EATING IN THE AGE OF SMARTPHONES: THE GOOD, THE BAD, AND THE NEUTRAL

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EATING IN THE AGE OF SMARTPHONES: THE GOOD, THE BAD, AND THE NEUTRAL

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Editorial: Eating in the Age of Smartphones: The Good, the Bad, and the Neutral

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Editorial on the Research Topic

Eating in the Age of Smartphones: The Good, the Bad, and the Neutral

Worldwide, an estimated 6.4 billion individuals own a smartphone—a cell phone that provides communication and computing functions through an operating system (Statista, 2021a). The average smartphone user now engages with their device shortly after waking up and will spend 3–4 h a day interacting with a variety of apps (Andrews et al., 2015; Rootmetrics, 2018; Nielson, 2020). This frequent use, coupled with an ever-expanding range of social functions, means that devices are readily available throughout the day. Beyond being a potential distraction while eating, such functionality also allows for thoughts or food-related behaviors to be captured and shared (Teo et al.; La Marra et al.). Unlike single function screen-based technologies of the past, smartphones are not only changing how we live but also how we conduct research in the digital age. Therefore, we commissioned a Research Topic to understand how smartphones are transforming the eating experience.

Recognizing the timely nature of this topic, we invited researchers to specifically document "the good, the bad, and the neutral" aspects of eating in the age of smartphones. While a large body of research previously described how other devices (e.g., televisions) influence eating behaviors (Martin et al., 2009; Zhang et al., 2016), only a handful of studies before this collection focused directly on smartphones (e.g., Gonçalves et al., 2019; Yong et al., 2021). The curated collection responds by articulating how smartphones have taken their place in an obesogenic environment. While articles span both research papers and commentaries, each describes how smartphones might alter appetite regulation or increase the risk for weight gain. These collectively demonstrate that, as with the impact of other digital technologies, changes to eating behavior may not be unique to the technology itself. Instead, impacts can often be aligned with well-established psychological processes including social facilitation or attentional limitations, which may also disrupt the encoding of memories that affect appetite control (La Marra et al.).

In terms of research papers, Tebar et al. surveyed adults on their use of smartphones, televisions, and computers during the COVID-19 pandemic. Compared to participants whose phone use did not change throughout this period, those who reported greater phone use were 1.5 times more likely to report increased consumption of sweetened food (Tebar et al.). This pattern also occurred amongst participants who watched more television, but not for participants who reported increased computer use. In a separate paper, Lopez et al. examined the weight status of pre-adolescent children aged 9–11. Children were then asked about their propensity to multi-task using digital devices—for example, by checking their phones while completing their homework. In line with Tebar et al.'s findings, children who engaged more frequently in media multi-tasking were more likely to have a greater body mass index. Finally, Teo et al. conducted an experiment to examine how two forms of phone use would impact snacking

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behaviors amongst male adolescents. The authors found that when adolescents used their phones to send and receive messages, they consumed more snacks than when they used their phones to browse a neutral article.

While these papers provide empirical data across the lifespan, two further commentaries discussed possible mechanisms through which smartphones may influence our eating behaviors. At the individual level, La Marra et al. consider how smartphones may simply interfere with physiological signals of hunger and satiety. If someone is less aware of how much he or she has eaten, this could result in overeating, but this can occur with a wide variety of distractions (technological or otherwise) (e.g., Gonçalves et al., 2019). Even results that appear specific to key smartphone functions may simply reflect group processes observed offline. For example, previous studies have found that eating behaviors increase in the presence of other people and the virtual company offered by smartphones through messaging, video calling or other social networks may increase food consumption *via* a similar mechanism (Teo et al.). On the other hand, Stephens et al. argue that the convenience offered by phone apps alone may be a larger societal driver of unhealthy eating. Notably, phone-based food delivery apps have grown in popularity over the past decade. While some apps can support a healthy diet, most that offer delivery services disproportionately provide access to "junk" food and a frequent user's weight may increase as a result.

Taken together, the articles in our Research Topic highlight several ways in which smartphones may alter the eating experience. Two decades after the first smartphone became available to the public, research questions and methods continue to evolve. Eating can consume attentional resources, but it often occurs alongside a variety of evolving digital distractions. These innovations can initially make research more challenging. However, changes to everyday experiences following the adoption of smartphones provides many new opportunities for advancing psychological theory. Triangulating results from experimental and observational approaches could, for instance, inform theories of attention that have implications for daily life (La Marra et al.; Lavie, 2010).

Future research might specifically explore whether the impact of smartphones differs as a function of (i) the phone user (e.g., adolescents versus adults); or (ii) the type of phone use (e.g., passively watching videos versus actively playing games). However, given the variety of other biological, environmental, social, and cognitive factors that can also impact dietary behavior, the direction of any effect may not always be inherently obvious. For example, engaging with content that is very distracting could result in over *or* under-eating and this may vary between different groups. Interactions between individual differences and specific technology behaviors will, in turn, become even more important if new research is to capitalize on recent methodological advances (Ellis, 2020).

Most designs continue to rely on snapshots of self-report to capture both phone use and dietary behavior, however, smartphones can become part of a researcher's toolkit. Such approaches help mitigate methodological limitations and allow for longitudinal designs with larger sample sizes that capture dynamic patterns of behavior *via* experience sampling (e.g., Yong et al., 2021). For example, the ubiquitous nature of smartphones means that they can be used to track eating patterns directly by allowing participants to keep diaries or take photographs of their food (Ellis, 2020). Advances in image recognition that allow photos of food to be automatically classified will likely provide even more exciting opportunities for researchers in this area (Tran et al., 2020). However, even without such developments, smartphones can already be used to deliver or monitor the effectiveness of behavioral interventions (e.g., Piazza et al., 2021). As smartphone adoption is predicted to grow over the next decade (Statista, 2021b), we hope that this collection contributes to the conversation, spurring further research on what it means to eat in an age of smartphones.

AUTHOR CONTRIBUTIONS

Both authors co-wrote the editorial and approve of the final version.

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To Message or Browse? Exploring the Impact of Phone Use Patterns on Male Adolescents' Consumption of Palatable Snacks

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Surveys of mobile phone usage suggest that adolescents habitually use their phones while eating. In this study, we explored whether the manner in which one uses a mobile phone – to engage in a social or non-social activity – can affect appetite regulation. Participants were fifty male adolescents randomly assigned to engage in one of the following phone-based activities: (1) sending and receiving messages (social activity), or (2) reading a neutral article (non-social activity). When given the opportunity to snack, participants in the messaging group consumed more snacks that those who read the article. Our findings correspond to a large literature emphasizing social influences on food intake, and suggest that phone use patterns may predispose an individual to overeating.

Keywords: technology, screen use, social facilitation, obesity, appetite

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INTRODUCTION

Within the span of a decade, smartphones have permeated almost every aspect of our daily lives. Young adults report multi-tasking with their phones: in the restroom, during bedtime, waiting at a red light, and during meal-times (Webby Awards, 2015). Indeed, for one in four adolescents, phone use is a near-constant activity (Lenhart, 2015). Reflecting on this technological landscape, there have been recent efforts to develop guidelines for the use of mobile phones – particularly for the pediatric population growing up with ready access to smartphones (American Academy of Pediatrics, 2015; Radesky et al., 2015).

Phone Use in an Obesogenic Environment

In the discussion of guidelines, one area of concern is the extent to which mobile phones may contribute to the obesogenic environment, predisposing children and adolescents to weight gain (Swinburn et al., 1999; AAP Council on Communications and Media, 2016a; Reid Chassiakos et al., 2016). Here, an analogy can be made to other forms of technology such as television and video games. For example, the increased consumption of television has been found to predict a higher body mass index and greater adiposity amongst children and adolescents (Coon and Tucker, 2002; Janz et al., 2002; Staiano et al., 2013). When given the opportunity to eat, those who do so while playing video games or watching television also show greater food intake (Temple et al., 2007; Chaput et al., 2011). Finally, interventions to decrease the use of television, videotapes, and video games have been successful in reducing the body mass index of school children (Robinson, 1999).

Taken together, the current evidence suggests that using these technologies – collectively referred to as 'screen time' (for devices involving a screen) – constitutes a risk factor for obesity.

Although corresponding evidence for mobile phones is lacking, the American Academy of Pediatrics (2017) has classified phone usage as 'screen time,' generalizing findings from television and video games to mobile phones. This is reasonable in the discussion of weight management, since phone use – like other forms of screen use – is a sedentary activity (Lanningham-Foster et al., 2006). Additionally, multi-tasking with one's phone has been found to be a distractor for tasks ranging from reading an article to crossing the road (Stavrinos et al., 2009; Chen and Yan, 2016). Since the primary account of why screen time promotes eating is that it distracts the user from satiety signals (Bellisle et al., 2004; Brunstrom and Mitchell, 2006; Hetherington et al., 2006; Robinson et al., 2013), multi-tasking with one's phone can likewise be expected to increase food intake.

Exploring the Social Nature of Phone Use

Beyond distraction, however, a key difference between smartphones and traditional forms of digital screens is that phone use is inherently social. Studies of phone use patterns consistently identify messaging functions as the top feature used in mobile phones (Lenhart, 2015; Smith, 2015), with adolescents estimating that they send 118 messages each day (Rideout et al., 2010). One implication of this usage pattern is that adolescents – when multi-tasking with their phones while eating – interact with friends and family in a way that they do not when multi-tasking with television or video games (with the exception of multi-player games).

The social nature of phone use is significant because individuals eat more with friends and family than they do alone – a phenomenon known as 'social facilitation' (de Castro and de Castro, 1989; de Castro, 1997; Herman, 2015). The mere company of one person can increase food intake by 44% (de Castro and de Castro, 1989; de Castro, 1997), with facilitation effects so robust that they have been observed: regardless of a person's homeostatic hunger (de Castro and de Castro, 1989), regardless of the time and place of eating (de Castro et al., 1990), across groups of various cultures and demographics (Feunekes et al., 1995; de Castro et al., 1997), and across diverse study methodologies (Klesges et al., 1984; Berry et al., 1985; see de Castro, 1997; Herman et al., 2003; and Herman, 2015 for reviews of this literature).

Given the ubiquitous nature of social facilitation, a corollary question is whether phone-based messaging confers a risk for overeating – over and above the potential for phone use to distract the user. Although facilitation effects have traditionally been observed in the physical presence of other people, research on non-eating behaviors suggests that virtual presence may be sufficient (with social facilitation broadly defined here as the promotion of a dominant response; Zajonc, 1965). Thus, the virtual company of another person has been found to facilitate tasks ranging from anagrams, mazes, arithmetic, to exercise (Park and Catrambone, 2007; Anderson-Hanley et al., 2011; Snyder et al., 2012). Extending these findings, we investigated whether the virtual presence of friends and family – connected via phone-based messaging – would likewise result in the social facilitation of eating.

The Current Study

To address this question, we conducted a randomized controlled trial monitoring the food intake of adolescents given the opportunity to snack. All participants used a mobile phone while eating, and differed only in how the phone was used: to engage in the social activity of sending and receiving messages (messaging group), or to carry out the non-social activity of reading a neutral article (control group). We hypothesized that messaging would result in the increased consumption of palatable snacks.

MATERIALS AND METHODS

Participants

Participants were 50 male adolescents enrolled in Years 7–10 of an all-boys public school in Singapore (mean age: 14.64 years; *SD*: 0.75). We chose to recruit male participants as gender has been found to moderate phone use (Lenhart, 2015), eating behaviors (Wardle et al., 2004), and the relationship between technology and eating behaviors (Robinson and Killen, 1995); as such, including both genders would have required a much larger sample size. The study was conducted as part of the school's research education program, and participants responded to school-wide advertisements inviting them to the study.

After written assent and written informed parental consent were obtained, participants were randomly allocated to either the messaging or control group. The two groups did not differ in age, ethnicity, body mass index, or baseline eating behavior (**Table 1**). All procedures were approved by the National University of Singapore's Institutional Review Board (#A-15-170). All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the National University of Singapore.

