Indirect associations between commercial television exposure and child body mass index

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\textbf{Running title}: Indirect associations between commercial exposure and child BMI

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\textbf{Abbreviations}: Body Mass Index, BMI; Television, TV; Structural Equation Model, SEqM; Generalised Structural Equation Model, GSEqM; Standardized root mean residual, SRMR; Tucker Lewis index, TLI; Root mean square error, RMSEA; Akaike information criterion, AIC; Bayesian information criterion, BIC.
INTRODUCTION

Television viewing has long been implicated in the rising prevalence of childhood obesity\(^1\), but over time increasing attention has been paid to the importance of commercial content, rather than only the sedentary nature of watching television. That is, studies have demonstrated that it is exposure to the unhealthy food and non-alcoholic beverage (hereafter food) advertising broadcast on commercial channels, rather than viewing per se, that is associated with negative dietary patterns\(^2\) and weight gain\(^3\). This notion is supported by a raft of evidence that experimental exposure to television food advertising leads to increased immediate consumption in children compared to when children view similar television program content with non-food advertising or no advertising\(^4,5\). Such changes to consumption are found to not be compensated for at later eating opportunities\(^6\) and therefore, over time, would likely lead to weight gain. When mapped against an established framework, the evidence for food advertising effects on eating behaviour meet the criteria for a potential causal relationship\(^7\).

The World Health Organization has called on governments worldwide to protect children’s health by introducing policies to reduce children’s exposure to television advertising for foods high in fats, sugar and/or salt (HFSS)\(^8,9\). Several countries now have policies\(^10\) but the limited studies linking food marketing to children’s weight has proven a barrier to progress in some cases\(^11\). In 2015, Kelly et al.\(^12\) mapped outcomes of studies assessing the impact of food promotions on children onto a logical sequence of effects linking food promotions to individual-level weight outcomes through purchase requests, purchase and consumption. Although studies cited in the review support effects at each step of the model, the proposed behavioral pathways through which food advertising exposure might lead to change in Body
Mass Index (BMI) in children have not yet been empirically tested. The current study seeks to address this gap and therefore inform future research directions. The primary hypothesis was that the behavioral pathways of the Kelly et al.\textsuperscript{12} model would be supported by these data, i.e. that commercial television exposure would be indirectly associated with child BMI via purchase requests, purchase and consumption.

**METHODS**

Additional details on methods can be found in Boyland et al.\textsuperscript{13}.

**Participants**

Parent-child dyads (children aged 7-11y) were recruited using an online survey platform (Qualtrics; SAP, Washington). Parents were existing members of the survey platforms’ research panel and were approached directly through email, which provided study information and an invitation to participate. If parents had more than one child in the age range, they were asked to consider their oldest qualifying child for participation and when completing the parent-directed questions. National representativeness for the UK was sought using quotas for geographical location and household income (based on panel data held by Qualtrics). Qualtrics provided a fixed point-based reimbursement to the parent participants for time and inconvenience. BMI z-score outliers (<-4 SD or >8 SD) were excluded based on the definition from Freedman et al.\textsuperscript{14}. Ethical approval for the original study was granted by the Research Ethics Subcommittee for Non-invasive Procedures at the University of Liverpool, UK. After data screening (detailed below), the sample analysed in the present study consisted of 2260 participant dyads.
Measures

Demographic and anthropometric information: Parents reported their child’s date of birth, sex, height and weight. BMI was calculated as kg/m².

Child commercial and non-commercial television exposure (adapted from 15): Parents reported on the duration of time (hours) their child spends viewing television (inclusive of live and on-demand “catch up” services, in line with official industry measures; 16) on a typical weekday and a typical weekend day, as well as the proportion (%) of that time spent on commercial channels (those carrying advertising, e.g. ITV, satellite subscription channels such as Sky). Data for typical weekday viewing were multiplied by five, data for typical weekend day viewing were multiplied by two and these data summed to calculate typical total weekly TV viewing. From this, weekly time (hours) spent watching commercial and non-commercial (public service broadcasting, e.g. BBC) television was calculated based the proportion of each viewing type indicated by parents.

