Media multitasking is associated with higher risk for obesity and increased responsiveness to
rewarding food stimuli

Richard B. Lopez^{1*}

Todd F. Heatherton²

Dylan D. Wagner³

¹Department of Psychology, Rice University, Houston, TX 77005, USA

²Department of Psychological and Brain Sciences, Dartmouth College,
Hanover, NH 03755, USA

³ Department of Psychology, The Ohio State University, Columbus, OH 43210, USA

*Corresponding author:

Richard B. Lopez

BioScience Research Collaborative, Rice University

6500 Main Street, MS-663, Houston, TX 77030

richard.lopez@rice.edu

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Abstract

Obesity among children and adolescents has dramatically increased over the past two to three decades and is now a major public health issue. During this same period, youth exposure to media devices also became increasingly prevalent. Here, we present the novel hypothesis that media multitasking (MMT)—the simultaneous use of and switching between unrelated forms of digital media—is associated with an imbalance between regulatory processes and reward-related responses to appetitive food stimuli, resulting in a greater sensitivity to external food cues among high media multitaskers. This, in turn, may contribute to overeating and weight gain over time. To test this hypothesis, we conducted two studies examining research participants who grew up during the recent period of escalating multitasking and obesity—and among whom 37% are overweight or obese. In Study 1, participants’ propensity to engage in MMT behaviors was found to be associated with a higher risk for obesity (as indicated by higher body mass index and body fat percentage). Next, in Study 2, a subset of participants from Study 1 were exposed to appetitive food cues while undergoing functional neuroimaging and then, using passive mobile sensing, the time participants spent in various food points-of-sale over an academic term was inferred from GPS coordinates of their mobile device. Study 2 revealed that MMT was associated with an altered pattern of brain activity in response to appetizing food cues, specifically an imbalance favoring reward-related activity in ventral striatum and orbitofrontal cortex—relative to recruitment of the frontoparietal control network. This relationship was further tested in a mediation model, whereby increased MMT, via a brain imbalance favoring reward over control, was associated with greater time spent in campus eateries. Taken together, findings from both studies suggest the possibility that media multitasking may be implicated in the recent obesity epidemic.

Keywords: media multitasking, obesity, self-control failure, cue reactivity, reward

1 Until the late 1980s, obesity in childhood was relatively uncommon. According to the
2 Centers for Disease Control, throughout the 1970s approximately 15% of children (age 2 – 19)
3 were overweight or obese. By 2004 the figure had more than doubled to 33.6% (Fryar, Carroll, &
4 Ogden, 2014) and remains high (Ogden, Carroll, Kit, & Flegal, 2014). Additionally, obesity rates
5 continue to increase among current teenagers, albeit not as steeply as during recent periods
6 (Ogden, Carroll, Lawman, Fryar, Kruszon-Moran, Kit, & Flegal, 2016).

7 Obesity is multifactorial, influenced by genes, nutrition, gut microbes, physical activity,
8 as well as a host of environmental factors, including prenatal environments, socioeconomic
9 circumstances, insufficient or poor sleep, and fast food marketing (Kit, Ogden, & Flegal, 2014).
10 However, few of these explanatory factors have changed since the 1980s sufficiently to account
11 for the dramatic increase in childhood obesity. So, an urgent question is: what happened during
12 this time period (i.e., the last 20 – 25 years) that might account for the dramatic rise in obesity?
13 For instance, if fast food marketing is behind the obesity increase, why might children nowadays
14 be more sensitive or responsive to such advertising? In this paper, we propose that media
15 multitasking may alter the functioning of brain networks associated with self-regulation and
16 reward processing in a way that may contribute to the observed obesity epidemic.

17 In the past two decades, children have increased their use of multiple forms of digital
18 media, portable computers, and mobile devices. The Kaiser Foundation examined children's
19 media use in large samples ($N > 2000$) of children aged 8 – 18 years and reported that total
20 media exposure across all devices by children increased dramatically, from 7:29 hours per day in
21 1999, to 8:33 hours in 2004, to 10:45 hours in 2009 (Rideout, Foehr, & Roberts, 2006).
22 Critically, this increased media exposure occurred despite only a small increase in actual time
23 spent with media. So, instead of consuming more, children maximized their total exposure by

1 *multitasking* (Carrier, Cheever, Rosen, Benitez, & Chang, 2009)—that is, the simultaneous use
2 of and switching between unrelated forms of digital media. From 1999 to 2009, children nearly
3 doubled their time spent media multitasking, from 16% of the time to 29% of the time.

