person component as performance on both the food Go/No-Go and colour Stroop task demonstrated a multilevel structure. However, no predictors of performance were identified for overall performance of each task. Additionally, it has been claimed that increased sensations of negative affect such as perceived stress can result in a disinhibited state (van Strien, 2018), though no evidence was found that stress had a moderating impact on the relationship between behavioural control and daily energy intake.

It was assumed that engagement with ER would impact task performance as exertion of control overtime would deplete the cognitive resources required for effective behavioural control that would eventually lead to a disinhibited state (Tice et al., 2007). Interestingly, in Chapter Five there was some evidence which demonstrated reductions in behavioural control from Week 1 to Week 4 of the intervention. Specifically, Behavioural control was higher on

ER days of the start of the intervention, but this effect was no longer present during the last week. This evidence suggested that during the initial week of IER behavioural control was successfully being exerted over automatic responses towards cues to consume on ER days which resulted in weight loss. However, as weight loss occurred throughout the intervention, changes to appetite regulation caused by maintaining a negative energy balance (Roberts et al., 2017) could have resulted in individuals finding it harder to inhibit automatic responses towards food cues during ER days of the final week of the intervention. One possible reason for this is that persistent use of cognitive resources to control automatic behavioural responses to increasing appetitive and affective responses of the maintained negative energy balance over time may have exhausted the ability to control behaviour on ER days later in the intervention resulting in more errors. However, due to methodological limitations of the task used, it is unclear as to whether this reduction in behavioural control was a result of ego depletion or more general practise or fatigue effects.

Unfortunately, the cognitive tasks employed within this thesis suffered from some methodological limitations that are discussed further in Section 6.3.3 and 6.3.4 which may have impacted the findings in this thesis. Questions surrounding the role of fluctuations in cognitive processes in response to ER and their determining effect on real-world eating behaviour are still not fully resolved. Given the requirement of control over eating behaviour for successful dietary adherence and long-term weight loss, further EMA investigations are required to better understand the dynamic nature of behavioural control during ER.

6.2.4 Early identification of barriers towards dietary adherence

The experimental studies in this thesis identified that there were significant levels of individual variation in most appetitive outcomes. Evidence was found for individual differences in appetitive responses to ER for hunger and cravings across the studies meaning that sensations increased as a result of engaging in ER and those who scored higher on certain baseline measures experienced even greater increases in these sensations as a result of ER. The findings in this thesis provide support that individual differences in appetitive responses to ER measured using EMA can be identified using baseline measures. This finding has implications for the early identification of individuals who may benefit from additional support during weight loss.

In Chapter Four, TFEQ-H score moderated the relationship between ER and hunger score which was also replicated using a baseline 7-day retrospective measure of hunger.

Additionally, PFS identified individual differences in levels of cravings, but this did not moderate the relationship between cravings and ER. In Chapter Five, no evidence was found that TFEQ-H or a baseline 7-day retrospective measure of hunger predicted individual differences in hunger responses to ER. However, PFS was found to moderate the relationship between ER and intensity of cravings. Cravings were higher on ER days and individuals who scored higher on the PFS experienced greater increases of cravings on ER days.

Greater baseline hunger as well as trait craving score has previously been associated with lower levels of weight loss (Franken & Muris, 2005; Sayer et al., 2018) implicating tendencies towards experiencing strong levels of these appetitive sensations as a barrier towards successful dietary adherence. One previous free-living investigation identified that increases in momentary intensity of craving score predicted subsequent snack consumption and this effect was greater in individuals who scored high on a trait craving questionnaire at baseline (Richard et al., 2017). This finding is in agreement with those found within this thesis that momentary increases in sensations of hunger and cravings accompany experiences of temptations as well as in the moments leading up to eating or a lapse episode. Individuals who have tendencies towards experiencing stronger sensations on average may struggle to cope with increases in these sensations during ER which could impact weight loss.

It is interesting that findings relating to TFEQ-H, 7-day retrospective ratings of sensations, and PFS were not consistent across the experimental studies. Whilst these could be a result of methodological differences between the two studies relating to the sample size, intensity of ER or the format of rating scales employed, this highlights that identifying baseline measure which are consistently associated with the real-world experiences of appetitive sensations is one of the major problems for establishing individual differences in appetitive responses to ER. In both Chapters Four and Five, multiple baseline measures were examined as potential moderators of appetitive responses to ER; however, only the TFEQ-H and PFS were identified as significant throughout the course of the thesis. Additionally, these measures only explained small amounts of variance in sensation scores in both experimental chapters meaning the utility of these in predicting meaningful difference may be questioned.

