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Computational mechanisms underpinning greater exploratory behaviour in excess weight relative to healthy weight adolescents

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ABSTRACT

Obesity in adolescence is associated with cognitive changes that lead to difficulties in shifting unhealthy habits in favour of alternative healthy behaviours, similar to addictive behaviours. An outstanding question is whether this shift in goal-directed behaviour is driven by over-exploitation or over-exploration of rewarding outcomes. Here, we addressed this question by comparing explore/exploit behaviour on the Iowa Gambling Task in 43 adolescents with excess weight against 38 adolescents with healthy weight. We computationally modelled both exploitation behaviour (e.g., reinforcement sensitivity and inverse decay parameters), and explorative behaviour (e.g., maximum directed exploration value). We found that overall, adolescents with excess weight displayed more behavioural exploration than their healthy-weight counterparts – specifically, demonstrating greater overall switching behaviour. Computational models revealed that this behaviour was driven by a higher maximum directed exploration value in the excess-weight group ($U = 520.00$, $p = .005$, $BF_{10} = 5.11$). Importantly, however, we found substantial evidence that groups did not differ in reinforcement sensitivity ($U = 867.00$, $p = .641$, $BF_{10} = 0.30$). Overall, our study demonstrates a preference for exploratory behaviour in adolescents with excess weight, independent of sensitivity to reward. This pattern could potentially underpin an intrinsic desire to explore energy-dense unhealthy foods – an as-yet untapped mechanism that could be targeted in future treatments of obesity in adolescents.

1. Introduction

The prevalence of obesity in adolescence is concerningly high, with over 340 million children and adolescents reported as obese in 2016 (World Health Organisation, 2021). Adolescent obesity is considered a major public health issue (Karnik & Kanekar, 2012; Sanyaolu et al., 2019), as it represents a risk factor for physical and psychological comorbidities, and is a predictor of adult obesity (Pulgarón, 2013; Simmonds et al., 2016; Whitaker et al., 1997). Obesity in adolescence is associated with the overconsumption of energy-dense foods, leading to a sustained imbalance between energy intake and expenditure (Hill et al., 2012; Kuźbicka & Rachoń, 2013; Turconi et al., 2008). However, treatments which aim to reduce the intake of unhealthy foods and engage adolescents in healthier options have had limited success in the long-term maintenance of weight loss (Butryn et al., 2010; Reinehr et al., 2009). This reflects the multifactored and highly heterogeneous nature of obesity, a condition linked to multiple etiological factors including genetic, intergenerational, environmental, cognitive, behavioural and socioeconomic drivers (González-Muniesa et al., 2017). One such factor which has been of interest in recent years is the neurocognitive drivers influencing obesity. For example, individuals with obesity may experience difficulty in shifting unhealthy habits in favour of alternative healthy behaviours – similar to the cognitive changes seen in addictive disorders (Pinna et al., 2015; Stice et al., 2013). Examining the cognitive mechanisms and decision-making behaviours that drive poor food choices and dietary regulation in adolescent obesity is therefore critical in understanding the nature of obesity in adolescence (Bozkurt et al., 2017; Liang et al., 2014; Stice et al., 2013).

The exploration/exploitation framework offers a new approach to investigating the cognitive processes driving decision-making behaviour, including those involved in obesity. This framework outlines the choices individuals make to either seek out unfamiliar options with potentially greater reward values (exploration), or select familiar options with known reward values (exploitation; Addicott et al., 2017).

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These processes operate together to facilitate the learning and acquisition of potential rewards in the environment (Addicott et al., 2017; Cohen et al., 2007). Approaches to solving the explore/exploit dilemma typically involve a balance between an initial period of exploration, and subsequent exploitation, although this can be influenced by factors such as the individual's learning rate or sensitivity to rewards (Addicott et al., 2017; Smith et al., 2020).

Associations between obesity and an unhealthy diet may reflect an imbalance in explore/exploit behaviour. One theory is that individuals with obesity tend to prioritise familiar, easily-accessible food rewards and behaviours (e.g., consuming sugary beverages throughout the day; Sahoo et al., 2015) over adopting new healthy foods or behaviours (e.g., joining a sports activity; Olds et al., 2011), thus leading to over-exploitation. However, an alternative view is that people with obesity seek out several sources of energy-dense food (Drewnowski, 1991; King, 2013), which may instead reflect the over-exploration of unhealthy foods. Examining the direction of such explore/exploit imbalances in adolescents allows for a better understanding of the processes driving decisions and behaviour in these populations, and guidance of future treatments of adolescent obesity.

Despite the potential utility of the explore/exploit framework in examining behaviours in obesity, it is currently unclear whether such behaviours in adolescents with obesity differ from those with a healthy weight. To date, only one study has directly examined explore/exploit behaviour in obesity (and was part of a larger study on alcohol-use disorder, and obesity with and without binge-eating disorder; Morris et al., 2016). This study found no significant group differences in exploration behaviour between obese and healthy groups. However, participants were adults with obesity, who may show different patterns of explore/exploit than adolescents (for example, due to greater sensitivity to rewards and less influence of control systems in adolescents compared to adults; Constantinidis & Luna, 2019; Telzer, 2016), and the task did not require the reinforcement learning of different reward outcome magnitudes across different choice options – which may be particularly relevant to behaviours relevant to food choice.