4 Multitasking is now common. For instance, approximately two-thirds of children in 7th –
5 12th grades reported high levels of multitasking across devices, such as using more than one
6 device while watching television or using social media while playing video games. Is it possible
7 that the explosion of media use and multitasking might be meaningfully related to the increase in
8 childhood obesity? If so, which mechanisms might account for this relationship? According to
9 our hypothesis, frequent media multitasking may create an imbalance between neural systems
10 sensitive to reward on the one hand, and self-regulatory capacity on the other (Heatherton &
11 Wagner, 2011; Lopez, Chen, Huckins, Hofmann, Kelley, & Heatherton, 2017). This imbalance
12 may encourage (over)eating in the face of food cues from the environment or from marketing.

13 **Cue-induced eating and self-regulation failure**

14 Previous work in the eating domain has demonstrated that exposure to environmental
15 cues that signal reward triggers strong impulses to eat and undermines efforts to exert self-
16 control (Heatherton & Wagner, 2011). Indeed, incidental exposure to food cues elicits activity in
17 the brain's reward system, and this activity reliably predicts eating behaviors across studies (for
18 reviews, see Boswell & Kober, 2016; Wagner, 2017). For example, one brain imaging study
19 demonstrated that first year students who showed the greatest reward-activity to incidentally
20 presented food cues gained the most weight in their first year at college (Demos, Heatherton, &
21 Kelley, 2012). Similarly, another study in which participants were incidentally exposed to food
22 images demonstrated that cue reactivity in the ventral striatum predicted daily eating behaviors

(Lopez, Hofmann, Wagner, Kelley, & Heatherton, 2014). More recent research implicates such cue reactivity in successful weight loss maintenance over time (Holsen et al., 2017).

Here, we propose that, over time, excessive multimedia multitasking may make those individuals who grew up during the time of increased media exposure (i.e., current college-aged students) hyper-responsive to external cues, such as food cues. Indeed, a recent large-scale survey found that approximately 37% of college students are overweight or obese (American College Health Association–National Health Assessment, 2016). Sensitivity to external cues, especially reward cues, may become manifest as a change in the balance between brain systems associated with successful self-regulation (i.e., the frontoparietal control network; Power et al. 2011) and reward processing (i.e., ventral striatum and orbitofrontal cortex).

Prior research has shown the measuring the relative balance of activity between regions implicated in self-regulation and those involved in reward processing predicts real-world self-control failure in the domain of eating and, critically for our argument, is a better predictor of self-regulation failures than either measure alone (Lopez et al., 2017). With respect to media multitasking, we propose that a history of excessive media multitasking might lead to increased food consumption and obesity by training the brain to become more responsive to external cues while at the same time weakening frontoparietal control over behavior. This tendency, combined with the present obesogenic environment in which individuals are surrounded by appetitive food cues, suggest that media multitasking may be an important and underappreciated factor in explaining the present obesity crisis. We acknowledge, however, that the proposed relationship may be reversed, such that a predisposition to be sensitive to external cues might lead to greater media multitasking in the present digital environment, and thus MMT is a symptom and not a cause of an underlying individual difference in self-regulatory ability.

To test our hypothesis about the relationship between obesity, MMT and brain systems involved in self-control and reward., we conducted two studies. In both cases, we used a newly developed measure, the MMT-Revised (MMT-R) scale¹ to assess participants' general tendency to media multitask. In Study 1, we examined relationships between participants' propensity to engage in MMT behaviors and measures of body composition (i.e., measured BMI and body fat percentage). In Study 2, we tested for relations between MMT, patterns of brain activity in reward and control systems during incidental exposure to appetizing food cues, as well as participants' proximity to real world cues (i.e., time spent in campus eateries)—as measured by passive smartphone sensing. Across both studies, we found converging evidence that supported the hypothesis that media multitasking is associated with higher risk of self-control failure in the eating domain. Moreover, we found evidence that such failures appear to arise from an altered balance of control and reward processes, tipped in favor of reward thereby leading to an increased sensitivity to food reward cues in the environment.

Method (Studies 1 and 2)

Participants

One-hundred thirty-seven healthy undergraduate students ($M_{\text{age}} = 19.16$, $SD_{\text{age}} = 1.22$, age range = 18–23; 93 females) participated in Study 1 in return for course credit or cash payment. A subset of these participants took part in Study 2, which consisted of an fMRI scanning session consisting of a food-cue reactivity task used in prior research (Lopez et al., 2014; Lopez et al., 2017; Wagner et al., 2013). In addition, participants consented to unobtrusive collection of mobile sensing data, specifically of GPS location data for the purposes of

¹See Method (and Appendix A) for additional details about MMT-R scale's items, reliability, and the underlying constructs it measures.

quantifying time spent in campus cafeterias throughout the academic semester. Inclusion criterion for both studies was that participants have complete and valid data for all measures of interest and covariates. For those participants enrolled in Study 2, we applied the following exclusion criteria: excessive head motion (as described in Method) during the fMRI scan, as well as missing mobile sensing data for more than half the sampling period (i.e., 4-5 weeks of a 10-week academic term). After applying the abovementioned inclusion and exclusion criteria, the final sample sizes for all reported analyses were 132 (Study 1) and 72 (Study 2), respectively. Those who enrolled in Study 2 did not differ from the overall sample ($M_{\text{age}} = 19.00$, $SD_{\text{age}} = 0.97$, Age range = 18–22; 52 females). All participants in both studies gave informed consent in accordance with guidelines set by the Committee for the Protection of Human Subjects at Dartmouth College.

