# Individual Differences and Technology Affordances Combine to Predict Mobile Social Media Distraction Behaviors and Consequences

Emily Sidnam-Mauch*
esidnam@clemson.edu
Clemson University
USA
University of Southern California
USA

Peter Monge†
monge@usc.edu
University of Southern California
USA

## ABSTRACT

Drawing upon theories from communication studies and cognitive psychology, this research develops a multitheoretical model that identifies human and technological factors that predict social media distraction engagement and explains how social media distractions can lead to negative consequences across various tasks. This model is empirically tested using data from a survey of U.S. mobile phone users ($N$ = 1,026). The results from a structural equation modeling analysis support the model's predictions that a person's age, fear of missing out, smartphone checking habit strength, and the number of social media applications with notifications enabled all impact a variety of distraction behaviors and consequences. The findings show that communication technology distraction behavior is influenced by a complex intertwining of goal-driven communication and information-seeking behaviors, automatic processes in the brain, and technology affordances.

## CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

## KEYWORDS

Computer Mediated Communication, Health - Wellbeing, Social Media/Online Communities, Tasks/Interruptions/Notification

**ACM Reference Format:**
Emily Sidnam-Mauch and Peter Monge. 2024. Individual Differences and Technology Affordances Combine to Predict Mobile Social Media Distraction Behaviors and Consequences. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11–16, 2024, Honolulu, HI, USA*. ACM, New York, NY, USA, 18 pages. https://doi.org/10.1145/3613904.3641950

*Emily Sidnam-Mauch is currently affiliated with the School of Computing at Clemson University; this research was conducted while Sidnam-Mauch was affiliated with the Annenberg School for Communication and Journalism at the University of Southern California.
†Peter Monge is Emeritus Professor of Communication at the Annenberg School for Communication, University of Southern California.



*CHI '24, May 11–16, 2024, Honolulu, HI, USA*

ACM ISBN 979-8-4007-0330-0/24/05
https://doi.org/10.1145/3613904.3641950

## 1 INTRODUCTION

Mobile phone distractions have multiple documented costs to users across a variety of contexts [25, 44, 71, 80, 93, 105], and users struggle to successfully limit or regulate their use of smartphones and mobile applications (apps) [10, 28, 45, 114]. While there is a growing body of literature on smartphone distractions and related interventions [46, 55, 75, 86], less is known about how specific mobile applications contribute to problematic behaviors. Understanding distraction behaviors relevant to specific mobile applications is important because app-level interventions to promote digital well-being may be more successful than phone-level interventions [86]. In particular, there is a need for research on what predicts the off-task use of mobile social media applications [49], as social media distractions can lead to costs like impaired recall [37], poor task performance [18], technostress [19], and driving errors [25].

Since mobile phone and mobile social media distractions have multiple documented costs to the user and attempts to manage technology distractions often fail, this paper develops and tests a multitheoretical Social Media App Distraction Engagement and Consequences (SMADEC) model. Applying uses and gratifications theory [51, 63] and the load theory of attention and cognitive control [64], the model identifies human and technological factors that predict mobile social media distraction engagement and explains how social media distractions can lead to negative consequences. Structural equation modeling is run on two representative samples ($n_1$ = 616; $n_2$ = 410) of U.S. mobile social media users to test and confirm the model. These findings can be applied to further ongoing efforts to develop interventions (e.g., 43, 59, 75, 76, 95, 100) that minimize costs and maximize the benefits of mobile social media use.

Notable contributions of this work include:

- a theory-driven model that predicts mobile social media distraction behaviors and related consequences and is validated across two research samples,
- two novel measures developed based on existing literature on mobile social media distraction behaviors and distraction-related consequences that show high reliability and validity across two samples,
- and findings that contribute to understanding the individual differences and technology factors that explain off-task mobile social media use and how this off-task use predicts consequences across a range of daily activities.

# 2 PREDICTING MOBILE SOCIAL MEDIA DISTRACTION ENGAGEMENT AND CONSEQUENCES

This paper uses the term social media *distraction engagement* (DE) to refer to off-task interactions with mobile technologies. In other words, if a person engages in an activity (e.g., working, walking, driving, etc.) and then interrupts that activity to interact with their social media application, that is considered distraction engagement. This DE can be internally-prompted (IPDE) or externally-prompted (EPDE). Since "distraction" and related terms are used in varied ways across disciplines, the terms used in this study are listed in Table 1. These definitions were coined for this study and are based on an understanding of attention and distraction management from neurobiology and cognitive psychology perspectives (e.g., 42, 67).

The following sections propose five hypotheses to develop and test core connections in the SMADEC model, which predicts why people engage in off-task social media use and how this DE leads to consequences. First, the human factors that predict intentional versus automatic DE are proposed; then, technology factors impacting DE are proposed. Last, connections explaining how DE leads to adverse outcomes are proposed.

## 2.1 Uses and Gratifications and Automatic Behaviors can Explain Why People Engage Mobile Social Media Distractions

Comparatively little research focuses on the antecedents versus the consequences of media-based DE [49]. Uses and gratifications theory (U&G) [51, 63] provides a helpful framework for theorizing the needs, motivations, or expectations that drive media and communication technology usage and related outcomes [109]. U&G theory posits that people actively select media and communication technologies for their perceived ability to satisfy needs or desires, and people's differing needs and expectations of media technologies lead to different patterns of usage and related outcomes [51]. While initial U&G research focused on users' purposeful choices about their media usage, subsequent developments of U&G [107, 108] explain that users' motivations for engaging technology can be both instrumental (i.e., intentional, goal-directed, purposeful) and ritualistic (i.e., habitual). It is essential to distinguish between what predicts intentional versus automatic mobile app DE since these behaviors are driven by different mechanisms requiring distinct interventions to mitigate related DE behaviors.

### 2.1.1 *Predictors of Intentional Social Media Distraction Engagement.*

According to U&G, to predict mobile social media DE, the key motivations, needs, or media expectations that underlie this type of DE must be identified. While there is U&G research on the motivations for using social media [45, 69, 70, 101, 120] and for multitasking on a mobile device [127], more research is needed to understand mobile social media multitasking (i.e., DE) [49]. The existing research on the usage motivations and gratifications of social media usage and media multitasking have common themes: people are seeking informational, social, and emotional gratifications through their use of social media and multitasking [69, 101, 120]. The following sections propose two specific personal factors related to these needs that should predict intentional mobile social media DE: Fear of Missing Out (FOMO) and Social Networking Site Intensity.

*FOMO captures informational, social, and emotional needs that can predict DE.* Przybylski et al. [99] define FOMO as the "pervasive apprehension that others might be having rewarding experiences from which one is absent" and is "characterized by the desire to stay continually connected with what others are doing" (p. 1841). People with high FOMO also have lower psychological need satisfaction (including unmet "relatedness" needs) [99] and higher need for popularity, higher need to belong [14], and higher anxiety [94]. FOMO is a personal factor that captures aspects of a person's need for social information/connection and emotional regulation.

Since social information can be quickly and easily accessed through mobile phones and social media, it is reasonable that a person with high FOMO would use these mobile communication technologies throughout their daily tasks to alleviate the emotional and psychological discomfort of FOMO. This could be accomplished by checking for notifications or social information (i.e., IPDE) and responding to notifications (i.e., EPDE) throughout the day. Past research has found that FOMO predicts the frequency of smartphone and social media engagement [1, 14, 16, 99], the use of mobile social media applications [40], and problematic mobile phone and social media usage [16, 31, 40, 132]. Moreover, FOMO predicts higher instances of distracted walking [4], distracted learning, and distracted driving [99]. Applying U&G theory and research, which indicates underlying informational, social, and emotional needs motivate social media usage and multitasking [69, 101, 120], FOMO's connection to mobile social media DE can be theoretically justified. Additionally, FOMO has been empirically connected to individual DE behaviors and negative distraction-related consequences from mobile phone and social media use [4, 94]. Thus, it is reasonable to hypothesize:

**H1a: FOMO will positively predict the frequency of mobile social media DE.**

**H1b: FOMO will positively predict how frequently consequences are experienced related to mobile social media DE.**

*Social Networking Site Intensity captures media expectations that can predict DE.* In addition to cognitive, social, and emotional needs, U&G theory explains that expectations about a medium's ability to gratify these needs will predict the usage of that medium [51]. Social Networking Site (SNS) Intensity is a measure developed from the Facebook Intensity Scale [32]. This construct captures the role social media (inclusive of desktop and mobile versions) play in a person's life regarding their feelings of attachment to their social media applications, their sense of community on the apps, and whether engaging social media is part of their daily life (e.g., see scale items listed in 112). SNS Intensity is positively associated with the number of social media contacts and predicts usage frequency [112].