Materials

Baseline Questionnaires

As a measure of baseline eating behavior, we administered the Dutch Eating Behavior Questionnaire (DEBQ; van Strien et al., 1986). This questionnaire assessed whether participants ate based on: external rather than internal cues ('external eating'), emotions ('emotional eating'), or concerns to restrict one's eating ('restrained eating'). Reliability for each of the subscales was acceptable (Cronbach's alpha for external eating = 0.77; emotional eating = 0.94; restrained eating = 0.88).

Additionally, we administered a questionnaire investigating participants' use of social networking platforms. This asked participants which mobile phone they used, the number of friends they had on their phone contact list, the number of messages they sent each day, which social networking platforms they used, what they used their phone for, and whether they used their phone in everyday settings (in bed, in the toilet, during meals, in class, during commute, and during idle times).

TABLE 1 | Baseline characteristics of participants allocated to the messaging and control groups.

Characteristic	Experimental Group[1]		Test statistic[2] (p-value)
	Messaging (n = 25)	Control (n = 25)	
Demographics			
(a) Age (years)	14.68 (0.69)	14.60 (0.82)	–0.37 (0.71)
(b) Ethnicity	20 Chinese	22 Chinese	3.09[3] (0.54)
	3 Indian	1 Indian	
	1 Malay	1 Malay	
	1 Others	1 Others	
(c) Body mass index	21.53 (2.53)	21.05 (2.24)	–0.72 (0.48)
Baseline eating behaviors			
(a) Dutch Eating Behavior Questionnaire			
Restraint	2.47 (1.01)	2.30 (0.65)	–0.67 (0.50)
Emotional eating	2.28 (1.11)	2.24 (0.89)	–0.14 (0.89)
External eating	3.56 (0.75)	3.35 (0.67)	–1.04 (0.30)
(b) Time interval from previous meal (h)	4.34 (2.69)	4.84 (2.94)	0.63 (0.53)

[1]*Data reported as means (standard deviation) or counts.* [2]*Unless otherwise stated, the test statistic refers to the t-statistic.* [3]*Pearson's chi-square statistic reported.*

Snack Food

For the snack food, we placed 50 g of chicken-flavored 'Twisties' (266 kcals; Mondelez International) in an unlabeled bowl. This corn puff snack was chosen because: (i) it is popular with adolescents, (ii) can be found in school vending machines, and (iii) comes in small regular-sized pieces. Pilot tests with a sample of students confirmed that the snack was palatable and that the portion size (50 g) exceeded what a typical student would consume in one setting.

Procedure

Each experimental session took place at the end of a school day (mid-afternoon) and lasted for approximately 30 min. The set-up was intended to mimic what participants would typically encounter – the opportunity to eat highly palatable snacks following a day of school. On average, participants reported having eaten 4.5 h (*SD*: 2.8 h) before arrival (**Table 1**).

As the cover story, participants were made to believe that the researchers were interested in how technology influenced health. After completing baseline questionnaires, participants were told to bring out their mobile phones and to follow the experimenter's instructions; additionally, they were told that they should not engage in any other activity with their phones. Compliance with phone use instructions was monitored through surreptitious observation from a distance.

In the messaging group, participants were asked to access the phone-based instant messaging service 'WhatsApp.' Within WhatsApp, participants identified an active chat group comprising of at least 10 users, and engaged in this group chat for a 10-min duration. Mimicking real-life situations, participants were given no other instructions regarding whom they should communicate with nor what they should discuss.

In the control group, participants were asked to access a neutral article sent to them via email. This was chosen to approximate web-browsing activities, implicated in phone use surveys as the top non-social function used on mobile phones (Rainie and Zickuhr, 2015). The article discussed a neutral topic (the immune system; MacPherson and Austyn, 2012), and was longer than what a typical student could finish reading during the session; additionally, 2 year 9 students who did not participate in the study assessed the article to be easy to read and neutral in tone. In short, this condition was comparable to previous distraction manipulations that had been found to increase food intake (e.g., listening to audio stories, listening to music, watching television; Bellisle and Dalix, 2001; Bellisle et al., 2004; Stroebele and de Castro, 2006; Long et al., 2011), and was designed to control for any distracting effects of mere phone use. Participants in this group read the article on their phones for a 10-min duration.

Across both conditions, the opportunity to eat was introduced in a casual manner. The bowl of snack food was left on the table throughout the 10 min, and the experimenter informed participants that the food was leftovers they were free to consume at will. At the end of the 10 min, participants were debriefed about the true aims of the study.

Data Analyses

As the primary analysis, we ran an independent samples t-test comparing the amount of food consumed by participants in the messaging and control groups. The Type 1 error rate was controlled at $\alpha = 0.05$, and power calculations showed that there was statistical power at the recommended 0.80 level to detect a large effect size ($d = 0.80$, comparable to effect sizes observed in previous social facilitation studies; Herman, 2015). All analyses were conducted using SPSS (IBM Corp., 2017) & R (R Core Team, 2017).

RESULTS

Participants' Baseline Patterns of Phone Usage

At baseline, 48% of participants reported regular use of their phones during meal-times (**Table 2**). Participants were most likely to use the messaging functions of their phones (**Table 3**), with 50% of participants sending at least 41 messages daily (**Table 4**). Together, these statistics suggest that the phenomenon being studied – texting while eating – is one participants themselves have likely engaged in on a regular basis.

Food Intake as a Function of Experimental Condition

Primary Analyses

As shown in **Figure 1**, participants in the messaging group consumed 58% more snacks than those in the control group

TABLE 2 | Messaging and control participants' self-reported mobile phone usage during common activities.

Activity	% Participants reporting phone usage during activity: Messaging group (n = 25)	Control group (n = 25)	Chi-square (p-value)
Waiting or idle time (e.g., queuing in line)	92	80	1.50 (0.22)
During commute	68	56	0.76 (0.38)
Using the toilet	56	60	0.08 (0.77)
In bed	52	64	0.74 (0.39)
Eating a meal	48	48	0 (1.00)
Attending class	28	28	0 (1.00)

TABLE 3 | Messaging and control participants' self-reported use of mobile phone functions.

Phone function	% Participants reporting regular use of this function: Messaging group (n = 25)	Control group (n = 25)	Chi-square (p-value)
Sending messages	84	92	0.76 (0.38)
Browsing websites	80	80	0 (1.00)
Watching videos or listening to music	76	76	0 (1.00)
Playing games	64	80	1.59 (0.21)
Taking photos	68	72	0.10 (0.76)
Making phone calls	68	72	0.10 (0.76)

TABLE 4 | Messaging and control participants' frequency of sending mobile phone messages each day.

No. of messages sent daily	% Participants reporting this frequency[1]: Messaging group (n = 25)	Control group (n = 25)
≤10	20	16
11–20	20	4
21–30	8	16
31–40	12	4
41–50	8	8
>50	32	52

[1]*The distribution of participants did not differ significantly according to group;* $\chi^2(5, N = 46) = 6.51, p = 0.26$.

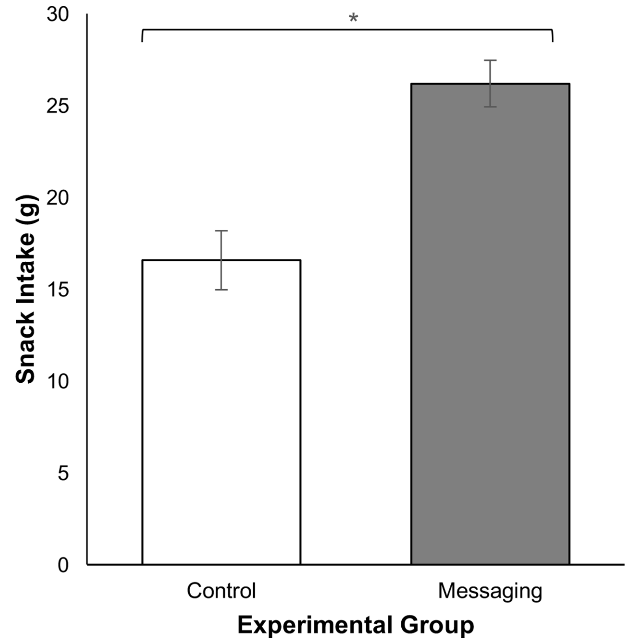

FIGURE 1 | Snack intake of participants in the messaging and control groups; vertical lines represent 1 standard error of the means (*p < 0.001).

[$t(48) = -4.68$, $p < 0.001$, $d = 1.32$]. The 95% confidence interval suggests that this corresponded to an average increase of 29.19–73.14 kcals consumed.

Accounting for Baseline Eating Behaviors

As a follow-up, we conducted a stepwise multiple regression to assess the influence of messaging after controlling for baseline eating behaviors. In Step 1, a model including: scores on the DEBQ (external, emotional, and restrained eating) and the time interval from the previous meal accounted for 5.2% of the variance in food intake, $F(4,41) = 0.56$, $p = 0.69$. Adding participants' experimental condition in Step 2 explained a further 28.4% of the variance – a statistically significant increase [$F(1,40) = 17.11$, $p < 0.001$].

Were Participants Primed or Distracted When Reading an Article?

Thus far, our results are consistent with the hypothesis that messaging activities would increase food intake relative to reading an article. However, an alternative account is the reverse – that reading the article reduced control participants' snack consumption instead. This may have occurred if, instead of distracting participants, the topic of the article (the immune system) primed participants to eat in a healthy manner. This, in turn, may have caused them to eat fewer snacks.

Whereas distraction effects have been observed across various groups and situations, the influence of health primes is not universal (Forwood et al., 2015), affecting primarily dieters for whom primes reinforce their goals (Papies and Hamstra, 2010; Buckland et al., 2013; Papies, 2016). Correspondingly, if our article did indeed prime participants, those with higher dietary restraint would be more likely to show reduced food intake than those with low restraint. To this end, we ran a Pearson's correlation between snack intake and DEBQ restraint scores amongst participants in the control condition. This correlation did not approach statistical significance [$r(20) = 0.02$, $p = 0.92$]. Similarly, amongst participants who had read the article, there was no significant difference in food intake between those with restraint scores at or above the median (≥ 2.3), as compared to those with scores below the median, [$t(20) = 0.33$, $p = 0.74$]. Taken together, we were unable to replicate a commonly observed pattern in the health priming literature, and found no evidence that priming mechanisms were at play.

DISCUSSION

In this study, we described the impact of smartphone messaging activities on appetite regulation. In line with research emphasizing social influences on food intake (de Castro, 1997; Herman, 2015), we found that male adolescents who sent and received text messages consumed more palatable snacks than those who used their phones to read an article. The difference between these two activities accounted for a third of the variance in snack consumption, and was a larger influence than time since the last meal or individual differences in eating behaviors (as measured by the DEBQ). To our knowledge, this is the first demonstration of how specific patterns of phone usage may predispose adolescents to over-eating.

A Case for Virtual Social Facilitation

In terms of theory, our findings are consistent with 'virtual social facilitation.' Outside the field of ingestive behavior, several studies have found that social influence is so pervasive that computer-based or online presence is sufficient to elicit facilitation effects (Park and Catrambone, 2007; Anderson-Hanley et al., 2011; Snyder et al., 2012). Our study extends these findings to the eating domain, suggesting that the mere online presence of friends and family is able to promote eating behaviors.

At the same time, we caution that virtual social facilitation remains a nascent concept that requires follow-up. For example, the effects we observed do not fit neatly into current theories. By convention, social facilitation is classified based on what others are doing (Zajonc, 1965): 'co-actors' who are also eating cause the familiar increase in food intake, but a 'passive (non-eating) audience' renders the individual self-conscious – leading to a decrease in food consumption (Herman, 2015). With mobile phones, however, whomever one messages may not be a co-actor who is also eating. Similarly, message recipients are not privy to how much one eats, minimizing the need to maintain an impression via food intake. Accordingly, virtual company cannot be described to have either co-action or passive audience effects, and future research will need to investigate whether current accounts of social facilitation apply to the digital realm.