Assessment of Media Multitasking Behaviors

All participants completed a questionnaire assessing levels of media multitasking and distractibility. Specifically, we used an 18-item scale titled the Media Multitasking-Revised (MMT-R) scale, which has been developed and validated in using a large, independent sample ($N=995$) and was found to have high internal reliability (Cronbach's $\alpha = 0.86$). In the current sample, scores on the MMT-R had the same reliability (Cronbach's $\alpha = 0.84$). As reported in the Appendix, the MMT-R scale has a two-factor structure, with items loading on factors that reflect either: (1) (pro)active behaviors of compulsive/inappropriate phone checking, e.g., *"When talking to someone face-to-face, how often do you feel the urge to check your phone for unread messages, notifications?"*; or (2) more passive tendencies, including distractibility and interference from using various media, e.g., *"How often does your multimedia use interfere with your homework or work?"* (See Appendix A for all MMT-R scale items). There is one reverse-

scored item, and all scale items (reflecting both abovementioned factors) are summed together, with a total possible score range of 18–90. In the present sample, the average MMT-R score was 49.1 (SD=8.13) and a Shapiro-Wilk test revealed that scores were normally distributed, $W = 0.99, p = 0.316$.

Body Composition Analysis

We measured all participants' body mass index (kg/m²) and body fat percentage using a Tanita Total Body Composition Analyzer (model TBF-300A; Tanita Corporation, Arlington Heights, IL, USA). This is a valid and efficient method to acquire measures of body composition and is comparable to other established techniques that use electrical impedance to estimate body composition metrics (e.g., see Jebb, Cole, Doman, Murgatroyd, & Prentice, 2000).

Study 1 - associations between media multitasking and obesity

Results

Overall, the average BMI in the sample was 23.06 (SD = 2.78; Range: 16.1–30.9), with 17.4% classified as overweight (i.e., BMI between 25 and 30) and 1.5% classified as obese (i.e., BMI 30 or greater)—as per classification guidelines set by the Centers for Disease Control and Prevention. First, in the whole sample of participants (Study 1), we examined the relationship between multitasking (as assessed by the MMT-R scale) and participants' body weight and composition. We found higher MMT-R scores were associated with higher BMI, $r(130) = .252$ (95% CI: .085, .406), $p = .003$ (see Figure 1 for scatter plot), and greater body fat percentage (controlling for gender), $b = .115$ (95% CI: .003, .227), $p = .044$.

Study 2 - associations between media multitasking, neural cue-reactivity and mobile sensing data.

Method

fMRI procedure and analysis

fMRI data were collected with a 3-Tesla Philips Intera Achieva scanner (Philips Medical Systems) equipped with a 32-channel SENSEitivity Encoding head coil. Stimuli were presented using SuperLab 4.0 (Cedrus Corporation) and projected to an Epson ELP-7000 LCD screen positioned at the end of the magnet bore. Participants were able to view the screen via a mirror mounted on the head coil. While in the scanner, subjects completed an event-related cue reactivity task (e.g., Lopez et al., 2014; Lopez et al., 2017; Wagner et al., 2013) in which they viewed a series of images and were instructed to make perceptual judgments as to whether each image depicted an indoor or outdoor scene. All judgments were made with a corresponding button press on a Lumina LU-400 fMRI response pad. The indoor/outdoor task incorporated image of food, people, animals, and nature scenes and no special attention was drawn to the food images in order to ensure that participants remained naïve to the purpose of the study. The cue reactivity task employed a rapid, event-related design, with all design parameters and trial timing following those from previous studies that administered the task (e.g., Lopez et al., 2014).

For each functional run, data were first corrected for differences in slice-timing and preprocessed to remove sources of artifact and noise. Functional data were then realigned within and across runs to correct for head movement and were unwarped to reduce any residual movement-related image distortions. Functional data were normalized into a standard stereotaxic space (3mm isotropic voxels) based on the SPM8 EPI template that conforms to the ICBM 152 brain template space (Montreal Neurological Institute; MNI) and approximates the Talairach and Tournoux atlas space. Normalized images were then spatially smoothed (6mm full-width-at-half-maximum) using a Gaussian kernel. Any participants were excluded from further analysis if they

1 showed excessive motion-related artifact (defined as more than 2 instances of movement greater
2 than 2 millimeters).