U&G posits that people are goal-directed and rational in their media choices, selecting media that are perceived to benefit them in some way. Since SNS Intensity is related to positive perceptions of social media [32, 122], it is reasonable that people with SNS Intensity would be incentivized to engage their social media accounts

**Table 1: Key Terminology and Categorizations of Distractions and Distraction Engagement**

| Term | Definition | Analogous Terms Used in Research on Distractions |
|---|---|---|
| **Distraction** | any input or stimulus that diverts perceptual or attentional resources from a primary task | Distraction, Distractor, Interruption |
| *Internal distraction* | any off-task information generating from the individual that diverts attentional resources | Distraction, Task-Unrelated Thought, Mind-Wandering |
| *External distraction* | any off-task information or stimulus generating from outside the individual that diverts attentional resources | Distraction, Interruption |
| **Automatic Awareness** (of a distraction) | the automatic allocation of available perceptual resources to an off-task stimulus | Distraction |
| **Distraction Engagement (DE)** | the act of diverting attentional resources to a distraction instead of attempting to refocus solely on the primary task | Interruption, Multitasking, Task-Switching |
| *Internally-Prompted Distraction Engagement* | the act of diverting attentional resources away from a primary task in response to an internal stimulus | Interruption, Multitasking, Task-Switching |
| *Externally-Prompted Distraction Engagement* | the act of diverting attentional resources away from a primary task in response to an external stimulus | Interruption, Multitasking, Task-Switching |

frequently or while performing other tasks. It can be hypothesized that SNS Intensity will predict social media DE:

**H2: SNS Intensity will positively predict the frequency of mobile social media DE.**

#### 2.1.2 *Predictors of Automatic Social Media Distraction Engagement.*

According to U&G theory [107, 108], media use can be intentional or habitual. LaRose's [63] model of habitual media consumption (proposed as a correction to and an extension of active selection theories like U&G) is particularly useful in explaining how instrumental media usage can lead to the development of automatic behaviors (i.e., habits). Following social psychology and neurology research, habits are defined as "a form of automaticity in responding that develops as people repeat actions in stable circumstances"(126, p.91). A behavior displays automaticity when it shows one or all of the following: cognitive efficiency (i.e., lack of effortful attention), lack of awareness, unintentionality, and/or uncontrollability [113]. Media habits should be understood as automatic processes or behaviors that have developed through repetition in contexts of initially stable goals or cues. Both habits and conscious intention work together to shape a person's behavior, but habit strength is a powerful predictor of behavior [63].

In line with U&G theory [107, 108], research has identified both instrumental and "habit" motivations for smartphone use [48], social media use [49, 130], and media multitasking [49]. Specifically, considering the technical definition of habits, there is evidence that certain mobile social media behaviors meet criteria for automaticity (e.g., they are perceived as uncontrollable [10, 45, 114]). In a series of three studies, [96] discovered that smartphone users develop habits around their smartphone and mobile social media usage. In particular, smartphone users can develop checking habits, which are "automated behaviors where the device is quickly opened to check the standby screen or information content in a specific application" (p. 107). Mobile social media applications were explicitly identified as applications around which checking habits form. Therefore, evidence supports the argument that users form automatic behaviors around their mobile social media usage. Since habits have been found to predict media behavior independently of conscious intentions [63], the strength of a checking habit (i.e., the extent to which it displays automaticity) should predict DE as people automatically check their mobile applications during other tasks:

**H3: Social media checking habit strength will positively predict the frequency of mobile social media DE.**

U&G theory helps explain why internally-prompted DE occurs; people do not need an external distraction to be motivated to check their social media or to enact an automatic checking habit. U&G theory also helps identify critical human factors (e.g., individual needs, media expectations, and behaviors) that predict DE. One limitation of U&G theory for understanding mobile phone distractions is that it does not explain what technological factors impact DE. Another limitation is that it does not explain why the positive gratifications sought from social media usage often result in unsought consequences. The load theory of attention and cognitive control can be applied to explain why mobile media distractions interfere even when people are attempting to focus solely on a primary task and identify what features of the task and distraction are relevant for predicting the likelihood of DE.

## 2.2 Load Theory can Explain Why Externally-Prompted DE Occurs and How DE Leads to Adverse Costs

The load theory of attention and cognitive control [64, 65, 68], often shortened to "load theory" or "perceptual load theory," integrates mechanisms of attention and awareness and helps explain how distractions occur and to what extent they divert processing resources. Lavie et al. [65] explain that attention is "the allocation of limited-capacity mental resources to processing," whereas awareness is "the phenomenal experience related to perception that is accessible for report" (p. 1). According to load theory, people have a limited capacity for perceptual processing regarding awareness and attention, but this perceptual processing is automatic, involuntary, and mandatory. This means that a person's total perceptual capacity is used every moment, but this capacity can only handle a specific "load" regarding sensory information. Load theory predicts that awareness of available stimuli depends on the perceptual load of what is currently being processed by attentional resources [64]. If a task or stimulus has a high perceptual load, then this can demand a person's total perceptual resources, resulting in a loss of ability to be aware of additional stimuli. On the other hand, a task or stimulus with a low perceptual load can result in a "spillover" capacity to be aware of additional stimuli, whether relevant or irrelevant [68]. In other words, if a primary task has a high perceptual load that demands a person's full processing capabilities, the person will not be able to be aware of internal or external distractions [11, 38, 64, 66]. If a primary task has a low load, then a person will automatically be aware of distractions, impacting the ability to complete the primary task efficiently [67]. While the literature on load theory uses the terms "high" and "low" load tasks (e.g., 38, 67), task load is not dichotomous but exists on a continuum.

Based on load theory, it is likely that people's mobile phone DE varies throughout the day, depending on the perceptual load of the primary tasks being performed (and the comparative incentive to engage the task versus the mobile media distraction). Another factor that can influence the likelihood of automatic awareness of distractions and related DE is the properties of the distraction itself. Research on distractor (e.g., a task-irrelevant stimulus) salience can be combined with perceptual load research to make predictions about the technology factors that increase the likelihood of people's DE throughout the day.

#### 2.2.1 *Distractor Salience Can Explain Mobile Social Media EPDE.*

From a load theory perspective, "not all distractors are equal" and "what you are trying to ignore is almost as important as what you are trying to attend to" (92, p. 1321). Studies have found that distractor salience, or the relative noticeability or importance of an external distraction, plays a vital role in predicting attention allocation [27, 34, 89, 136]. There is evidence that distractions can still interfere in conditions of high perceptual load if the distractions are highly salient [34, 35]. This may be because some salient distractions are processed automatically, without demanding additional perceptual resources to gain awareness [2, 47].

Distractions that are perceptually distinct or are associated with rewards are more salient [2, 3, 90, 97, 125]; they can divert attention even when people are attempting to ignore them [47]. Mobile social media notifications can meet both physical- and reward-based criteria for salience. First, depending on how the phone or application notifications have been configured, social media application notifications can have multiple properties associated with high physical salience: abrupt visual onset [5, 27, 34, 88, 133], bright color and contrast from other items on the screen [87, 136], and luminance change [124]. Phones can additionally provide auditory and haptic cues with notifications [111]. Second, visual distractions associated with a high probability of positive social feedback elicit attentional capture [3]; mobile social media notifications are distractions that are likely associated with positive social rewards [33, 70, 101].

Since notifications from mobile social media can be salient both in their physical properties and their reward association, it is reasonable to hypothesize that phone notification settings and the number of social media apps that generate notifications will impact the awareness of mobile social media notifications and therefore, EPDE frequency:

**H4a: Phone notification settings which allow more perceptual information will positively predict the frequency of mobile social media DE.**

**H4b: The number of social media apps with notifications enabled will positively predict the frequency of mobile social media DE.**

#### 2.2.2 *Mechanisms that Explain How Social Media DE Predicts Distraction Consequences.*

While there is substantial evidence that mobile social media users experience distraction-related consequences from these applications [44, 71, 80, 105], even including physical harm [93], few works attempt to explain *how* mobile social media distractions lead to negative consequences. Research on load theory often focuses on how the load of the primary task impacts one's ability to ignore distractions [92]. When viewed from a different angle, load theory can also predict how the perceptual load of a distraction impacts the ability to perform a primary task.

In DE, attentional resources are focused on a distraction as a secondary task while also trying to complete a primary task. When tasks demand a sufficiently high processing load, they can deplete attentional resources to the point where unattended information is not visually perceived [77, 119], auditorily perceived [78, 84, 103], nor even subconsciously processed by the brain [6]. Based on these findings, if the perceptual load of a distraction is high, attending to distractions would result in disrupted task performance and a decreased ability to see, hear, or be aware of stimuli relevant to the primary task. Thus, load theory predicts mobile phone distractions with high perceptual load could lead to negative consequences through diverting attentional resources from a primary task and potentially depleting the ability to perceive task-relevant stimuli.

*Social media distractions often demand high perceptual loads.* It has been found that visual-manual tasks, or tasks that require engaging visual and tactile information (e.g., scrolling through social media posts), require a high perceptual load [77, 84, 103, 134]. Past research shows that visual-manual tasks demand sufficient perceptual resources to initiate "load-induced blindness" [77] and "load-induced deafness" [83, 103] that can inhibit task performance. For example, engaging visual-manual distractions has been found to increase driving errors and diminish awareness of surroundings [134, 135]. Additionally, emotional stimuli (e.g., pictures of faces smiling, frowning, etc.) are strong competitors for visual processing resources. Researchers found that participants' task performance suffered when off-task emotional (pleasant and unpleasant) images were present, indicating that emotional stimuli divert processing resources from a primary task [89]. Lastly, audio distractions also have been found to impair primary task performance and safety [91].

While visual, tactile, emotional, and audio distractions have separately been found to lead to negative consequences for a primary task, [121] note that mobile phones provide multimodal distractions. Certainly, mobile social media provide visual-manual, emotional, and auditory distractions simultaneously in much of their content. Social media posts require tactile interaction to create, view, like, and contribute comments, and the posts usually involve pictures with faces and other emotional visual content. Mobile-based social media platforms like Snapchat, Instagram, and TikTok often feature video content accompanied by audio. Because of their multimodal nature, social media posts provide multiple high-load distractions likely to interfere with successfully completing another task. In line with this proposition, studies have found that touchscreen motions on smartphones demand significant visual-manual resources that can impact one's ability to safely or effectively complete another task [7, 61, 110, 117].