Ruling Out Distraction Accounts

To strengthen the case for virtual social facilitation, future research will also need to rule out a solely cognitive explanation of our results. As described in the introduction, the primary account for why screen use affects food intake is that it diverts attention from the act of eating; with diminished cognitive resources, the screen-user engages in 'mindless eating' and consumes more (Ogden et al., 2013; Dohle et al., 2017). Although distraction effects were addressed through a control group engaged in a non-social phone activity, it remains possible that our activity – reading an article – was not as distracting to participants as messaging was. To the extent this was true, participants in the messaging group may have simply eaten more because they were more distracted (Bellisle et al., 2004; Brunstrom and Mitchell, 2006; Hetherington et al., 2006; Robinson et al., 2013) – rather than because the act of messaging was social in nature. Further studies are needed to tease apart these accounts by including other phone-use conditions (e.g., playing a solitary game), or by assessing cognitive resources required for messaging versus reading (e.g., through dual task paradigms).

Toward Evidence-Based Guidelines on Pediatric Phone Use

More broadly, our findings add to the ongoing discussion of how technology contributes to the obesogenic environment. Beyond guidelines on whether or not digital screens should be used during meal-times (AAP Council on Communications and Media, 2016a,b), we found that the *manner* in which one uses a mobile phone can compound the problem of over-eating. This research is timely as our own participants reported the habitual use of mobile phones during a meal. While urging replication of our work, we tentatively suggest that switching from one of these activities (messaging) to the other (browsing and reading) could reduce the consumption of palatable snacks amongst adolescents.

Study Limitations

Although we discuss the potential implications of our study, we highlight several limitations. First, our participants came from a homogenous all-boys school, and the extent to which these results generalize to other populations is unknown. Second, we chose to use an experimental design such that causality can be inferred. However, this required us to make several design choices that could limit generalizability. For example, we modeled our design on an everyday scenario where adolescents have the opportunity to snack after school. In so doing, we were focusing on the hedonic drive to eat, and are unclear whether similar results will be found when food intake is more strongly driven by homeostatic concerns (e.g., in a breakfast meal after an overnight fast; Lutter and Nestler, 2009). Similarly, in striving for ecological validity, we allowed participants in the messaging group to converse freely. This meant that we had little control over discussion topics, and cannot preclude the possibility that participants discussed the experiment in their chat groups (and perhaps were encouraged by their friends to eat). Finally, in the control condition, we opted to have participants use their phones for a non-social activity – reading an article. Although our analyses suggest that the article was unlikely to have attenuated food consumption (e.g., by priming a health message), we cannot rule out this possibility in the absence of a no-phone condition. In light of these limitations, we suggest that future research extend our findings through alternate operationalization of the experimental conditions. The use of diary or epidemiological designs would also allow the true impact of phone activities to be estimated amongst free-living adolescents.

CONCLUSION

Our study was motivated by the observation that smartphones provide unprecedented opportunities for adolescents to connect with friends and family. Although the social feature of phones can have beneficial effects (Reid Chassiakos et al., 2016), choosing to message while eating can promote the overconsumption of food. Over time, this may predispose adolescents to weight gain, and is a potential risk factor that requires further study.

AUTHOR CONTRIBUTIONS

ET and DG conceptualized and designed the study, collected the data, drafted the initial manuscript, and approved the final manuscript as submitted. KV and JL conceptualized and designed the study, carried out statistical analyses, reviewed and revised the manuscript, and approved the final manuscript as submitted.

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Media Multitasking Is Associated With Higher Body Mass Index in Pre-adolescent Children

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Obesity rates among children have climbed dramatically in the past two decades, a time period in which children also experienced greater exposure to portable media devices and smartphones. In the present study, we provide evidence of a potential link between media multitasking – using and switching between unrelated forms of digital media – and risk for obesity, as indexed by body mass index (BMI). Specifically, we recruited 179 pre-adolescent children (aged 9–11 years, 88 females) to participate in a study in which we assessed their media multitasking (MMT) tendencies, as well as BMI. Controlling for the influence of a known genetic risk factor for obesity and other covariates, including physical activity, we found a positive association between the frequency of children's MMT behaviors and age- and sex-standardized BMI z-scores, $b = 1.07$, $p = 0.011$. These findings are consistent with other recent work showing similar patterns of covariation between MMT and risk for obesity in young adults. The present work can also inform future work in this realm, such as the design of longitudinal studies that prospectively measure children's MMT behaviors and body composition to begin to identify directionality in the association.

Keywords: media multitasking, obesity, body mass index, health risk, adiposity

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INTRODUCTION

For much of the 20th century, obesity in childhood was rare, with only 15% of children aged 2–19 classified as overweight or obese in the 1970s. However, by 2004 the childhood obesity rate climbed to nearly 34% and since then has remained high (Fryar et al., 2014; Ogden et al., 2014). Understanding which factors contribute to weight gain early in life is critical, as childhood obesity and overweight have been associated with increased risk for a host of medical conditions, including cardiovascular disease and metabolic syndrome, among others (Must and Strauss, 1999; Dietz, 2004; Daniels et al., 2005; Freedman et al., 2007).

Many genetic and physiological variables contribute to an individual's risk for developing obesity (e.g., Frayling et al., 2007), as well as dys-regulation of endogenous, homeostatic mechanisms (e.g., Monteleone et al., 2008). For example, the *FTO* rs9939609 single nucleotide polymorphism genotype has been reliably linked to increased obesity risk in large scale studies (Frayling et al., 2007; Loos and Yeo, 2014). But in our modern, 21st-century environment, hedonic features, such as the palatability of foods, can exert a strong influence on eating behaviors, especially among children. This is compounded by the fact that foods, especially obesogenic foods, have become readily available for consumption and are often much less expensive than healthier, nutrient-rich alternatives. Moreover, marketing agencies have targeted children by tailoring food advertisements to increase appeal among children (Bernhardt et al., 2013), and exposure to advertisements has been linked to BMI percentile (McClure et al., 2013) as well as *ad libitum* eating in the absence of hunger (Gilbert-Diamond et al., 2017) – a known correlate of weight status and weight gain (Birch et al., 2003; Lansigan et al., 2015; Balantekin et al., 2016). In general, such exposure to tempting food cues has been associated with increased impulse strength and higher likelihood of un-regulated eating and self-control failure (Heatherton and Wagner, 2011).

Despite these demonstrated links between exposure to appetitive cues and obesity, a key question is: what makes *some* children (and not others) more sensitive and responsive to food cues in their environment? In the present study, we took an individual differences approach by operationalizing, on a person-by-person basis, children's responsiveness to food cues. To do this, we first drew from Stanley Schachter's theorizing about the relative influence of internal (e.g., hunger cues) versus external (e.g., the sight or smell of freshly prepared food) cues on eating behaviors. Schacter's externality theory proposed that individuals with obesity are, on average, more externally driven, meaning they are more responsive to environmental cues that trigger food cravings (Schachter, 1971). While Schachter conceptualized these as group-level differences in the obese and non-obese populations, respectively, we wanted to identify a continuous construct that would manifest behaviorally and capture, at least in part, the extent to which children would be (externally) driven by environmental cues (e.g., food cues).

Media multitasking may be one candidate in the behavioral domain, given that it may train attention to be broader and more sensitive to external cues (Cain and Mitroff, 2011). Indeed, a recent study proposed the novel hypothesis that frequent media multitasking, defined as the simultaneous, often mindless switching between unrelated forms of media, is a risk factor for obesity, as it is associated with increased responsiveness to rewarding cues in one's environment and poorer self-control (Lopez et al., 2019a). The researchers found supporting evidence for this hypothesis, as those participants who more frequently engaged in media multitasking also tended to have increased adiposity and an imbalance of food cue elicited activity in brain systems involved in reward processing and self-control. Specifically, high media multitaskers showed higher activity in the ventral striatum and orbitofrontal cortex, key regions in the mesolimbic dopamine system that support reward-seeking behaviors, including eating (Haber and Knutson, 2010), while simultaneously exhibiting less recruitment of the frontoparietal control network, which has generally been implicated in flexible exertion of self-control (Power et al., 2011), including self-control in the eating domain (Lopez et al., 2017, 2019b).

In the above-mentioned study by Lopez et al. (2019a), media multitasking tendencies were assessed in college-aged participants, but what about media multitasking habits among developing children and adolescents? Multitasking across several, unrelated forms of media or devices has become common in childhood. Children's ownership of diverse media devices is increasing. For example, ownership of a cell phone went from fewer than 40% of children in 2004 to 66% by 2009, and the use of other electronic devices (e.g., iPods) increased from 18 to 76% during that period (Rideout et al., 2010). With this rise in device ownership has been a concurrent rise in media multi-tasking; from 1999 to 2009 children nearly doubled their time spent media multi-tasking, from 16% of the time to 29% of the time that they were using media (Rideout et al., 2010). Critically, this trend shows no signs of slowing. From 2011 to 2013, children's access to mobile devices increased from 52 to 75% (Rideout, 2013), and according to a recent PEW study conducted in 2018, 95% of teens have ready access to a smartphone and 45% report being online almost constantly, up from 24% only a few years prior (Pew Research Center, 2018).

Given the high prevalence of media multi-tasking in youth, as well as the associations observed between multi-tasking and risk of overweight in older populations, we sought to examine the association between children's media multitasking tendencies and adiposity. Specifically, we conducted a study in which we recruited 179 pre-adolescent children and assessed their media multitasking tendencies and body mass index (BMI). We also controlled for participants' *FTO* rs9939609 single nucleotide polymorphism genotype, a known genetic risk factor (Frayling et al., 2007; Loos and Yeo, 2014). Given the previous related work that has specifically linked MMT and obesity risk (Lopez et al., 2019a), we hypothesized that, in both unadjusted and adjusted regression models, there would be a positive association between frequency of media multitasking behaviors and BMI.

MATERIALS AND METHODS

Participants

Participants were 198 pre-adolescent children who had taken part in a study that examined the link between an *FTO* polymorphism and food consumption during an eating in the absence of hunger (EAH) task (Gilbert-Diamond et al., 2017). Some of the children who participated in this study were siblings. To ensure the assumption of independence was met for statistical analyses, we included only one randomly selected sibling per family chosen at random. The final sample used for all subsequent analyses consisted of 179 participants (88 females, M_{age} = 9.93 years, SD_{age} = 0.580 years; see **Table 1** for additional summary statistics). As per inclusion criteria determined by that study, all participants had to be fluent in English, present with no food allergies or restrictions, and not have any health conditions nor be taking any medication that would impact appetite or attention span (as reported by participants' parents). A caregiver accompanied each child who participated, and caregivers and children provided written consent and assent, respectively, in accordance with guidelines set by the Committee for the Protection of Human Subjects at Dartmouth College.

Procedure

Media Multitasking Assessment

One of the most commonly used instruments to comprehensively assess media multitasking tendencies is the Media Multitasking Inventory (MMI; Ophir et al., 2009), but this scale was originally

TABLE 1 | Participant characteristics of sample used in all reported analyses.

	n* or *M	**% or *SD***
Gender		
Male	91	51%
Female	88	49%
Age	9.93	0.58
***FTO* Genotype**		
TT	63	35%
AT	86	48%
AA	29	16%
MMT score (untransformed)	0.53	0.68
Weight status		
Healthy weight	138	77%
Overweight/Obese	41	23%

Weight status was determined by BMI percentile guidelines set by the CDC, whereby Healthy Weight ≤ 85th and Overweight/Obese > 85th BMI-age-sex-percentile.

designed to be administered to adults, who sometimes find it cumbersome to complete, given multiple instances of having to estimate hours spent multitasking with various other media (Lopez et al., 2019a). Here, we adapted and shortened the MMI so it would be more easily administered in – and more applicable to – a younger population.

Specifically, we asked participants to report their own multitasking with other print and digital media during four primary activities (versus ten in the original MMI), namely: watching TV or movies, playing video games, reading books or magazines (not assigned for school), and doing homework. There were multiple response options for time spent, daily, for each of these activities (i.e., 0 h, 30 min, 1 h, 1.5 h, 2 h, etc., up to 5 h). For each activity, participants also reported the frequency with which they multitasked by engaging in other activities by using a 5-point likert scale (i.e., *Never*, *Rarely, Sometimes, Often, Always*). For example, after reporting the number of hours spent watching TV and movies, participants also responded to the question "*While you are watching TV and movies, how often do you also play video games or online games at the same time*?" followed by questions to assess multitasking with three additional activities, respectively. This question structure was repeated for each primary activity.