3 For each subject, we ran a general linear model (GLM) that incorporated task conditions
4 (convolved with a canonical hemodynamic response function) and covariates of non-interest
5 (i.e., translation and rotation motion parameters from realignment correction and a linear trend to
6 account for drifts in scanner signal over time). Results of the GLM were then used to compute t-
7 contrast images (weighted parameter estimates) reflecting food (versus non-food) related activity
8 at each voxel.

9 Lastly, following the procedure described in our prior work (Lopez et al., 2017), we
10 standardized and averaged activity in the reward system and frontoparietal network, respectively,
11 using the same regions of interest (ROIs). For the reward system, we extracted activity in the
12 bilateral ventral striatum and lateral orbitofrontal cortex (Wagner et al., 2013), and for the
13 frontoparietal control network, there were eight ROIs placed in frontal and parietal cortex, as
14 defined in Power and colleagues' 2011 study.

15 ***Smartphone Passive Sensing Procedure***

16 In order to quantify participants' exposure to real-life food cues, we used mobile sense of
17 GPS location data using unobtrusively inferred participants' behaviors with smartphone sensors,
18 via the StudentLife app developed in the computer science department at Dartmouth (Wang et
19 al., 2014). Using logged location data (GPS coordinates), coupled with known geo-coded
20 boundaries of various locales on the Dartmouth campus (e.g., libraries/study spaces, dorm
21 rooms, etc.), we estimated a participants' proximity to real world food cues by calculating the
22 average number of hours participants spent in campus cafeterias during an academic term.

Results

For participants who took part in Study 2, we first fit a simple linear regression model revealing that higher MMT (as assessed by the MMT-R scale) was associated with lower self-regulation/reward balance scores (i.e., more reward-related activity relative to control activity), $r(70) = -.328$ (95% CI: $-.104, -.520$), $b = -0.026$, $t = -2.90$, $p = .005$ (see Figure 2 for scatter plot), and this relationship held when controlling for BMI, $b = -0.028$, $t = -3.01$, $p = .004$ and for body fat percentage, $b = -0.028$, $t = -3.03$, $p = .003$, showing that this association is not simply a result of altered neural processing of food cues among participants higher in BMI. In addition, we found that the strength of the association between MMT and self-regulation/reward balance scores is stronger than when relating MMT to aggregate activity in each system alone. Specifically, using only the aggregate response of activity in the frontoparietal system ($b = -0.001$, $t = -0.08$, $p = .935$; controlling for BMI) or the reward system ($b = 0.027$, $t = 2.40$, $p = .019$; controlling for BMI), we see in one case no association and in the latter a smaller effect. This highlights the importance of considering the balance between these systems rather than treating each in isolation.

Second, to test whether MMT may account for differences in time spent in close proximity to food cues in daily life, via an imbalance favoring reward activity, we conducted a mediation analysis in which MMT-R scores were entered in as the predictor variable (X), regulation–reward balance scores were specified as the mediator (M), and time spent, in hours, in campus eateries was the outcome variable (Y). We also included BMI and gender as covariates in all model paths to control for potential influence of these variables (e.g., see review by Chao and colleagues, 2017 on gender differences in brain responses to food stimuli; also see review by Pursey and colleagues, 2014 on neural food cue reactivity modulated by weight status). All effect

sizes and corresponding confidence intervals were computed from 10,000 re-samplings of the data, an established approach in mediation modeling that minimizes bias in parameter estimates (Shrout & Bolger, 2002). We specified a path model with the abovementioned predictor, mediator, outcome variables and covariates using the *lavaan* package (version: 0.6-2) in R (Rosseel, 2012). First, satisfying Steps 2 and 3 for establishing mediation (as per Baron & Kenny, 1986), MMT-R scores were significantly associated with brain balance scores (path a), $b = -0.028$ (95% bootstrapped CI: -0.045, -0.011), $Z = -3.241$, $p = .001$, and higher brain balance scores (i.e., activity favoring frontoparietal network activity over reward activity) predicted less time spent in campus eateries (path b), $b = -0.253$ (95% bootstrapped CI: -0.437, -0.068), $Z = -2.739$, $p = .006$. There was also a partial mediation effect, indicated by a significant indirect effect of MMT-R scores on time spent in campus eateries (via brain balance scores), $b = 0.007$ (95% bootstrapped CI: 0.001, 0.014), $Z = 2.168$, $p = .03$; this accounted for 45.3% of the total effect (as specified by the model; see Figure 3 for depiction of the model and partial mediation effect).