The Iowa Gambling Task (IGT; Bechara et al., 1994) is a widely-used cognitive measure of decision-making, which is amenable to investigate explore/exploit behaviours (Ligneul, 2019; Robinson et al., 2022). The IGT requires participants to select cards from one of four decks, two of which contain more advantageous cards, and two of which contain more disadvantageous cards. Participants must learn which decks yield greater net rewards, and sample them accordingly to maximise their rewards. Thus, the IGT incorporates elements of both exploration (initially selecting across multiple decks to learn which are advantageous), and exploitation (consistently selecting the decks which are more rewarding; Ligneul, 2019; Robinson et al., 2022). Importantly, although the IGT has proven to be useful in investigating explore/exploit behaviour in the context of substance use disorders (e.g., by examining and modelling various behavioural patterns throughout the task; Robinson et al., 2022), the IGT has not yet been used to examine explore/exploit behaviour in obesity research. For example, previous work applying the IGT in adolescents with obesity has instead focused mainly on overall task performance (e.g., total rewards) as a measure of altered decision-making, with overall mixed results (Kittel et al., 2017; Lensing & Elsner, 2017; Rotge et al., 2017; Umbach et al., 2019; Verdejo-García et al., 2010). Thus, understanding the computational mechanisms driving explore/exploit behaviour on the IGT in adolescents with obesity has the potential to clarify discrepancies between studies.

In this study, we asked whether adolescents with obesity demonstrated different explore/exploit behaviour during decision-making than healthy-weight age-matched controls. Participants performed the IGT, and we computationally modelled their behaviour using a model that captures specific parameters involved in explore/exploit behaviour – the Value plus Sequential Exploration model (VSE; Ligneul, 2019). In contrast to previous models of the IGT used in the wider non-obesity research, which have focused on exploitation behaviour alone (i.e., value-based learning), the VSE considers the additional role of exploration (i.e., information-seeking shaped by choice history). By simultaneously measuring mechanisms involved in exploitation (reinforcement sensitivity, inverse decay), and directed exploration (directed exploration learning rate, directed exploration bonus), the VSE allows for a greater understanding of the mechanisms underlying explore/exploit behaviour.

2. Materials and methods

2.1. Design

We analysed a cross-sectional dataset of adolescents with excess and healthy weight, who performed the IGT as part of a larger study examining cognition and decision-making in obesity (Verdejo-Garcia et al., 2015; Westwater et al., 2019).

2.2. Participants

The initial screening and exclusion procedure has been described previously (Verdejo-Garcia et al., 2015; Westwater et al., 2019). In brief, participants were excluded if they: 1) had comorbid medical conditions (e.g., diabetes, fatty liver disease, and hypertension); or, 2) reported neurological or psychological disorders, as indicated by clinical interviews, scores on the Beck Depression Inventory (Beck et al., 1996), and self-report items adapted from the DSM-5 (APA, 2013). Data were available for 81 adolescents aged between 14 and 19 years of age (*M* ± *SD*, 16.69 ± 1.51, 46 female). Participants were divided into two groups based on their age-adjusted BMI percentile (Cole & Lobstein, 2012): the healthy-weight group comprised individuals whose weight ranged from the 5th to 85th percentile (exclusive; n = 38), and the excess-weight group comprised individuals whose weight was ≥85th percentile (n = 43). Participants were recruited in Granada, Spain via flyers distributed in universities, local newspapers, social media, hospitals and clinics, and surrounding schools. Table 1

Table 1
Descriptive statistics of sociodemographic characteristics in adolescents with excess and healthy weight.

	Excess weight group	Healthy weight group	Frequentist Mann. Whit.	Bayes Factor Mann. Whit.	Chi-Square
Sex (F/M)	25F/18M	21F/17M	$p = .800$	$BF_{10} =$ 0.27	
Age	16.74 (1.65)	16.63 (1.36)	$p = .559$	$BF_{10} =$ 0.30	
Education (years)	10.74 (1.65)	10.63 (1.36)	$p = .559$	$BF_{10} =$ 0.29	
Height (cm)	167.22 (8.06)	167.16 (8.54)	$p = .991$	$BF_{10} =$ 0.25	
Weight (kg)	84.23 (14.04)	59.58 (8.95)	$p < .001$	$BF_{10} =$ 14771.26	
BMI (percentile)	94.95 (3.33)	45.72 (20.09)	$p < .001$	$BF_{10} =$ 21863.05	
Fat %	29.70 (2.58)	16.04 (7.51)	$p < .001$	$BF_{10} =$ 817.26	
Monthly Income					$Chi^2 = 5.79$ $p = .33$
<600€	9.4%	10.7%			
601-1000€	9.4%	25.0%			
1001–1500€	28.1%	21.4%			
1501–2000€	18.8%	3.6%			
2001–2499€	9.4%	7.1%			
>2500€	25.0%	32.1%			

Note. The International Obesity Task Force healthy weight cut-off for adolescents (weight ≥85th percentile score; Cole & Lobstein, 2012) was used to classify excess weight. Household monthly income intervals as per guidelines of the Spanish National Institute of Statistics.

presents sociodemographic and body composition statistics for each group.

