Switching between foods: A potential behavioral phenotype of hedonic hunger and increased obesity risk in children

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ABSTRACT

Context: Reward-based eating is a trait that increases risk for eating in the absence of hunger (EAH) and obesity. Eating behaviors such as switching more frequently between different foods may increase intake during EAH by delaying the onset of sensory-specific satiation (SSS); however, this question has not been empirically tested.

Objectives: 1) Test whether switching between foods mediates the relationship between reward-based eating and EAH intake. 2) Test whether switching between foods during EAH moderates the relationship between reward-based eating and weight status.

Methods: Data were analyzed from a study assessing decision-making in children (n = 63 children; 9.4 ± 1.4 years, 77.0 ± 22.4 BMI%tile). Reward-based eating was quantified using the Children’s Eating Behaviour Questionnaire. EAH was assessed as the amount of palatable food consumed following ad libitum consumption of a standard meal. Videos of eating behavior were coded for eating time, number of different foods consumed, and food switches. Ordinary least squares regressions were conducted to test hypotheses.

Results: Switching was positively associated with EAH intake for both kcal (p < 0.01) and grams (p < 0.01) such that each additional switch was associated with an increased intake of 17.0 kcal or 3.5 gs. Switching mediated the relationship between reward-based eating and EAH (p < 0.01) such that more frequent switching fully accounted for the positive association between reward-based eating and EAH (ps < 0.01). While reward-based eating was also positively associated with weight status (p < 0.01), this association was moderated by food switching (p < 0.01) such that the relationship was stronger for children who switch more frequently (p < 0.01).

Conclusions: Frequent switching between foods was positively associated with EAH intake and mediated the relationship between reward-based eating and EAH. Moreover, reward-based eating was more strongly related to weight status in children who switched more frequently. Thus, food switching may contribute to over-consumption and be an important behavioral indicator of increased obesity risk in children. Studies across multiple meals and contexts will help determine if switching is a reliable behavioral phenotype.

1. Introduction

It is well understood that the variety of foods presented during an eating event contributes to hyperphagia [1–3]. The orexigenic effect of variety, specifically in the context of nutrient-poor, high-energy dense foods, has been posited to be a contributor to the obesity epidemic [4–6]. However, the mechanisms that lead to greater intake due to variety are unclear. One speculation is that variety delays the onset of sensory-specific satiation (SSS), defined as the decline in hedonic value of an eaten food relative to uneaten foods [7,8]. If this supposition is true, switching between different foods at a snack or meal should produce greater sensorial variety, which could delay SSS and increase intake. This theoretical mechanism is supported by a recent study in adults that examined switching between bites of macaroni and cheese

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and sips of water. The study found that greater switching related to greater meal intake for a similar magnitude in hedonic decline; this indicates switching may have slowed the development of SSS. [9]. However, it is still unknown how food intake is affected by switching between different food items (compared to switching between food and water) or whether this process generalizes to children. In the current study, we examine if switching is related to how much children consume in a hedonic eating paradigm independent of the effect of the number of different foods consumed.

Frequent switching between foods may be a behavior more common in children who have greater susceptibility to the effects of food variety on intake. Variety contributes to a positive energy balance, especially in an obesogenic environment where higher energy-dense foods are plentiful [10]. However, despite common exposure to an obesogenic environment, not all children overeat and develop obesity. According to the Behavioral Susceptibility Theory, individual differences in appetitive traits and weight status are inconsistent [23], a finding that may be related to limitations in the assessment of EAH by only measuring total intake [11]. The drive to consume food for its rewarding properties in the absence of energy needs has been referred to as reward-based eating [12,13]. While reward-based eating is thought to be an underlying trait that increases susceptibility to obesity [14], how this trait manifests in eating behaviors is not fully understood. For example, children higher in reward-based eating may also exhibit greater variety seeking tendencies [15-17]. We theorize that children who are higher in reward-based eating (a trait) will engage in state-based behaviors to maximize both reward value derived from foods and variety of sensory exposures. In our current theoretical model, children with higher reward-based eating would therefore be prone to increased switching between foods, which would delay SSS, thus contributing to greater intake.