Importantly, we altered the model specification by using either the frontoparietal network or reward system as the mediator variable and re-estimating path coefficients and indirect effects. In these alternative models, mediation analysis was not justified, since path b (i.e., brain mediator variable (M) to time spent in campus eateries (Y)) was not significant in both cases ($Z_{FP} = -0.795$, $p_{FP} = .427$; $Z_{Reward} = 1.069$, $p_{Reward} = .285$). Additionally, the indirect effects in these models were not significant, both p 's $\geq .332$. Including BMI and gender as covariates did not appreciably change the findings, with path b remaining insignificant with either the frontoparietal control network or reward system as predictors ($Z_{FP} = -0.961$, $p_{FP} = .337$; $Z_{Reward} =$

0.957, $p_{\text{Reward}} = .339$); indirect effects in these models with covariates were also not significant, both p 's $\geq .44$.

Discussion

Taken together, the findings of these two studies suggest that high media multitasking is associated with greater sensitivity to external food cues and decreased ability to exert control over these responses—which potentially may result in weight gain and obesity. These results support the hypothesis that media multitasking may make people more vulnerable to rewarding food stimuli, which may arise from an imbalance of brain systems associated with self-regulation (i.e., frontoparietal control network) and reward (i.e., ventral striatum and orbitofrontal cortex).

Specifically, in Study 1, we assessed media multitasking tendencies using a newly developed scale (MMT-R scale; see Appendix A) and measured body weight and body fat percentage. Those participants who reported more frequent multitasking behaviors tended, on average, to be at higher risk for obesity (i.e., had higher BMI; see Figure 1) and increased body fat percentage. Next, in Study 2, we investigated a potential neural mechanism that may account for high media multitaskers' increased risk for weight gain and be predictive of time spent in close proximity to food cues. Specifically, we tested the relationship between participants' propensity to engage in media multitasking behaviors (again with the MMT-R scale), neural responses to rewarding food cues using fMRI, and exposure to real world food cues (i.e., time spent in settings with proximate food cues) via passive smartphone sensing.

First, we observed a negative linear relationship between MMT tendencies and a brain-based, regulation—reward balance measure, which captures patterns of activity in both control and reward systems during incidental exposure to food cues (Lopez et al., 2017). This finding suggests that, whereas low media multitaskers (MMTs) tended to have lower reward-related

activity in response to appetizing food cues and greater capacity to exert control over these responses, high MMTs exhibited relatively *higher* reward-related activity and *less* recruitment of the frontoparietal network (see Figure 2). This pattern was in support of our hypothesis that high MMTs may be especially vulnerable to rewarding stimuli, as indexed by greater responsiveness in brain regions that process the reward value of appetitive cues (i.e., ventral striatum and orbitofrontal cortex).

The relationship between MMT and the brain-based balance measure was tested further in a mediation model, demonstrating a negative relationship between MMT and regulation–reward balance scores (path a), as well as a negative relationship between balance scores and time spent in campus eateries (path b), indicating that those with lower self-regulation/reward balance scores spent more time in proximity to real world food cues. We speculate that this may be an example of a proactive self-regulatory strategy, where those with a higher self-control capacity are not putting themselves in tempting contexts in the first place (Hofmann, Baumeister, Förster, & Vohs, 2012). Lastly, and critically, there was a significant partial mediation effect, whereby *increased* MMT tendencies—via *lower* balance scores (i.e., less recruitment of the frontoparietal control network and more reward activity)—predicted *more* time spent around food cues (see Figure 3 for depiction of model and all path estimates). This suggests that frequent MMTs, who on average show an imbalance of food cue-evoked activity that favors reward (over control) activity, tend to spend more time in close proximity to food cues in daily life. Since cue exposure is a common threat to self-control and can lead to self-regulation failure (see Wagner & Heatherton, 2014), then high media multitasking— with its associated imbalance favoring reward and increased food cue exposure—may serve as a risk factor for self-control

1 failure suggesting a potential mechanism for the results of study 1 that showed a positive
2 association between MMT tendencies and BMI.

3 Our hypothesis about the link between MMT and hyper-sensitivity to food cues and cue-
4 induced eating resembles social psychologist Stanley Schachter's Externality Theory developed
5 in the 1960s, which stressed the impact of environmental cues on eating behaviors, and how
6 people differentially respond to such cues. Specifically, Externality Theory proposed that eating
7 patterns of obese individuals are more readily affected by external, environmental cues, such as
8 the smell or palatability of food, than by internal, physiological cues signaling hunger and satiety
9 (Schachter, 1971). Schachter even characterized the obese as more "stimulus-bound" than
10 normal weight participants, as they tended to eat larger quantities whenever sensory aspects of
11 the food stimulus were salient (e.g., they ate more when an open container of cashews was
12 illuminated by a higher versus lower wattage light bulb) (Rodin, 1981).