2.3. Procedure

Eligible participants took part in face-to-face experimental sessions, where they undertook assessments of weight, height and body fat measures, and completed the IGT. BMI was calculated for each participant by dividing their weight in kilograms by the square of their height in metres. Weight and body fat percentage information were collected using a digital scale and body composition analyser (TANITA BC-420; GP Supplies Ltd, London, UK). A percentile cut-off for excess weight was set to 85, in line with the International Obesity Task Force healthy weight cut-off for adolescents (Cole & Lobstein, 2012). Study procedures were approved by the Ethics Committee for Human Research of the Universidad de Granada, and informed consent was obtained from participants and parents.

2.4. Measures

2.4.1. Iowa Gambling Task

The IGT (Bechara et al., 1994) is a computer-based task which requires participants to select 100 cards from four card decks (A, B, C, D), with the aim of maximising net rewards. Each card is associated with either a small or large reward or loss in game-based currency, and each deck of cards contain a different number of reward and loss cards. Two of the decks (A and B) provide large rewards but even larger losses, leading to a net loss, and are thus considered “disadvantageous”. The other two decks (C and D) provide modest wins but even smaller losses, leading to net gains, and are thus considered “advantageous”. Further, the likelihood of drawing ‘loss’ cards is higher in decks A and C (50% likelihood) than decks B and D (10% likelihood). Participants were given standardised instructions of the task, that informed them to be aware that some decks are more advantageous than others. However, they were not specifically told any other details about the reward/loss nature of the decks. The main performance metric derived from the IGT is the net score, calculated with the formula [(C + D) - (A + B)], which reflects overall preference for advantageous versus disadvantageous decks across the 100 trials. During the task, participants were shown a green bar indicating the amount of game money they had accumulated at any point in time, but were not told how this would translate into the task net score.

2.4.2. Choice behaviour

We analysed raw choice data on the IGT with five behavioural measures: win/stay, lose/switch, mutual information, choice entropy, and sequential exploration (Ligneul, 2019). Win/stay and lose/switch behaviour respectively refer to the frequency that participants choose from the same deck after a reward or select from a different deck after a loss. Mutual information measures the degree to which a choice on the current trial predicts future choices, with higher values reflecting better predictions. Choice entropy indicates the degree to which individuals' sample across the four decks: at 0, this value means the participant only selected from one deck; at the maximal value of 2, participants would have selected evenly from across all four decks (i.e., 25 choices each). Finally, sequential exploration measures the frequency with which individuals sample from separate decks over three (‘sequential exploration 3’) or four (‘sequential exploration 4’) consecutive trials. Together, these measures supplement the VSE model by providing an overall understanding of participants' choice behaviours on the IGT, as well as help to place findings into context with prior research.

2.4.3. Exploration/exploitation modelling: value plus sequential exploration model

We modelled participants' choices using the VSE model – a recent computational model which disentangles exploitation and directed exploration (Ligneul, 2019). Parameter recovery, model recovery and simulation analyses have confirmed that the VSE model provides a better fit than other commonly applied models of the IGT (Ligneul, 2019; Obeso et al., 2021; Robinson et al., 2022). The VSE model estimates five key parameters (Table 2): reinforcement sensitivity, inverse decay, directed exploration bonus, directed exploration learning rate, and consistency.

2.5. Statistical analyses

To compare choice behavioural measures and VSE parameters between groups, we conducted Bayesian and frequentist Mann-Whitney *U* tests, using JASP 0.16.1.0. For Bayesian analyses, a Bayes Factor (BF_{10}) of $<1/3$ indicated evidence that the groups did not differ, and >3 indicated evidence that the two groups differed (van Doorn et al., 2021). For frequentist analyses, alpha was set at $\alpha = 0.05$. We implemented the VSE model (Ligneul, 2019) using the VSE Toolbox in MATLAB 2017a (MATLAB, 2017).

Outliers were defined as individuals whose choices on one or more measures of raw behaviour (i.e., net score, win/stay, lose/switch, mutual information, choice entropy, and sequential exploration over three/four trials) were >3.29 standard deviations from the mean (Tabachnick & Fidell, 2013). This affected two participants from the excess-weight group and one participant from the healthy-weight group, who were removed from the analyses.

To confirm that the VSE model provided a good fit to participants' choices, we compared the Akaike Information Criterion (AIC) of six different models: 1) the VSE model; 2) the Expectancy Valence model (Stout et al., 2004); 3) the Prospect Valence Learning model (Ahn et al., 2008); 4) the PVL-delta model (Ahn et al., 2008); 5) the Value Plus Perseverance model (Worthy et al., 2013); and 6) the Outcome-Representation Learning model (Haines et al., 2018). Appendix A provides a brief explanation of these models.

Table 2
Definitions of Parameters in the VSE model.

Parameter Name	Definition	Interpretation
Reinforcement Sensitivity, θ	Influences the strength of rewards and losses on estimates of value.	Smaller values reflect a weaker sensitivity to the value of rewards/losses equally. Greater values reflect a greater sensitivity to the value of rewards/losses equally.
Inverse Decay, Δ	The number of previous trials that participants use to guide their choice.	Smaller values indicate a lower number of previous trials used to guide the current decision. Greater values reflect a higher number of previous trials used to guide the current decision.
Directed Exploration Bonus, φ	The maximal value that a person's exploration value can reach.	Negative values indicate an overall preference to keep selecting familiar decks (exploitation). Positive values indicate an overall preference to explore recently unselected decks (directed exploration).
Directed Exploration Learning Rate, α	The rate at which the value of exploring returns to the maximum exploration value, following a recent decision to explore.	Smaller values reflect a slow return to the maximal explore value. Greater values reflect a quick return to the maximal explore value.
Consistency, C	Reflects stochastic behaviour	Greater values reflect behaviour with greater consistency to the VSE model. Smaller values reflect more unpredictable behaviour to the VSE model.