Child purchase requests for advertised foods or “pester power” (adapted from 17): Children self-reported how frequently they asked their parent to buy food or beverage items they had seen advertised on television (7-point Likert scale from ‘never’ to ‘more than once per day’).

Child purchasing of unhealthy foods: Children self-reported how frequently they spend their own money (pocket money, allowance) to buy chocolate, sweet biscuits (including chocolate covered), crisps, bakery goods (e.g. cakes, doughnuts), takeaway foods (e.g. chips,
pizza), sweets and non-chocolate confectionery, and non-diet fizzy drinks (7-point Likert scale from ‘never’ to ‘more than once per day’).

Child unhealthy food consumption (adapted from\textsuperscript{18,19}): Children self-reported how frequently they consumed chocolate, crisps, pastries, cakes, biscuits and non-diet fizzy drinks (7-point Likert scale from ‘never’ to ‘more than once per day’).

Procedure

The measures were completed online. Informed consent was obtained from adult participants, with parent-confirmed verbal assent obtained from child participants before the survey questions could be accessed. Questions for parents to complete appeared first, before parents were instructed to facilitate their child’s completion of the remaining measures (ensuring understanding, but not prompting responses). Finally, both child and parent participants were provided with an age-appropriate debrief.

Statistical analysis

To test the hypothesised model (Figure 1), a structural equation model (SEM) was used. This enabled the creation of two latent variables (for purchase and consumption) and the quantification of indirect effects of TV viewing on BMI through the suggested mechanisms. All modelling was conducted in STATA 14 (Stata Corporation, Release 14 College Station, Tex, 2015). Firstly, confirmatory factor analysis\textsuperscript{20} using a maximum likelihood estimator was used to test the measurement of consumption and purchasing using latent variables, before the full structural model was tested. To assess fit of measurement and structural models a
range of fit indices were produced. The standardized root mean residual (SRMR) absolute fit index was calculated as this measure is less affected by sample size, distribution, and kurtosis than other measures (SRMR < 0.08 represents good model fit; 20). Two baseline comparisons, the Tucker Lewis index (TLI) and comparative fit index (CFI) were deemed as being acceptable at above .90 and good at above .95. Finally, the root mean square error (RMSEA) parsimony-adjusted measure was reported, with values less than 0.06 being good fit and values greater than 0.06 but less than 0.08 being acceptable. The Satorra-Bentler adjustment was also applied to all fit indices barring SRMR, to assess the extent that non-normal distribution of variables may have influenced fit. Finally, the fit of both the measurement and structural models was compared to versions using generalised SEqM (GSEqM) with appropriate variables (see Figure 1) labelled as ordinal (logit link). Comparisons between SEqM and GSEqM models were done using Akaike information criterion (AIC) and Bayesian information criterion (BIC), lower values being indicative of better fit, and differences >10 being indicative of very strong evidence for the model being better. Regarding the individual pathways in the models, regression coefficients and their standard errors along with their associated p-values and 95% CIs are reported.
**Figure 1:** The hypothesised relationships between television exposure, purchase requests, purchasing, consumption and BMI in children (values are regression coefficients and standard errors, *p*=.025, **p*<.001)

### RESULTS

#### Data Screening

The initial dataset included 2501 cases. Those with missing information (n=101) or not meeting inclusion criteria (n=12 reported child’s age as below 7 years) were excluded from analysis. BMI values were converted to age- and sex appropriate z-scores, using the World Health Organization Anthropometric Calculator (WHO Anthro version 3.2.2). From this, 128 met the criteria for BMI z-score outliers so were excluded from analysis.