13 Despite findings that supported his theory, Schachter did not articulate any cognitive or
14 neural mechanisms that could account for what makes someone especially responsive to external
15 cues in the first place. With functional brain imaging, neural activity evoked by incidentally
16 presented food images can serve as a marker of reward cue sensitivity, as well as represent the
17 extent to which external cues influence behavior outside conscious awareness. We propose that
18 MMT may alter brain functioning such that eating and other cue-driven behaviors might become
19 automatically triggered (Neal, Wood, Labrecque, & Lally, 2012).

20 Despite the promising support of our hypothesis, there are several important limitations.
21 First, the relationships between MMT and all other measures are correlational. And although our
22 hypothesis was tested using a mediation model, it is nevertheless the case that mediation alone
23 cannot establish direction of causality. For our hypothesis to be tested more directly, MMT

1 would first have to be experimentally manipulated, followed by measurement of subsequent
2 eating-related behavior. However, media multitasking habits that develop gradually over time
3 (e.g., over the course of years) may not be amenable to manipulation in short laboratory sessions.
4 Indeed, without longitudinal studies that begin early in childhood, it is difficult to know whether
5 multitasking or obesity came first.

6 Second, and as mentioned earlier, even though we postulate that MMT behaviors lead to
7 increased cue sensitivity and overeating, it is plausible that the relationship might operate in the
8 opposite direction, such that individual differences in brain systems that underlie sensitivity to
9 external reward cues may simultaneously predispose some people to be more likely to media
10 multitask more in the first place. Some recent neuroimaging work suggests that brain networks in
11 obese individuals have a different functional organization compared with that of normal weight
12 individuals. Obese participants show increased global connectivity observed in the dorsal
13 attention network, which supports attentional orienting to external stimuli, as well as decreased
14 connectivity in regions associated with monitoring somatic/internal cues, such as ventromedial
15 prefrontal cortex and insula (Geha, Cecchi, Constable, Abdallah, & Small, 2016). This suggests
16 that the possibility that MMT is comorbid symptom and not a cause of obesity remains a
17 plausible alternative explanation of these data.

18 In spite of these limitations, the increase in media multitasking in the past several decades
19 is one of the most prominent changes in the environment during the period in which childhood
20 obesity showed its sharpest increases. As such, the observed associations here between MMT
21 and body weight, as well as an imbalance toward reward processing, appear worthy of further
22 consideration. Moreover, there is other evidence that supports the existence of this proposed link.
23 For instance, the recent rise in childhood obesity (i.e., reaching 33.6% in 2004 and remaining

high since then) (Fryar, Carroll, & Ogden, 2014; Ogden et al., 2014) mirrors the increase in children's multitasking with various media devices (i.e., $\geq 53\%$ of 7th-12th graders reporting MMT some or most of the time; Foehr, 2006). Additionally, boys and minority groups tend to be at higher risk obesity compared to girls and White children (e.g., Ng et al., 2014; Ogden et al., 2014), and, perhaps not uncoincidentally, these same groups report more frequent MMT behaviors (Rideout, Foehr, & Roberts, 2010). Thus, these demographic and temporal trends, although correlational, support a potential association between MMT and obesity. Here we propose a neural mechanism for how MMT may contribute to dietary self-control failure by providing evidence of an imbalance between brain systems associated with reward and self-regulation, respectively that makes high MMTs more likely to notice (and be responsive to) rewarding cues in the environment.

Indeed, this bias toward external orienting (vs. internal monitoring) may be a critical brain-based correlate for hyper-sensitivity to rewarding, extraneous cues. As Kelley, Wagner, and Heatherton (2015) proposed, and in line with what Geha and colleagues found, MMT may be associated with increased connectivity in (and functioning of) the dorsal attention network (Kelley et al., 2015). Moreover, this proposal is consistent with Anderson, Yantis, and others' model of how attention is more readily captured by cues previously associated with reward (Anderson, Faulkner, Rilee, Yantis, & Marvel, 2013; Anderson, Laurent, & Yantis, 2011a, 2011b). MMT may intensify such attentional capture effects, especially in response to extraneous, reward-laden, cues—due to a strengthening of the dorsal (or possibly other) attention networks in the brain. Recently developed analysis tools have made it possible to accurately differentiate individuals' attentional capacity based on patterns of brain connectivity. For example, Rosenberg and others have developed an elegant modeling approach that jointly

incorporates both positive and negative patterns of whole-brain connectivity to predict attention and attendant behaviors (Rosenberg, Finn, Scheinost, Constable, & Chun, 2017).