In Chapter Three, EMA studies were identified which utilised between-person differences in average levels of sensations to predict lapse reporting. For example, Goldstein et al. (2018b) established that using between-person differences in aspects of negative affect as well as hunger could be used to predict a greater likelihood of reporting lapses. This prompted the N-of-1 exploratory approach taken in Chapter Five towards building a baseline appetite profile prior to engagement with the IER intervention. This profile was used to predict individual differences in appetitive responses to ER prior to engagement with the intervention. Past behaviour is one of strongest predictors of future behaviour (Ouellette & Wood, 1998), which may explain why the baseline phase of real-time hunger and cravings ratings were among the strongest predictors of individual differences identified within this thesis. Interestingly, these also performed better at predicting individual differences in appetitive responses to ER than baseline 7-day retrospective measures of appetite spanning the same time suggesting a baseline real-time measurement phase may be more suited at establishing individual differences in appetitive processes compared to retrospective accounts. In summary, this thesis has demonstrated the possibility of explaining individual differences in real-time appetitive responses to ER at baseline using retrospective recall measures, eating behaviour trait inventories, and a baseline measurement phase.

6.3 Limitations

6.3.1 Issues in lack of experimental control

The most limiting factor of the investigations detailed within this thesis is the lack of experimental control inherent in studies conducted in naturalistic settings. Given that control is not exerted over the environment where testing takes place, it is difficult to establish true causality. Whilst sensitivity analyses were performed to assess whether factors relating to consumption or distractions during completion of cognitive tasks impacted results, it is likely there are many other confounding factors that could not be controlled. In addition, there was no validation that participants engaged in ER during ER days for either of the interventions. In Chapter Five, weight was measured weekly which is likely to improve compliance and does provide an indication that a negative energy balance had been achieved. However, weight change does not provide information on whether the negative energy balance was entirely achieved by compliance with the study protocol.

6.3.2 Issues in self-reported measures

In addition to the confounding factors which relate to recent consumption, self-reported measures could also be subject to demand characteristics, particularly under naturalistic settings. For example, participants would intuitively know that hunger and cravings would be expected to be raised on ER days. Given the lack of validation of whether participants engaged in ER, responses could have been a result of reporting the expected effects of appetite responses rather than a direct effect of the manipulation to energy balance. Additionally, reactivity to assessments could also have an impact on subjective ratings given the intensity of monitoring involved in EMA. Self-monitoring a certain behaviour may alter the frequency of that behaviour (Kazdin, 1974). Reactivity to EMA protocol has been investigated in other areas such as alcohol and smoking cessation and these have found evidence of a small effect (Hufford et al., 2002; Rowan et al, 2007). Nonetheless, reactivity in EMA investigations of eating behaviour has yet to be investigated, therefore the extent of this issue in the investigations of this thesis is unknown.

In addition, food diaries are known to suffer from a degree of underreporting, particularly in individuals with overweight and obesity (Wehling & Lusher, 2019). In Chapter Five, an app-based calorie counter was employed which was used to investigate a supplementary research questions relating to reductions in daily energy intake on nER days of IER diets (Harvey et al., 2018), though underreporting of energy intake could contribute to the apparent carryover effect reported in this literature. In Chapter Four, a photographic food diary was employed which was likely to have suffered from underreporting as participants may experience reluctance to photograph food, particularly if the food was unhealthy or constituted as a moment of dietary inadherence on ER days. This limitation could also apply to rating of temptations and lapses. Given lapses are incidences where participants have broken their diets and are accompanied by lowered self-attitudes (see Chapter Three), there is a possibility that this could affect whether a participant reported a lapse occurring.

6.3.3 Limitations of study materials

OpenSesame runtime for Android was used as the platform for *APPetite* because this programme allowed the implementation of cognitive testing and subjective ratings in one platform and operated similar to smartphone apps. However, this programme had limited capabilities for use on smartphone devices. For example, VAS were not implemented in Chapter Four due to time constraints as these measures could not be adapted to run on smartphone devices. VAS ratings are sensitive to small effects (Livingstone et al., 2000), therefore it is possible that these rating scales may be better suited to detect individual differences given there is more possibility for variation in responses compared to the Likert scales that were employed.

In addition, technological capabilities of the loaned smartphone devices were limiting factors for the cognitive tasks employed within the study. For example, in Chapter Four as it was deemed important to employ both an attentional and inhibitory measure, the colour Stroop task was implemented as an index of behavioural control due to the similarities of this task with the Food-related Stroop task. Employment of a more appropriate cognitive task to measure food-related inhibitions such as the Go/No-Go in addition to the food-related Stroop task was not possible. Additionally, in Chapter Five a limited number of images could be utilised for the Go/No-Go task. Given the extent of repeated implementation of this measure throughout the study period, practise and fatigue effects are likely to have occurred which would likely impact long-term performance on tasks employed within this thesis.