#### Descriptive Statistics

Descriptive statistics are shown in Table 1. The final analysed sample consisted of 2260 children (and parents), including 1258 (55.7%) boys and 1002 (44.3%) girls.
Table 1: Descriptive statistics for the final dataset (n=2260)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age in years</td>
<td>8.9 (1.4)</td>
</tr>
<tr>
<td>BMI z-score</td>
<td>+1.25 (2.1)</td>
</tr>
<tr>
<td>Weekly commercial television viewing (hours)</td>
<td>12.11 (9.79)</td>
</tr>
<tr>
<td>Weekly non-commercial television viewing (hours)</td>
<td>9.75 (8.26)</td>
</tr>
<tr>
<td>Purchase requests for advertised foods&lt;sup&gt;a&lt;/sup&gt;</td>
<td>3.44 (1.76)</td>
</tr>
<tr>
<td>Purchase of unhealthy foods&lt;sup&gt;b&lt;/sup&gt;:</td>
<td></td>
</tr>
<tr>
<td>Chocolate</td>
<td>2.82 (1.65)</td>
</tr>
<tr>
<td>Sweet biscuits</td>
<td>2.25 (1.67)</td>
</tr>
<tr>
<td>Potato chips</td>
<td>2.67 (1.73)</td>
</tr>
<tr>
<td>Bakery goods</td>
<td>2.16 (1.60)</td>
</tr>
<tr>
<td>Takeaway foods</td>
<td>2.01 (1.59)</td>
</tr>
<tr>
<td>Candy and non-chocolate confectionery</td>
<td>2.86 (1.65)</td>
</tr>
<tr>
<td>Non-diet soda</td>
<td>2.40 (1.68)</td>
</tr>
<tr>
<td>Consumption of unhealthy foods&lt;sup&gt;b&lt;/sup&gt;:</td>
<td></td>
</tr>
<tr>
<td>Chocolate</td>
<td>4.74 (1.21)</td>
</tr>
<tr>
<td>Potato chips</td>
<td>4.92 (1.23)</td>
</tr>
<tr>
<td>Pastries</td>
<td>3.15 (1.55)</td>
</tr>
<tr>
<td>Cakes</td>
<td>3.98 (1.29)</td>
</tr>
<tr>
<td>Cookies</td>
<td>4.66 (1.31)</td>
</tr>
<tr>
<td>Non-diet soda</td>
<td>4.08 (1.97)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>N (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethnicity&lt;sup&gt;b&lt;/sup&gt;</td>
<td></td>
</tr>
<tr>
<td>White British</td>
<td>1861 (82.3)</td>
</tr>
<tr>
<td>White Irish</td>
<td>22 (1.0)</td>
</tr>
<tr>
<td>Other white background</td>
<td>105 (4.6)</td>
</tr>
<tr>
<td>Black – Caribbean</td>
<td>20 (0.9)</td>
</tr>
<tr>
<td>Black – African</td>
<td>34 (1.5)</td>
</tr>
<tr>
<td>Other black background</td>
<td>5 (0.2)</td>
</tr>
<tr>
<td>Asian – Indian</td>
<td>52 (2.3)</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>Count (Proportion)</td>
</tr>
<tr>
<td>------------------------------------------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>Asian – Pakistani</td>
<td>55 (2.4)</td>
</tr>
<tr>
<td>Other Asian background</td>
<td>21 (0.9)</td>
</tr>
<tr>
<td>Mixed – White and Black Caribbean</td>
<td>18 (0.8)</td>
</tr>
<tr>
<td>Mixed – White and Black African</td>
<td>12 (0.5)</td>
</tr>
<tr>
<td>Other mixed background</td>
<td>21 (0.9)</td>
</tr>
<tr>
<td>Chinese</td>
<td>14 (0.6)</td>
</tr>
<tr>
<td>Other</td>
<td>6 (0.3)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Socioeconomic quintile(^b,c)</th>
<th>Count (Proportion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (least deprived)</td>
<td>1193 (52.8)</td>
</tr>
<tr>
<td>2</td>
<td>306 (13.5)</td>
</tr>
<tr>
<td>3</td>
<td>179 (7.9)</td>
</tr>
<tr>
<td>4</td>
<td>177 (7.8)</td>
</tr>
<tr>
<td>5 (most deprived)</td>
<td>391 (17.3)</td>
</tr>
</tbody>
</table>