With potentially such broad, system level brain changes, MMT may alter attention in ways that make it promiscuous and attracted to all manner of environmental cues, not just rewarding food stimuli. Indeed, if our proposal is correct, this suggests that any disorder that involves biased attention towards particular stimuli may be exacerbated by MMT. For example, depression, anxiety disorders, PTSD, eating disorders, and various addictions have been linked to hyper-sensitivity to specific external cues. As such, MMT may heighten symptoms in those with these syndromes by decreasing the threshold required by an external cue to trigger an episode. For example, those with depression and anxiety disorders show attentional biases to threatening stimuli (Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, & van IJzendoorn, 2007; Mathews, Ridgeway, & Williamson, 1996). In this context, we note that depression and anxiety disorders are on the rise among youth (Collishaw, 2015; Twenge, 2015), and particularly on college campuses (Beiter et al., 2015). If MMT in fact alters cue responsiveness across domains, then one would expect an overlap of conditions and comorbidities. Indeed, one recent study of obese children found that 18.4% of the sample was diagnosed with ADHD (Wentz, Björk, & Dahlgren, 2016). Thus, MMT might serve as a critical behavior to target and potentially modify during a child's development in order to inure them against the lure of external reward cues (e.g., food, alcohol, risky behaviors).

In summary, the opportunity to use many forms of media at the same time, via multitasking, is new and unprecedented for our species. Indeed, the rate at which digital, mobile technologies have developed is exceedingly disproportionate to the time scale over which evolution operates on neurobiological systems (Wilson, Ochman, & Prager, 1987), and our

brains may simply lack the cognitive abilities to multitask effectively. There also may be unrecognized, harmful effects of indulging in media multitasking, such as impaired functioning of brain networks associated with cognitive control and attention. The available evidence, although tentative, indicates that that media multitasking may be an important contributing factor in the recent obesity epidemic, possibly via altering the balance between control and reward regions. But, it might also cause problems in other behavioral domains, such as producing ADHD in children, impairing children's ability to focus attention in classrooms, and maybe creating greater difficulty for addicts to achieve or maintain abstinence. Here, the observed patterns linking media multitasking to increased responsiveness to external food cues and time spent in campus eateries (Study 2) and body weight and composition (Study 1) support the hypothesis that multitasking may be playing an important but overlooked role in the childhood obesity epidemic. We call for continued research to understand how the avalanche of new technologies affects the developing minds and bodies of children and adolescents.

Compliance with Ethical Standards

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Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent: Informed consent was obtained from all individual participants included in the study.

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Figures

Figure 1.

Scatter plot with fitted regression line and 95% confidence interval band, depicting a positive correlation between MMT-R scores, capturing participants' propensity to engage in media multitasking, and body mass index (kg/m²) in Study 1.

Figure 2. Scatter plot, with fitted regression line and 95% confidence interval band, depicting a negative linear relationship between MMT-R scores and the relative balance of brain activity in the frontoparietal control network (versus reward system) in response to appetizing food stimuli in Study 2.

Figure 3. Mediation model from Study 2, with media multitasking as the predictor (X) variable, brain-based balance as the mediator (M), time spent in campus eateries as the outcome (Y) variable, and BMI and gender as covariates. Lines between variables are labeled with path coefficients and standard errors are indicated in parentheses. $*p < 0.05$, $**p < 0.01$, two-tailed.

Appendix A

Validity Testing of the Media Multitasking Inventory

Before running Studies 1 and 2 reported above, we examined whether the most popular assessment of MMT, the media multitasking inventory (Ophir, Nass, & Wagner, 2009), would be a viable assessment of media multitasking tendencies, and whether it related to proxies for self-control success/failure in the eating domain. To this end, we administered the Ophir inventory along with an assessment of BMI and trait self-control (Tangney, Baumeister, & Boone, 2004), in a web-based survey to the Dartmouth introductory psychology and neuroscience participant pool across several terms ($N = 673$, 426 females). We found a significant but weak association between MMT scores and self-reported BMI, $r(671) = .082$, $p = .034$, as well as a significant negative association between MMT scores and trait self-control, $r(671) = -.254$, $p < .001$.

Participants in this sample often reported that the MMT inventory was tedious and at times difficult to complete, due to format of the questions and what participants were asked to report (i.e., separately estimating the percentage of time using 10-11 forms of unrelated media while engaging in a primary communications medium, and then repeating this estimation procedure 11 additional times with other media serving as the primary medium). Moreover, the relatively small effect sizes raise the possibility of low construct validity of Ophir and colleagues' MMT inventory. With these considerations in mind, we developed a new scale (MMT-Revised; MMT-R) that more concisely assesses media multitasking and its related distractibility (see below, also: Lopez & Heatherton, 2017; Lopez, Salinger, & Heatherton, submitted).

Psychometric development and validation of the MMT-R scale

Originally, there were 30 candidate items in the MMT-R that we administered in a large participant pool sample at Dartmouth (N=995). Some of these items tapped other traits that we hypothesized may show overlap with multitasking (e.g., impulsiveness, conscientiousness). With all 30 items, we calculated item-total correlations, which ranged widely (-0.022 to 0.561). For all subsequent analysis, we excluded items that had relatively weak or near zero correlations (i.e., by $r < .3$ by convention).