In this way, the kinds of behavior that the MMT measure intends to capture is the simultaneous use of secondary, unrelated media while one uses a primary medium or is engaged in a focal task (e.g., being distracted and checking one's phone while doing homework). Therefore, it is a different kind of behavior than if a person consciously decides to take a break from an activity. Media multitasking is also different from being in an environment in which media are available or turned on, but one does not seek nor interact with them (e.g., doing homework in one room while the TV happens to be on in the other room). Listening to music was not assessed in the present study because we figured that some participants may be able to focus more intently on the primary task/medium when listening to music, while others would potentially be distracted by it. Thus, the media multitasking score for listening to music would not be straightforward to interpret and combine with other media multitasking scores.

We should note that another research group has encountered the same issues with original MMI as we do here (i.e., the scale's length and difficulty due to estimating many instances of various primary/secondary media multitasking), and accordingly has shortened and adapted the MMI for use with older adolescents (i.e., ages 11–15; Baumgartner et al., 2014, 2016). These scales (e.g., the short media multitasking measure, or MMM-S; Baumgartner et al., 2016) were not yet published or available when we conducted the present study, but the format and questions overlap considerably because in both cases the items and their wording were taken and adapted from the same source (the original MMI). Moreover, work by Baumgartner et al. (2014) has shown that these shortened scales have high internal reliability in large samples (Cronbach's alpha = 0.93 in sample of 523) and correlate well with the original MMI (r = 0.84; Baumgartner et al., 2016), while being easier and more efficient to administer to adolescents than the original MMI. For all question wording and items included in the abbreviated MMI administered here, see **Supplementary Materials**.

Media multitasking scores were calculated using a similar procedure described by Ophir et al. (2009). The total time spent on each activity was multiplied by the frequency of multitasking with other media and then scaling that by the total time spent on all (four) activities (Ophir et al., 2009). This computation was repeated for all four activities, resulting in four MMT sub-scores (one for each activity). These were then summed to create a composite MMT index for each participant (M_{index} = 0.53 SD_{index} = 0.68, range = 0–3). The distribution of MMT scores was highly positively skewed (γ_1 = 1.53), so we applied a log transformation with the log10() function from the *base* R package. The resulting distribution exhibited reduced skewness (γ_1 = 0.85).

Body Mass Index

We measured participants' weight to the nearest 0.1 kg and height to the nearest 0.5 cm using a digital scale (Model 703, Seca, Hamburg, Germany) and wall-mounted stadiometer (Model 216, Seca, Hamburg, Germany). We used these measurements to compute BMI percentile and z-score using U.S. Center for Disease Control (CDC) 2000 age- and sex-specific distributions (Kuczmarski et al., 2002). Using the BMI percentiles, we defined healthy weight as ≤85th percentile, overweight as between the 85th and 95th percentile, and obese as ≥95th percentile. We opted to use age- and sex-standardized BMI z-score as our outcome of interest, rather than BMI percentile to avoid BMI percentile ceiling effects in the analysis. For age- and sex-standardized BMI scores, we used the y2z() function in the *AGD* (Analysis of Growth Data) R package, with participants' raw BMI, sex, and age as vectorized inputs, and the CDC 2000 growth curves as the reference table.

Covariates

In addition to age and sex, we incorporated all participants' average physical activity as a covariate into adjusted models by computing a weighted average of time spent (in minutes) being active on weekdays and weekend days, as reported by participants' caregivers in response to the question(s): "On an average weekday/weekend day, how much time does your child spend doing physical activity, such as running around, climbing, biking, dancing, swimming, playing sports, etc.?"

Importantly, we also controlled for each participant's genotype status arising from the *FTO* rs9939609 single nucleotide polymorphism to account for the known influence of *FTO* rs9939609 on weight status and risk for obesity (Frayling et al., 2007; Loos and Yeo, 2014). Specifically, buccal cell swabs were collected and stored at room temperature with desiccant capsules (Isohelix, Kent, United Kingdom). DNA was isolated using DDK-50 isolation kits (Isohelix). Genotyping for rs9939609 was conducted with real-time PCR and Taqman chemistry using the 7500 Fast Real-time instrument (primers and instrument from Thermo Fisher Scientific (Waltham, MA, United States). All samples were successfully genotyped and there was 100% genotyping consistency among the 10% blinded replicates.

Analytic Approach

We fit both unadjusted and adjusted models with BMI *z*-scores as the outcome measure in order to test for a linear association between MMT and adiposity. In the unadjusted model, log-transformed MMT scores were entered as the sole predictor variable. In the adjusted model, we added participants' age, sex, *FTO* genotype status, and physical activity as covariates. We indicated a simple contrast for sex (Female > Male) and for *FTO* genotype we indicated a linear contrast to test an additive model of obesity risk (i.e., AA > AT > TT). We also specified an alternative model specification to test the dominant model of obesity risk (i.e., AA and AT > TT) by changing the contrast weights for the *FTO* genotype variable. All regression models were fit using the lm() function from the *stats* R package. To improve interpretation from that model, we then compared BMI *z*-scores between participants with MMT scores at or above the median and participants with MMT scores below the median using unadjusted *t*-tests.

RESULTS

First, upon examining the unadjusted regression model, there was a significant positive association between log-transformed MMT scores and BMI *z*-score, $r = 0.181$, $b = 1.037$ (95% CI: 0.202, 1.871), $t(177) = = 2.452$, $p = 0.015$. Next, we examined parameter estimates from an adjusted multiple regression model predicting BMI *z*-score as a function of log-transformed MMT scores, while controlling for the potential influence of participants' age, sex, physical activity, and *FTO* genotype status, as described above. Overall, the model was statistically significant, $F(6,171) = 4.89$, $p < 0.001$, and accounted for 11.6%[1] of the variance in BMI *z*-scores. There was a statistically significant association between sex and BMI *z*-score, $b = 0.270$ (95% CI: 0.002, 0.538), $t = 1.99$, $p = 0.048$, as well as a statistically significant linear trend in BMI *z*-score as a function of *FTO* genotype status, $b = 0.494$ (95% CI: 0.213, 0.776), $t = 3.47$, $p = 0.001$. Importantly, and central to the aims of the present study, the positive relationship between MMT and BMI *z*-score remained statistically significant in this adjusted model, $b = 1.069$ (95% CI: 0.253, 1.885), $t = 2.59$, $p = 0.011$. This relationship remained unchanged in the sensitivity analysis that included a dominant model of obesity risk as a function of *FTO* genotype, i.e., AA and AT > TT. Moreover, from a model comparison perspective, the AIC was lower and the overall model fit statistically significantly improved when including MMT as a predictor (versus only having age, sex, and *FTO* genotype as predictors), AIC = 472.9 (versus 477.7), $F(1,172) = 6.68$ $p = 0.011$. See **Table 2** for complete results from this model, including regression coefficients, confidence intervals, and inferential statistics.

Lastly, a median split of the sample based on untransformed MMT scores revealed that those participants who reported relatively more frequent MMT behaviors tended to have higher BMI *z*-scores ($M = 0.515$, $SD = 1.05$) than those with less frequently reported MMT behaviors ($M = 0.243$, $SD = 0.82$); this difference was marginally significant, $t(177) = 1.90$, $d = 0.285$, $p = 0.059$.

DISCUSSION

In this study, we examined the relationship between children's propensity to engage in media multitasking behaviors and their risk for higher adiposity. Overall, we found support for our hypothesis, as both unadjusted and adjusted regression models revealed a modest but statistically significant positive

[1] Adjusted *R*-Squared.

TABLE 2 | Parameter estimates from a linear regression model predicting BMI *z*-score as a function of log-transformed MMT scores while controlling for age, sex, physical activity, and FTO rs9939609 genotype (additive genetic model: AA > AT > TT).

			95% confidence interval			
Predictor	**Estimate**	***SE***	**Lower**	**Upper**	***t***	***p***
MMT (log-transformed)	1.069	0.414	0.253	1.885	2.59	0.011
Age in years	−0.154	0.117	−0.385	0.077	−1.32	0.189
Sex (Female > Male)	0.270	0.136	0.002	0.538	1.99	0.048
Physical activity	−0.001	0.001	−0.003	0.001	−1.24	0.215
FTO rs9939609 genotype (AA > AT > TT)	0.494	0.143	0.213	0.776	3.47	0.001

relationship between frequency of MMT behaviors and adiposity, as indicated by BMI z-score, such that those children who reported more frequent media multitasking also tended to have higher adiposity, on average. These findings are consistent with other work showing similar associations in young adults (Lopez et al., 2019a). Critically, this positive relation between MMT and sex and age-adjusted BMI z-score held in an adjusted regression model, suggesting unique co-variation above and beyond the influences of sex, age, physical activity, and *FTO* rs9939609 status – one of the genetic factors most robustly associated with obesity (Frayling et al., 2007; Loos and Yeo, 2014).

Although preliminary, the association observed in this sample between MMT tendencies and adiposity is important to demonstrate, especially in the pediatric population – a group for whom the correlates of media use and media multitasking are not yet well established. In general, children show a pattern in their neurobiological development whereby subcortical systems that support motivated behaviors (e.g., eating) develop early, while maturation of prefrontal systems important for self-control lags behind; this imbalance is especially prominent leading up to and during adolescence (Somerville and Casey, 2010). Because of this imbalance of brain systems, children and adolescents are prone to experience self-control failure and engage in various risk-taking behaviors. It is possible that media multitasking may exacerbate or exploit this imbalance, rendering those children who frequently media multitask unable to exert control over desires to eat that are elicited by tempting food cues in their environment. This is true of young adults, as those who frequently engage in MMT behaviors also tend to show an imbalance in response to appetizing food cues, characterized by more reward related brain activity and less recruitment of the frontoparietal control network (Lopez et al., 2019a), which has been generally implicated in cognitive control as well as self-regulation of eating behaviors (Power et al., 2011; Lopez et al., 2017; Turner et al., 2018). Co-occurrence of such an imbalance and (frequent) media multitasking may arise from biased cognitive and/or attentional processes shaped by children's exposure to multiple media devices. For example, children who habitually use and switch between multiple, unrelated media may widen their attentional spotlight (Cain and Mitroff, 2011) and this can potentiate reward-related attentional capture (Anderson et al., 2011). This could result in altered global processing of other cues in one's environment and guide behaviors across domains; indeed, frequent media multitaskers incorporate irrelevant, peripheral cues during person perception, as indicated by biased judgments when forming first impressions (Lopez et al., 2018). This is further consistent with the finding that high media multi-taskers are known to have a greater spread of attention to peripheral cues (Yap and Lim, 2013).

Although the present study supports that media multitasking may be a risk factor for obesity among children, there are several limitations that bear mentioning. First, the associations here are only measured at one point in time, so the directionality of the association cannot be established. As discussed above, it may be that increased exposure to multiple media, and subsequent MMT behaviors, impacts cognition and attention in such a way that some children become more sensitized and responsive to rewarding cues in their environment, increasing hedonically driven consumption. However, alternative explanations are also possible, as it could be that some children have altered cognitive processes and functioning to begin with, and that makes them more likely to become frequent media multitaskers and to be more externally driven by food cues so that non-homeostatic eating patterns result in weight gain over time. Future research is needed to tease apart and test these competing accounts. For example, longitudinal studies that assess children's MMT tendencies and weight status over longer periods of time can begin to shed light on whether MMT precedes weight gain, or vice versa. Relatedly, it would be important to assess younger children's baseline responsiveness to external food cues and determine whether that is predictive of subsequent increases in MMT and/or BMI. This is now possible via a newly developed scale that can be completed by parents of preschool-age children (Masterson et al., 2019).