\(^b\) N=14 (0.6%) missing data


**Constructing Latent Variables**

**Latent variable 1 – Unhealthy food purchases.** Confirmatory factor analysis of the latent variable consisting of children’s self-reported purchase of chocolate, sweet biscuits, crisps, bakery goods, takeaway foods, sweets, and non-diet fizzy drinks was produced. The initial fit did not meet the established cut offs (barring for the SRMR) (CFI = .86/ CFI\(_{sb}\) = .88, TLI = .78/TLI\(_{sb}\) = .82, RMSEA = .26/RMSEA\(_{sb}\) = .19, SRMR = .06). Modification indices suggested covariances needed to be added between several items (chocolate and sweets, takeaway foods and bakery goods, takeaway foods and biscuits, and bakery goods and biscuits). This led to a
notable improvement in the model which was acceptable to good (CFI = .99/CFI_{sb}=.99, TLI = .99/TLI_{sb}=.98, RMSEA = .07/RMSEA_{sb}=.05, SRMR = .02), with the information criteria indices also showing improvement (original model AIC = 47802.65, BIC = 47922.83; covariance model AIC = 45748.38, BIC = 45891.46), all variables were associated with the latent variable (ps<.001). This model was compared to the ordinal generalised model (which did not include covariance’s due to the GSEqM method employed), the information criteria methods showed the ordinal model to be substantially better (AIC = 35336.38, BIC = 35616.81), all p’s<.001 and critical ratio’s >12.1. Figure 1 demonstrates regression coefficients when part of the structural model.

Latent variable 2 – unhealthy food consumption. Confirmatory factor analysis of the latent variable consisting of children’s self-reported consumption of chocolate, crisps, pastries, cakes, biscuits and non-diet fizzy drinks was produced. The initial fit of the model did not meet cut offs (CFI = .81/CFI_{sb}=.82, TLI = .69/TLI_{sb}=.71, RMSEA = .16/RMSEA_{sb}=.15 SRMR = .07). Modification indices suggested covariances needed to be added between chocolate and crisps as well as cakes and pastries. This led to a notable improvement in the model which was acceptable to good (CFI = .97/CFI_{sb}=.97, TLI = .93/TLI_{sb}=.93, RMSEA = .08/RMSEA_{sb}=.07, SRMR = .03), with the information criteria indices also showing some improvement (original model AIC = 45331.69, BIC = 45434.71; covariance model AIC = 44891.47, BIC = 45005.93), all variables were strongly associated with the latent variable (ps<.001). This model was compared to the ordinal generalised model (which, again does not include covariance’s), the information criteria methods showed the ordinal model to be substantially better (AIC = 43021.33, BIC = 43261.71), again all ps<.001 (all critical ratio’s >7.8). Figure 1 demonstrates regression coefficients when part of the structural model.
Model evaluation (see Figure 1 for a graphical representation of the hypothesised model). In order to evaluate the fit of the structural model, the linear model was initially fitted and proved to be a very good fit to the data barring the TLI which was just acceptable (CFI = .95/CFI_{sb} = .95, TLI = .94/TLI_{sb} = .94, RMSEA = .060/RMSEA_{sb} = .05, SRMR = .06). The ordinal generalised SEqM model (whereby the indicators for the latent variables and purchase requests were ordinal with a logit link, sex was binomial with a logit link, and the remaining variables were Gaussian) was a substantially better fit (linear model-AIC = 154363.97, BIC = 154816.09; ordinal model AIC = 95594.96, BIC = 96241.68). All subsequent associations reported are taken from the latter model (Table 2).

Table 2: Direct Associations Between Variables from the GSEqM Model (n=2260)