The remaining set consisted of 18 items (see Table 1, below), and we found there were strong inter-correlations among these items based on Bartlett's Test of Sphericity, $\chi^2(153) = 4948.6, p < .001$. Internal consistency was also sufficiently high, Cronbach's $\alpha = 0.86$ (Cronbach, 1951). Next, in order to test whether these items were conducive to factor analysis, we calculated measure of sampling adequacy (MSA; Kaiser, 1974) for all items. MSA values ranged from 0.835 to 0.923, and the Kaiser-Meyer-Olkin (KMO) index was 0.881. Given this relatively high covariance between items, we submitted the items to a principal components analysis, which we performed with an orthogonal (varimax) rotation, to see if there would be unrelated factors that jointly contributed to capture MMT behaviors.

This factor analysis returned two factors that collectively explained 39% of the total variance. Item loadings were relatively interpretable, in that items generally loaded on one factor or the other, with 14 out of the 18 items having $\geq .5$ loadings on either factor and factor loadings across all items were strongly negatively correlated, $r(16) = -0.85$ (95% CI: -0.636, -0.943), $p < .001$.

The factors seemed to generally reflect either: (1) *(pro)active* behaviors of compulsive or inappropriate phone checking (e.g., *"When talking to someone face-to-face, how often do you feel the urge to check your phone for unread messages, notifications, etc.?"*); or (2) more *passive*

- 1 tendencies that encompass interference, distractibility, procrastination, and multitasking (e.g.,
 2 "*How often do you find yourself procrastinating by viewing media content online?*") (See Table 1
 3 for all item loadings).

Table 1. Eighteen items from MMT-Revised (MMT-R) scale with factor loadings

Item wording	Factor 1 loading (phone checking)	Factor 2 loading (distraction/ interference)
When you sit down to do work or homework, how successful are you at avoiding distraction? [<i>Reverse scored</i>]	0.05	0.72
How often do you check your phone when you shouldn't? (e.g., during a meeting or lecture).	0.53	0.40
When driving, how often do you reach for your phone to check for texts/calls/notifications?	0.55	0.09
How urgently do you feel the need to check for possible text messages or emails?	0.58	0.34
How often do you find yourself procrastinating by viewing media content online (e.g., YouTube, Netflix, Hulu, etc.)	-0.03	0.71
How distracted are you by alerts or notifications on your phone's lock screen?	0.49	0.42
How often do you multitask? (i.e., begin a task or activity but then find yourself doing another task or activity?)	0.19	0.55
How often do you multitask with multiple media devices? (e.g., answer a text message on your phone while browsing Facebook on your computer?)	0.26	0.52
How often do you send texts during class?	0.61	0.17
When talking to people, how often are you distracted by your surroundings?	0.38	0.31
How often do you check for texts or emails while watching a movie in a theater?	0.66	0.00
If you are in the middle of a conversation and receive a notification for a new text or email, how likely are you to check it?	0.64	0.07
How often do thoughts about what you are doing next interfere with what you are doing in the moment?	0.33	0.29
How often do alerts/notifications on your phone interfere	0.51	0.40

with what you're doing?		
When talking to someone face-to-face, how often do you feel the urge to check your phone for unread messages, notifications, etc.?	0.68	0.17
How often does your multimedia use interfere with your homework or work?	0.15	0.76
How much would other people describe you as being easily distracted?	0.20	0.58
In a movie theater, how often are you distracted by other people sitting around you?	0.42	0.04

To test for multiple types of validity of the MMT-R scale, we administered Ophir and colleagues' original MMT inventory, the MMT-R scale, and trait self-control in a separate college-aged sample ($N=87$, 59 females). First, we found that the MMT inventory by Ophir and colleagues and the MMT-R scale were significantly correlated, $r(85) = .381$, $p < .001$. The original MMT inventory was negatively correlated with trait self-control, $r(85) = -.199$, $p = .065$, but scores from the MMT-R scale were more robustly associated with (reduced) trait self-control, $r(85) = -.588$, $p < .001$. This latter correlation coefficient ($-.588$) was significantly lower than the former ($-.199$), $z = 3.741$, $p < .001$.

Lastly, to examine test-retest reliability, we found that scores on this 18-item version were relatively stable over time (i.e., beginning versus end of an academic term) in a separate participant pool sample ($N=135$), $r(133) = .80$ (95% CI: .73, .85), $p < .001$.

Scale availability

We have made the MMT-R scale available for research purposes at the following link:

<https://mfr.osf.io/render?url=https://osf.io/vrdh6/?action=download%26mode=render>