The Eating in the Absence of Hunger (EAH) paradigm has been used to objectively assess vulnerability to reward-based eating in the laboratory. EAH has been described as a behavioral phenotype for obesity [18] because it is associated with increased weight status in both cross-sectional [19,20] and longitudinal [20-22] studies. However, a recent systematic review showed that the associations between EAH and both appetitive traits and weight status are inconsistent [23], a finding that may be related to limitations in the assessment of EAH by only measuring total amount of food consumed. Measures of total intake can be confounded because they are also related to individual child characteristics, such as sex, age, and weight status [24]. Identifying stable, behavioral phenotypes that are theoretically independent of factors related to child energy needs may provide more generalizable results from this paradigm. This secondary data analysis tests the theoretical models presented in Fig. 1. In Fig. 1a, we hypothesize that reward-based eating will be positively associated with children’s intake, but this relationship will be mediated by children’s food switching during EAH. In Fig. 1b, we hypothesize that the relationship between reward-based eating and child weight status is moderated by food switching, such that the relationship will be stronger for high compared to low switchers. This hypothesis is based on the premise that the presence of high levels of both reward-based eating (i.e., trait) and food switching (i.e., behavior) would exacerbate the tendency to overconsume when not hungry, and as a result, these behaviors would be related to excess weight gain over time. Additionally, we hypothesize that the relationships will be independent of the time spent eating and the total number of different foods consumed.

2. Materials and methods

This was a secondary analysis from a larger study designed to assess the behavioral and neurological correlates of decision making in 7–11-year-old children (NCT02855398). Data collection took place between April 2015 and September 2016 and included children living in central Pennsylvania. This study was approved by the Pennsylvania State University Institutional Review Board. Parental consent for child participation and child assent were obtained on the first visit to the laboratory.

2.1. Study design

The protocol for each visit has been previously reported [25–29]. In brief, a within-subjects, cross-over design consisting of four visits was conducted. The order of the first three visits, which included assessment of eating behaviors in the laboratory, was randomly assigned and counterbalanced across participants. During the fourth visit, children underwent functional magnetic resonance imaging (fMRI), the results of which have been previously published [25,26]. The current analyses focused on the data obtained from the EAH paradigm, which occurred

![Fig. 1. Theoretical Models. 1a: mediation model where children with greater reward-based eating will switch more during EAH, with increased switching driving increased intake. 1b: moderation model whereby reward-based eating will be related to greater weight status, but this relationship will be stronger for high food switchers.](image-url)
during one of the first three visits. All children arrived having fasted for at least three hours and completed visits during either lunch (11:00am - 1:00pm) or dinner (4:00pm - 6:30pm), depending on participants’ availability. Prior to the EAH paradigm, children were served a multi-item meal and allowed to eat ad libitum until satiation was reached. In addition to weighing foods before and after consumption, the EAH paradigm was video recorded, allowing for coding of active eating time, number of different foods consumed, bites, and frequency of food switches. While children were eating/completing tasks, parents completed surveys (e.g., demographics, behavioral questionnaires) in a separate waiting room.

2.2. Participants

Seventy children participated in the primary study, but only data for 63 subjects were analyzed due to drop-out (n = 1), non-compliance with protocol (n = 4), corrupted data (n = 1) or uncorrectable errors in food weighing (n = 1; for enrollment flowchart see Supplementary Fig. A). Participants were recruited through physical flyers and electronic ads on popular websites, and eligibility was assessed via a parental report during phone screening. Exclusion criteria were having overweight (i.e., the Center for Disease Control’s BMI-for-age < 5%) [30], pre-existing food allergies and/or dietary restrictions, learning disabilities, neurological or psychiatric conditions (e.g., depression, attention-deficit/hyperactivity disorder), a family history of neurological or psychiatric conditions (e.g., diabetes, depression, schizophrenia), or taking any medication known to affect neural function or appetite. Children were required to be between the ages of 7-to-11-years and accompanied by at least one biological parent. Participants were balanced by sex (n = 30 male; n = 33 female) and weight status (n = 30 healthy-weight; < 85th% BMI-for-age; n = 33 with overweight or obesity: ≥ 85th% BMI-for-age). Children were mostly white (92%) and non-Hispanic (94%; see Table 1), which is representative of the population in rural Pennsylvania.

2.3. Anthropometric measurements

During the initial visit, children were weighed and measured without shoes and in light clothing. Both weight and height were measured twice using a standard scale (Detecto model 437, Webb City, MO) and stadiometer (Seca model 202, Chino, CA), respectively. The average of the two scores for both height and weight were used to calculate BMI (kg/m²). We chose to assess weight status using percent of overweight, %BMIp85, as this measure has been shown to be more predictive of adiposity for our age group than both the standard BMI% and BMIz values [31]. %BMIp85 was calculated by dividing each child’s measured BMI by the BMI score at the 85th percentile for their respective age and sex, and then multiplying by 100 to get a percentage of overweight. A%BMIp85 of 100 indicates the child has a BMI at the overweight cutoff, a value greater than 100 indicates the child’s BMI is above the overweight cutoff, and a value below 100 indicates a BMI below the overweight cutoff. Lastly, we calculated estimated resting energy expenditure (REE) for each child using Schofield equations for children using measures of weight, height, and age [32].

