Association Between Smartphone Use and Eating Behavior in Daily Life

A Major Qualifying Project

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Abstract

Previous research has demonstrated that viewing television while eating is related to increased caloric consumption. However, smartphone usage is exceeding television usage over time. Despite the prevalence of smartphone use, only a few laboratory studies have investigated the relationship between phone use and eating behavior. This study sought to fill this research gap by investigating smartphone use and eating behavior in everyday life. One hundred and thirty-eight participants used MyFitnessPal and the native iPhone screen time function for three days (Thursday, Friday, and Saturday) in order to track daily calories and time spent using their smartphones. There are no correlations between total Thursday calories and total Thursday screen time minutes, total Friday calories and total Friday screen time minutes, and total Saturday calories and total Saturday screen time minutes. Morning screen time minutes did not predict calories eaten in subsequent meals for Thursday, Friday, or Saturday. Additionally, the type of screen time (e.g., social networking, reading, etc.) was not related to participants' total daily calorie intake. These findings suggest that smartphone use may not lead to increased calorie intake, as television viewing does.

Keywords: smartphone, eating behavior, mindless eating, screen time, behavior tracking

Effects of Smartphone Use on Eating Behavior

Smartphone use has become increasingly prevalent in recent years, as 2.5 billion people worldwide currently have access to smartphones (Silver, 2019). This technology has become integrated into our daily lives, yet our understanding of how smartphones affect our eating habits is limited. Past research which investigated television viewing and consumption determined that television increases calorie intake through distracted eating. This prior research may provide clues as to the effects of smartphone usage on consumption, which are especially relevant in perhaps understanding factors responsible for the prevalence of obesity and overweight in the United States; roughly one-third of adults have obesity, and another one-third have overweight (Bubnis, 2020). Besides overweight, unhealthy eating patterns contribute to disease and poor health (Willett, 2019).

One factor which plays a role in global disease rates is overeating and unhealthy diets. The availability of inexpensive, energy-dense foods, especially in tandem with the rise of sedentary lifestyles, has contributed significantly to this issue (Prentice, 2001). The negative health effects that result from overeating and unhealthy diets cannot be overstated; overeating endangers mortality and morbidity to a greater degree than the combined effects of alcohol, drug, and tobacco use (Willett, 2019). Thus, understanding the mechanisms which regulate normal eating behaviors is a crucial aspect of determining what drives overeating. Consumption monitoring is an example of such mechanisms.

Consumption Monitoring

Consumption monitoring is a conscious process through which people track how much they eat (Wansink, 2004; Wansink & Sobal, 2007). It requires that an individual actively pays attention to their food to gauge the amount consumed. In turn, this prevents overconsumption and its health consequences, in the case that overeating becomes chronic. Environmental cues or stimuli can alter the quantity of food a person consumes by interfering with normal consumption monitoring by drawing attention away from the food. Examples of such cues or stimuli include the size of the food portions or packages, the variety of food available, whether or not we are eating while others are present (Wansink & Sobal, 2007), and the duration of the eating period (Wansink, 2004). These cues all increase the amount of food eaten. Specifically, larger portions or package sizes, greater available food varieties, the presence of at least one other person while eating (Wansink & Sobal, 2007), and longer eating durations correspond to greater food intake (Wansink, 2004). Additionally, eating distractions reroute attention from signals of satiety, such as feelings of fullness, which are then ignored when they arise (Wansink, 2004). People are generally unaware of the effects of such cues (Wansink & Sobal, 2007), or they deny that these cues have any effect on their eating behavior (Ogden et al., 2013).

TV and Consumption

Given the aforementioned prevalence of smartphone use, my current study investigates how smartphone usage while eating interferes with the process of consumption monitoring. However, because the research in this area is limited, I explored past research aimed towards understanding how TV viewing affects caloric consumption. Both smartphones and TV are distractors which inhibit consumption monitoring, and research on TV viewing could potentially shed some light on how phones affect eating behaviors.

Watching TV while eating is an example of an environmental stimuli which affects consumption monitoring and leads to mindless eating. This distraction can instigate episodes of consumption regardless of hunger and can extend the length of the eating period (Wansink, 2004). Therefore, because the eating episode is not influenced by hunger, it may instead be due to an individual’s habit of eating while watching TV (Wansink, 2004). Furthermore, distraction while eating may impair episodic memory formation of the eating episode (Ogden et al., 2013).