Future studies that experimentally manipulate MMT, in an acute fashion, and measure effects on attention and cued eating, could also help in the determination of causality. This can be difficult, especially given the trade-off between experimental control and ecological validity, but some studies have begun to administer in-lab paradigms that simulate people's real world exposure to multiple forms of media and in this way provide a context in which media multitasking can occur (e.g., Segijn et al., 2016; Garaus et al., 2017). Another promising avenue for future investigations is to mitigate the negative impacts MMT on cognition and attention via mindfulness-based attention training. Mindfulness interventions are uniquely promising because they promote the opposite of the automatic-based, poorly filtered attention thought to underlie the negative effects of media multi-tasking. A short-term intervention that has been shown to improve mindfulness in undergraduates (Mrazek et al., 2012) has also been shown to reduce the maladaptive attentional processing associated with media multi-tasking. The study conducted with a large sample of young adults showed that a breath counting task, a validated behavioral index of mindfulness (Levinson et al., 2014), improved performance on a battery of attention tasks – including filtering and distractibility – in both high- and low-usual media multi-taskers, but this effect was greater for high media multi-taskers (Gorman and Green, 2016).

We chose to study pre-adolescent children, because this age represents a critical time in development to characterize children's MMT tendencies and obesity risk; however, the findings may not necessarily be generalizable to children of other ages. We recommend that future work assess MMT and weight status across several age groups to determine if associations vary by age.

We assessed MMT tendencies in children using an adapted version of the MMI scale developed by Ophir et al. (2009). The original MMI is a validated measure that captures people's propensity to multitask, but it has only adequate predictive and convergent validity, as far as assessing constructs germane to the present work (e.g., trait self-control; Lopez et al., 2019a), and therefore our adapted MMI may also be limited. Baumgartner et al. (2014) have similarly adapted the MMI for use in older adolescents (ages 11–15) and created a 9-item scale that partly overlapped with items administered in the present study (Baumgartner et al., 2014). This 9-item scale exhibited high internal reliability (Cronbach's alpha = 0.93) while correlating strongly with the original MMI ($r = 0.84$; Baumgartner et al., 2014). Because this scale was not available at the time we collected data from the present sample, we suggest that future work validates this scale in the younger, pre-adolescent population. Future studies may also benefit from administering a recently developed MMT scale that overlaps – in terms of shared variance – with the original MMI but has more construct and convergent validity in the domain of self-regulation (Lopez et al., 2019a). Indeed, stronger associations between MMT and BMI may be observed with either or both of these newly developed MMT scales, given these scales' respective high internal reliability (Cronbach's alpha ≥ 0.86; Trafimow, 2016).

Lastly, we generally caution against overinterpretation of the present findings, as the results reported here represent a secondary analysis and therefore we did not have additional covariates. For example, we did not have a measure of participants' total media consumption or exposure, as that would help determine the nature of the association between MMT and adiposity over and above general media consumption. And despite controlling for a known genetic risk factor for adiposity (*FTO*), we acknowledge the complexity of obesity and its etiology and encourage future researchers to replicate these results while controlling for additional genetic covariates.

To conclude, we have shown that there is a positive association between pre-adolescent children's media multitasking behaviors and their risk for obesity, as indexed by BMI z-score. Specifically, those children who reported frequently using other, secondary media while using a primary medium/device also tended to have higher adiposity. Although definitive causal inferences cannot be drawn from this work, we believe that demonstrating that such an association exists is important and timely, given the rapid rise in both childhood obesity as well as children's exposure to and use of multiple media devices. Indeed, it is not yet clear how children's MMT behaviors might impact other cognitive and behavioral domains beyond the realm of eating. And despite the fact that this research is still in its early days, the present findings and their implications suggest that further research is warranted on media multitasking in relation to childhood obesity.

DATA AVAILABILITY STATEMENT

The datasets generated for this study can be found in the following OSF project (link: https://osf.io/tzv4r/?view_only=7fc5fb7c9b374bf4a5ae52eb8f0189b4).

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Committee for the Protection of Human Subjects, Dartmouth College. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

DG-D designed the study. DG-D and RL contributed to hypotheses and research questions. RL and JB conducted the analyses. RL wrote the initial draft of the manuscript. JB and DG-D provided edits and contributed to the final version of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.02534/full#supplementary-material

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Food Delivery Apps and the Negative Health Impacts for Americans

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Keywords: smartphone, food delivery, applications, fast food, obesity

INTRODUCTION

Food delivery applications have seen a surge in growth over the past decade. Digital ordering represents half of all food delivery visits, expanding beyond traditional dinner delivery to encompass breakfast and lunch delivery (1). Digital orders, ordered via a mobile app, Internet, or text message, have grown 23% over the past 4 years representing a $26.8 billion dollar industry (2). In most instances, digital food ordering can be done directly with a restaurant app or third party food service, which allow people to view local restaurants and menus (2). GrubHub, founded in 2004, was the first successful third-party food delivery system (3). The company rapidly grew, acquiring other online businesses and expanded into the delivery service arena. With approximately 44,000 restaurants on GrubHub's platform, food sales reported in October 2019 grossed about 1.4 billion dollars, an estimated 15% gross year-over-year increase (4). With their success came other services, like UberEats, which grew by 230% in 2017 (5). It is expected that food delivery applications will have over 44 million users in the United States in 2020 (6). While this growth has both positive and negative outcomes for restaurants, expanding their market yet costing them in fees, what does it mean for the American consumers and their health?

Roughly two-thirds of the American consumer utilizing a popular food-delivery platform, DoorDash, reported that food delivery was their preferred way of eating dinner (7). However, what many of these individuals might not realize is that the frequency of eating food from outside of the home is positively associated with a high body mass index (8). In a study done by Zion et al. (5), it was reported that 40% of people surveyed had used a multi-restaurant food delivery application in the past 90 days. Of those using the application services, 53% used it greater than 3 times in the past 3 months and of those, 7% had used it more than 11 times. Other data suggests that 10% of Americans use delivery services weekly and 52% typically order food delivery for lunch (9). When considering the increasing prevalence rates for overweight and obesity in the U.S., the effects of these digital food-delivery apps could be of great concern.

Overweight and obesity is a persisting epidemic in both pediatric and adult populations, with the most recent U.S. obesity (not including overweight) prevalence rates indicating that roughly 40% and 18% of adult and children are overweight or obese, respectively (10). In particular, the prevalence rate for obesity among young adults was reported to be 35.7% in 2016. Similarly, teens between 12-19 years of age had a reported obesity prevalence rate of 20.6% (10). These statistics are alarming considering that the majority users (63%) of food-delivery apps are youth adults ages 19–29 years of age (5).

It is well-established from longitudinal studies that that adolescents who have better diet quality gain less weight in adulthood compared to those with poorer diet quality (11), Due to diverse and competing food-delivery platforms, users have the potential to select healthy options when opting to use digital ordering. However, reports from the most frequently used platforms highlight that American consumers' top ordered foods include a cheeseburger and fries, pizzas, nachos, cheesecake, baby back pork rib, chicken and waffle sliders, etc., indicating that calorie-dense options are some of the most popular selections to be delivered (7). Other sources report that in 2016, pizza was the most popular takeout/delivery food, followed by Asian cuisine, sandwiches, and Italian

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cuisine (9). GrubHub noted that over 70% of users utilized their applications to order quick service or fast casual foods (12). Over the past 30 years, fast food portion sizes have increased, calories have increased, and sodium levels have increased, intensifying the potential problem these applications might pose to the ongoing obesity epidemic (8).

In addition to the frequent use in the young-adult age group, these food delivery services continue to rise in popularity across adolescent American students (13, 14). With up to 15 deliveries a day, school districts are reevaluating their policy and banning meal delivery services due to safety concerns (13, 14). A synopsis of school lunch delivery services that provide, "healthy," "fresh," "organic," or "from scratch" foods average a cost of $4–$8 per entrée (15). This is a dramatic increase when compared to State School Nutrition data from 2017 highlighting lunch costs ranging from $2.48 to $2.74 per meal (16). In order to access more elite school lunch delivery services, schools must register with the service or parents must go online to coordinate/meal plan their child's food, or food service must align with National School Lunch Program standards (15). Meaning that access to healthy food deliveries is not equal across all student groups.

DISCUSSION

While we have a basic understanding of who is using these food delivery service applications and what they are ordering, there is currently no research to support how digital food ordering affects health and wellness on an individual level or from a public health perspective in the U.S. Are the most frequent users of these applications overweight or obese? If so, do these individuals have a desire to consume fewer calories and lose weight? If so, what behavior change techniques may be designed into digital ordering software to help promote health? The convenience of these applications may present a greater risk to adverse health outcomes among overweight or obese individuals, who consume more calories than their normal weight counterparts (17). Similarly, will rates of fast food consumption continue to increase among low-income individuals ages 20–39, who are known to consume a higher percentage of calories from fast food compared to those with higher income levels? (17).

These questions highlight critical gaps in the literature. We strongly advocate for unbiased additional research in this arena to objectively report on user demographics, wants, and needs in the United States. Considering the ease of digital food ordering, we also strongly advocate that digital food ordering platforms adapt ethical design to improve human situations, including health.

AUTHOR CONTRIBUTIONS

JS, LM, and HM assisted in the concept of the manuscript and the writing of all sections.

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Using Smartphones When Eating Increases Caloric Intake in Young People: An Overview of the Literature

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Recent literature highlights that the use of smartphones during meals increases the number of calories ingested in young people. Although the distraction interferes with physiological signals of hunger and satiety, a social facilitation effect has also been suggested. Cognition is a pivotal component in regulating food intake, and activities requiring high perceptual demands should be discouraged during meals.

Keywords: social facilitation, distraction, obesity, food intake, smartphone

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INTRODUCTION

In recent decades, the use of smartphones has gradually increased worldwide. Currently, more than three billion people in the world own a smartphone with an expected increase in the next few years of several hundred million (O'Dea, 2020).

The mobile device has become an essential tool in everyday life, especially among young people, where one in four teenagers claims to use their smartphone constantly (Kabali et al., 2015; Lenhart, 2015).

In the United States, cell phone access in young people has increased from 40% in 2004 to 75% in 2013 (Rideout et al., 2010, 2013), and 53% report having a smartphone from the age of 11, with an increase of more than 80% to 14 years (Anderson and Jiang, 2018; Rideout and Robb, 2019). European figures also record a progressive rise, where 64% of young people have a smartphone at 15–16 years, 55% at 13–14, 40% at 11–12, and 20% at 9–10 years (Mascheroni and Cuman, 2014). Social media applications, in particular, are the most used, with 38% of young people claiming their use several times per hour and 16% interacting with them continuously (Rideout and Robb, 2018).

Linearly related to owning a mobile device, teenagers report a growing increase in media multitasking activities during their ordinary daily activities: in the bathroom, in bed, on the street, and especially during mealtimes (Webby Awards, 2015). This trend does not seem to slow down and could increase further.

Although technological development has led to some improvements across society (such as fast communication and content transmission facilities), certain negative aspects have also been highlighted. These include social isolation, addictive use behavior (Takao et al., 2009) and, more recently, interference with eating behavior, and the amount of calories ingested has been suggested.

Overall, current evidence reveals that the use of digital technologies referred to as "screen time" (devices using a screen) represents an obesity risk factor, especially for young people.

Investigations previously conducted using media devices, such as television and video games, showed a consistent correlation between time spent watching television, body mass index (BMI), and adiposity level (Coon and Tucker, 2002; Janz et al., 2002; Staiano et al., 2013). It was pointed out that people increased their food intake when they were allowed to eat snacks while playing video games or watching television (Temple et al., 2007; Chaput et al., 2011).

More recently, some preliminary studies extend a similar effect to smartphone use (Kenney and Gortmaker, 2017). However, unlike studies conducted with other multimedia devices, research investigating the relationship between food intake and smartphone use is at an early stage. Nevertheless, the American Academy of Pediatrics (2016) expands the effects of television and video games to mobile phones. This is reasonable in the discussion on weight management, since smartphone use—like other forms of screen time device—is also a sedentary activity (Lanningham-Foster et al., 2006). Furthermore, the compact size and one-handed operation make the smartphone the most popular multimedia device currently used during meals.