Note. Adapted from Robinson, A. H., Chong, T. T.-J., & Verdejo-Garcia, A. (2022).

3. Results

3.1. Behavioural analyses

On average, neither group achieved a positive net score (excess weight: $M \pm SD$, -2.21 ± 17.75; healthy weight: $M \pm SD$, -3.67 ± 29.25), indicating that they were consistently selecting more disadvantageous than advantageous decks throughout the task. Overall, there was a null difference in net scores between the groups, $U = 857.00$, $p = .708$, $BF_{10} = 0.25$ (Fig. 1).

However, there were significant differences in choice behaviour between the two groups (Fig. 2). Notably, the excess-weight group were less likely than the healthy-weight group to choose a deck that had just been rewarded (win/stay: $U = 1167.50$, $p < .001$, $BF_{10} = 11.34$), and more inclined to select a different deck after losing money (lose/switch: $U = 518.50$, $p = .005$, $BF_{10} = 8.35$). The excess-weight group also showed higher mutual information – indicating that subsequent choices were autocorrelated ($U = 488.00$, $p = .002$, $BF_{10} = 14.29$), and greater choice entropy – indicating that individuals chose more evenly across the four decks of the task ($U = 484.50$, $p = .002$, $BF_{10} = 14.19$). Further, the excess-weight group showed greater sequential exploration scores across consecutive trials throughout the task (three consecutive trials, $U = 423.50$, $p < .001$, $BF_{10} = 29.17$; four consecutive trials, $U = 412.50$, $p < .001$, $BF_{10} = 30.67$; Fig. 3). Overall, this pattern of behaviour suggests that the excess-weight group were more likely to engage in behavioural exploration. To understand the mechanisms driving this behaviour, we proceeded to analyse choices with the VSE model.

3.2. Modelling and comparing explore/exploit mechanisms between groups

The VSE model had the best fit in both excess-weight and healthy-weight groups compared to all other models: EV (ΔAIC relative to the VSE = 1669.93), ORL (ΔAIC = 385.02), PVL (ΔAIC = 1578.15), PVLdelta (ΔAIC = 1760.26), and VPP (ΔAIC = 1092.00). Appendix B outlines the AIC values for each group.

There was substantial evidence that the excess-weight group had a higher exploration bonus than the healthy-weight group, indicating that the former had a greater preference to explore recently unselected decks ($U = 520.00$, $p = .005$, $BF_{10} = 5.11$; Fig. 4). This is consistent with the earlier analyses showing that individuals with excess weight had a greater tendency to sample more widely across different decks. In keeping with this result, we also found anecdotal evidence that the excess-weight group had less stochastic behaviour than the healthy-weight group (consistency parameter; $U = 546.00$, $p = .010$, $BF_{10} = 2.62$). Importantly, there was substantial evidence that the groups did not differ in either their reinforcement sensitivity ($U = 867.00$, $p = .641$, $BF_{10} = 0.30$), or the rate at which they reached their respective maximal exploration values (directed exploration learning rates; $U = 770.00$, $p = .662$, $BF_{10} = 0.24$). There was also anecdotal evidence that the excess-weight group used fewer previous trial outcomes to guide any given decision, as indicated by a lower inverse decay parameter ($U = 1014.00$, $p = .063$, $BF_{10} = 1.18$).

3.3. Testing attention levels of adolescents with excess weight

To ensure that our findings were not due to differences in attention between groups, we conducted further analyses on participant reaction times. If the greater exploration of adolescents with obesity was due to differences in attentiveness during the IGT, we hypothesised that they would show greater response time variability. We recorded each participant's response time variability across the task, and compared these responses between groups. Response time variabilities were calculated by finding the coefficient of variation for each individual (dividing the standard deviation of response times by the mean response time for each individual; Epstein et al., 2011). A Mann-Whitney U test found no significant group differences regarding response times ($U = 896.00$, $p = .460$, $BF_{10} = 0.30$).

4. Discussion

Obesity in adolescence is associated with decision-making patterns that may reflect an imbalance in explore/exploit behaviour, but it is unclear whether this in the direction of over-exploitation or over-exploration. We aimed to address this question by examining the mechanisms underlying explore/exploit behaviour on the IGT amongst adolescents with excess and healthy weights. We found that adolescents with excess weight displayed more behavioural exploration than their healthy-weight counterparts. This was demonstrated through choice behaviour patterns of lower win/stay, as well as higher lose/switch, and higher mutual information, choice entropy, and sequential exploration, in the excess-weight relative to the healthy-weight group. Computational models were then used to extract the underlying factors driving choice behaviour patterns, revealing that this behaviour was driven by a higher maximum directed exploration value (i.e., higher exploration bonus) in the excess-weight group. We additionally demonstrate that the greater exploration displayed by the excess-weight group was not explained by a difference in sensitivity to reinforcement. Furthermore, we found similar attention between groups during the IGT (indicated by nonsignificant differences in overall response time variabilities), which provide support for our findings. Overall, our study shows that adolescents with obesity have a preference for exploratory behaviour, independent of sensitivity to reward.