*More frequent social media DE provides more opportunities for impeded primary tasks.* Mobile social media provide a range of visual, auditory, and tactile stimuli that divert attentional resources. Load theory predicts that high perceptual load distractions will negatively impact the performance on a primary task. So, it can be argued that the more often mobile social media users engage these distractions throughout the day, the more they will experience negative consequences due to impaired or failed task performance. To test this, the last hypothesis proposes:

**H5: The overall frequency of social media app DE behaviors will positively predict how frequently people experience negative consequences from mobile social media DE.**

## 2.3 SMADEC Model

The hypothesized relationships derived from U&G theory and load theory are combined to create the mobile Social Media App Distraction Engagement and Consequences (SMADEC) model shown in Figure 1. The SMADEC model identifies key human and technological factors that predict mobile social media distraction engagement and related consequences. Human factors like FOMO (i.e., needs) and SNS Intensity (i.e., media expectations) work together to predict intentional, internally prompted mobile social media DE. Mobile social media checking habits predict automatic IPDE. Additionally, technological factors, including phone notification settings (i.e., physical salience) and the number of mobile social media with notifications enabled (i.e., the number of sources of salient distractors), predict EPDE. Together, these factors predict the frequency of mobile social media distraction engagement across multiple tasks. In turn, the frequency of these DE behaviors predicts the frequency of various consequences resulting from primary task disruption.

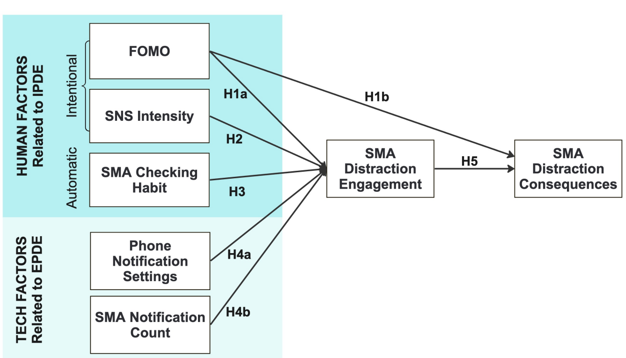


**Figure 1: SMADEC model with hypothesized constructs. Each path is labeled with the associated research hypothesis.**

# 3 METHOD

## 3.1 Procedures

An online Qualtrics survey was created to collect information about participants' individual differences, smartphone settings, mobile social media DE, and distraction consequences. After the researchers' Institutional Review Board approved the study as ethical research, participants were recruited through Qualtrics online survey panels service. To promote the sample's representativeness, recruitment quotas for sex, age, and race/ethnicity were established based on the distribution of these characteristics in the U.S. population, according to the most recently available data from the U.S. Census Bureau [20] at the time of data collection (see Table 2).

If they chose to participate, participants were redirected to the online survey, which obtained informed consent and confirmed their participation eligibility through a series of screener questions. Participants were included in the study if they indicated they were 1) age 18 or older, 2) consented to participate, 3) agreed to provide thoughtful responses, 4) resided in the United States, and 5) indicated they owned a smartphone with social media applications installed on it. Participants were excluded from the study if they did not meet these criteria, if they ended the survey before reaching the final section, or if there was an indication that they did not provide thoughtful answers to the survey (e.g., participants who completed the survey in less than a third of the median response time were excluded from the analysis). Eligible participants could exit the survey or skip a question at any point. Qualtrics gave participants compensation equivalent to about 2.50 USD upon survey completion.

## 3.2 Data Collection and Observed Power

To achieve sufficient statistical power for structural equation modeling (SEM), a sample should maintain between a 10:1 [13] and 20:1 [58] participants-to-parameters ratio. Since there were 20 parameters to be estimated in the hypothesized model, a sample size between 200 and 400 was required. Additionally, to confirm any respecifications made on an SEM model, it is necessary to retest the model on an independent sample of adequate size [58]. To obtain two independent samples, data were collected in two waves (one week apart) during February and March of 2020. The final samples consisted of 616 and 410 participants. The actual $n$ for each analysis fluctuated because only complete responses were used. For the primary SEM analysis of the hypothesized SMADEC model, the test of not-close-fit for the RMSEA had an observed power of .80 (with $n = 523$, $\epsilon_0 = .05$, $\epsilon_a = .01$, $df = 17$; calculated in R from code by 98). This means there was an 80 percent chance of detecting a model with an approximate fit to the population (based on the RMSEA score), which is considered well-powered.

## 3.3 Measures

Reliability and validity measures were obtained for all scales. Cronbach's $\alpha$ was obtained for each scale in each sample; $\alpha$'s ranged from .88 to .95 (all well above the .7 threshold for reliability). Additionally, confirmatory factor analysis (CFA) was run on each scale for each sample; all CFAs showed sufficient model fit, indicating

**Table 2: Participant Characteristics for Samples 1 and 2 with Census Data for Comparison**

| Characteristic | Sample 1 ($n$ = 616) | | Sample 2 ($n$ = 410) | | U.S. Population |
|---|---|---|---|---|---|
| | $n$ | % | $n$ | % | % |
| **SEX** | | | | | |
| Female | 367 | 60 | 208 | 51 | 51 |
| Male | 248 | 40 | 197 | 48 | 49 |
| **AGE** | | | | | |
| 18-24 | 96 | 15 | 54 | 13 | 13 |
| 25-34 | 149 | 24 | 81 | 20 | 18 |
| 35-44 | 139 | 23 | 87 | 21 | 17 |
| 45-54 | 98 | 16 | 62 | 15 | 18 |
| 55-64 | 60 | 10 | 62 | 15 | 16 |
| 65+ | 74 | 12 | 64 | 16 | 19 |
| **RACE/ETHNICITY*** | | | | | |
| White | 406 | 66 | 295 | 72 | 62 |
| Black | 88 | 14 | 51 | 12 | 12 |
| Hispanic | 86 | 14 | 67 | 16 | 17 |
| Asian | 75 | 12 | 21 | 5 | 5 |
| American Ind./Pacific Islander | 3 | 0.5 | 4 | 1 | 0.7 |
| Other | 11 | 1.8 | 4 | 1 | 2.5 |
| **LEVEL OF EDUCATION** | | | | | |
| Less than HS | 14 | 2 | 12 | 3 | 13 |
| HS diploma/GED | 153 | 25 | 85 | 21 | 28 |
| Some college | 145 | 24 | 99 | 24 | 21 |
| Associate's degree | 74 | 12 | 35 | 9 | 8 |
| Bachelor's degree | 154 | 25 | 107 | 26 | 19 |
| Graduate degree | 75 | 12 | 68 | 17 | 11 |
| **HOUSEHOLD INCOME** | | | | | |
| $0 < $25K | 115 | 19 | 66 | 16 | 18 |
| $25k < $50K | 210 | 34 | 120 | 30 | 22 |
| $50K < $75K | 112 | 18 | 71 | 17 | 19 |
| $75K < $100K | 79 | 13 | 78 | 19 | 14 |
| $100K < $150K | 60 | 10 | 41 | 10 | 15 |
| $150K+ | 40 | 6 | 31 | 8 | 12 |
| **EMPLOYMENT STATUS** | | | | | |
| Employed | 269 | 44 | 171 | 42 | - |
| Self-employed | 97 | 16 | 67 | 16 | - |
| Unemployed | 67 | 11 | 41 | 10 | - |
| Student | 44 | 7 | 20 | 5 | - |
| Retired | 89 | 14 | 75 | 18 | - |
| Disabled | 33 | 5 | 25 | 6 | - |

*Note:* *Participants could select more than one race/ethnicity, so the percentages total more than 100%. Also, for all demographic questions, participants were given the option to select "Prefer not to answer", so some columns do not add up to the sample total because a few participants opted out of answering some of these characteristic questions. Data on the U.S. population is from the 2018 estimates from the U.S. Census Bureau.

construct validity. Detailed results are documented in the Supplemental Material's "Quality of Measures" section. Since all scales met conventional standards for reliability and validity, the observed values for these scales (i.e., the scale averages) were used in the analyses.

*3.3.1 Dependent Variables.* To measure the DE dependent variable, an extensive review of scales measuring multitasking and problematic mobile phone and social media usage was performed, but no existing scales measured mobile social media distraction engagement behaviors, and no single scale measured behaviors similar enough to be modified into a DE scale. Thus, the *Social Media App Distraction Engagement* (SMA-DE) measure was created for this study. This scale was informed by and adapted from multiple scales on multitasking and problematic mobile phone and social media usage (e.g., 15, 29, 50, 73, 81). See "Development and Validation of Novel Measures" in the Supplemental Materials for a complete description of the scale creation and validation.

SMA-DE (the DV for H1a, H2, H3, H4a, and H4b) was measured by averaging participants' responses to 10 items which probed participant's mobile social media DE behaviors (Sample 1 Cronbach's $\alpha$ = .91; Sample 2 Cronbach's $\alpha$ = .93). Responses were recorded on a 5-point Likert scale ranging from 0 (*Never*) to 4 (*Always*). Table 3 shows the complete list of scale items and their statistics.

The 10-item *Social Media App Distraction Consequences* (SMA-DC) scale (the DV for H1b and H5) measures how often people experience negative costs from mobile social media DE across everyday tasks (Sample 1 Cronbach's $\alpha$ = .95; Sample 2 Cronbach's $\alpha$ = .95). This measure was developed based on previous research on documented mobile social media distraction costs. (See the "Development and Validation of Novel Measures" in the Supplemental Materials for details on its development and validation). Responses were recorded on a 6-point Likert scale ranging from 0 (*This never happens*) to 5 (*This happens all the time*). See Table 4 for the complete list of items.