It has been highlighted that media multitasking via smartphone provides a distracting effect for tasks including reading an article and crossing the street (Stavrinos et al., 2009; Chen and Yan, 2016). Drawing on this observations, in our review, we will analyze the first experimental evidence that smartphone use, similar to other technological devices (Bellisle et al., 2004; Brunstrom and Mitchell, 2006; Hetherington et al., 2006; Robinson et al., 2013), promotes food intake by distracting users from eating behavior.

SMARTPHONE DISTRACTION AND EATING BEHAVIOR

Research identifying distraction as something that can promote food intake has been ongoing for quite a few years now. Eating in competition with other tasks has been shown to increase food intake, especially when the tasks are cognitively demanding (Hetherington et al., 2006). For instance, ambient music and the social context in which people consume their meals affect the number of calories ingested (Van der Bilt, 2011; Chapman et al., 2014; Higgs, 2015; Marsh et al., 2015). In a similar vein, experimental evidence indicates that several factors can distract from eating including listening to a story (Bellisle and Dalix, 2001; Long et al., 2011), background music (Stroebele and de Castro, 2006), playing a computer game (Oldham-Cooper et al., 2011), and engaging in a counting task (Boon et al., 2002). This effect was linearly related to the distraction provided by concomitant activities which affected the ability to correctly record the actual amount of food ingested (Higgs and Woodward, 2009; Marsh et al., 2015). Therefore, engaging in a task that diverts attention away from food could interfere with eating behavior and lead to greater caloric intake.

Similarly, studies using multimedia devices show that the distraction produced by watching a television program interferes with the amount of food consumed (Hetherington et al., 2006; Bellissimo et al., 2007; Patel et al., 2011; Marsh et al., 2013; Ogden et al., 2017). In particular, television content affects attention influencing eating behavior (Chapman et al., 2014), regardless of appetite level (Blass et al., 2006). In addition, Moray et al. (2007) found that the amounts of food ingested were less accurate if participants watched television while eating.

The distraction provided by smartphone use has also been highlighted in recent years (Kenney and Gortmaker, 2017). In a study conducted among 62 university volunteers between 18 and 28 years of both sexes, da Mata Gonçalves et al. (2019) evaluated the distraction produced by smartphone use during meals on both the total caloric intake and the type of calories ingested. During the trial sessions, participants were introduced to a snack task in which they were asked to eat under three different experimental conditions: no distraction, using their smartphones, or reading a printed text. After each session, the total calorie intake and nutritional composition of the food ingested were measured. The results showed that eating in the presence of distractors (smartphone/reading of printed articles) increased the total calorie intake by 15% with higher lipid ingestion. These results showed that smartphone use during meals, as well as reading a printed text, significantly affects the number of calories ingested.

Further, taking into account the external factors influencing eating behavior, coupled to the most recent observations concerning distraction effects on the number of calories ingested, Lopez et al. (2019a) tested the hypothesis by which children engaged in smartphone media multitasking activities (MMT) would be more driven by environmental stimuli. In their study, they verified the relationship between media multitasking—the use and switching from unrelated forms of digital media—and obesity risk. The authors recruited a sample of 179 pre-adolescent children aged 9–11 years and investigated the relationship between media multitasking and BMI. Their results showed a positive association between the frequency of children's MMT behavior and BMI, regardless of physical activity, suggesting that the use of screen time technologies affects food intake by diverting attention to external stimuli. In line with previous findings, individuals eat more as a result of reduced cognitive control about the amount of food ingested (Ogden et al., 2013; Dohle et al., 2017).

Psychological research examined in more detail the role of attention during meals. Through experimental paradigms, it has been proved that eating distractedly increases both the current food intake and the amount of food consumed at subsequent meals (Higgs and Woodward, 2009; Higgs and Donohoe, 2011; Mittal et al., 2011; Oldham-Cooper et al., 2011; Ogden et al., 2017). Distractors significantly affect dietary memory formation, preventing the proper awareness of food ingested and interfering with hunger and satiety signals. Satiety is a key component of appetite control and refers to the feeling of fullness which suppresses additional intake (Blundell and Tremblay, 1995; Morris et al., 2020). It is the result of physiological processes that tend to split into early cognitive and sensory influences and, subsequently, into post-ingestive effects (Blundell and Tremblay, 1995; Bellisle and Blundell, 2013). More recent cognitive models of eating behavior suggested that satiety is partly cognitively constructed and memory dependent (Higgs et al., 2017). These models are supported by consistent evidence that reducing memory for food consumed by interfering with attention at the time of consumption increases subsequent food intake (Higgs and Woodward, 2009; Mittal et al., 2011; Oldham-Cooper et al., 2011; Robinson et al., 2013; Higgs, 2015). Besides, the impact of distraction on calorie intake could be related to the way that different types of dietary contexts influence an individual. According to Ogden et al. (2013), a possible explanation lies in the multidimensional nature of the distraction, which could affect the link between hunger and changes in the desire to eat. From this perspective, she proposed two forms of distraction: distraction away from hunger and distraction away from eating. Once external factors are distracted from internal stimuli, such as hunger and satiety, the individual eats mindlessly and food intake would not be encoded to affect their desire to eat. Nevertheless, food intake requires a certain cognitive effort in itself, and if too distracted, the subject will have insufficient cognitive resources to engage in eating behavior. To date, the influence of attention and memory on eating behavior is well known (Chieffi et al., 2011a,b, 2015; Robinson et al., 2014a; Higgs and Spetter, 2018), and neuropsychological evidence shows that memory deterioration, or amnesia, corresponds to increased food intake (Rozin et al., 1998; Higgs et al., 2008; Chieffi et al., 2017). Furthermore, experimental evidence shows that increased awareness of the calories ingested during previous meals reduced the number of calories ingested subsequently in both normal and overweight subjects (Higgs et al., 2008; Higgs and Donohoe, 2011; Robinson et al., 2014b; Seguias and Tapper, 2018). Similarly, weight reduction treatments, which limited the time spent watching television or playing video games during meals, produced a greater decrease in BMI (Robinson, 1999). However, no correlation between digital device use and caloric intake has also been reported (Whitelock et al., 2018; Whitelock and Robinson, 2018) and further investigations are needed.

SMARTPHONE AND SOCIAL FACILITATION

The main difference between smartphones and traditional digital technologies is that the phone provides an easier way to enjoy intrinsically social activities. Studies investigating mobile phone usage models reveal that social interaction and peer chat features are the most used, and teenagers are estimated to send over 110 messages per day (Lenhart, 2015; Smith and Page, 2015; Teo et al., 2018).

Smartphone use implies that adolescents engaging in multitasking activities during meals interact with friends and family in a distinctly different way than other screen time devices. It has been observed that individuals tend to overeat in the presence of friends and family, so social activity with their smartphones during meals could play a significant role in eating behavior.

The construction of "social facilitation" implies that people tend to change their behavior according to others' behavior (Herman, 2015). Concerning eating behavior, eaters tend to activate food intake in people who do not eat (de Castro and de Castro, 1989; de Castro, 1997). In the same way, the presence of passive individuals who do not eat will make eaters more aware of their behavior, inducing them to decrease food consumption (Herman, 2015).

It has been shown that simple companionship can increase food intake by about 44% (de Castro and de Castro, 1989; de Castro, 1997), exerting a facilitating effect that manifests itself independently of real food needs (de Castro and de Castro, 1989). Moreover, this effect is cross-cultural (Herman, 2015).

Several studies indicated that social influence is so pervasive that even a simple online presence through digital technologies is enough to trigger facilitation effects in a variety of activities ranging from labyrinth resolution and arithmetic tasks to physical exercise (Park and Catrambone, 2007; Anderson-Hanley et al., 2011; Snyder et al., 2012).

Extending these results, Teo et al. (2018) tested the hypothesis by which the virtual presence of friends and parents—interconnected through a telephone messaging service—exerts a social facilitation effect on eating behavior. In a study of 50 Singaporean male adolescents, they examined whether social activity via smartphone could affect the number of calories ingested. Participants were randomly assigned to one of the following telephone activities: (i) sending and receiving messages (social activity) or (ii) reading a neutral article (non-social activity). Their results showed that participants consumed more calories when interacting virtually than those reading the article.

These findings seem to confirm the scientific literature highlighting the role of social influences on food intake (de Castro, 1997; Herman, 2015) and suggested that different ways of smartphone use may influence individuals to eat more than required. However, as suggested by the authors, virtual social facilitation is an emerging concept which needs further investigations.

Using mobile phones, people interacting via messaging service cannot be considered as eating co-actors. Analogously, people receiving messages are not aware of the amount of food their counterpart eats, minimizing the importance of maintaining an impression through food intake.

To date, virtual social facilitation cannot be described in the same way of a group exerting co-action or passive audience effects, and future research will have to investigate whether the impact of social facilitation can also apply to the digital realm.

DISCUSSION

In recent years, smartphone use has progressively increased in the youth population, especially during meals (Kabali et al., 2015).

As reported in our review, preliminary findings suggest that distraction and social facilitation can be taken into account to explain the link between smartphone use and food intake. However, although a social facilitation effect has been observed even in a virtual context, further investigations should exclude any alternative cognitive explanations (Teo et al., 2018). Indeed, participants engaged in a social interaction activity via smartphone messaging service could eat more because they were more distracted (Bellisle et al., 2004; Brunstrom and Mitchell, 2006; Robinson et al., 2013) rather than because the act of messaging was social.

As reported in the above sections, smartphone use affects food intake by diverting attention from eating behavior; with reduced cognitive resources, the user engages in "mindless eating" and consumes more food (Ogden et al., 2013; Dohle et al., 2017).

Some potential mechanisms have been proposed to explain the role of distraction in eating behavior (La Marra et al., 2009; Robinson et al., 2014a; Higgs, 2015; Higgs and Spetter, 2018). However, more recently, it has been highlighted that the perceptual load theory could be successfully applied to the study of ingestive behavior (Morris et al., 2020). The perceptual load theory is a key theory in the literature on selective attention and implies that the extent to which task-irrelevant stimuli are processed is regulated by attention availability (Lavie, 2005, 2010). It is a passive process carried out automatically by the perceptual system at an early stage of selection and is determined by whether the primary task leaves adequate spare perceptual capacity (Lavie, 2005, 2010). Similarly, it has been suggested that appetite control based on satiety could be altered when attention is absorbed in a perceptually demanding task (Morris et al., 2020). A reliable satiety response is provided by cognitive and physiological stimuli integration (Yeomans and Chambers, 2011; Chambers et al., 2013; Camps et al., 2016; Chen et al., 2016; McCrickerd et al., 2020). Therefore, physiological signals can be altered by the perceptual load, affecting appetite control during consumption. These results are based on existing models of appetite regulation (Bellisle and Blundell, 2013), which emphasize the role of cognitive influences on satiety.

Although the role of biological, environmental, and cultural factors in determining dietary behavior is widely recognized (Monda et al., 2017; Qasim et al., 2018), recent experimental evidence also supports the role of cognition in satiety (Higgs et al., 2017), which could be altered by a high perceptual load. Therefore, factors acting on satiety (such as post-ingestive stimuli derived from nutrients) may also depend on the availability of basic perceptual capacity. The perceptual load is known to substantially interfere with the processing of information, from the early stages of perceptual elaboration to the encoding of memory, as indexed by both behavioral and neural measurements (Lavie, 2005, 2010).

A further interpretation points to the role of dopaminergic pathways. These are mainly implied in the "reward dependence" mechanisms. These mechanisms are related to the activity of projections to the limbic areas, mainly exerting facilitation, and controlled by the prefrontal cortex which inhibits (DLPFC) or stops (orbitofrontal cortex) food assumption, in particular as regards its compulsive-like behaviors (Lopez et al., 2019b). On the other hand, the same areas are heavily implied in attentional processes (Supervisory Attentional System—SAS; Shallice et al., 1989), in the cognitive estimation of stimuli of the environment (including the food) and the consequences of eating behaviors. It is possible that the allocation of resources to stimuli other than food (the smartphone) could divert the frontal areas from exerting executive control on food assumption.