2.4. Eating in the absence of Hunger (EAH)

EAH was measured on one of the first three visits [33]. Children were first provided with a standardized, multi-item meal to consume ad-libitum (see Fig. 2a). Foods and serving sizes selected for the meal were those that were commonly consumed [34] and well-liked [35–37] by this age group, including macaroni and cheese, garlic bread, tomatoes, grapes, broccoli, and water (see Supplementary Table A). Children were given 30 min to consume as much as they wanted and were prompted to ask for additional helpings, if desired. To provide a neutral distraction, a research assistant read a pre-approved, non-food related book to the children during the meal. Twenty minutes following the end of the standard meal, children were provided with a selection of sweet and savory palatable foods (see Fig. 2b) as well as age-appropriate toys and games (e.g., coloring books, cards, toy cars, etc.). Each of the 10 EAH foods was served in a separate bowl on one of two blue trays (see Fig. 2b). Children were provided 15 min to eat as much as they wanted and/or play with any of the toys/games.

Leftovers were weighed to the nearest 0.1 g on a scale (Ohaus, Parsippany, NJ). Intake was computed as the difference between pre-to-post-meal weights (grams) of each food. Grams consumed were converted to kilocalories (kcal) using information from the nutritional facts panel and/or from a standard nutrition database [38].

2.5. Fullness and food liking

Before and after both the standardized meal and the EAH paradigm, children rated their perceived fullness using a validated age-appropriate 150 mm visual analog scale (VAS) [39]. After rating pre-meal fullness, children were presented with samples (< 3 g) of the 6 food items served at the standard meal and water (see Fig. 2). Children rated their liking of each food item using a 5-point facial hedonic scale ranging from “super bad” to “super good” [40]. Liking ratings were repeated for the EAH foods (see Fig. 2) after the pre-EAH fullness ratings.

2.6. Parental report measures

2.6.1. Demographics

As part of the study, parents (82% mothers) completed surveys to report demographics, feeding practices, and child eating behaviors. Relevant demographic variables included race, household income, and maternal education. Parent self-reported race of the child is displayed in Table 1. Household income was determined by asking the parent for their total combined family income before taxes and was indexed into 3 categories: less than $50,000 a year, between $50,000 and $100,000 a year, and greater than $100,000 a year. Maternal education was assessed by asking the attending parent for their highest level of education. In the 18% of cases where the mother did not accompany the child to the visit, maternal education was reported by a proxy family member. For analysis, maternal education was indexed into 3 categories: any level of education up to the completion of a bachelor’s degree, completion of a bachelor’s degree, and any education beyond a bachelor’s degree.

Table 1

<table>
<thead>
<tr>
<th>Continuous Characteristics</th>
<th>Mean ± SD</th>
<th>Range</th>
</tr>
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<tbody>
<tr>
<td>Age in months</td>
<td>113.0 ± 16.6</td>
<td>84–143</td>
</tr>
<tr>
<td>BMI Percentile</td>
<td>77.0 ± 22.4</td>
<td>31–99</td>
</tr>
<tr>
<td>BMI z-score (kg/m²)</td>
<td>1.0 ± 0.9</td>
<td>–0.5–2.6</td>
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<tr>
<td>Resting Energy Expenditure (kcal/day)</td>
<td>1377.0 ± 238.9</td>
<td>987.2–2014.3</td>
</tr>
<tr>
<td>Categorical Characteristics</td>
<td>N         %</td>
<td></td>
</tr>
<tr>
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<td></td>
</tr>
<tr>
<td>Male</td>
<td>30</td>
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</tr>
<tr>
<td>Female</td>
<td>33</td>
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</tr>
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<tr>
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<td>94</td>
</tr>
<tr>
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<td>3</td>
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<tr>
<td>Black</td>
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<td>5</td>
</tr>
<tr>
<td>White</td>
<td>58</td>
<td>92</td>
</tr>
<tr>
<td>Total Combined Income</td>
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</tr>
<tr>
<td>&lt;$50,000</td>
<td>14</td>
<td>22</td>
</tr>
<tr>
<td>$50,000–$100,000</td>
<td>30</td>
<td>48</td>
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<tr>
<td>&gt;$100,000</td>
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<td>30</td>
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<tr>
<td>Maternal Education level</td>
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</tr>
<tr>
<td>&lt;$ Bachelor’s degree</td>
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<td>27</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
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<td>35</td>
</tr>
<tr>
<td>&gt; Bachelor’s Degree</td>
<td>24</td>
<td>38</td>
</tr>
</tbody>
</table>