*3.3.2 Independent Variables.* *FOMO* was measured using the [99] 10-item scale, which is a 5-point Likert scale consisting of items like: "I get anxious when I don't know what my friends are up to" ($M_1$ = 2.13, $SD_1$ = .97; $M_2$ = 2.21, $SD_2$ = 1.03).

*SNS Intensity* was measured using [112]'s five-item scale, which is a 7-point Likert scale consisting of items like: "I feel out of touch when I haven't logged into my social networking site(s) for a day" ($M_1$ = 4.74, $SD_1$ = 1.47; $M_2$ = 4.66, $SD_2$ = 1.53).

*SMA Checking Habit* ($M_1$ = 3.51, $SD_1$ = 1.09; $M_2$ = 3.36, $SD_2$ = 1.15) was measured by customizing the four-item Self-Report Behavioral Automaticity Index (SRBAI) [41], which is designed to capture habit-based behavior in self-report data, and it can be modified to measure a specific behavior of interest. The SRBAI is a 5-point Likert scale which includes items like "[Behavior X is something...] I do without thinking". For this study, "Behavior X" was replaced with "Checking my social media on my phone" for all four items. The SRBAI was chosen to capture mobile social media checking habits, because it aligns with the social psychology/neurology definition of habits as "a form of automaticity in responding" [126]; instead of measuring behavioral frequency, it captures to what extent a person's mobile social media checking behaviors display automaticity.

*Phone Notification Settings* ($M_1$ = 3.03, $SD_1$ = 1.30; $M_2$ = 3.17, $SD_2$ = 1.31) were measured by asking "Please indicate which item best reflects your phone's notification settings": Notifications are turned off (1), Notifications are turned on (no sound or vibration) (2), Notifications are turned on (with vibration) (3), Notifications are turned on (with sound) (4), Notifications are turned on (with sound and vibration) (5).

*SMA Notification Count* ($M_1$ = 3.18, $SD_1$ = 2.01; $M_2$ = 3.14, $SD_2$ = 2.14) is an interval measure ranging from 0 to 7 and reflects the number of mobile social media apps with notifications enabled. Participants were asked to indicate which social media apps they had on their phone that had notifications turned on (i.e., Facebook, Messenger, Instagram, Twitter, Snapchat, TikTok, LinkedIn). The total number of mobile social media apps with notifications enabled was summed.

*3.3.3 Control Variables and Covariates.* In addition to the main predictors, *Age* was included as a control variable for predicting SMA-DE. This is because age has been associated with problematic mobile phone and social media use in past research, with young adults being seen as particularly at risk for problematic use [94, 106, 132]. FOMO has also been associated with age in past research [99]. Age is also likely associated with the number of social media apps with notifications enabled since the users of some social media apps, such as Instagram and Snapchat, vary by age [22]. Because of these considerations, Age is modeled as a predictor for SMA-DE and a covariate with FOMO and SMA Notification Count in the SEM model (see Figure 2). Age is a continuous variable and was operationalized by asking participants to report their age in years ($M_1$ = 41.23, $SD_1$ = 15.77; $M_2$ = 44.39, $SD_2$ = 16.47). Based on previous findings that suggest a connection between FOMO and SNS Intensity [94], FOMO and SNS Intensity were also specified to covary in the model.

## 3.4 Analyses

*3.4.1 Data Diagnostic Plan.* Several strategies were employed to ensure the quality of the data. Key information on these procedures are outlined below. Details and related statistics are reported in the Supplemental Material's "Quality of Measures" section.

In addition to screening out participants who did not meet the eligibility criteria, the data were manually inspected for missing data and unusual responses. Responses with substantial missing data or evidence of inauthentic responses (e.g., gibberish text entry with fast response times or unusual response patterns) were removed. Responses with missing data were excluded from the analyses. A test for common method bias was performed, as well. Descriptive statistics were obtained for all variables, and the data were checked to ensure they met the assumptions for SEM [58]. Univariate histograms and skewness and kurtosis statistics for each variable were obtained. Mardia's tests were used to check the assumption of multivariate normality [21]. Regression plots and bivariate plots were obtained to check assumptions of linearity. Regression plots (identifying outliers using Cook's Distance) and the EQS output (identifying outliers that inflate the multivariate kurtosis score) were used to detect any influential outliers. The variance inflation factor (VIF) scores were obtained to check for multicollinearity, and Breusch-Pagan tests were used to test the assumption of homoskedasticity. If any assumptions were violated, the appropriate corrections were made (e.g., removing influential outliers, using robust estimation methods, etc.).

*3.4.2 Analyses and Analytical Tools.* The data cleaning and post hoc analyses were performed in R [102] using the psych [104], car [39], VIM [60], Routliers [72], ggplot2 [131], and ppcor [56] packages. The primary analyses (H1 through H5) were tested using SEM with observed variables (i.e., path analysis). The CFA and SEM analyses were performed in EQS 6.3 [12].

# 4 RESULTS

## 4.1 Participant Characteristics

The research sample consists of mobile social media users in the United States. A summary of the demographic data for participants can be found in Table 2. The mean age for participants in Sample 1 was 41.23 years (Min. = 18, Max. = 84, *SD* = 15.77). The mean age for participants in Sample 2 was 44.39 years (Min. = 18, Max. = 87, *SD* = 16.47). Both samples represent a diversity of age, sex, race, education, and income similar to the distributions from the 2018 estimates of the U.S. adult population [20]. Participants' median

**Table 3: SMA-DE Items and Statistics for Samples 1 and 2**

| **SMA-DE Items**: *"On a regular day, how often do you use social media on your phone..."* | **Sample 1** | **Sample 2** |
|---|---|---|
| | ***M (SD)*** | ***M (SD)*** |
| While having a face-to-face conversation with another person (e.g., friend, family, colleague) (V1) | 2.77 (1.47) | 2.75 (1.43) |
| While hanging out with another person (V2) | 2.62 (1.29) | 2.55 (1.26) |
| While trying to fall asleep (V3) | 2.63 (1.44) | 2.56 (1.40) |
| While eating a meal (V4) | 2.70 (1.34) | 2.54 (1.32) |
| While working on tasks for a job or for school (V5) | 2.24 (1.30) | 2.28 (1.35) |
| While watching a movie/TV, reading a book, or browsing the Internet in your leisure time (V6) | 2.96 (1.29) | 2.86 (1.30) |
| While doing household work or chores (V7) | 2.53 (1.32) | 2.58 (1.33) |
| While you are driving (V8) | 1.66 (1.19) | 1.74 (1.21) |
| While walking (V9) | 2.24 (1.32) | 2.41 (1.30) |
| During a meeting or lecture for work or school (V10) | 1.88 (1.26) | 1.88 (1.26) |
| **SMA-DE Average (Min. = 0, Max. = 4)** | **2.44 (1.98)** | **2.43 (1.02)** |

*Note:* Responses were recorded on a 5-Point Likert scale with the following response options: Never (0), Sometimes (1), About half the time (2), Often (3), Always (4).

**Table 4: SMA-DC Items with Statistics for Samples 1 and 2**

| **SMA Distraction Consequences Items** | **Sample 1** | **Sample 2** |
|---|---|---|
| | ***M (SD)*** | ***M (SD)*** |
| It's taken me longer to complete school, work, or other important tasks because I was distracted by social media on my phone. (V1) | 1.75 (1.59) | 1.74 (1.62) |
| I've made mistakes on school, work, or other important tasks because I was distracted by social media on my phone. (V2) | 1.18 (1.46) | 1.24 (1.50) |
| I've had trouble focusing on school, work, or other important tasks because I was distracted by social media on my phone. (V3) | 1.40 (1.51) | 1.42 (1.54) |
| I've missed or forgotten important information because I was distracted by social media on my phone. (V4) | 1.26 (1.48) | 1.33 (1.49) |
| I've had poor interactions with friends or family because I was distracted by social media on my phone. (V5) | 1.34 (1.50) | 1.34 (1.50) |
| I've had trouble falling asleep or staying asleep because I was distracted by social media on my phone. (V6) | 1.57 (1.62) | 1.72 (1.69) |
| I've tripped or bumped into something while walking because I was distracted by social media on my phone. (V7) | 1.12 (1.46) | 1.16 (1.46) |
| While driving, I've found myself in dangerous situations because of my mobile social media use. (V8) | .72 (1.34) | .93 (1.49) |
| I've been in an accident or injured because I was distracted by my social media while commuting. (V9) | .67 (1.35) | .86 (1.49) |
| I've felt stressed about how social media interferes with my daily tasks. (V10) | 1.03 (1.48) | 1.29 (1.59) |
| **SMA-DC Average (Min. = 0, Max. = 5)** | **1.20 (1.21)** | **1.31 (1.29)** |

*Note:* Participants were shown the following text before answering the items: "Sometimes social media distractions can interfere with everyday tasks. How often have you experienced the following things because you were distracted by social media on your phone? (This can include any time you were distracted by a social media notification popping up on your phone, by scrolling through social media, by creating a post for social media, etc.)"; Responses were recorded on a 6-point Likert scale with these response options: This never happens (0), This has happened once or twice (1), This happens a few times a month (2), This happens a few times a week (3), This happens a few times a day (4), This happens all the time (5).

response time for the first wave of the survey was 8.33 minutes and 8.88 minutes for the second wave.