Our findings appear consistent with reported differences in executive functions involved in goal-directed strategies between adolescents with healthy and excess weight (Reinert et al., 2013). Adaptive behaviour on

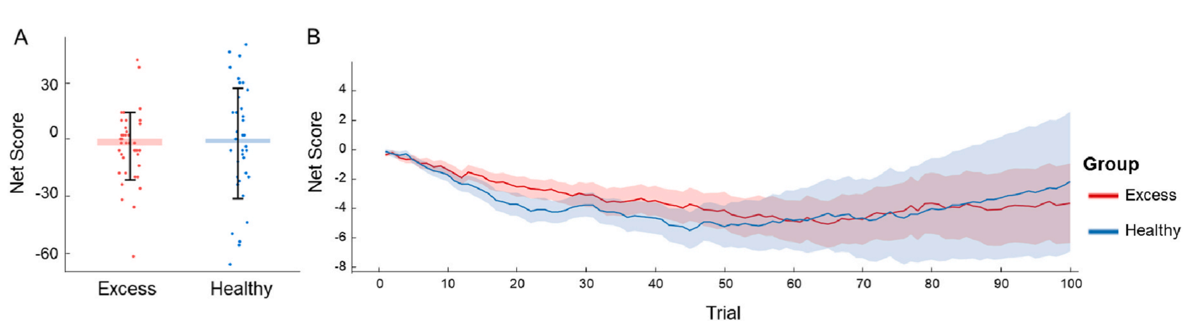

Fig. 1. *IGT Net Scores*
Note. A) Overall IGT scores did not differ between excess-weight (red) and healthy-weight (blue) groups. Individual dots represent each participant in each group, solid lines represent one standard deviation above and below the mean, and shaded areas represent the mean values of each group. B) Similar patterns in net score over time were observed in the excess-weight (red) and healthy-weight (blue) groups. Solid lines represent the mean, and shaded areas represent the 95% confidence intervals.

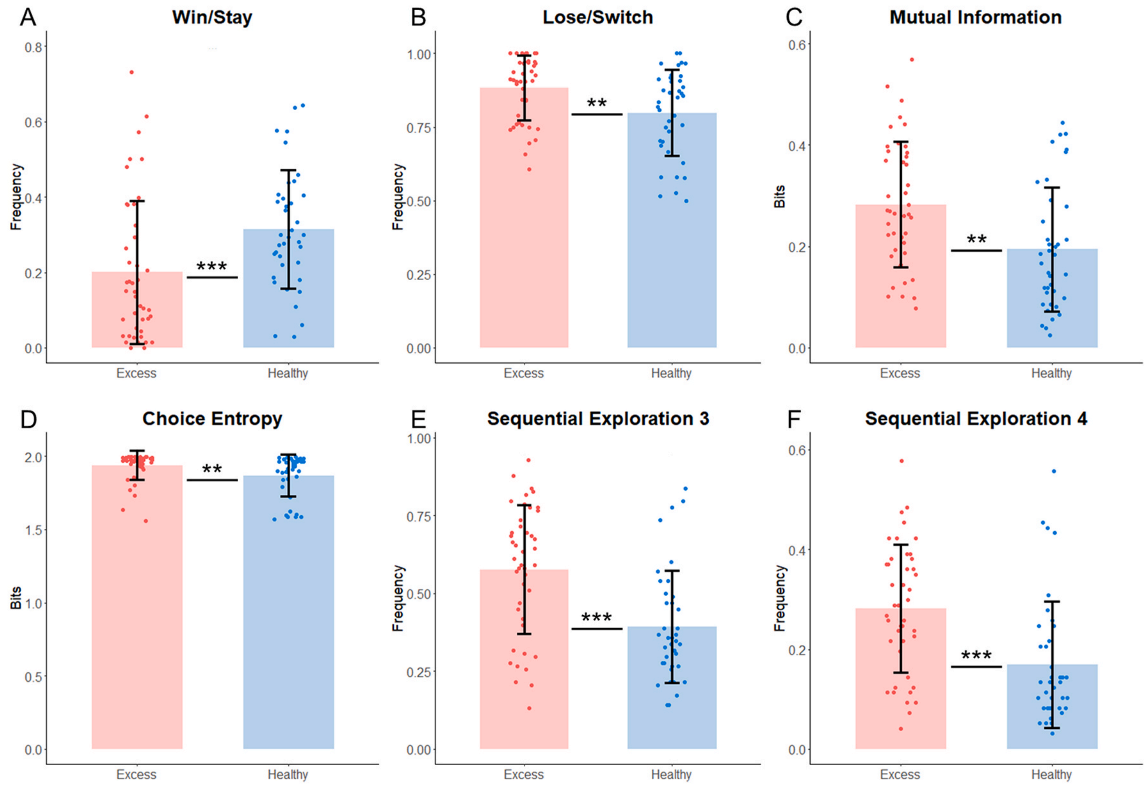

Fig. 2. *Choice Behaviour Measures in Excess- and Healthy-Weight Groups*
Note. Compared to the healthy-weight group, the excess-weight group demonstrated lower win/stay scores (A), and higher scores for lose/switch (B), mutual information (C), choice entropy (D), and sequential exploration over 3 and 4 trials (E and F). Individual dots represent each participant in each group, solid lines represent one standard deviation above and below the mean, and shaded areas represent the mean values of each group. $** = p < .01$, and $*** = p < .001$. $BF_{10} > 3$ was observed for all group comparisons.

the IGT requires an initial period of exploration of different decks, followed by the exploitation of only the decks participants have learned are advantageous. However, in our study, choice behaviour data demonstrated that adolescents with excess weight tended to switch decks throughout the task, regardless of whether the trial outcome was a win or loss. This preference towards exploratory behaviour, and lack of adaptation to outcomes, may reflect a reduction in goal-directed behaviour, which aligns with prior research in obesity in both humans (Janssen et al., 2017) and non-human animals (Seabrook et al., 2023).