<table>
<thead>
<tr>
<th>Association</th>
<th>B</th>
<th>(SE)</th>
<th>p</th>
<th>95%CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial TV -&gt; purchase requests</td>
<td>.023</td>
<td>.002</td>
<td>&lt;.001</td>
<td>.018 to .028</td>
</tr>
<tr>
<td>Non-commercial TV -&gt; purchase</td>
<td>.011</td>
<td>.005</td>
<td>.03</td>
<td>.001 to .022</td>
</tr>
<tr>
<td>Commercial TV -&gt; BMI</td>
<td>.005</td>
<td>.003</td>
<td>.06</td>
<td>-.001 to .007</td>
</tr>
<tr>
<td>Non-commercial TV -&gt; BMI</td>
<td>.008</td>
<td>.004</td>
<td>.16</td>
<td>-.003 to .018</td>
</tr>
<tr>
<td>Commercial TV -&gt; purchase</td>
<td>.076</td>
<td>.006</td>
<td>&lt;.001</td>
<td>.065 to .088</td>
</tr>
<tr>
<td>Non-commercial TV -&gt; purchase</td>
<td>.040</td>
<td>.010</td>
<td>&lt;.001</td>
<td>.020 to .059</td>
</tr>
<tr>
<td>Commercial TV -&gt; consumption</td>
<td>.016</td>
<td>.003</td>
<td>&lt;.001</td>
<td>.010 to .022</td>
</tr>
<tr>
<td>Non-commercial TV -&gt; consumption</td>
<td>-.008</td>
<td>.006</td>
<td>.14</td>
<td>-.020 to .003</td>
</tr>
<tr>
<td>Purchase -&gt; consumption</td>
<td>.075</td>
<td>.012</td>
<td>&lt;.001</td>
<td>.046 to .10</td>
</tr>
<tr>
<td>Purchase -&gt; BMI</td>
<td>.111</td>
<td>.014</td>
<td>&lt;.001</td>
<td>.084 to .138</td>
</tr>
<tr>
<td>Purchase requests -&gt; consumption</td>
<td>.291</td>
<td>.030</td>
<td>&lt;.001</td>
<td>.223 to .350</td>
</tr>
<tr>
<td>Consumption -&gt; BMI</td>
<td>-.041</td>
<td>.029</td>
<td>.15</td>
<td>-.097 to .015</td>
</tr>
<tr>
<td>Age -&gt; BMI</td>
<td>-.173</td>
<td>.031</td>
<td>&lt;.001</td>
<td>-.234 to -.112</td>
</tr>
<tr>
<td>Sex* -&gt; BMI</td>
<td>-.491</td>
<td>.086</td>
<td>&lt;.001</td>
<td>-.660 to -.322</td>
</tr>
</tbody>
</table>

Note: A significant covariance existed between commercial and non-commercial TV viewing p<.001.
*males heavier than females.*

P values less than $p<.05$ were considered significant.

**Direct Effects**

**Purchasing.** As shown in Table 2, although TV exposure (whether commercial or non-commercial) was not directly associated with BMI in this sample, both types of exposure were associated with children’s purchasing of unhealthy foods. The strength of the associations between both commercial TV exposure and purchasing, and non-commercial TV exposure and purchasing, were compared and two tailed $p$-values for the differences were generated. The association between commercial TV exposure and purchasing was significantly greater than the relationship between non-commercial TV exposure and purchasing ($Z=3.09, p=.002$). Notably, there was a positive association between purchasing and BMI (Table 2).

**Purchase Requests.** There were also direct associations between both commercial and non-commercial TV exposure and purchase requests. The association between commercial TV exposure and purchase requests was significantly greater than for non-commercial TV exposure ($Z=2.23, p=.03$). Frequency of purchase requests was a significant predictor of consumption.

**Consumption.** Commercial TV exposure only (not non-commercial) was directly associated with consumption, and, accordingly, the association between commercial TV exposure and consumption was substantially stronger ($Z=3.58, p<.001$). Notably, there was no direct association between consumption and BMI in this sample.
Indirect Effects

Based on the findings above, analyses were used to identify any indirect effects of commercial and non-commercial TV exposure on BMI through purchasing, as well as effects of commercial and non-commercial TV exposure on consumption through purchase requests. To analyse indirect effects, non-linear combinations of the association between the independent variable (non-commercial or commercial TV exposure) and mediator (purchasing in the first set of analyses, purchase requests in the second set), and mediator to the DV (BMI) were computed (i.e. producing a nonlinear product of the coefficient)\textsuperscript{26,27}. The non-commercial models controlled for commercial TV exposure and vice versa.