## 4.2 Fitting the SMADEC Model

The hypothesized Social Media App Distraction Engagement and Consequences Model shown in Figure 2 was tested using an SEM with robust maximum likelihood (ML) estimation and was run on the complete responses from Sample 1 ($n$ = 523). The initial model showed poor fit (see Figure 2), so the model was respecified by dropping variables with non-significant paths and adding covariates. See the "SMADEC Model Respecification" section in the Supplemental Materials for full details on the initial model fit and the rationale for the respecified paths and covariances.

The respecified SMADEC model (depicted in Figure 3) was rerun on the data from Sample 1 using robust ML estimation. The EQS output confirmed the model was identified. The robust results show that the modified model was a good fit to the data. The hypothesized model was significantly better fitting than the null ($\chi^2_{\text{diff}}$ = 1002.36, $df_{\text{diff}}$ = 12, $p$ < .001) and significantly better fitting than the initial model ($\chi^2_{\text{diff}}$ = 435.55, $df_{\text{diff}}$ = 14, $p$ < .001). The model $\chi^2$ was nonsignificant ($\chi^2_{\text{SB}}$ = 5.14, $df_{\text{model}}$ = 3, $p$ = .16), meaning that the hypothesized model is a good fit to the structure that generated the observed data. This shows very good fit, considering that the sample size was large ($n$ = 523) and a non-significant model $\chi^2$ is difficult to obtain for a large sample [52]. The other fit indices show the model has a strong fit (CFI = .998, RMSEA = .037, 90% C.I. = .000, .090; SRMR = .013).

To confirm that the modified SMADEC model reflects a larger pattern in the population, the modified model was fit on an independent sample. The model shown in Figure 3 was run on the complete responses from Sample 2 ($n$ = 325) using a robust ML estimation. The SEM findings confirm the validity of this respecified model. The model was significantly better fitting than the null ($\chi^2_{\text{diff}}$ = 706.38, $df_{\text{diff}}$ = 12, $p$ < .001). The model fit well to the data, as shown by the non-significant $\chi^2$ for the model ($\chi^2_{\text{SB}}$ = 7.41, $df_{\text{model}}$ = 3, $p$ = .060). The other robust fit indices also show good fit (CFI = .994; RMSEA = .067, 90% C.I. = .000, .130; SRMR = .021).

A summary of the path results for the modified SMADEC model on Samples 1 and 2 are listed in Table 5. These results show that all the predictors in the modified model are significant in each sample, and the path coefficients have the same signs and follow a similar pattern. A similar amount of variance is explained in each independent sample. There was a large effect [26] of the predictor variables on SMA-DE in Sample 1 ($R^2$ = .51) and Sample 2 ($R^2$ = .55). There was also a very large effect of the predictor variables on Distraction Consequences in Sample 1 ($R^2$ = .58) and Sample 2 ($R^2$ = .67). Since the modified model fits well to the data in both samples and the results are consistent across independent samples, it is reasonable to conclude that the modified SMADEC model reflects larger patterns in the general population rather than reflecting the idiosyncrasies of an individual sample.

## 4.3 Hypothesis Testing

After sufficient global fit was achieved for the model, the research hypotheses were tested using the path results from the modified model. For simplicity, only results from Sample 1 are reported. The Sample 2 results are not meaningfully different and can be found in Table 5.

FOMO positively predicted ($\beta$ = .300, $p$ < .05) the frequency of SMA-DE, supporting H1a. FOMO also directly predicted ($\beta$ = .494, $p$ < .05) distraction-related consequences, supporting H1b. SMA Checking Habit was a significant, positive predictor ($\beta$ = .230, $p$ < .05) of SMA-DE, supporting H3. SMA Notification Count was a significant, positive predictor ($\beta$ = .275, $p$ < .05) of SMA-DE, supporting H4b. SMA-DE was a positive, significant predictor of SMA-DC ($\beta$ = .360, $p$ < .05), supporting H5. Additionally, the model specified age as a control variable for SMA-DE. The results showed that age covaried with all the predictor variables and also independently predicted SMA-DE ($\beta$ = -.166, $p$ < .05), with frequency of SMA-DE decreasing with age.

In the original SMADEC model results, SNS Intensity and Phone Notification Settings were not significant predictors of SMA-DE. H2 and H4a were not supported. Sample 1 was highly powered to detect a significant effect for these parameters. The observed power for the nested regression model with SMA-DE as the dependent variable was 1.00 (for $p$ < .01), meaning these results are likely not due to Type II error.

## 4.4 Post Hoc Analyses

A mediation analysis was conducted to determine whether SMA-DE mediates any exogeneous variable's impact on SMA-DC. The standardized beta coefficients for the total, indirect, and direct effects are reported in Table 6. The results show that SMA-DE fully mediates the impact of Age, SMA Checking Habit, and SMA Notification Count on SMA Distraction Consequences. SMA-DE partially mediates FOMO's impact on SMA-DC, but FOMO has a direct effect on SMA-DC, as well.

Hierarchical regressions were run a) to examine how much unique explained variance each predictor adds to the model and b) to explore whether additional demographic variables traditionally included as controls (i.e., Sex, Education, or Income) or other potentially relevant technology features (Distraction Management Settings and Phone Type) should be considered. Since Age is a demographic control variable, it was entered in Step 1. Next, each independent variable from the SMADEC model was entered separately to examine its unique impact, starting with FOMO (Step 2), then SMA Checking Habit (Step 3), then SMA Notification Count (Step 4). Step 5 examined whether additional demographic characteristics (i.e., Sex, Education, or Income) and mobile phone variables (i.e., Distraction Management Settings and Phone Type) should be included as controls in future studies. The results for the hierarchical regressions are listed in Table 7. All the SMADEC model exogenous predictors individually explained significant variance in SMA-DE (shown by the meaningful $R^2\Delta$ and $f^2$ values). No meaningful control variables were identified in the last step (all $p$ > .05).

Hierarchical regressions were also run to explore the comparative contribution of SMA-DE (Step 1) versus FOMO (entered in Step 2) in explaining variance in SMA-DC. Results are in Table 8.

Because a connection between SNS Intensity and problematic social media use had been identified in past studies [94] and because there is a substantial correlation between SNS Intensity and SMA Checking Habit ($r$ = .51), a post hoc regression was run to examine whether SNS Intensity predicted SMA-DE when SMA Checking Habit was excluded from the model. The results show SNS Intensity positively predicts SMA-DE when SMA Checking Habit is excluded ($F$(4, 518) = 122.40, $p$ < .001, $R^2$ = .49; see Table 9).

These results indicate that SMA Checking Habit likely mediates the relationship between SNS Intensity and SMA-DE, suggesting multicollinearity exists between these variables that was not apparent in the standard tests for multicollinearity. These post hoc findings show that, while H2 was not supported, the non-significant finding for SNS Intensity in the initial SMADEC model should be interpreted cautiously (this point is further examined in the discussion section). It should be noted that, while the post hoc analyses suggest multicollinearity in the initial model, removing the SNS

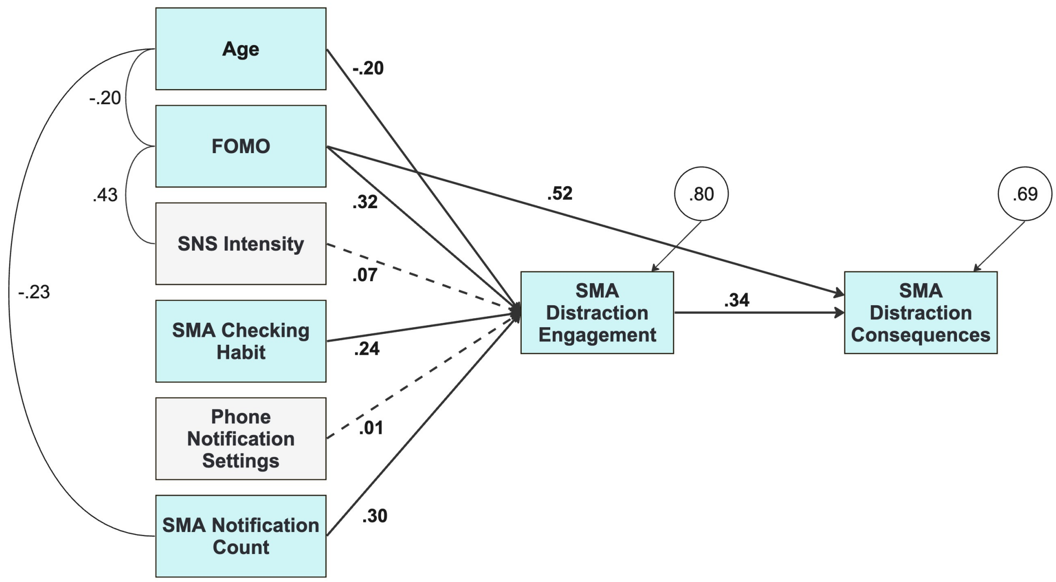


**Figure 2: Original SMADEC path model with standardized results from the Sample 1 data. Paths significant at $p < .05$ are indicated by solid lines. Dashed lines indicate non-significant paths. (These paths were removed in the respecified model.) Standardized betas are reported for each path. Disturbance terms for the dependent variables are reported in the circles. Correlations are reported next to the curved lines showing which variables were specified to covary in the model. The SEM results for this model showed very poor fit ($\chi^2_{SB}$ = 440.69, $df_{model}$ = 17, $p < .001$; CFI = .671, RMSEA = .219, 90% C.I. = .201, .236; SRMR = .230), so this model was not retained.**