In addition, through modelling the behavioural data, we found that this exploratory behaviour was driven by a greater preference in the excess-weight group to select from decks that had not been recently explored. This tendency towards exploration in the excess-weight group indicates a preference to explore unfamiliar variables in an environment (Addicott et al., 2017). Taken together with the substantial evidence that reward sensitivity did not vary between excess- and healthy-weight groups, our findings are suggestive of an intrinsic desire in adolescents with excess weight to explore the reinforcement landscape. This is in line with various works which outline exploratory behaviours as those evoked by an internal state (i.e., desire to explore) or which are inherently rewarding (Alcaro et al., 2007; Alcaro & Panksepp, 2011; Barnett, 1958), rather than motivated by an end-result. This pattern might underpin elevated exploration of richly available energy-dense unhealthy foods in the current obesogenic environment. Furthermore, greater exploration could also impact seeking of healthy food products. Previous studies have observed a greater responsiveness to healthy foods in adults with obesity (Contreras-Rodriguez et al., 2020), as well as greater engagement with multiple "healthy" diets (Santos et al., 2017). Although this may seem intuitively positive and health-oriented, there is also a risk that this may lead to the increased exploration of so-called "healthy options" (as defined by vested industries) that are in fact potentially unhealthy (Gearhardt & DiFeliceantonio, 2022) – for example, healthy food alternatives which are marketed as being low in fat, but are instead high in sugar.

Such findings of greater exploration in adolescents with excess weight contrasts with findings from a previous study in adults, which reported no significant group differences in exploratory behaviour, albeit on a different task (Morris et al., 2016). Given the differences in target populations and experimental design, it is difficult to be certain of the reason for these contrasting outcomes. For instance, decision-making skills develop over adolescence into adulthood (Best & Miller, 2010; Christakou et al., 2013), and exploration/exploitation mechanisms may change across the lifespan (Ligneul, 2019). It remains for future studies to determine the longitudinal trajectory of explore/exploit mechanisms in obesity. Furthermore, whereas the task in Morris et al. (2016) did not involve a learning component (i.e., the relationship between choice selections and the probability of rewards or punishments was random), the IGT is a reinforcement learning task, in which levels of rewards and punishments vary systematically across the four card decks, and guide explore/exploit decisions throughout the task. As such, the IGT can be used to investigate the strength of rewards and losses on participants' decision-making behaviour, in order to directly examine whether differences in exploration between groups are due to sensitivity to reinforcement.

Importantly, we found substantial evidence that reinforcement sensitivity did not vary between excess- and healthy-weight groups in this task. Prior studies have found that sensitivity to rewards predicted BMI in a large sample of children indirectly through overeating (van den Berg et al., 2011), and was associated with compulsive over-eating on a food addiction scale (Loxton & Tipman, 2017). Our results clarify that differences in exploration behaviour in adolescents with excess weight are not solely driven by differences in reinforcement learning, but