There were significant indirect effects of commercial (B=.037, SE=.004, p<.001, 95%CI = .030 to .044) and non-commercial (B=.034 SE=.004, p<.001, 95%CI = .027 to .040) TV exposure on BMI through purchasing. These effects were not significantly different in magnitude (Z=.53, p=.60). There were also significant indirect effects of commercial (B=.006, SE=.001, p<.001, 95% CI = .004 to .007) and non-commercial (B=.003, SE=.001, p=.01, 95%CI = .001 to .006) TV exposure on consumption through purchase requests, with the commercial pathway being significantly stronger (Z=2.12, p=.03).

DISCUSSION

A lack of understanding of the full range of behavioral impacts of children’s commercial television exposure remains an important barrier to policy progress worldwide. The current study sought to address this by empirically testing the Kelly et al.\textsuperscript{12} hierarchy of effects.
model, primarily hypothesising that commercial television exposure would be indirectly
associated with child BMI via purchase requests, purchase and consumption. As predicted,
there was an indirect association between commercial TV exposure and consumption of
unhealthy foods through purchase requests. As such, the greater the volume of commercial
TV a child was exposed to, the greater the frequency of their requests to parents to purchase
the advertised products, which in turn was associated with more frequent consumption of
unhealthy foods. This indirect pathway was also significant for non-commercial TV
exposure, but the association was significantly weaker than for commercial. It is important
for the interpretation of the findings of this study to note that there was significant co-
variance in viewing in this sample (i.e. those children watching larger volumes of commercial
TV were also likely to watch large volumes of non-commercial TV).

There was also an indirect association between both commercial and non-commercial TV
exposure and BMI through purchasing. The effect of commercial exposure on purchase
propensity has been summarised elsewhere but this is the first study to statistically
demonstrate associations between children’s independent spending on unhealthy foods and
increased body weight. Consumer spending data for the UK shows that soft drinks, eating out
(hot and cold foods) and confectionery all fall within the top 9 categories for biggest average
weekly expenditure for children aged 7-15 years. Unhealthy snacks from these food
categories are key contributors to per capita energy, saturated fat, sodium and/or added sugar
intake in young people. Given that cohort studies indicate that a daily caloric excess of just
48-72kcal is all that is required for the development of overweight in children, it is clear
that, over time, additional intake of these foods would be sufficient to cause weight gain in
children.
Also consistent with the model and the evidence base underpinning it\textsuperscript{12}, there were significant
direct associations between commercial TV exposure and the frequency of (i) children’s
purchase requests to parents for advertised products (often referred to as “pestering”), (ii)
independent food purchases, and (iii) habitual consumption of unhealthy foods. There were
also direct associations between non-commercial TV exposure and both purchase requests
and purchasing, although effects for commercial TV were consistently significantly stronger
than those for non-commercial.

The discovered direct effects support previous studies showing relationships between food
advertising and purchase requests in children\textsuperscript{33} as well as those demonstrating associations
between sedentary behaviour, particularly television viewing\textsuperscript{34}, and unhealthy eating among
children. Snacking on unhealthy food while watching television is commonplace\textsuperscript{35} and
television viewing has been shown to predict unhealthy food preferences\textsuperscript{36} as well as
disrupting habituation to food cues increasing motivation to eat\textsuperscript{37}. Increases in television
viewing are associated with additional caloric intake\textsuperscript{38,39} and exposure to food advertising
leads to greater acute snack consumption in children\textsuperscript{4,5}. While one previous study of 9-11
year old children suggested that television viewing time was more strongly associated with
unhealthy diet than total sedentary time\textsuperscript{40}, it is clear that further research is needed to fully
disentangle the relative contributions of each factor in determining overall consumption
patterns.