Past research on the effects of TV viewing on eating behavior has determined that watching TV while eating leads to increased caloric consumption (Bellisle, Dalix, & Slama, 2004; Blass et al., 2006; Braude & Stevenson, 2014; Ogden et al., 2013; Thorp et al., 2013; Vik et al., 2013). Interestingly, watching TV while eating may also influence caloric consumption in subsequent meals or snacking episodes. This is likely due to the negative impact of TV viewing on memory formation for foods eaten while watching (Higgs & Woodward, 2009).

For instance, in their research, Bellisle et al., (2004) instructed a sample of adult women to eat lunch once a week for four weeks in a laboratory under different conditions. During the first and last lunch, participants ate with no distractions present. In the second and third lunches, participants ate while watching television or while listening to a tape recording of a story. Both of these conditions led to increased food intake in participants; furthermore, because there was no change in overall perceived food palatability, this change can be attributed only to the distractions.

Work done by Braude & Stevenson (2014) demonstrated similar findings. Their sample consisted of sixty-two college-aged women. Participants were either presented a single food or a variety of foods. All participants, regardless of which food group they were assigned to, had two study sessions: one in which there were no distractions while eating, and another in which they watched TV. Watching TV was associated with increased consumption, both of snack items eaten and of total calories. Additionally, watching TV reduced sensitivity to feelings of hunger and satiety in participants.

The eating behaviors that emerge while viewing TV have health implications for both adults and children. The primary mechanisms through which TV viewing influences body weight and health are by promoting a sedentary lifestyle, decreasing the resting metabolic rate, and exposing consumers to advertisements featuring unhealthy foods (Barr-Anderson et. al, 2009; Bellisle, Dalix, & Slama, 2004). Commercials of foods may also affect children, as the advertisements on TV programs targeted to child audiences often promote the consumption of high-calorie, low-nutrient foods (Vik et al., 2013).

Viewing TV while eating is associated with being overweight or obese in children. In children ages 10 - 12, the probability of being overweight is significantly greater for individuals who reported eating lunch and dinner while watching TV, in comparison to children who did not. The average BMI of children who more frequently watched TV while eating meals was also greater than the BMIs of children who less frequently watched TV while eating meals. Similarly, in another sample of children in 5th grade (roughly age 10), eating while watching TV was linked to both being overweight and having a nutrient-poor diet (Vik et. al, 2013).

In adults, TV viewing is positively associated with metabolic syndrome (Thorp et al., 2013). Metabolic syndrome refers to risk factors which contribute to heart disease, diabetes, and stroke. It includes issues such as high blood pressure, low HDL cholesterol and high triglycerides, and high fasting blood glucose (National Heart, Lung, and Blood Institute, n.d.). TV viewing contributes to metabolic syndrome because it couples sedentary behavior with the increased consumption of high-calorie, low-nutrient snack foods.

Smartphone Prevalence Estimates

As mentioned previously, according to the Pew Research Center, at least 2.5 billion people worldwide have smartphones (Silver, 2019). Smartphones have also become significantly more prevalent in recent years. In 2011, only 35% of people in the United States reported owning a smartphone; that number skyrocketed to 81% in 2019 (Pew Research Center, 2019). Daily smartphone use has also recently surpassed TV use. In 2014, the average adult in the United States spent almost two more hours watching TV than they spent using their phones. Currently, it is estimated that 3 hours, 43 minutes are spent using smartphones daily, whereas 3 hours, 35 minutes are allotted to watching TV. This shift towards smartphone use is estimated to increase with time - for example, predictions for 2021 state that daily smartphone use will reach about four hours, and time spent watching TV will be 3 hours, 22 minutes (He, 2019). Considering the prevalence of smartphone use, research should begin investigating how these devices affect us.

Phone Use and Consumption

Although research on how phone usage affects eating is limited, the studies conducted have yielded results similar to TV viewing. Gonçalves et al., (2019) investigated how phones influence energy intake in comparison to a participant's baseline food intake with no distractions present. The study included three snack sessions under different conditions: one without distraction, one where participants used their phones, and a third where participants read a printed text. Participants who snacked while using their phones experienced an increase in both total caloric and lipid intake. This was especially pronounced in older male participants. In another similar study conducted by Teo et al., (2018), a sample of adolescent males were asked to eat a snack food while using their phone to either communicate with others via text message or to read an article. The calorie consumption was greater in the males who used their phones to message others. This can also be related to how having others present - albeit virtually - can influence eating behavior by increasing food intake.