SD = standard deviation; kg = kilograms; m² = meters squared.
factor structure of the CEBQ items. Through iterative comparisons of analysis was conducted to identify underlying factors and determine the factor structure of the CEBQ items. Through iterative comparisons of different factor models, it was found that a three-factor solution provided the best fit and clinical interpretability. One of the identified factors was labeled as "reward-based eating" based on the interpretation of the factors that loaded significantly onto this factor and their conceptual relevance. These 12 items consisted of all 5 items from the food responsiveness scale, 4 items from the enjoyment of food scale, 2 from the slowness in eating scale, and 1 from the satiety responsiveness scale. Examples of these items include questions such as “My child eats slowly” (food responsiveness), “My child finishes his/her meal quickly” (slowness in eating), and “My child has a big appetite” (satiety responsiveness). For the reward-based eating scale, 2 items from the slowness in eating scale (“My child eats slowly” and “My child finishes his/her meal quickly”) and 1 item from the satiety responsiveness scale (“My child has a big appetite”) are reverse scaled. Parents responded to each question on a 5-point Likert scale ranging from “never” (1 point) to “always” (5 points), with higher scores reflecting higher levels of a trait. After reverse scoring of the 3 items, the score for the 12 items was averaged to calculate a continuous reward-based eating score (possible range from 1 (lowest) to 5 (highest)). The reward-based eating measure has been validated against the external eating subscale of the Eating in the Absence of Hunger Questionnaire (r = 0.61, p < .001) [43], and has good internal consistency (α = 0.89). The internal consistency of these items in our cohort was also good (α = 0.89).

2.6. Children’s eating behaviour questionnaire

The Children’s Eating Behaviour Questionnaire (CEBQ) was administered to assess children’s appetitive traits [41]. The reward-based eating score was based on a recent exploratory factor analysis of the CEBQ in 148 school-age children with overweight/obesity [42]. The analysis was conducted to identify underlying factors and determine the factor structure of the CEBQ items. Through iterative comparisons of different factor models, it was found that a three-factor solution provided the best fit and clinical interpretability. One of the identified factors was labeled as "reward-based eating" based on the interpretation of the factors that loaded significantly onto this factor and their conceptual relevance. These 12 items consisted of all 5 items from the food responsiveness scale, 4 items from the enjoyment of food scale, 2 from the slowness in eating scale, and 1 from the satiety responsiveness scale. Examples of these items include questions such as “My child loves food” (enjoyment of food), “My child is always asking for food” (food responsiveness), “My child finishes his/her meal quickly” (slowness in eating), and “My child has a big appetite” (satiety responsiveness). For the reward-based eating scale, 2 items from the slowness in eating scale (“My child eats slowly” and “My child finishes his/her meal quickly”) and 1 item from the satiety responsiveness scale (“My child has a big appetite”) are reverse scaled. Parents responded to each question on a 5-point Likert scale ranging from “never” (1 point) to “always” (5 points), with higher scores reflecting higher levels of a trait. After reverse scoring of the 3 items, the score for the 12 items was averaged to calculate a continuous reward-based eating score (possible range from 1 (lowest) to 5 (highest)). The reward-based eating measure has been validated against the external eating subscale of the Eating in the Absence of Hunger Questionnaire (r = 0.61, p < .001) [43], and has good internal consistency (α = 0.89). The internal consistency of these items in our cohort was also good (α = 0.89).

2.7. Behavioral coding

Video recordings from the EAH paradigm were acquired using an Axis M3004-V network camera, which was conspicuously located in a corner of the room. Coding was conducted using Noldus Observer XT v16 [44]. Every bite of food taken was coded according to an established protocol based on a systematic review by Pearce and colleagues [45]. Using this protocol, we established definitions for bites, active eating time, food switches, and number of different foods consumed (see Table 2 for definitions). Since children were allowed to move around the room during the EAH paradigm, not all bites were able to be directly viewed. In these cases, the sound of the bite was used as a proxy. Gnawing on food (continuously biting a piece of food) was considered one bite unless the child pulled the food away from their mouth or paused to chew or swallow in between gnawing. In cases where more than one food was combined into the same bite, this was considered a new flavor and treated as a unique food when counting switches. When assessing active eating time, preparatory behaviors were defined as those that occurred within 15 s of an eating behavior (e.g., moving food with a fork was a preparatory behavior if it led to a bite within 15 s but was considered playing with food [i.e., non-active eating time], if no bite was taken within 15 s). The end of active eating time was marked by the cessation of eating without another active eating behavior occurring for at least 15 s. The EAH videos were coded by two independent research assistants and the inter-rater reliability for each behavior was calculated using the intraclass correlation coefficient (ICC; see Table 2) [46].

2.8. Statistical analyses

Statistical analyses were conducted using SPSS v28 (IBM Corp. 2021). The PROCESS (v4.1) macro [47] in the Statistical Package for Social Sciences (SPSS, v28) was used to test the study hypotheses (see Fig. 1). All statistical tests were two-tailed and α was set to 0.05. One-way analyses of variance (ANOVA) were performed to test whether
variables of interest (reward-based eating, switching, intake, and weight status) differed by household income and maternal education. Independent-sample t-tests were used to test whether variables of interest differed by sex. Pearson correlations were used to test associations between variables of interest and continuous measures (i.e., food liking, REE, pre-EAH fullness, the number of different foods consumed, and active eating time). Descriptive statistics were adjusted for multiple comparisons using the Benjamini-Hochberg procedure to avoid a potentially type I error [48].