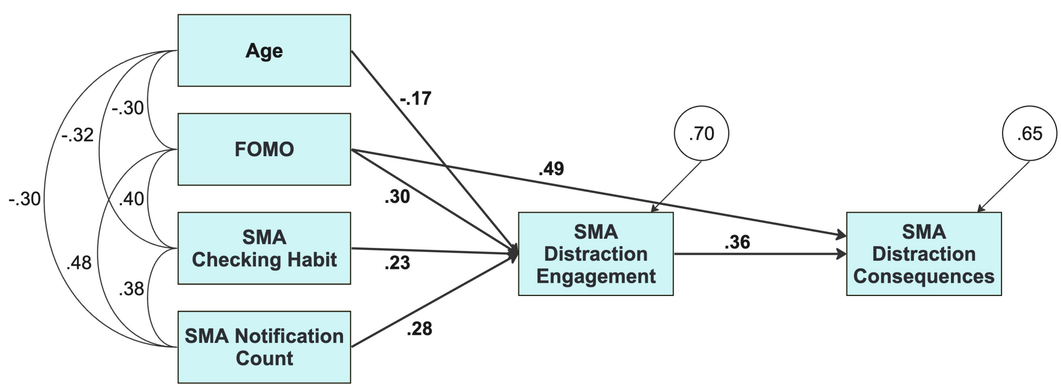


**Figure 3: Respecified SMADEC model with standardized results from the Sample 1 data. Solid lines represent paths significant at $p < .05$, and solid arcs represent covariances significant at $p < .05$. (All paths were significant). Standardized betas and disturbance terms and correlations of specified variables are reported.**

Intensity variable from the final SMADEC model corrects this multicollinearity for the main analyses [115]. Indeed, in the final model, there is no indication of problematic multicollinearity. This is shown by the following facts: the bivariate correlations are well under .85; the VIFs are well under the conservative value of 5; and the large $R^2$ for the model is supported by significant partial correlation coefficients [115]. Additionally, if there were high multicollinearity in the final model, it would be expected that the estimates of the regression slopes would vary "considerably" from sample to sample [17]. Instead, Table 5 shows the regression estimates remain stable across both samples, further signifying multicollinearity is not a problem in the final model.

**Table 5: Path Results for the Modified SMADEC Model with Robust Standard Errors**

| Path (DV~IVs) | Sample 1 Results ($n$ = 523) | | | | Sample 2 Results ($n$ = 323) | | | |
|---|---|---|---|---|---|---|---|---|
| | $\beta$ | $b$ | $SE$ | $R^2$ | $\beta$ | $b$ | $SE$ | $R^2$ |
| SMA-DE | | | | .51 | | | | .55 |
| ~ Age | **-.166*** | **-.010*** | .002 | | **-.149*** | **-.009*** | .002 | |
| ~ FOMO | **.300*** | **.303*** | .044 | | **.380*** | **.382*** | .048 | |
| ~ SMA Checking Habit | **.230*** | **.203*** | .029 | | **.196*** | **.170*** | .033 | |
| ~ SMA Notifications | **.275*** | **.133*** | .019 | | **.281*** | **.134*** | .025 | |
| ~ Disturbance Term | .700 | | | | .671 | | | |
| SMA-DC | | | | .58 | | | | .67 |
| ~ DE | **.360*** | **.438*** | .052 | | **.339*** | **.422*** | .066 | |
| ~ FOMO | **.494*** | **.608*** | .053 | | **.557*** | **.696*** | .064 | |
| ~ Disturbance Term | .649 | | | | .577 | | | |

*Note*: $p < .05^*$; The estimated standardized beta values are listed for the disturbance terms.

**Table 6: Standardized Results from the Post Hoc Mediation Analysis Testing Whether SMA-DE Mediates Exogenous Variables' Impact on Distraction Consequences (Sample 1, $n$ = 523; DV = SMA-DC; Mediator = SMA-DE)**

| Predictor | Total Effect | Indirect Effect | Direct Effect |
|---|---|---|---|
| FOMO | .603 | .108 | .494 |
| Age | -.060 | -.060 | 0 |
| SMA Checking Habit | .083 | .083 | 0 |
| SMA Notification Count | .099 | .099 | 0 |

*Note:* All values are significant at $p < .05$. The results show that SMA-DE fully mediates the impact of Age, SMA Checking Habit, and SMA Notification Count on SMA Distraction Consequences. This is indicated by the direct effects being equal to zero; their relationship to SMA-DE fully explains any impact these variables have on SMA-DC. Additionally, SMA-DE partially mediates FOMO's impact on SMA-DC. Since FOMO's direct effect on SMA-DC is greater than zero ($\beta$ = .494), this means FOMO's connection to SMA-DC is partly explained by its connection to SMA-DE ($\beta$ = .108), but FOMO also uniquely predicts SMA-DC beyond this connection.

# 5 DISCUSSION

This study's hypotheses tested the SMADEC model, which proposed human factors related to IPDE and technological factors related to EPDE work together to predict mobile social media distraction engagement and consequences. The following sections discuss how the SEM findings support or diverge from the proposed model. Implications of the individual paths are discussed first; then, the SMADEC model is examined as a whole.

## 5.1 The Impact of Human Factors on Distraction Engagement

H1, H2, and H3 tested three human factors relevant to IPDE: FOMO, SNS Intensity, and SMA Checking Habits. Two of the three hypotheses were supported.

*5.1.1 People with higher FOMO engage mobile social media distractions more frequently.* The results show that FOMO positively predicts the frequency of mobile social media DE, supporting H1a. This finding aligns with past studies that identified a link between FOMO and problematic phone use, including distracted walking, learning, and driving [30, 40, 132]. It adds to these findings by showing that FOMO predicts a person's overall mobile social media DE behaviors across common tasks (e.g., face-to-face interactions, eating, sleeping, walking, driving, working). The results in Table 7 show that, after accounting for the impact of Age as a predictor, FOMO uniquely explains 22% of the variance in SMA-DE ($R^2\Delta$ = .22; $f^2$ = .36), which is a large effect [26]. This research contributes to past work by applying U&G to theorize the connection between FOMO (as a psychological and emotional need) and social media DE; the findings confirm FOMO is a meaningful predictor of social media DE.

*5.1.2 People with higher FOMO report experiencing more frequent consequences from mobile social distractions.* FOMO directly predicted how frequently distraction-related consequences were experienced (supporting H1b). The post hoc results in Table 6 show that FOMO also indirectly impacts SMA-DC through SMA-DE. Interestingly, the standardized results show that more of FOMO's total effect ($\beta$ = .603) on SMA-DC is explained by its direct effect ($\beta$ = .494) rather than its indirect effect ($\beta$ = .108). Additionally, the results in Table 8 show this direct effect is substantial; FOMO uniquely explained 16% of the variance in SMA-DC even after accounting for SMA-DE ($R^2\Delta$ = .16), which is a large effect, $f^2$ = .36 [26].

This finding is consistent with past studies that show a connection between FOMO and negative smartphone and social media consequences [4, 99]. This can be accounted for within a U&G framework, which explains that media use can result in unsought consequences. As people seek to alleviate FOMO by interrupting a current task to check their social media applications, they can experience negative consequences related to the DE. More research is needed to understand the exact mechanisms that explain why FOMO directly predicts distraction consequences even after accounting for FOMO's connection to the frequency of DE behaviors. FOMO's direct impact on negative DE outcomes is likely explained by an additional mediator, which has not yet been identified. Many

**Table 7: Hierarchical Regression Analysis Results Showing the Unique Effect of Each Predictor on SMA Distraction Engagement (Sample 1, $n$ = 519, DV = SMA-DE)**

| Predictors | (1) Demographic Control | (2) Human Factors related to Intentional IPDE | (3) Human Factors related to Automatic IPDE | (4) Technical Factors related to EPDE | (5) Exploratory Controls |
|---|---|---|---|---|---|
| Age | -.03*** | -.02*** | -.01*** | -.01*** | -.01*** |
| FOMO | | .50*** | .41*** | .30*** | .30*** |
| SMA Checking Habit | | | .25*** | .20*** | .21*** |
| SMA Notif. Count | | | | .13*** | .14*** |
| Sex | | | | | -.06 |
| Education | | | | | -.04 |
| Income | | | | | .01 |
| DM Settings | | | | | -.06 |
| Phone Type | | | | | .06 |
| $R^2$ | .17*** | .39*** | .46*** | .51*** | .52*** |
| $R^2\Delta$ | | .22*** | .07*** | .05*** | .01 |
| $f^2$ | | .36*** | .13*** | .10*** | |

*Note:* $p < .001$***, $p < .01$ **, $p < .05$*. The $R^2\Delta$ and $f^2$ are measures of the effect size for an individual predictor in a multiple regression model. According to Cohen [26], $f^2 = .02$ is a small effect, $f^2 = .15$ is a medium effect, and, $f^2 = .35$ is a large effect. Sex was a dummy-coded variable (Male = 0, Female = 1). Education was measured on a scale of 1 (Less than high school degree) to 6 (Graduate degree). Income was measured on a scale from 1 (Less than 10K USD) to 12 (150K or more). DM Settings was a dummy-coded variable (No DM Settings = 0; DM Settings = 1). Participants were asked to indicate whether they regularly used any of these smartphone features: "Do Not Disturb" mode, driving mode, time limits for apps, tools that temporarily block certain apps or notifications; if they used at least one of these, they were given a DM Settings score of 1. Phone Type was included as a binary control variable (iPhone = 0; Android = 1).