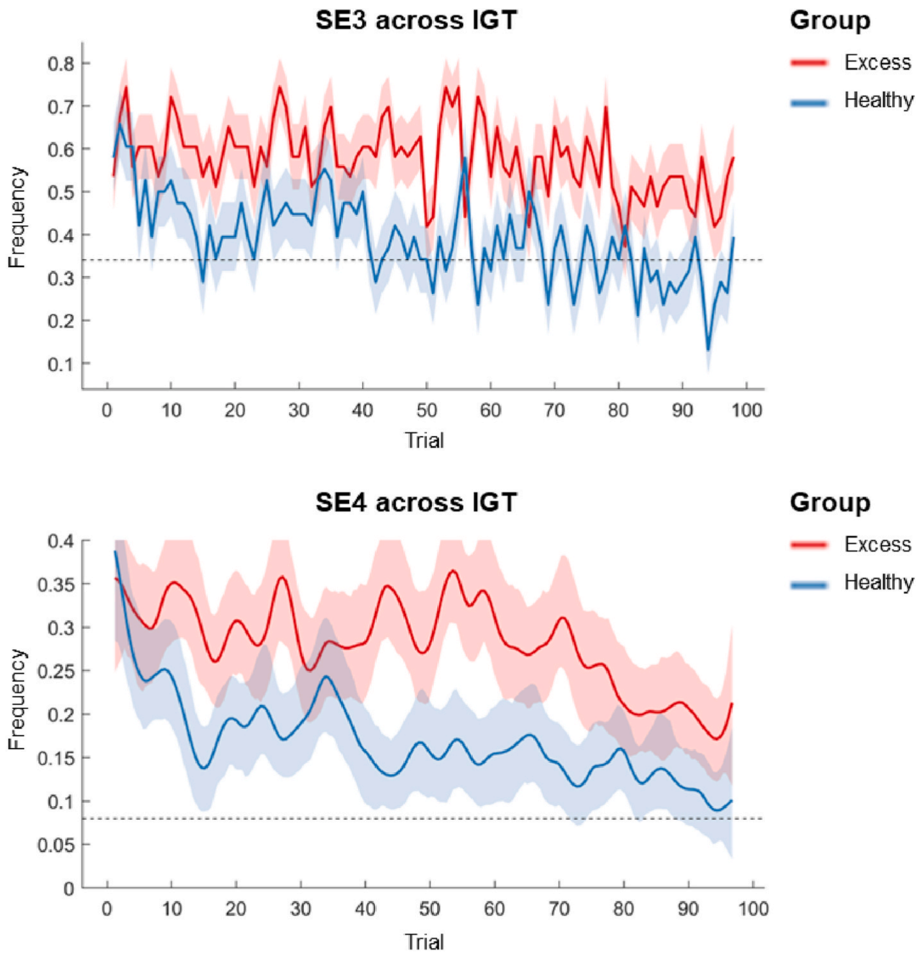

Fig. 3. *Comparison of behavioural indices of sequential exploration (SE3 and SE4) between excess- and healthy-weight groups*
Note. Sequential exploration measures the frequency of individuals sampling from separate decks over three ('sequential exploration 3'; SE3) or four ('sequential exploration 4'; SE4) consecutive trials. Dotted lines represent the theoretical chance of each event (0.33 for SE3, and 0.09 for SE4), solid lines represent the mean, and shaded areas represent the 95% confidence intervals.

instead appear to be due to a primary change in decision-making behaviour.

Our finding of increased preferences for exploration may also be associated with other choice-related biases observed in adolescents with obesity. For example, greater exploration of food options could be linked to greater sensitivity to the multifarious food cues available in the environment, and to higher levels of external eating (Burton et al., 2007; Stice et al., 2013). We also found that greater exploration was independent of reinforcement sensitivity, and thus greater exploration could interact with preference for immediate versus delayed rewards, as steeper rates of delay discounting have also been observed in adolescents with obesity (Barlow et al., 2016). However, these relationships have not been yet tested, and thus these links remain speculative and warrant further research.

One possible way of leveraging increased exploration (considering preserved reinforcement sensitivity) for therapeutic purposes is the use of behavioural activation approaches, which stimulate exploration of pleasurable activities and have shown promising effects in adolescents with obesity and comorbid mood symptoms (Arnott et al., 2020). Furthermore, when considering potential effects of greater exploration on seeking multiple treatment options (some of which could be suboptimal), the observed pattern may call for a "no wrong door" approach, which offers evidence-based approaches across multiple settings and services upon first point of contact, and thus prevents fruitless exploration of treatment alternatives.

A potential limitation of this study is selection bias, given that our sample comprised adolescents who volunteered to participate in the study. Our sample may therefore have been more motivated to lose weight, engage in research programs, and perform well on the IGT, compared with the general population of adolescents with obesity. In addition, our study was based on a paradigm that involved making decisions for monetary rewards, which are distinct from decisions to obtain primary reinforcers, such as food. Although this approach is common in research on choice behaviour in obesity (Dan et al., 2021), future studies should aim to replicate our findings with food-based, rather than monetary, rewards.

Furthermore, although we observed an overall greater preference for explorative behaviour among adolescents with obesity relative to the control group, individual differences in the exploration/exploitation trade-off may also exist within the obesity population. Obesity is a highly heterogeneous disorder, and previous studies have observed separate food choice phenotypes involving not only broad food pleasure seeking, which would be aligned with the exploration pattern found here, but also the consumption of a highly selective and smaller selection of preferred unhealthy foods, which would be more aligned with an exploitative pattern (Costa et al., 2018; Hyldelund et al., 2022; Nicklaus, 2016). More research is needed to map out the relationships between underlying exploration/exploitation patterns and distinct food choice phenotypes relevant to obesity.

Our overall findings are that reward-based decisions in adolescents with excess weight are characterised by over-exploration relative to healthy-weight controls. These findings suggest an important mechanism that, if proven relevant for clinical outcomes, may be targeted in future treatments of obesity in adolescents.