6.3.4 Ecological Momentary Assessment for use in dietary investigations

In Chapter Four, a pilot test was run to establish that the EMA study protocol was viable for 1-week of engagement with an IER intervention which deemed measurements were suitable for repeated implementation for the study timeframe. During this initial pilot test, one factor which was considered to be important was establishing a personal rapport with the participant. Given the lack of experimental control following the initial lab visit, it was deemed necessary to keep regular contact with participants to ensure no problems occurred during the study. This included requesting confirmation texts from participants to verify assessments were completed, reminders that the following day was an ER day, and check-up messages to ensure participants were not experiencing any problems with the smartphone or dietary intervention. This constitutes as a major strength of the implementation of EMA in these investigations as problems could be dealt with as and when they arose limiting the impact of problems on subsequent data collection.

Another strength of the implementation of EMA in the investigations in this thesis was utilising both random assessment as well as event-contingent assessments which provided data on both random moments throughout the day as well as salient experiences that are common to dieting attempts. This design provided insights into appetitive and affective processes during IER which could not have been identified with traditional recall methods. However, one limitation of this component was that emphasis was put on completing RAs which may have impacted the other EMA measures such as the photographic food logs (Chapter Four) and event assessments (Chapter Five). Financial compensation was contingent on the amount of RAs completed as well as requesting confirmation texts for when these were completed. This may have inadvertently taken focus away from other measures that were employed within the studies. Future investigations employing EMA in dietary interventional studies may benefit from placing equal emphasis on all measures employed within the study, i.e. text reminders to complete temptation and lapse assessments during ER days.

One major limitation of EMA in these investigations was the additional burden associated with completing cognitive tasks. In both Chapters Four and Five, RAs took approximately five minutes to complete which is a substantial amount of time required out of a participant's day, particularly during working hours. Additionally, as the cognitive tasks require maintained attention for this period, participants were instructed to find a safe place to perform an assessment free from any distractions. This means that participants were required to find a suitable time and place within 45 minutes of receiving a random prompt impacting both the ecological and momentary aspect of these assessments. Notably, in Chapter Five, to reduce participant burden there was a 25% chance that EAs would also include a cognitive task. However, very few EAs including the Go/No-Go task were performed. During analyses, many of the EA datafiles were cut short when these tasks were implemented, meaning participants would close the application following VAS and contextual questions if the Go/No-Go appeared. However, this was not observed to be a frequent occurrence for RAs throughout Chapters Four and Five. This seems to suggest that due to the emphasis being placed on completion of RAs, participants would deal with the burden of completing cognitive tasks which was potentially influenced by financial consequence of not properly completing assessments. However, when they had knowledge that there was an element of chance for this task to be implemented, participants would not be willing to take on this additional burden.

In light of these limitations, it may be the case that cognitive testing on EMA platforms may be unviable due to the additional burden it places on participants as they go about their daily lives. It is unclear as to the extent of how these limitations impacted the findings within this thesis or whether these cognitive tasks are generally not predictive of eating-related behaviours. Undoubtably, the technological capabilities of the smartphones used had an impact on measures (discussed in Section 6.3.3) meaning future investigations may benefit from gamification of tasks which may optimise participant engagement as well as personalised stimuli which may increase their predictive validity (Forman et al., 2018). However, a well-designed task will not change the burden and fatigue effects resulting from the time taken to complete these tasks whilst adhering to study protocol (i.e. within the timeframe provided for completing an assessment). These effects are also likely to be momentary in nature such as higher levels of engagement after working hours. This could mean that findings which are yielded from EMA may suffer from issues relating to reliability which will reduce the ability to adequately assess their predictive validity for eating behaviours.

This problem may also have ramifications for the development of cognitive training aimed at modifying cognitive processes that underlie problematic eating behaviours. It may prove to be the case that tasks are most effective when engagement is high. If this is the case, then studies investigating the effectiveness of cognitive training on reducing energy intake or weight through methods such as Ecological Momentary Intervention would need to assess whether there is any additional benefit of cognitive training tasks compared to a sham training task or no task after accounting for study engagement.

6.4 Implications and future directions

The findings from this thesis indicate that whilst appetite is raised during engagement with ER, it is dynamic fluctuations in appetite and negative affect which accompany momentary subjective states that pose as a problem for dietary adherence. Engagement with coping strategies during moments of temptation is what distinguishes whether a temptation leads to a lapse. Furthermore, individual differences in appetite responses to ER can be identified at baseline before engagement with a dietary intervention. Previous research into temptation management strategies have identified that tailoring the delivery of management strategies based on key individual differences may improve intervention success rate (Appelhans et al., 2016). Early identification of those who may struggle to cope with raised sensations during ER could help tailor personalised strategies to manage temptations which may aid with increasing adherence to dietary interventions.