The mechanism behind the association between advertising and BMI needs further
investigation\textsuperscript{41}. The SEqM approach offers unique advantages in this endeavour, as direct
effects were controlled for while exploring indirect effects – that is, this study was able to
explore how multiple variables interact with each other rather than viewing each individual variable in isolation, as has been the case in a majority of prior studies. Effects of non-commercial TV exposure on body weight through purchasing may be partly explained by non-commercial food cue exposure in programming, which has been found to depict unhealthy foods more frequently than healthy, to associate unhealthy foods with value and reward to a significantly great extent and to affect eating behaviour in children. A recent study demonstrated that exposure to cooking programs, for example, affected food choice in 10-12 year old children. The impact of exposure to healthy food cues on healthy food selection in that study suggests a promising avenue for television-based nutrition education.

Limitations of this work include the cross-sectional nature of the research design. Inferences surrounding indirect effects in cross-sectional research are a contentious issue. Without longitudinal analyses and careful control of confounders any pathways remain somewhat speculative. The qualification of indirect effects should be viewed with consideration for these limitations, and the conduct of longitudinal studies should be prioritised.

The use of self- or parental-report measures is also a limitation. TV viewing outcomes were measured by parent-report, and while this has been shown to correlate with actual viewing time these data are of unknown accuracy and may be affected by social desirability biases that may differ by socioeconomic status. Additionally, child-report of purchase and consumption behaviours is likely to involve some error. While the cognitive abilities required to self-report behaviour (e.g. a well-developed concept of time, good memory) typically
increase rapidly from the age of 8 years\textsuperscript{47}, it is important to interpret the results presented here with caution due to the age range of the sample.

Interestingly, in this sample, neither TV exposure (commercial or non-commercial) nor consumption of unhealthy foods was directly associated with BMI. These are not altogether surprising findings. Body weight was measured via parental report, and there is robust evidence that parents differentially underestimate their child’s weight, such that parents of heavier children underreport their child’s weight to a greater extent\textsuperscript{48}. Further, at the individual level, body weight (and indeed excess weight) in children is known to be determined by a multitude of factors including parental BMI, dietary patterns, but also physical activity, sleep duration, and intrauterine influences among others\textsuperscript{49} that were not measured or accounted for here. Rather than dismissing the importance of these other factors, the likely interplay of food marketing effects with physiological (e.g. epigenetics) and contextual influences (e.g. social factors) is explicitly recognised in the full version of the model\textsuperscript{12}. Indeed, evidence suggests that children with overweight (as determined by international standardised cut-points\textsuperscript{50}) may be more susceptible to marketing effects\textsuperscript{5,6,51}, which is consistent with this proposed interplay between marketing, weight and other factors.

Food marketing is, of course, only one of many known environmental determinants of obesity\textsuperscript{52}, a notion supported by the findings of the current study.

The study was not powered to explore multi-categorical confounds such as ethnicity and socioeconomic status.
Strengths of this work include the large and nationally representative sample, the use of SEqM that controls for direct effects of exposure while looking at indirect effects, the use of latent variables (error free measures) and the application of generalised linear models.

IMPLICATIONS FOR RESEARCH AND PRACTICE

This study elucidates potential behavioural pathways through which television food advertising exposure may be linked to poorer dietary outcomes and increased body weight in children. As well as reinforcing findings from previous studies of the direct associations between commercial TV exposure and food behaviours, this study provides novel evidence of the indirect influences of commercial exposure on self-reported purchase, consumption and BMI that may inform future research and policy directions in this field. Future studies should explore ethnicity and socioeconomic factors in more detail, this would necessitate stratified sampling with sufficient numbers (approximately N=400) in each level for a random slope multilevel framework to be applied. Longitudinal studies should be prioritised, if evidence supports causal effects of commercial exposure on eating and health outcomes then this has clear implications for public health policy. Policies to restrict unhealthy food advertising to children should also be robustly evaluated to ensure effective reductions in exposure are achieved and whether the anticipated changes to dietary behavior (as intimated by the current study) follow over time. Expanding understanding of these behavioural pathways would also help identify potential opportunities for intervention, including how to maximise the salience and impact of nutritious food promotion on positive health behaviors among youth. The findings reported support the recommendations of the American Academy of Pediatrics that parents and pediatricians should work together to ensure appropriate use of media to maximise benefits and minimise potential harms for school-aged children.
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