Ethics statement

The Human Research Ethics Committee of the University of Granada

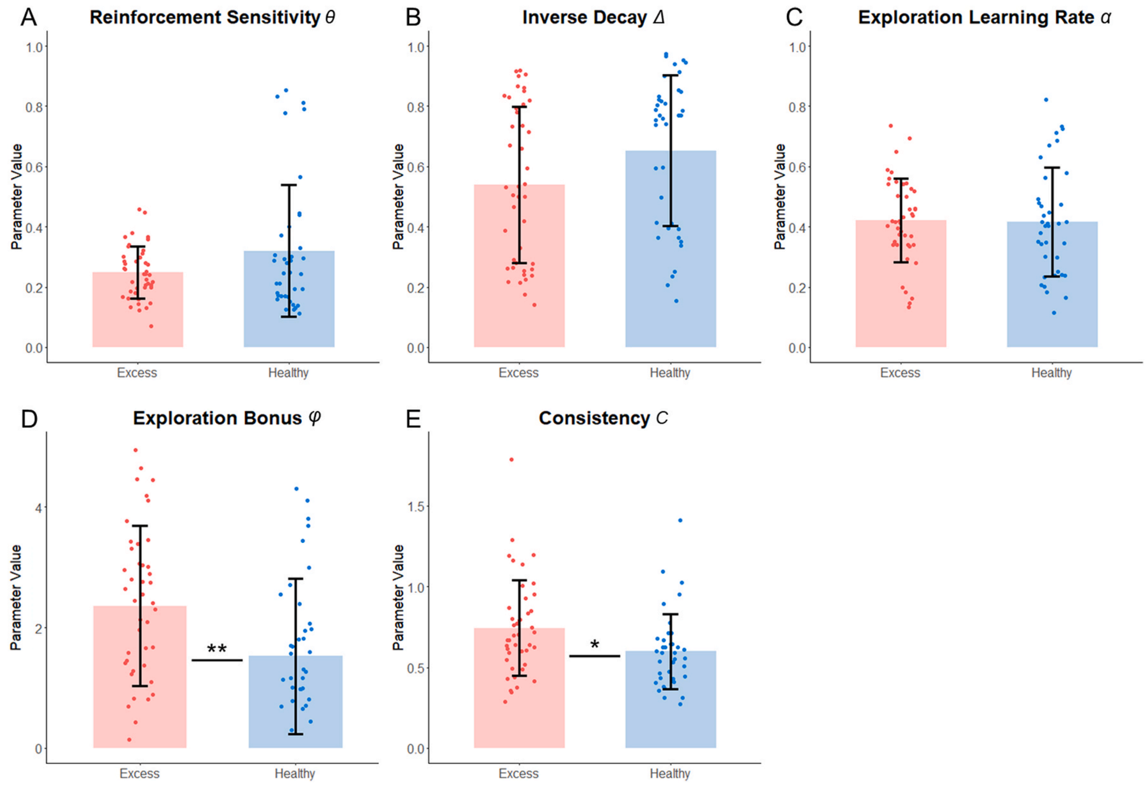

Fig. 4. *VSE Parameters in Excess-Weight and Healthy-Weight Groups*
Note. Exploration bonus scores (D) were higher in the excess-weight group than the healthy-weight group ($BF_{10} > 3$). There was also anecdotal evidence that compared to healthy-weight individuals, inverse decay was lower (B; $BF_{10} > 1$), and consistency higher (E; $BF_{10} > 1$), in the excess-weight group. Individual dots represent each participant in each group, solid lines represent one standard deviation above and below the mean, and shaded areas represent the mean values of each group. * = $p < .05$, and ** = $p < .01$.

approved the study, and all participants, and their parents if they were minors, were informed about the aim of the study and signed an informed consent.

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Declaration of competing interest

TT-JC has received honoraria from Roche for lectures. AVG has received honoraria from Servier and Elsevier for editorial work. All other authors declare no conflicts of interest.

Data availability

Data will be made available on request.

Appendix A

Brief explanation of IGT models

Expectancy Valence Model
The Expectancy Valence model (EV; Stout et al., 2004) was designed to investigate various components of the decision process involved in the IGT. It consists of a reinforcement valence parameter (which indexes the sensitivity of the individual to losses versus wins), update rate parameter, and consistency parameter.

Prospect Valence Learning Model
The Prospective Valence Learning model (PVL; Ahn et al., 2008) uses the Prospect Utility function, which is a non-linear function that contains parameters accounting for the gain-loss frequency effect (e.g., losing $1 four times may feel worse than losing $4 once, despite the sum of losses being equivalent; Erev & Barron, 2005). This is in contrast to the EV model, which uses a linear utility function. In the PVL model, past outcomes are also discounted with a decay parameter, and a response consistency parameter indexes the degree to which an individual's choice is deterministic vs random.

PVL-Delta Model
The PVL-Delta model (Ahn et al., 2008) is similar to the PVL model, but uses learning rate (as in the EV model) instead of a decay parameter, as well as a delta learning rule (Rescorla–Wagner rule).

Value Plus Perseverance Model

The Value Plus Perseverance model (VPP; Worthy et al., 2013) is a version of the PVL-Delta model which consists of the same utility function, learning rule, and consistency parameter, but which has an additional "perseveration module" consisting of parameters which account for participants' tendencies to either stay with the same option, or switch.

Outcome-Representation Learning Model

The Outcome-Representation Learning model (Haines et al., 2018) accounts for the effects of expected value, gain-loss frequency, and choice perseveration, as in previous models. However, this model also accounts for reversal learning (i.e., learning to inhibit previously rewarded actions).

Value plus Sequential Exploration Model

The Value plus Sequential Exploration model (VSE; Ligneul, 2019) differs from the previous models outlined above in that it allocates an exploration bonus to behavioural options (decks in the IGT) which are sampled less frequently or less recently compared to other options. As such, compared to other models, the VSE considers the additional role of exploration (i.e., information-seeking shaped by choice history).

Appendix B

Model Comparisons

AIC values of each model across the excess-weight and healthy-weight groups

Model Name	AIC value	
	Excess-weight group	Healthy-weight group
EV	11887.07	10012.85
ORL	10713.41	9479.53
PVL	11745.58	9851.51
PVL-Delta	11859.76	9919.45
VPP	10679.51	9587.36
VSE	10417.18	9390.74

Note. The VSE model had the best fit in both the excess-weight and healthy-weight groups.

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