**Table 8: Hierarchical Regression Results Comparing Impact of SMA-DE and FOMO on SMA Distraction Consequences (Sample 1, $n$ = 519, DV = SMA-DC)**

| Predictor | Model 1 | Model 2 |
|---|---|---|
| SMA-DE | .78*** | .44*** |
| FOMO | | .61*** |
| $R^2$ | .41*** | .58*** |
| $R^2\Delta$ | | .16*** |
| $f^2$ | | .40*** |

*Note*: $p < .001$***

**Table 9: Regression Testing Whether SNS Intensity is a Predictor of SMA-DE when Checking Habit is Excluded (Sample 1, $n$ = 519, DV = SMA-DE)**

| Predictor | $b$ | SE |
|---|---|---|
| Intercept | 1.41*** | .15 |
| Age | -.01*** | .00 |
| SNS Intensity | .10*** | .02 |
| FOMO | .31*** | .04 |
| SMA Notification Count | .14*** | .02 |

*Note*: $F(4, 518) = 122.40$***, $R^2 = .49$; $p < .001$***

of the FOMO scale items mention words like "worry", "fear", "anxious", and "bothers me" [99], and past work has shown that measures of anxiety predict FOMO scores [94]. It is possible that the connection between anxiety and FOMO could be relevant for explaining FOMO's connection to DE consequences. Future research could apply load theory to examine whether people with higher FOMO engage in more dangerous DE behaviors (e.g., higher load distractions or longer durations of DE), are more preoccupied with anxious, task-unrelated thoughts, or allocate more attentional resources to the social media distraction and away from the primary task, resulting in a higher risk of primary task interference.

*5.1.3 SNS Intensity is not a significant predictor of DE when Checking Habits are included in the model.* H2 predicted that SNS Intensity would positively predict SMA-DE, but the results from the initial model did not support this; SNS Intensity was not a significant predictor. This contradicts previous studies which found that SNS Intensity can predict certain types of mobile phone DE and negative outcomes related to social media usage, even when accounting for FOMO [94]. A post hoc analysis showed that the nonsignificant results for H2 should be considered with caution. When SMA Checking Habit was excluded from the model, SNS Intensity significantly predicted SMA-DE. This shows that SMA Checking Habit may be a confounding variable (or, more specifically, a mediator [79]) that better explains SMA-DE than SNS Intensity. Thus, the relationship between SNS Intensity and DE appears stronger in studies where habits are not accounted for than in studies that account for them.

SNS Intensity captures whether engaging social media is part of a person's daily life and predicts the frequency of mobile social media use [112]. Thus, it is likely that people with higher SNS Intensity form stronger checking habits through this more frequent use, and it is this habit strength that explains automatic DE (i.e., checking habits mediate SNS Intensity's impact on DE). Even though SNS Intensity was not a significant predictor when accounting for SMA Checking Habits, the positive correlations between SNS Intensity and the other predictors (e.g., FOMO, SMA Checking Habit, SMA Notification Count) suggest an interplay between these variables, which deserves further study.

*5.1.4 People with stronger Social Media App Checking Habits engage SMA distractions more frequently.* Supporting H3, SMA Checking Habit positively predicted SMA-DE. Table 7 also shows that, even after accounting for Age and FOMO as predictors, SMA Checking Habits uniquely explained 7% of the variance in SMA-DC ($R^2\Delta$ = .07), which is close to a medium effect ($f^2$ = .13) [26]. It is essential to know that checking habits predict DE, because these habits are a form of automaticity, which means the actions can occur without effortful attention, without intentionality, without awareness, and/or without the ability to be controlled [8]. Since habitual behaviors are resistant to informational interventions [126], this can explain why informational interventions designed to curb smartphone DE, like distracted walking, often fail to produce long-term behavior change [9, 116].

These findings add to U&G theory and research by highlighting the importance of attending to habitual media use within an active selection framework. In particular, these findings support LaRose's [63] extension of U&G and the argument that habits should be operationalized as automatic processes (as opposed to attitudes about use being habitual). This study shows the SRBAI [41] can produce a reliable and valid measure of SMA Checking Habits. Future studies should account for automatic habits when examining the predictors of problematic mobile application behaviors.

## 5.2 The Impact of Technological Factors on Distraction Engagement

H4a and H4b explored two technological factors relevant to DE: phone notification settings and the number of mobile social media apps with notification settings enabled.

*5.2.1 More social media apps with notifications enabled predicts more frequent DE.* Phone notification settings did not predict SMA-DE (H4a was not supported), but the number of social media apps with notifications enabled did (H4b was supported). These mixed results on the impact of notifications-related variables are discussed further in 5.5. Table 7 shows that SMA Notification Count uniquely explained 5 percent of the variance in SMA-DE ($R^2\Delta$ = .05), which is between a small and medium effect ($f^2$ = .10) [26].

*5.2.2 Load theory provides a useful theoretical explanation of the connection between social media DE and consequences.* Applying insights from load theory [64], H5 predicted that the overall frequency of social media distraction engagement would positively predict how frequently people experience consequences from mobile social media DE. H5 was supported, with SMA-DE explaining 41% of the variance in SMA-DC, which is a large effect [26]. This finding aligns with a load theory perspective that mobile social media provide distractions with a high perceptual load that can negatively impact performance on primary tasks.

The findings related to the SMA-DC items in Table 4 also add to the current distraction literature by showing how mobile social media users experience a range of distraction-related consequences (e.g., mistakes on important tasks, trouble focusing, poor relational interactions, interrupted sleep, physical endangerment) across multiple common tasks (e.g., school/work, interpersonal interactions, sleeping, walking, driving). The average response for most of the individual SMA-DC items ranged between a 1 ("This has happened once or twice") and a 2 ("This happens a few times a month"). For people whose SMA-DE score was equal to or greater than 4 (meaning they engage mobile social media distractions "often" or "always"), their SMA-DC average was 2.98, meaning they experience negative distraction consequences weekly. This shows that people with frequent social media DE behaviors regularly experience negative consequences across various tasks.

## 5.3 The Modified SMADEC Model is Useful for Predicting Mobile Social Media Distraction Engagement and Related Consequences

While the results from the individual hypotheses bring insight on their own, one of the most valuable contributions of this study is demonstrating how all these predictors work together as a whole. While the original version of the SMADEC model was not supported at the global level, a viable nested version of the model was identified. The modified SMADEC model still fits within the higher-level conceptual framework, explaining that human and technological factors related to intentional IPDE, automatic IPDE, and EPDE predict mobile social media DE. The results from the SEM analysis show that the multitheoretical SMADEC model could explain the structures present in the data from two representative samples of U.S. smartphone users. The model held together, and the predictors explained over half the variance of each dependent variable ($R^2$ > .50), showing that the model identified meaningful predictors of mobile social media DE and related consequences.

The post hoc findings show that each predictor explained meaningful variance in the dependent variables. In particular, FOMO explained the largest unique variance in SMA-DE, followed by SMA Checking Habit and SMA Notification Count. Additionally, SMA Distraction Engagement had the largest impact on SMA Distraction Consequences ($R^2$ = .41) and fully mediated the impact of all exogenous variables except FOMO (which also had a large direct effect). The SMADEC model results show that mobile social media DE predictors are not monolithic. While research and theory implications have been discussed concerning each component of the SMADEC model, the concluding sections discuss how these findings might be applied to further research on mobile app distractions and to develop interventions that minimize costs and maximize the benefits of mobile social media use.

## 5.4 Implications for Technology Distraction Research and Design of Intervention Tools

At a high level, this work showed the usefulness of employing multitheoretical models to understand technology distraction behaviors.

Developing multitheoretical models can maximize models' explanatory power and increase explained variance in analyses [85] (p. 45), and future work could utilize this approach. Though this study identifies predictors specific to the context of mobile social media DE, the higher-level conceptual framework of the SMADEC model could be applied to additional technology distraction contexts to identify predictors of intentional IPDE, automatic IPDE, and EPDE to explain DE for other applications.

More concretely, this paper's findings have implications for the design of interventional tools. There has been a growing interest in HCI research to design tools and interventions to decrease compulsive, excessive, or distracting social media and/or smartphone use [43, 54, 55, 59, 86, 95, 100]. Many of these fall under the umbrella of either digital self-control [75] or digital wellbeing apps [86]. Recent work advocates for a move toward app-level [86] or even feature-level [95] interventions (in contrast to phone-level interventions) for problematic smartphone and social media use. The SMADEC model and the related findings can be used to posit three recommendations for developing tools to mitigate mobile social media DE and promote digital wellbeing.

First, *interventional tools should simultaneously consider internal and external drivers of distraction behaviors, paying particular attention to how to mitigate internally prompted distraction engagement.* The SMADEC model explains that FOMO, SMA Checking Habits, and SMA Notification Count all meaningfully predict DE and consequences, so holistic interventions should consider how to address these three predictors in tandem.

There is already substantial HCI work and resources on notifications [36, 57, 128, 129] that can be applied to interventional tools to create features that promote reflection on the impact of notifications or make social media notifications less disruptive (e.g., increasing awareness of notification counts, batching notifications). While techniques focused on decreasing notification-related EPDE should be employed, the SMADEC model findings show that the notifications-related variables explained the least amount of variance in DE, compared to the human factors related to IPDE. In line with this, an observational study [46] found that only 11% of smartphone interactions were prompted by notifications. Thus, future research and tool design must focus on finding effective ways to mitigate internally-prompted social media DE in addition to EPDE. The next two recommendations provide insights on potential paths forward.