Ordinary least squares regressions were conducted to test whether food switching mediates the relationship between reward-based eating and EAH intake in kcal and grams; 1000 bootstrap samples were used for 95% confidence intervals. A separate model was conducted to test whether food switching moderates the relationship between reward-based eating and children’s weight status. For ease of interpretation, the interaction between reward-based eating and food switching was graphed using three levels of switching including: –1 SD from the mean (low), the mean (average), and +1 SD from the mean (high). The Johnson-Neyman procedure [49] was used to identify the number of switches that represented the point at which the relationship between reward-based eating and %BMI<sub>p85</sub> changes. All models were adjusted for food liking and pre-EAH fullness. Mediation models were further adjusted for REE to assess whether individual differences in energy needs affected our intake results. Since%BMI<sub>p85</sub> factors in sex, age, and child size, REE was not added to the main moderation model to avoid over-adjusting; it was instead tested in sensitivity analyses. Sensitivity analyses were also conducted using more widely used measures of weight status including BMIZ, BMI%, and raw BMI to examine the robustness of the moderation model.

Because children who select a greater variety of foods and/or eat for longer theoretically have greater opportunities to switch we decided not to include these variables in our main models. Controlling for potential mediators may lead to biased estimates of effect sizes and spurious results. We instead ran all models further adjusting for active eating time and number of unique foods consumed and reported these results separately. Additionally, to assess whether our models were robust against possible confounding effects of intake at the meal served prior to EAH and visit order, we controlled for both grams and kcal consumed in our sensitivity analyses. In order to ensure that reported findings reflected non-homeostatic eating, additional sensitivity analyses were conducted to assess whether results were consistent if the sample was limited to children who reported being full prior to EAH, defined as >75% on the fullness measure (n = 49). Lastly, we tested models that adjusted for sex, age, and weight status instead of REE.

3. Results

3.1. Descriptive statistics

Descriptive statistics for food intake, pre-EAH liking, fullness, food switches, number of different foods consumed, and active eating time are presented in Tables 3 and 4; these variables did not differ by age, sex, household income, or maternal education (p > 0.05). The only exception was a significant difference (t(61) = –2.60, p = 0.01) in standard meal food liking such that boys reported higher liking than girls, but this was no longer significant when adjusting for multiple comparisons (see Supplementary Table C). We also found no difference for reward-based eating scores or%BMI<sub>p85</sub> across age, sex, household income, or maternal education (ps > 0.05; Supplementary Table C). The only exception was a significant association between maternal education and %BMI<sub>p85</sub> scores (F(2,60) = 3.67, p = 0.03) such that children whose mothers did not attain a 4-year college degree had a significantly higher %BMI<sub>p85</sub> than children whose mothers completed a 4-year college degree (p = 0.03). However, this difference was no longer significant when adjusting for multiple comparisons (see Supplementary Table C). Amount consumed for each individual food item can be viewed in Supplementary Table D.

3.2. EAH intake

After adjusting for covariates (pre-EAH fullness, food liking, and REE), food switching was positively related to EAH intake for both kcal and grams (ps < 0.01). In terms of magnitude of effect, for each additional switch, children consumed 17.0 kcal or 3.5 gms more food. These relationships are illustrated in Fig. 3. Reward-based eating was also positively associated with EAH intake in kcal (β (SE) = 107.82 (37.01), p < 0.01) and grams (β (SE) = 22.58 (7.71), p < 0.01). However, these associations were mediated by food switching [kcal: β (SE) = 82.08 (30.98), 95% CI (21.18, 142.25), p < 0.01; grams: β (SE) = 16.86 (6.46), 95% CI (4.68, 31.31), p < 0.01] such that greater reward-based eating was associated with a greater number of food switches [β (SE) = 4.83 (1.58), p < 0.01], which in turn was associated with greater EAH intake [kcal: β (SE) = 16.98 (2.36), p < 0.01; grams: β (SE) = 3.49 (0.51), p < 0.01] (Figs. 3 and 4). These models remained significant after adjusting for visit order, pre-EAH ad libitum intake, number of unique foods consumed, and active eating time, and when limiting only to children who reported sufficient levels of fullness prior to EAH (see Supplementary Tables E and F). These models were also robust when controlling for age and sex instead of REE. These results support the theoretical model that children with higher reward-based eating consume more during EAH, potentially due to more frequent switching.

Table 3
Pearson correlation coefficients between study variables.