Despite the widespread and increasing popularity of smartphones, research investigating how the usage of these devices affects eating behavior is limited. My study seeks to fill this research gap by investigating the link between smartphone use and daily caloric intake in everyday life. This ecologically valid approach is critical as similar research has taken place in a laboratory setting. In these studies, participants may not feel fully comfortable, or may limit their consumption; this may inadvertently influence participant eating behavior. My research takes place in the participant's typical settings. I hypothesize the following:

1. There will be a positive association between a participant's daily screen time and calorie consumption.
2. Screen time during morning hours will predict higher calorie intake for subsequent afternoon and evening meals.
3. Calorie consumption will be greater on Saturday in comparison to Thursday and Friday.
4. There will be a positive correlation between screen time spent on social apps and calorie consumption.

Method

Participants

One-hundred four participants were recruited through flyers posted on social media or through email advertisements sent to large email lists. These participants were compensated with $20 and entry into a raffle for one of five $100 gift cards. Thirty-four participants were also recruited through Worcester Polytechnic Institute's SONA subject pool and were compensated with 1.5 research credits. All participants provided informed consent. Exclusion criteria includes not owning a smartphone, being on a strict diet, and having a prior eating disorder diagnosis. Twenty-six participants dropped out of the study after providing informed consent. The sample was 30.4% male and 68.8% female. The sample's self-reported race/ethnicity was 67.4% White, 17.4% Asian or Pacific Islander, 9.4% Hispanic or Latino/a, 2.2% Black, 2.9% other or multiracial. The average age was 21.9 years (*SD* = 7.4).

Procedure

Participants' screen time and caloric intake was tracked over the course of three days - Thursday, Friday, and Saturday. Participants were asked to download MyFitnessPal, a freely available smartphone app, in order to track calories. To measure screen time, participants were asked to utilize Screen Time on their iPhones, which is Apple's built-in screen time monitoring capability. Participants were sent detailed instructions on how to use both MyFitnessPal and Screen Time, as well as how to screenshot and export the requested data from both apps. Participants were asked to email the data screenshots on the Sunday following their study completion. Once all data had been received, participants were then compensated either in cash or course credit.

Measures

Calorie Intake over the Day.

Participants were asked to manually set their daily caloric goal to 5,000 calories. Normally, MyFitnessPal sets it automatically to between 1,200 - 1,800 calories. The increased limit prevents the app from warning participants that they have exceeded their daily caloric limit so that they would not feel any pressure to change their eating. Participants were asked to input the foods they ate throughout the day into their corresponding category: breakfast, lunch, dinner, or snacks. Participants were also asked to take enough screenshots so that all foods eaten in one day could be seen. For each day, the relevant caloric totals that were collected included the total daily caloric intake, and intake during breakfast, lunch, dinner, and snacks.

Screen Time Data.

Participants were asked to take screenshots of both the total daily screen time graph and of the list of most-used app categories. For each day, total screen time was recorded, and screen time was also calculated in minutes for the following time ranges: 12 AM - 6 AM (overnight), 6 AM - 12 PM (morning), 12 PM - 6 PM (afternoon), and 6 PM - 12 AM (evening).

Screen Time Categories. Each participant's most used screen time category was coded as either 1 (social networking) or 0 (any other category). Examples of other categories include information and reading, entertainment, and gaming.

The Stanford Leisure-Time Activity Categorical Item (L-CAT 2.2).

Participants were asked to complete the Stanford Leisure-Time Activity Categorical Item (L-CAT 2.2) (Kiernan et al., 2013). The L-CAT 2.2 was used to assess a participant's overall activity and exercise level outside of the three-day study period. The options categorized activity levels by both intensity and frequency. An example of an available option is as follows: "Once or twice a week, I did light activities such as getting outdoors on the weekends for an easy walk or stroll. Or once or twice a week, I did chores around the house such as sweeping floors or vacuuming."

Demographics.

Participants were asked to provide their age, gender identity, sex, race and ethnicity, height, weight, and year in school. The gender identity options were man, woman, non-binary/gender non-conforming, transgender, other, and prefer not to say. The options for sex were male, female, intersex, and prefer not to say. The options for race/ethnicity were White, Black, Hispanic or Latino/a, American Indian, Asian or Pacific Islander, other or multiracial, and prefer not to answer.

Data Analytic Plan

Correlation tests were used to measure the associations between screen time and calorie intake. Regression analyses tested screen time during specific intervals as continuous predictors for calorie intake at subsequent intervals. A repeated measures ANOVA was used to evaluate differences between the calorie intake means across Thursday, Friday, and Saturday.

Results

Descriptive statistics for daily calorie and screen time variables, as well as the L-CAT, can be seen in Table 1 below.