Furthermore, another neurobiological mechanism could be ascribed to the role of serotonergic pathways. These are mainly related to "harm avoidance" behaviors. According to the theory of serotonin/dopamine balance (Cools et al., 2011), increased activity of dopaminergic pathways entails reduced activity of serotonergic ones. Attempting to include all these insights in a coherent pathophysiological framework, we would suggest the following cascade of events: (1) The reward dependence activates dopaminergic extrafrontal pathways (in particular mesolimbic); (2) the interfering stimuli prevent frontal areas to exert normal control on the cognitive estimation of food assumption and/or to stop the calorie intake; and (3) the imbalance of dopaminergic/serotonergic mechanisms led to acting worrying food-related behaviors. Finally, the well-known neurobiological mechanisms of long-term potentiation and neural plasticity may give rise to a stable pattern of eating behaviors and to increase the risk of affective disorders like depression.

This evidence seems to be particularly worrying considering that mobile phone overuse in some cases represents a risk behavior comparable to addiction (Domoff et al., 2020).

Our review underlines that the use of mobile devices during meals interferes with eating behavior contributing to calorie increase in a segment of the population for which the international scientific community is particularly concerned. This knowledge could help to inform cognitive dietary interventions about the importance of encouraging participants to pay attention to food intake.

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All authors read and approved the final manuscript.

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Increased Screen Time Is Associated With Alcohol Desire and Sweetened Foods Consumption During the COVID-19 Pandemic

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Background: Elevated screen time has been associated with addictive behaviors, such as alcohol and sugar intake and smoking. Considering the substantial increase in screen time caused by social isolation policies, this study aimed to analyze the association of increased screen time in different devices during the COVID-19 pandemic with consumption and increased desire of alcohol, smoking, and sweetened foods in adults.

Methods: A sample of 1,897 adults with a mean age of 37.9 (13.3) years was assessed by an online survey, being composed by 58% of women. Participants were asked whether screen time in television, cell phone, and computer increased during the pandemic, as well as how much time is spent in each device. Closed questions assessed the frequency of alcohol and sweetened food consumption, smoking, and an increased desire to drink and smoke during the pandemic. Educational level, age, sex, feeling of stress, anxiety, depression, and use of a screen device for physical activity were covariates. Binary logistic regression models considered adjustment for covariates and for mutual habits.

Results: Increased television time was associated with increased desire to drink (OR = 1.46, 95% CI: 1.12; 1.89) and increased sweetened food consumption (OR = 1.53, 95% CI: 1.18; 1.99), while an increase in computer use was negatively associated with consumption of alcohol (OR = 0.68, 95% CI: 0.53; 0.86) and sweetened foods (OR = 0.78, 95% CI: 0.62; 0.98). Increased cell phone time was associated with increased sweetened food consumption during the pandemic (OR = 1.78, 95% CI: 1.18; 2.67). Participants with increased time in the three devices were less likely to consume sweetened foods for $\geq$5 days per week (OR = 0.63, 95% CI: 0.39; 0.99) but were twice as likely to have sweetened food consumption increased during pandemic (OR = 2.04, 95% CI: 1.07; 3.88).

Conclusion: Increased screen time was differently associated with consumption and desire for alcohol and sweets according to screen devices. Increased time in television and cell phones need to be considered for further investigations of behavioral impairments caused by the pandemic.

Keywords: sedentary behavior, dietary pattern, substance use, COVID-19, pandemic

INTRODUCTION

The polices of social isolation to counteract the spread of the COVID-19 pandemic has caused an increase in screen time (1), which is associated with impairments in mental and general health (2).

The elevated time in screen devices has been associated with addictive behaviors since before the pandemic, including alcohol consumption (3), smoking (4), and sugar intake (5). In this sense, due to the substantial increase in screen time caused by social isolation, it is possible that people are being very exposed to unhealthy advertisements in television and social media (6–8), as well as excessive information about the pandemic (9), which has been associated with poor mental health status (10) and may lead to an increase in addictive behaviors, mainly in regard to alcohol and tobacco (11–13). Besides that, excessive sugar intake has also been considered as an addiction (14), since high-palatable foods activate brain regions, which are responsible for pleasure and reward, as drugs (15). Sugar intake from sweetened foods was prospectively associated with poor mental health (13).

To test this hypothesis, this study aimed to analyze the association of increased screen time in different devices during the pandemic with alcohol consumption and the desire to drink, smoking and the desire to smoke, and high-sweetened food consumption and its increase during the pandemic in adults.

METHODS

This electronic survey research was conducted in Brazil, with data collection between May 5 and May 17, 2020. Participants were invited through social media (Facebook, Twitter, Instagram, and WhatsApp) to answer an online questionnaire using the Google Forms platform (Mountain View, CA, USA). This study was approved by the Universidade Nove de Julho' Ethics Committee before data collection (CAAE #30890220.4.0000.5511). Inclusion criteria was to be $\geq$18 years old and answer all the questions. Participants did not identify themselves, and their answers were only included in the sample if they authorized it before the protocol started, after reading the Informed Consent Form. All procedures followed the national legislation and the Declaration of Helsinki.

The survey was composed by 70 questions divided into seven domains: (1) personal information; (2) COVID-19 personal care; (3) physical activity; (4) eating behavior; (5) health risk habits; (6) mental health; and (7) overall health (16). For the purpose of the present study, specific questions were considered from personal information (age, sex, and educational level), COVID-19 personal care (use of screen device for the practice of physical activity), eating behavior (weekly frequency of sweetened food consumption, and increased sweetened food consumption during the pandemic), health risk habits (screen time, alcohol consumption, desire to drink during pandemic, smoking, and desire to smoke during pandemic), and mental health (feeling of anxiety, stress, and depression).

Screen Time

The daily hours spent in television viewing, cell phone, and computer were used to assess the screen time of the sample, through specific questions for each device: "How many hours per day do you spend on television/cellphone/computer during the COVID-19 pandemic?" Responses were: (i) <1 h/day; (ii) 1 h/day; (iii) 2 h/day; (iv) 3 h/day; (v) 4 h/day; and (vi) 5 or more h/day.

The increase in screen time during the COVID-19 pandemic was assessed for each device through the question: "During the COVID-19 pandemic, has your time on television/cellphone/computer increased?" Answers were "yes" or "no."

Alcohol Consumption and Desire to Drink

The alcohol consumption was assessed by the question: "During the COVID-19 pandemic, how many days per week do you drink alcoholic beverages?" Answers ranged from 0 to 7 days. Those participants who reported drinking at least once a week were classified as "alcohol consumption," for being considered as current drinkers according to Wood et al. (17).

Participants were asked about the desire to drink through the question: "During the COVID-19 pandemic, do you have an increase in the desire to drink alcoholic beverages?" Answers were "yes" or "no." Those participants who answered "yes" for this question were classified as "increased desire to drink."

Smoking and Desire to Smoke

Participants' smoking habits were assessed through the question: "In the last 30 days, did you smoke?" Answers were "yes" or "no." Those participants who answered "yes" were classified as "smokers."

The desire to smoke was assessed by the question: "During the COVID-19 pandemic, did you have an increase in the desire to smoke?" Answers were "yes" or "no." Those participants who answered "yes" were classified as "increased desire to smoke" even among those who said they had not smoked in the last 30 days.

Sweetened Food Consumption

The weekly frequency of sweetened foods consumption was assessed by the question: "How many days per week do you eat sweetened foods?" Responses ranged from 0 to 7 days.

Those participants who reported to eat sweetened foods for 5 or more days per week were classified as "high sweetened food consumption" (18).

Participants were also asked about how much their sweetened food consumption increased during the pandemic through the question: "During the COVID-19 pandemic, how much your sweetened food consumption increased?" Responses were: (i) nothing; (ii) increased slightly, (iii) increased moderately, and (iv) increased a lot. Participants who answered "increased moderately" and "increased a lot" were classified as "increased sweetened food consumption."

Covariates

Sociodemographic factors (age, sex, and educational level), mental health status (feeling of anxiety, stress, and depression), and use of screen devices for physical activity were considered as covariates. The educational level was self-reported through the question: "What is your educational level?" Answers were: (i) elementary school or less; (ii) high school; (iii) college; and (iv) post-graduate. Participants were asked about frequency that they felt stressed, anxious, and depressed during the pandemic. Responses for each feeling were: (i) never; (ii) rarely; (iii) sometimes; (iv) frequently; and (v) always. Those adults who answered "frequently" and "always" were classified for each question as having a frequent "feeling of stress," "feeling of anxiety," or "feeling of depression." The use of a screen device for the practice of physical activity was assessed through the question: "During the COVID-19 pandemic, do you use social media or video conference for practicing physical activities?" Responses were "yes" or "no".

Statistical Analysis

Sample characteristics were presented in mean and standard deviation for continuous and in frequency for categorical variables. Binary logistic regression models were used to analyze the association between the increased screen time in each screen device and assessed outcomes: Model 1 was adjusted by sociodemographic factors (age, sex, educational level), mental health (feeling of stress, feeling of anxiety, feeling of depression), use of screen device for physical activity, and total screen time; while Model 2 was adjusted by variables from Model 1 and mutually by the other outcomes (i.e., the association between increased screen time and alcohol consumption considered smoking and sweetened food consumption as adjustments). Clusters of increased screen time, in different devices, were used to analyze whether the chance of having the outcomes was higher, according to the following categories: (i) screen time did not increase in any device (as reference); (ii) increased time in one screen device; (iii) increased time in two screen devices; and (iv) increased time in three screen devices. Analyses were performed by SPSS Statistical Package version 24.0, with significance level fixed at $p < 0.05$ and confidence interval in 95%.

TABLE 1 | Characterization of sample ($n = 1,896$).

Categorical variables	*n* (%)
Sex, female	1,111 (58.6)
Educational level:	
Elementary	11 (0.6)
High school	158 (8.3)
College/graduated	807 (42.6)
Post-graduation	920 (48.5)
Feeling of stress	481 (25.4)
Feeling of anxiety	581 (30.6)
Feeling of depression	252 (13.3)
Alcohol consumption	1,245 (65.7)
Increased desire to alcohol drink during pandemic	512 (27.0)
Smoking	103 (5.4)
Increased desire to smoke during pandemic	65 (3.4)
Sweetened foods consumption for ≥5 days/week	711 (37.5)
Increased sweetened foods consumption during pandemic	807 (42.6)
Use of screen device for physical activity	709 (37.4)
Increased television time during pandemic	1,294 (68.2)
Increased cellphone time during pandemic	1,671 (88.1)
Increased computer time during pandemic	1,391 (73.4)
Cluster of screen time increased during pandemic:	
Not increased in any device	88 (4.6)
Increased in 1 device	210 (11.1)
Increased in 2 devices	635 (33.5)
Increase in the 3 devices	963 (50.8)
Continuous variables	**Mean (SD)**
Television time, h/day	1.7 (1.3)
Cellphone time, h/day	3.1 (1.2)
Computer time, h/day	2.5 (1.6)
Total screen time, h/day	7.2 (2.5)

SD, standard deviation.

RESULTS

A total of 1,929 adults participated in the survey, being composed by 58% of women. For this study data analysis, 33 participants were excluded due to incomplete responses, totalizing a sample of 1,896. The mean age of participants was 38.2 (13.1) years, with minimum of 18 and maximum of 88 years. The sample characteristics is presented in **Table 1**.

The association of increased screen time in different devices with smoking, alcohol, sweetened food consumption, and desire is presented in **Table 2**. Adults who reported that computer time increased during the COVID-19 pandemic were less likely to report both alcohol consumption (OR = 0.68, 95% CI: 0.53; 0.86) and high sweetened food consumption (OR = 0.78, 95% CI: 0.62; 0.98). Adults whose television time increased during the COVID-19 pandemic were more likely to report increased desire to drink (OR = 1.46, 95% CI: 1.12; 1.89) and increased sweetened food consumption (OR = 1.53, 95% CI: 1.18; 1.99). Increased cell phone time was also associated with increased sweetened food consumption during the pandemic (OR = 1.78, 95% CI: 1.18; 2.67), whereas increased computer time was negatively associated with high sweetened food consumption (OR = 0.78, 95% CI: 0.62; 0.98).

TABLE 2 | Association of increased time in screen devices with smoking, alcohol, sweetened food consumption, and increased desire during the COVID-19 pandemic in adults ($n = 1,896$).