<table>
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<th>1</th>
<th>2</th>
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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Reward-Based Eating</td>
<td>–</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>2. Food Switches</td>
<td>0.41‡</td>
<td>–</td>
<td></td>
<td></td>
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<tr>
<td>3. Number of different foods consumed</td>
<td>0.28‡</td>
<td>0.68‡</td>
<td>–</td>
<td></td>
<td></td>
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<tr>
<td>4. Resting Energy Expenditure</td>
<td>0.27</td>
<td>–</td>
<td>0.23</td>
<td>0.12</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td>5. Food Liking</td>
<td>–0.04</td>
<td>0.10</td>
<td>0.33‡</td>
<td>–0.21</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td>6. Active Eating Time</td>
<td>0.22</td>
<td>0.68‡</td>
<td>0.55‡</td>
<td>0.03</td>
<td>0.27§</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>7. Pre-EAH Fullness</td>
<td>–0.21</td>
<td>–0.05</td>
<td>–0.03</td>
<td>0.08</td>
<td>0.09</td>
<td>0.03</td>
<td>–</td>
<td>–</td>
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</tr>
<tr>
<td>8. EAH Intake (kcal)</td>
<td>0.38‡</td>
<td>0.77‡</td>
<td>0.56‡</td>
<td>0.29†</td>
<td>0.15</td>
<td>0.71‡</td>
<td>0.05</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>9. EAH Intake (grams)</td>
<td>0.37‡</td>
<td>0.75‡</td>
<td>0.55‡</td>
<td>0.29†</td>
<td>0.15</td>
<td>0.71‡</td>
<td>0.05</td>
<td>0.99‡</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>10.%BMI&lt;sub&gt;p85&lt;/sub&gt;</td>
<td>0.36†</td>
<td>0.31*</td>
<td>0.17</td>
<td>0.77‡</td>
<td>–0.15</td>
<td>0.04</td>
<td>0.02</td>
<td>0.31*</td>
<td>0.30*</td>
<td>–</td>
</tr>
</tbody>
</table>

* indicates statistical significance (p < 0.05) before, but not after, adjustment for multiple comparisons.
† adjusted p < 0.05;
‡ adjusted p < 0.01.
### Table 4
Descriptive statistics for study variables.

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Sex Boys (n = 30)</th>
<th>Sex Girls (n = 33)</th>
<th>Weight Status</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean ± SD</td>
<td>Range</td>
<td>Mean ± SD</td>
<td>Range</td>
</tr>
<tr>
<td>Pre-meal fullness (mm)</td>
<td>37.6 ± 30.8</td>
<td>0-100</td>
<td>42.3 ± 30.8</td>
<td>0-100</td>
</tr>
<tr>
<td>Pre-meal food intake</td>
<td>3.9 ± 2.6-5.0</td>
<td>± 0.5</td>
<td>3.8 ± 2.6-4.6</td>
<td>± 0.5</td>
</tr>
<tr>
<td>Intake (kcal)</td>
<td>645.1 ± 202.5-1130.2</td>
<td>202.5-1130.2</td>
<td>645.4 ± 307.5-1130.2</td>
<td>307.5-1130.2</td>
</tr>
<tr>
<td>Intake (grams)</td>
<td>486.6 ± 218.0-944.4</td>
<td>218.0-944.4</td>
<td>484.7 ± 218.0-803.4</td>
<td>218.0-803.4</td>
</tr>
<tr>
<td>EAH Paradigm</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-EAH fullness (mm)</td>
<td>124.9 ± 25.7</td>
<td>31-150</td>
<td>130.3 ± 16.9</td>
<td>84-150</td>
</tr>
<tr>
<td>Pre-EAH food liking (VAS)</td>
<td>4.2 ± 0.4</td>
<td>3.0-5.0</td>
<td>4.3 ± 0.5</td>
<td>3.5-5.0</td>
</tr>
<tr>
<td>Intake (kcal)</td>
<td>380.5 ± 36.5-1046.1</td>
<td>408.8-1046.1</td>
<td>409.0 ± 36.5-804.6</td>
<td>36.5-804.6</td>
</tr>
<tr>
<td>Intake (grams)</td>
<td>197.9 ± 7.9-218.0</td>
<td>229.4-163.9</td>
<td>163.9 ± 49.1</td>
<td>149.1</td>
</tr>
<tr>
<td>Food switches</td>
<td>14.2 ± 1-30</td>
<td>14.9 ± 1-29</td>
<td>12.5 ± 7.6</td>
<td>7.6</td>
</tr>
<tr>
<td>Number of different</td>
<td>6.1 ± 2-10</td>
<td>6.3 ± 2-10</td>
<td>5.9 ± 1.7</td>
<td>1.7</td>
</tr>
<tr>
<td>foods consumed</td>
<td>2.0 ± 2.2</td>
<td>2.2 ± 2</td>
<td>1.7 ± 2.2</td>
<td>2.2</td>
</tr>
<tr>
<td>Active eating time</td>
<td>11.0 ± 4.2</td>
<td>31-17.5</td>
<td>11.0 ± 4.7</td>
<td>3.1-16.3</td>
</tr>
<tr>
<td>Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reward-based eating</td>
<td>3.1 ± 1.7-4.7</td>
<td>3.1 ± 1.7-4.3</td>
<td>3.1 ± 1.9-4.7</td>
<td>1.9-4.7</td>
</tr>
<tr>
<td>%Mdp85</td>
<td>0.6 ± 0.6</td>
<td>0.6</td>
<td>0.6 ± 0.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>104.5 ± 101.5</td>
<td>79-169</td>
<td>107.8 ± 101.5</td>
<td>79-139</td>
</tr>
</tbody>
</table>