Table 1

Calorie Intake, Screen Time, and L-CAT Descriptive Statistics

Variables	*N*	Minimum	Maximum	Mean	Std. Deviation
Total Thursday Calories	138	553	4495	1682.43	685.02
Total Friday Calories	138	460	4526	1636.90	661.28
Total Saturday Calories	138	450	4164	1653.56	707.056
Total Thursday Minutes	138	14	1023	389.89	202.07
Total Friday Minutes	138	19	856	374.97	181.81
Total Saturday Minutes	138	5	1139	368.65	191.76
L-CAT	138	1	6	3.22	1.425

Hypothesis 1: There will be a positive association between a participant's daily screen time and calorie consumption.

Total calories eaten on Thursday positively correlated with the total calories eaten on Friday, $r(136) = .496$, $p < .001$, and total calories eaten on Saturday, $r(136) = .686$, $p < .001$. The total calories eaten on Friday also correlated with the total calories eaten on Saturday, $r(136) = .584$, $p < .001$. Total screen time minutes on Thursday positively correlated with total screen time minutes on Friday, $r(136) = .788$, $p < .001$, and total screen time minutes on Saturday, $r(136) =$

.685, $p < 0.001$. Total screen time minutes on Friday also positively correlated with total screen time minutes on Saturday, $r(136) = .688$, $p < .001$. Because calorie consumption values for each day were correlated, calorie consumption was averaged across the three days into one variable. The same was the case for screen time, which was also averaged across all three days.

Correlation tests were used to determine if associations exist between participant screen time and calorie consumption. Average total calories and average total screen time were not correlated ($r(136) = -.084$, $p = .328$). There were no correlations between total Thursday calories and total Thursday screen time minutes ($r(136) = -.048$, $p = .579$), total Friday calories and total Friday screen time minutes ($r(136) = -.058$, $p = .503$), and total Saturday calories and total Saturday screen time minutes ($r(136) = -.114$, $p = .184$).

Hypothesis 2: Screen time during morning hours will predict higher calorie intake for subsequent afternoon and evening meals.

Linear regression analyses tested screen time during morning hours as a continuous predictor of calorie intake for afternoon and evening meals. To do this, new variables were created for Thursday, Friday, and Saturday, respectively, in which the total number of calories eaten during lunch and dinner were averaged. Snacks were not included because it is not specified at what time they were eaten. The screen time interval used was morning minutes.

Morning screen time minutes did not predict calories eaten in subsequent meals on the same day for Thursday ($B = -0.53$, $SE\ B = 0.43$, $\beta = -.11$, $p = .225$), Friday ($B = 0.01$, $SE\ B = 0.39$, $\beta = .003$, $p = 0.971$), or Saturday ($B = -0.32$, $SE\ B = 0.38$, $\beta = -.07$, $p = 0.407$).

Hypothesis 3: Calorie consumption will be greater on Saturday in comparison to Thursday and Friday.

A repeated measures ANOVA indicated that the mean number of calories eaten on Thursday (*M* = 1682.43, *SD* = 685.03), Friday (*M* = 1636.90, *SD* = 661.28), and Saturday (*M* = 1653.56, *SD* = 707.06) did not significantly differ, $F(2, 274) = 0.38$, $p = .683$.

Hypothesis 4: There will be a positive correlation between screen time spent on social apps and calorie consumption.

There was no correlation between the time in minutes that each participant spent using social networking apps and their average number of calories eaten, $r(135) = -.076$, $p = .377$.

Exploratory Analysis

A series of exploratory regression analyses were run to assess whether different screen time intervals were predictors for subsequent calorie intake (Table 2).

Table 2

Regression Analyses for Screen Time and Subsequent Calorie Intake.

Variables	*B*	*SE B*	β	*p*-value
Thursday overnight ST and total calories	-0.04	0.8	-.004	.964
Friday overnight ST and total calories	0.56	0.83	.06	.506
Saturday overnight ST and total calories	-0.95	0.74	-.11	.204
Thursday afternoon ST and dinner calories	-0.38	0.48	-.07	.422
Friday afternoon ST and dinner calories	-0.68	0.41	-.14	.094
Saturday afternoon ST and dinner calories	-0.26	0.48	-.05	.588
Thursday afternoon ST and snack calories	-0.22	0.37	-.05	.564
Friday afternoon ST and snack calories	0.18	0.46	.03	.704
Saturday afternoon ST and snack calories	0.19	0.45	.04	.666

A paired samples *t* test indicated that there is no significant difference between the number of calories eaten on weekdays (Thursday and Friday) and the weekend (Saturday), $t(137) = 0.15$, $p = .882$

Total average screen time minutes was split median-wise. The median was 353 minutes, and participants at the median were included in the high group. A one-way ANOVA indicated that there is no significant difference between the daily calorie intake of participants with screen time minutes above or below the median, $F(1, 135) = 1.363$, $p = .245$.