Future research could build on the design that was employed in Chapter Five by utilising a baseline measurement phase whereby individuals rate their appetite using EMA prior to engagement with an intervention. This would provide an appetitive profile that could be used to tailor a temptation management strategy and could be implemented using Ecological Momentary Intervention. Participants would be taught to engage with this strategy anytime they experienced a dietary temptation during ER. The efficacy of this approach for aiding with weight loss could also be investigated in an RCT whereby participants are randomised to receive either the personalised temptation management plan, a generic temptation management plan or no aid.

However, the effectiveness of this approach may be limited if baseline ratings do not predict weight loss. Currently, there has yet to be an investigation of whether baseline differences in appetite responses can be used to predict weight loss over the course of a structured IER intervention. One previous study has been identified which investigated 3-months of 2d/week consecutive IER intervention and employed both baseline ratings of hunger as well as ratings of hunger on ER days during 1-month follow-up (Harvie et al., 2013). Following correspondence with the primary author, an analysis protocol is currently under preparation which will answer the research question of whether baseline differences in hunger can predict weight loss at 3-month follow-up, and whether this relationship is mediated by hunger scores on ER days during 1-month follow-up of the intervention.

Additionally, the studies within this thesis were of the short-term impact of ER on appetitive processes and dietary adherence, therefore the longer-term effects were not investigated. Many weight loss attempts are unsuccessful in the long-term, with individuals regaining weight within 3-5 years after initial weight loss (Maclean et al., 2015). In addition, average levels of appetite appear to change over the course of IER interventions (Harvey et al., 2018). Longer investigations are required to better understand the prolonged impact of IER appetite and its impact on dietary adherence throughout the course of weight loss as well as throughout a period of weight loss maintenance.

Finally, the findings in this thesis have implications for future dietary interventional research employing measures of appetite. Retrospective measures of appetite demonstrate varying degrees of correlation with real-time measures, particularly for measures of satiety which may lead to erroneous conclusions surrounding changes that occur to appetite throughout weight loss. Investigations which assess the impact of intervention on sensations may wish to use EMA probe weeks whereby appetite is rated in real-time at specific time-points in the intervention (e.g. Forman et al., 2017) rather than employing retrospective recall methods.

6.5 Concluding remarks

Appetite is fundamentally a biologically driven process influenced by environmental and affective processes which is compromised during negative energy balance to orientate behaviours towards restoring a state of energy balance. However, these responses are seldom measured in the context where they take place, meaning that the impact of dynamic changes on dietary adherence is an understudied area.

This thesis examined appetite control during ER in naturalistic settings in a sample of individuals with overweight and obesity using EMA. The primary aim of this thesis was to examine how dynamic fluctuations in appetitive responses to ER differ between momentary subjective states which pose as barriers towards successful dietary adherence. Evidence was found for heightened appetitive and affective responses among temptations and immediately prior to eating behaviour including dietary lapses, and engagement with coping strategies are what distinguishes temptations from lapses. These findings demonstrate the importance of measuring real-time dynamic fluctuations in appetitive and affective responses to ER to aid in the understanding of the impact of appetite regulation on moments of dietary (in)adherence.

Appetite regulation also demonstrates large amounts of individual differences in responses to manipulations of energy balance which may underlie the large diversity in eating behaviours and weight-related responses to dietary manipulations. To better understand these differences, the secondary aim of this thesis was to examine whether baseline measures of appetite and eating behaviours could be used to explain individual differences in appetitive responses to ER. Evidence was found that baseline measures of eating behaviours relating hunger and cravings explained individual differences in changes in these sensations that occur as a result of ER. Additionally, it was demonstrated that utilising a baseline measurement phase prior to engagement with an intervention could predict large amounts of individual differences in appetite responses to ER which could be used as early identification of appetitive processes which may pose as barriers to dietary adherence so individuals could receive additional personalised support based on their appetitive profile.

In closing, this thesis expands on previous laboratory-based investigations by demonstrating that EMA is an effective methodology for assessing the interplay between dynamic fluctuations in appetite and affect, and their impact on momentary subjective states which pose as barriers to dietary adherence during a negative energy balance. The findings presented here provide the basis for future investigations into the real-time measurement of appetite responses to ER in naturalistic settings as well as for the development of personalised strategies to aid in adherence to energy-restricted diets.

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