SD: Standard deviation; VAS: visual analog scale.  
† Differences were analyzed by independent-samples t-tests.  
* Significance α = 0.05.  
** Significance after adjusting for multiple comparisons.

Fig. 3. Associations between mediation model variables after adjusting for pre-EAH fullness, food liking, and REE. Shaded region reflects 95% confidence interval for the line of best fit.
3.3. Weight status

Independent of switching, there was a significant relationship between reward-based eating and %BMIp85 ($p = 0.04$), such that a one-point increase in reward-based eating was associated with an increase of 8.5% for %BMIp85. There was a significant interaction between reward-based eating and food switching on weight status ($\beta = 1.64, t = 3.59, p < 0.01$) (Fig. 5). The interaction was also significant when further adjusting for REE, active eating time, the number of unique foods consumed, pre-EAH ad libitum intake, and visit order ($ps < 0.05$; see Supplementary Table G). This interaction also remained significant in sensitivity analyses using BMIz, BMI%, or raw BMI as dependent variables ($ps < 0.02$) as well as when limiting the sample to children who reported > 75% fullness on the scale prior to EAH ($n = 49; p < 0.01$; see Supplementary Table G). At the average number of switches ($M = 14$), each 1-point increase in reward-based eating was associated with an increase of 9.6% for %BMIp85. As switching increased, the association between reward-based eating and weight status became stronger. For example, for a child who switches 10 more times than average, each 1-point increase in reward-based eating would be associated with an increase of 26.3% for %BMIp85. The Johnson-Neyman procedure [47] identified 12 switches as the point at which the association between reward-based eating and %BMIp85 ($\beta = 6.49, t(55) = 2.00, p = 0.05$) became significant. This indicates that for over half the sample (57%), switching exacerbated the effect of reward-based eating on weight status.

4. Discussion

This study advances the field by demonstrating, for the first time, that switching between foods at a snack paradigm promoted greater consumption in children beyond energy needs. As expected, children with higher reward-based eating consumed more during the EAH paradigm. However, our results indicate that this increased intake may be due to children switching between foods more frequently, which could delay the development of SSS. Additionally, we showed that the positive relationship between reward-based eating and weight status was stronger for children who switched more frequently between foods.
Thus, frequently switching between foods can contribute to overconsumption during EAH. Moreover, frequent switching may exacerbate the impact of reward-based eating tendencies on risk for obesity in children.

Studies have demonstrated that individuals with higher reward-based eating are more susceptible to food cues and are more likely to overconsume in obesogenic environments [50]. The current study adds to this literature by presenting a potential behavioral mechanism for these associations. Prior literature indicates greater sensorial variety delays SSS and drives short-term intake [7,8]; therefore, we hypothesized that food switching would drive intake by increasing sensorial variety. Our results support the theory that children with higher reward-based eating tend to eat more during EAH due, in part, to increased switching. Reward-based eating is associated with high variety seeking [16,17], so the tendency to switch more while eating may be driven by variety seeking tendencies. Our findings are in line with literature demonstrating that the total number of foods served is a less potent driver of intake than the frequency of different sensory exposures across foods [51,52]. Switching may therefore modulate SSS development by affecting orosensory exposure to flavors. Examination of switching within a snack or meal may provide a more nuanced understanding of how the number of foods served affects intake.