	Unadjusted OR (95% CI)	Adjusted Model 1 OR (95% CI)	Adjusted model 2 OR (95% CI)	Unadjusted OR (95% CI)	Adjusted model 1 OR (95% CI)	Adjusted Model 2 OR (95% CI)
	Alcohol consumption[a] ($n = 1,245$)			**Increased desire to alcohol drink during pandemic[d] ($n = 512$)**		
Increased television time ($n = 1,294$)	1.07 (0.87; 1.31)	0.97 (0.78; 1.20)	0.97 (0.78; 1.21)	**1.54 (1.21; 1.96)**	**1.51 (1.16; 1.95)**	**1.46 (1.12; 1.89)**
Increased cellphone time ($n = 1,671$)	1.08 (0.80; 1.45)	1.05 (0.76; 1.43)	1.08 (0.79; 1.48)	1.34 (0.94; 1.92)	1.25 (0.86; 1.83)	1.24 (0.84; 1.82)
Increased computer time ($n = 1,391$)	0.88 (0.71; 1.10)	**0.67 (0.53; 0.86)**	**0.68 (0.53; 0.86)**	0.95 (0.75; 1.22)	0.87 (0.66; 1.14)	0.87 (0.66; 1.14)
	Smoking[b] ($n = 103$)			**Increased desire to smoke during pandemic[e] ($n = 65$)**		
Increased television time ($n = 1,294$)	0.90 (0.59; 1.36)	0.89 (0.56; 1.40)	0.87 (0.55; 1.38)	0.81 (0.48; 1.39)	0.71 (0.39; 1.30)	0.58 (0.31; 1.09)
Increased cellphone time ($n = 1,671$)	0.72 (0.41; 1.27)	0.79 (0.43; 1.45)	0.78 (0.42; 1.43)	0.84 (0.38; 1.85)	0.80 (0.34; 1.87)	0.58 (0.24; 1.40)
Increased computer time ($n = 1,391$)	0.70 (0.45; 1.07)	0.66 (0.41; 1.06)	0.71 (0.44; 1.14)	0.73 (0.41; 1.30)	0.62 (0.32; 1.18)	0.60 (0.30; 1.18)
	Sweetened foods consumption for ≥5 days per week[c] ($n = 711$)			**Increased sweetened foods consumption during pandemic[f] ($n = 807$)**		
Increased television time ($n = 1,294$)	1.15 (0.94; 1.40)	1.02 (0.82; 1.27)	1.02 (0.83; 1.27)	**1.77 (1.45; 2.17)**	**1.56 (1.25; 1.96)**	**1.53 (1.18; 1.99)**
Increased cellphone time ($n = 1,671$)	1.16 (0.86; 1.57)	1.01 (0.73; 1.38)	1.01 (0.73; 1.38)	2.11 (1.54; 2.90)	**1.53 (1.08; 2.15)**	**1.78 (1.18; 2.67)**
Increased computer time ($n = 1,391$)	0.93 (0.75; 1.14)	**0.79 (0.63; 0.99)**	**0.78 (0.62; 0.98)**	**1.49 (1.20; 1.84)**	1.12 (0.88; 1.43)	1.16 (0.88; 1.53)

Model 1: Adjusted by age, sex, educational level, feeling of stress, feeling of anxiety, feeling of depression, use of screen device for physical activity, and total screen time per day in each device; Model 2: Model 1 + adjusted mutually by a, b, and c, or by d, e, and f, according to the column; OR, odds ratio; CI, confidence interval. Bold values were statistically significant at $p < 0.05$ level.

The **Table 3** shows the association of smoking, alcohol, and sweetened food consumption and the desire with the clustering of increased time in different screen devices. Participants who reported that screen time increased in the three screen devices were less likely to have sweetened food consumption ≥5 days per week than those without an increase in any screen device during the pandemic (OR = 0.63, 95% CI: 0.39; 0.99). Otherwise, the increased time in the three screen devices was associated with twice the chance of sweetened foods consumption has been increased during pandemic (OR = 2.04, 95% CI: 1.07; 3.88).

DISCUSSION

This study observed that increased time in television and cell phone usage was associated with addictive behaviors and increased substance craving during the COVID-19 pandemic, while increased time on the computer was negatively associated with consumption of alcohol and sweetened foods. Adults with increased time in the three devices (television, cell phone, and computer) were less likely to consume sweetened foods for ≥5 days per week but were more likely to have their sweetened food consumption increased during the pandemic.

Increased time watching television was associated with an increased desire for alcohol consumption in this study. This result may be related to a larger exposure to advertisements on television, since the association of advertisements with alcohol consumption and alcohol-related cognitions has been described even before the COVID-19 pandemic (19), and greater alcohol craving was an observed event in the home environment (20). Although the moderate alcohol consumption has been associated with psychological benefits, such as stress reduction, happiness, and decreases in tension and depression since decades prior (21), frequent alcohol consumption results in neuroadaptive changes (22), which is associated with alcohol dependence (23). Therefore, the increases in screen time and increased desire to alcohol drink during the COVID-19 pandemic can be a potent trigger to higher alcohol consumption and consequently alcohol dependence in the future. In addition, both excessive alcohol consumption and high television viewing have been associated with psychological distress and moderate-to-severe depression in adults (24, 25), which may also be aggravated by such difficult times due to the pandemic.

Television viewing was also associated with increased sweetened food consumption in the present study. The consumption of sweetened foods and other energy-dense snacks have been positively associated with television viewing in adults even before the pandemic (26, 27). The link between television and sweetened food consumption can be related with the mentally passive characteristics of television viewing that allows concomitant eating behaviors and could also increase the risk of depression (28). In addition, television has also presenting excessive content about the COVID-19 pandemic, which may

TABLE 3 | Association of the clustering of increased time in different devices with smoking, alcohol, sweetened food consumption, and increased desire during the COVID-19 pandemic in adults ($n = 1,896$).

	Unadjusted OR (95% CI)	Adjusted model 1 OR (95% CI)	Adjusted model 2 OR (95% CI)	Unadjusted OR (95% CI)	Adjusted model 1 OR (95% CI)	Adjusted model 2 OR (95% CI)
	Alcohol consumption[a] ($n = 1,245$)			**Increased desire to alcohol drink during pandemic[d] ($n = 512$)**		
Screen time did not increase ($n = 88$)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Increased time in 1 screen device ($n = 210$)	1.04 (0.62; 1.73)	1.01 (0.59; 1.73)	1.06 (0.62; 1.81)	1.24 (0.63; 2.44)	1.20 (0.61; 2.34)	1.21 (0.62; 2.38)
Increased time in 2 screen devices ($n = 635$)	1.28 (0.80; 2.03)	1.16 (0.71; 1.88)	1.23 (0.75; 2.00)	1.72 (0.93; 3.17)	1.68 (0.92; 3.07)	1.63 (0.89; 3.01)
Increased time in 3 screen devices ($n = 963$)	1.11 (0.71; 1.74)	0.85 (0.52; 1.38)	0.90 (0.55; 1.46)	1.79 (0.98; 3.27)	1.62 (0.89; 2.97)	1.56 (0.84; 2.87)
	Smoking[b] ($n = 103$)			**Increased desire to smoke during pandemic[e] ($n = 65$)**		
Screen time did not increase ($n = 88$)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Increased time in 1 screen device ($n = 210$)	0.88 (0.35; 2.25)	0.86 (0.33; 2.23)	0.86 (0.33; 2.24)	0.56 (0.15; 2.14)	0.81 (0.21; 3.16)	0.68 (0.17; 2.69)
Increased time in 2 screen devices ($n = 635$)	0.59 (0.25; 1.38)	0.60 (0.25; 1.43)	0.58 (0.24; 1.39)	0.58 (0.18; 1.88)	0.93 (0.28; 3.13)	0.65 (0.19; 2.24)
Increased time in 3 screen devices ($n = 963$)	0.63 (0.28; 1.43)	0.61 (0.26; 1.44)	0.61 (0.26; 1.47)	0.50 (0.16; 1.56)	0.66 (0.20; 2.20)	0.45 (0.13; 1.55)
	Sweetened foods consumption for ≥5 days per week[c] ($n = 711$)			**Increased sweetened foods consumption during pandemic[f] ($n = 807$)**		
Screen time did not increase ($n = 88$)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)	1.00 (Reference)
Increased time in 1 screen device ($n = 210$)	0.66 (0.39; 1.10)	0.60 (0.36; 1.02)	0.60 (0.35; 1.02)	1.34 (0.74; 2.43)	1.00 (0.56; 1.79)	1.08 (0.53; 2.21)
Increased time in 2 screen devices ($n = 635$)	0.83 (0.53; 1.31)	0.68 (0.43; 1.09)	0.68 (0.43; 1.09)	**2.10 (1.23; 3.60)**	1.27 (0.75; 2.16)	1.59 (0.84; 3.04)
Increased time in 3 screen devices ($n = 963$)	0.83 (0.53; 1.30)	**0.62 (0.39; 0.99)**	**0.63 (0.39; 0.99)**	**3.13 (1.85; 5.32)**	**1.74 (1.03; 2.94)**	**2.04 (1.07; 3.88)**

Model 1: Adjusted by sex, age, educational level, use of screen device for physical activity, and total time spent in screen time per day; Model 2: Model 1 + adjusted mutually by a, b, and c, or by d, e, and f, according to the column; OR, odds ratio; CI, confidence interval. Bold values were statistically significant at $p < 0.05$ level.

cause negative effects in mood and boredom, and sweetened food consumption could counteract the frequent news about the current period by the releasing of dopamine, which activates pleasurable and rewarding sensations, improving psychological well-being (29).

This study also observed that increased time on the computer was a protective factor for both alcohol and high-sweetened food consumption during the pandemic. A possible hypothesis is that computer time could be mostly related to occupational tasks, such as home-office and virtual classes, which leads to a higher time spent in mentally active screen behaviors. It has been previously observed that mentally active screen behaviors as computer use have been related with better mental health (30) and higher moderate-to-vigorous physical activity (31), which presented a protective role in the physical and nutritional health impairments of the pandemic (32).

The cluster of increased screen time was associated with increased sweetened food consumption during the pandemic. It is possible that increased time in different devices may be related to higher exposure to unhealthy food advertisements with negative effects on food choice, since previous pandemic studies reported that people who were exposed to food advertising chose 28% more unhealthy snacks when compared to those who were exposed to non-food advertisements (6). However, the present study also observed that adults with increased time in three screen devices were less likely to have sweetened food consumption for 5 days per week and more, even being more likely to have their consumption increased during the pandemic. It is possible that increased sweetened food consumption during the pandemic was not sufficient to make it more frequent, although it was not known whether the portions per day could have been increased.

Although we have filtered discrepant and improbable responses to improve the data quality, this study was susceptible to information bias, as well as the invitation procedures precluded participation of individuals without access to social media. The total weekly amount of drinking was not assessed, as well as the daily quantity of sweetened foods consumed, which would add valuable information. This study did not consider which body position the screen devices were used, which compromise inferences about sedentary behavioral patterns related to screen time. The lack of information about the employment status and labor activities may be seen as a limitation of the study, as well as other reasons for increases in screen time during the pandemic. The adjustments for mental health, sociodemographic factors, and total time spent on screen devices in the analysis by different screen devices were the strengths of the study.

CONCLUSION

During the COVID-19 pandemic, increased screen time was differently associated with alcohol and sweets according to screen devices. Increased television and cell phone time was associated with increased sweetened food consumption and increased desire to drink alcoholic beverages, while increased computer time was a protective factor for both alcohol and high sweetened food consumption. The increased screen time spent on the television and cell phone needs to be considered for further investigation of unhealthy behaviors caused by the pandemic.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Universidade Nove de Julho' Ethics Committee before data collection (CAAE #30890220.4.0000.5511). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

WRT, DGDC, and TAD: conceptualization, data analysis, writing, and manuscript draft. MCL-P, JPB, MAC, and GGC: writing and data curation. WLP and RMR-D: conceptualization and writing. All the authors approved the final version of manuscript.

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