Discussion

All four hypotheses were unsupported by statistical analyses. Specifically, screen time and calorie intake did not correlate. Across the study period, there was no correlation between screen time and calorie intake, or between minutes spent using social apps and calorie intake. There was also no significant difference between weekday and weekend calories. Screen time during morning hours was not a predictor for subsequent calories.

Previous laboratory research on the use of smartphones while eating found that caloric consumption increased in conditions where participants were asked to use a smartphone (Gonçalves et al., 2019). The present study was inconsistent with previous work. This may reflect that, although smartphone usage increases calorie intake in a laboratory setting, this trend does not exist in daily life. One explanation is that smartphones do not lead to mindless eating, which is a factor that promotes overeating while watching TV. Additionally, they may be used periodically throughout the day instead of a specific time period, which is often the case with TV. Participant eating schedules may not coincide with their periodic smartphone usage, and their eating habits would therefore be unaffected by technology. Alternatively, smartphones may still induce mindless eating. However, this effect may be mitigated by the requirement that at least one hand is occupied by the smartphone. Typically, while watching TV, both hands are free, which allows us to eat more freely. Having one hand occupied at all times may cause us to eat more slowly, which reduces calorie intake.

The COVID-19 pandemic may also be at play here as well. For instance, over the course of the pandemic, global smartphone use has increased by 70%. In the United States alone, it has risen by 40% (Statista, 2020). Along with this, social media use and texting have increased by almost 40% (Twigby, 2020). As a result, the overall screen time minutes, as well as social networking minutes, recorded in this study may be higher than normal. This may have created a ceiling effect, which would contribute to the null findings.

One limitation in this research is that participants self-reported their calorie intake through MyFitnessPal. In order to avoid stigma associated with eating large amounts of food, they may have reported eating less than they actually consumed. Participants may have also not remembered to log some foods, especially if they engage in mindless eating, as it impairs memory formation for foods that are eaten (Ogden et al., 2013). Calorie totals may also be incorrect if the wrong food or quantity is logged. Some food quantities may be difficult to estimate without a scale. However, despite these limitations, previous research has determined that MyFitnessPal is an accurate tool for calorie and macronutrient estimation (Evenepoel, 2020).

One strength of this study is that it possesses ecological validity. The study followed participants throughout their daily life and did not manipulate their environment. This allows participants to act as they normally would, which is not the case in laboratory settings, where participants may alter their behavior. This may explain why the results contradict those achieved in laboratory smartphone studies. Other strengths include that both MyFitnessPal and the Screen Time function are low-burden. Screen time minutes were objective, as they are automatically logged by the iPhone. Thus, this measure was unaffected by self-reporting. Because the study ran from Thursday to Saturday, the calorie and screen time data was able to capture weekday and weekend variation.

Future research should repeat this study to determine if the findings are replicable. Additionally, modifications to the design can be made to improve the study. Research should be conducted for a longer time than the three day period utilized in this study. Consistent patterns in eating behavior, such as chronic overeating, may not have been detectable over a short three-day time span. This may partially explain the null findings. A longer study period may allow such patterns to become evident or to appear more pronounced. As previously mentioned, the current study results were inconsistent with previous laboratory research findings. Future work is required to determine which of these conflicting results is actually the case for smartphone use.

Furthermore, research in this area could also investigate how smartphones affect eating behaviors in samples from lower economic statuses (SES) or compare effects between samples from both low and medium or high SES. This is because people from lower socioeconomic backgrounds are at higher risk of experiencing overeating and face higher risks of overweight or obesity (Pigeyre et al., 2016). Additionally, people from all SES own and use smartphones; if these devices impact eating behavior, people in lower SES may be disproportionately affected. Although the current study did not assess SES, a portion of the sample was college students, which are usually higher SES than the general population.

Future work could also investigate how other forms of technology, such as computers or tablets, affect eating behavior (if at all). Computers and tablets are often used for streaming purposes, which can mimic the effects that television has on eating behavior. Using several types of technology may create a joint effect on eating behavior as well.

Due to the study's null findings, it is unclear whether or not smartphones induce mindless eating as watching TV does. Smartphone use, especially when spread out across the day, may not lend itself to producing mindless eating, especially if eating periods do not coincide with smartphone use. This suggests that smartphone use may not pose the same threat to public health that viewing TV does. Future work is required to determine if smartphones only have effects on eating in laboratory studies, as demonstrated by Gonçalves et al. (2019), or if this trend exists in real world scenarios as well.

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