These data also support our theoretical model by showing that reward-based eating was associated with higher weight status, especially for children who switched frequently. To put these results in perspective, a child with a reward-based eating score of 4 (equivalent to answering often on all items) would be predicted to have a BMI% of 86% (in the overweight range). However, at this same level of reward-based eating, a child who is a high switcher (+1 SD) would be predicted to have a BMI% of ~95% (in the obese range), while a low-switcher (~1 SD) would be predicted to have a BMI% of ~77% (in the normal weight range). The implications from the current findings are that high reward-based eating may be a risk factor for obesity in children who are also prone to frequent food switching. This highlights the importance of assessing food switching in this age group as a potential behavioral phenotype conferring increased risk of both hedonic eating and obesity. Behaviors are thought to be more malleable in childhood and become harder to change with age [53]. In addition, behaviors that develop in childhood tend to track into adulthood [54,55]. Thus, middle childhood represents a developmental period where behavioral interventions for obesity may be particularly effective. Interventions focused on changing eating behaviors to lower hedonic eating are important targets due to the associations between EAH and heightened risk of childhood obesity [18–22]. Prior interventions targeting eating behaviors (e.g., eating rate) have been effective in reducing intake in children [56–58]; whether these results are sustainable, though, remains to be tested. If the tendency to switch between foods generalizes to other eating occasions, it may be a phenotype that can be targeted to prevent obesity. For example, encouraging more frequent switching between nutrient dense foods and vegetables and less frequent switching between high energy-dense foods could be tested as a strategy to improve dietary quality in children. This may lead to greater satiety and displacement of nutrient poor, high energy-dense foods over time [59]. Alternatively, if switching proves resistant to change, switching behavior may still be a useful indicator for identifying children who are at risk for development of obesity in the future. However, longitudinal studies are needed to determine whether switching is a reliable pattern of eating within children across time.

While this study used a rigorous coding protocol and analytic approach, there are several limitations to consider. Firstly, the cross-sectional design of the study prevents us from making strong causal inferences from our findings. Future research should employ longitudinal or experimental designs to better investigate the temporality of the relationships between switching, reward-based eating, and obesity. Additionally, there exists the possibility that unmeasured confounding variables may explain the observed mediation and moderation effects [60]. Next, while%BMIp85 is more strongly related to adiposity than BMI% or BMIz [31], it is not a direct measure of adiposity. The study is also limited in its generalizability to different populations and eating contexts. Although the sample reflected the population demographics in central PA, the lack of diversity limits the generalizability of these findings to other populations. Similarly, these results may not be generalizable to other free-living eating occasions. The EAH protocol used in this study included a variety of 10 snack foods, which may have increased switching behavior as compared to a more naturalistic eating context with fewer available choices. Additionally, due to EAH protocols varying on number of foods served, our results may not be generalizable to paradigms serving fewer food choices. Lastly, there are also some limitations due to the nature of microstructure behavioral coding. As there were some blind spots with the camera, some bites may have been missed during coding. However, 100% of our videos were double-coded, and our inter-rater reliability was high for all relevant behaviors.

To strengthen the relationships proposed in our theoretical model, several future studies should be considered. We propose that children with greater reward-based eating and a greater tendency to switch between foods will be at greater risk for obesity. Longitudinal studies are needed to test if switching between foods increases risk for future weight gain. Next, our theory supposes that switching is a behavioral trait, however, this has not been empirically tested. Therefore, future studies are needed to determine the stability of switching across multiple eating contexts (e.g., meals, snacks, at home, etc.) and food types (e.g., fruits, vegetables, sweet and savory snacks, etc.). SSS in the current study was not assessed; therefore, it was not possible to directly test the assumption that switching between foods delays SSS. However, a recent study that assessed switching between bites and sips of water in adults found that switching was positively related to intake and attenuated hedonic decline, suggesting that switching increases intake by delaying SSS [9]. In addition to measuring SSS, future studies are needed that experimentally manipulate food switching to confirm a causal relationship between switching and intake. In adults, experimental manipulation of food switching by Brondel et al. 2009 showed that moderate switching increased intake and delayed the decline in subjective palatability ratings for the meal relative to low switching [61]. Contrary to their expectations, the researchers found that the high switching group did not show increased intake, possibly because constant switching was unpleasant or unnatural for subjects. Whether switching tendency can be experimentally manipulated in children remains to be tested.

This study is a crucial first step in understanding the relationships between reward-based eating, food switching, and child weight status. Considering that eating behaviors develop early in childhood and persist into adulthood, a better understanding of which behaviors drive overconsumption will have important public health implications. Given the abundance of food types and brands available in the environment, children who are high in reward-seeking and exhibit greater tendency to switch between foods may be especially vulnerable. The tendency to switch between foods could be a potentially modifiable behavior that could be targeted by interventions aiming to prevent childhood obesity.

Ethics statement

The studies involving human participants were reviewed and approved by The Pennsylvania State University Institutional Review Board (IRB approval number: 674). Written informed consent to participate in this study was provided by the participants’ legal guardian.

CRediT authorship contribution statement

Nicholas V. Neuwald: Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal analysis. Alaina L. Pearce: Writing – review & editing, Formal analysis, Conceptualization. Shana Adise: Writing – review & editing, Conceptualization, Data
Declarations of Competing Interest
None.

Data availability
Data will be made available on request.

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Supplementary materials
Supplementary material associated with this article can be found in the online version, at doi:10.1016/j.physbeh.2023.114312.

References