Second, *interventional tools must consider how to alleviate FOMO when mitigating distractions.* This research found that FOMO was the strongest predictor of off-task social media engagement, and thus, this factor must be attended to carefully. One consideration is that attempts to decrease external distractions must be implemented so as not to exacerbate FOMO. This has already been observed in studies testing interventions that limited the number of notifications or social media posts shown to a user, which found that these restrictions resulted in increased FOMO [36, 76, 100], as users worried they were missing important information. The SMADEC model suggests that checking social media frequently meets users' needs to alleviate FOMO; successful interventions must find a way to meet user needs that are associated with FOMO while also helping users avoid negative costs related to their social media usage. Future work should explore how users could alleviate FOMO through social media usage or other means without disrupting primary tasks. This could entail applying strategies like the "enlightener" or "supporter" features outlined by [43] or the goal-reminders tested by [76], including designing context-aware interventional apps with features that prompt users to return to or engage in a primary task when off-task social media use is detected. Additionally, context-aware interventions like these could identify situations where it *is* appropriate to check one's social media. A prompt could encourage the user to engage in mindful social media checking as a primary task, which could potentially help prevent DE by alleviating FOMO in opportune moments and could increase satisfaction with the social media interaction due to awareness of being "present" in the interaction [53].

Third, *interventional tools should both break problematic checking habits and promote the formation of habits that promote goal-directed social media use.* Another internal predictor of DE identified in SMADEC is social media checking habits, suggesting effective interventions must combat these habits to mitigate social media DE. Indeed, in a review of digital wellbeing apps, [86] found that most apps are designed solely to break negative habits like checking habits, but these have limited effectiveness for long-term behavior change. In [86], the researchers call for digital wellbeing tools grounded in habit formation research, suggesting that these tools employ tactics like positive reinforcement and social support to help users develop new media habits to replace problematic ones. In addition to these recommendations, our findings suggest the usefulness of applying [63]'s conception of media habits to inform the design of interventions and digital wellbeing tools. For example, how could social media interfaces be redesigned to discourage the formation of problematic checking habits from the beginning? Or, how could a better understanding of the triggers of social media checking habits be applied to lessen the automaticity of checking behaviors and instead promote cues that could help users develop positive habits around their social media use?

In particular, future research on digital wellbeing or distraction intervention apps must investigate how to promote the formation of positive habits to combat distracted driving and walking, which are increasing and significant problems for personal and public safety [74, 93]. Mobile social media pose dangerous distractions to drivers [25] and pedestrians [24, 62]. Future research could investigate context-aware applications that combine more persuasive approaches (e.g., blocking social media when active walking is detected) to stop existing DE habits while driving/walking, while also promoting the formation of new, positive habits (e.g., implementing digital rewards that accumulate for each instance of safe driving; providing a cue at the beginning of a walking instance to put one's phone in a pocket/bag instead of holding it, etc).

## 5.5 Limitations and Future Directions

While this study has interesting theoretical and practical contributions, it also has some limitations that should be considered. The main limitations of this study relate to the self-report measures, the mixed findings about the relevance of notifications, the cross-sectional nature of the study, and the model's scope. This section explains these limitations and connects them to opportunities for future research.

First, some limitations of the study relate to its reliance on self-report data. Self-report data has been used in many studies as a useful way to understand problematic mobile phone and social media use and related outcomes [29, 40, 49, 50, 73, 99, 132], but there are limitations to self-report data that should be noted. For example, while self-report data that provide general estimates of DE behavior correlate more highly with observed behaviors compared to self-reports that require specific estimates [118], these self-report data do not capture the exact frequency of people's DE behaviors or related consequences. Future studies could conduct controlled experiments and use tools to record phone use and observe mobile phone DE behaviors in situ.

It should also be noted that the SMA-DE and SMA-DC measures were developed for this study. While the results of the quality checks show that these measures were reliable and valid for two separate samples, these measures should be tested on data from a variety of sources to confirm their usefulness beyond this study.

Second, another limitation of the study is that there were mixed findings on the relevance of phone notifications for predicting mobile social media DE. One possible explanation for these mixed findings is that the number of external social media notifications is more relevant to SMA-DE than the phone's notification settings. People with multiple social media applications may likely receive more notifications, which could invite higher levels of externally prompted distraction engagement. One limitation of the SMA Notification Count measure was that it captured how many social media apps were generating notifications, but it was unable to capture the exact number of notifications received from these apps or how these notifications were spread throughout the day. Another explanation for why Phone Notification Settings did not predict SMA-DE could be that notification settings are relevant for predicting the frequency of automatic awareness of a distraction but are not sufficient to explain the choice to disrupt the primary task and engage the distraction. This would align with findings from an observational study, which found that most smartphone interactions are initiated by users rather than prompted by notifications [46]. Future studies could use tools that record notifications [128] and mobile phone use to conduct experiments to test how the frequency of mobile social media notifications and other factors related to notification salience impact DE behaviors.

Third, the limitations of the scope of the model should be noted. The findings show that the SMADEC model was useful for predicting the frequency of mobile social media DE and related consequences in two samples that were fairly representative of the U.S. adult population. It should be noted that the model captures the human and technological predictors relevant to general mobile social media DE behaviors, but it does not identify contextual or task-specific predictors related to the outcome variables. While it is useful to know the general predictors of DE to inform overarching interventions for DE, future studies could explore task, context, and content level predictors of DE and consequences. Additionally, this study focused on the predictors of negative distraction outcomes, but there is some evidence that DE can produce positive outcomes in certain contexts, like providing mental breaks during demanding tasks [23, 82, 123]. More research is needed to understand if, when, and how mobile social media DE can produce net positive outcomes.

Further, the SMADEC model focuses on how the relationships between the variables function at a particular point in time. While the cross-sectional nature of this study provides insight into how predictors like existing mobile social media habits impact the frequency of DE behaviors for social media users, longitudinal research is needed to understand how these causal relationships form, change, or create feedback loops over time.

# 6 CONCLUSION

Applying U&G theory, load theory, and research on media habits and distractor salience, a SMADEC model was developed, which identifies human and technological factors that predict mobile social media DE and explains how these distractions can lead to negative consequences. The SMADEC model was tested using survey research and structural equation modeling. The SEM findings support a nested version of the model and show that age, fear of missing out, checking habits, and the number of notification-enabled social media apps predict mobile social media distraction engagement. In turn, the frequency of mobile social media distraction engagement predicts how often people experience distraction-related consequences. Together, these findings show that communication technology distraction behavior is influenced by a complex intertwining of goal-driven communication and information-seeking behaviors, automatic processes in the brain, and technology affordances.

# ACKNOWLEDGMENTS

We thank Janet Fulk for her feedback, which improved the research design, particularly her input on creating and validating the novel measures. We also thank Mike Ananny, Dmitri Williams, Lian Jian, and Janet Fulk for their input on an earlier version of the research manuscript. We acknowledge Chih-Ping Chou, Sheila Murphey, Larry Gross, and the 2018 Oxford Internet Institute Summer Doctoral Program cohort for their useful input on earlier versions of the research ideas and instruments. This research is based upon work supported by a research award from the University of Southern California Graduate School and a research grant from the USC Annenberg School for Communication and Journalism.

# REFERENCES

[1] Dorit Alt. 2015. College students' academic motivation, media engagement and fear of missing out. *Computers in human behavior* 49 (2015), 111–119. https://doi.org/10.1016/j.chb.2015.02.057

[2] Brian A Anderson. 2016. The attention habit: How reward learning shapes attentional selection. *Annals of the new York Academy of Sciences* 1369, 1 (2016), 24–39. https://doi.org/10.1111/nyas.12957

[3] Brian A Anderson. 2016. Social reward shapes attentional biases. *Cognitive Neuroscience* 7, 1-4 (2016), 30–36. https://doi.org/10.1080/17588928.2015.1047823

[4] Markus Appel, Nina Krisch, Jan-Philipp Stein, and Silvana Weber. 2019. Smartphone zombies! Pedestrians' distracted walking as a function of their fear of missing out. *Journal of Environmental Psychology* 63 (2019), 130–133. https://doi.org/10.1016/j.jenvp.2019.04.003

[5] Paul Atchley, Arthur F Kramer, and Anne P Hillstrom. 2000. Contingent capture for onsets and offsets: Attentional set for perceptual transients. *Journal of Experimental Psychology: Human Perception and Performance* 26, 2 (2000), 594. https://doi.org/10.1037/0096-1523.26.2.594

[6] Bahador Bahrami, David Carmel, Vincent Walsh, Geraint Rees, and Nilli Lavie. 2008. Unconscious orientation processing depends on perceptual load. *Journal of Vision* 8, 3 (2008), 12–12. https://doi.org/10.1167/8.3.12

[7] Sarah E Banducci, Nathan Ward, John G Gaspar, Kurt R Schab, James A Crowell, Henry Kaczmarski, and Arthur F Kramer. 2016. The effects of cell phone and text message conversations on simulated street crossing. *Human factors* 58, 1 (2016), 150–162. https://doi.org/10.1177/0018720815609501

[8] John A Bargh and Tanya L Chartrand. 1999. The unbearable automaticity of being. *American psychologist* 54, 7 (1999), 462. https://doi.org/10.1037/0003-066X.54.7.462

[9] Erica N Barin, Cory M McLaughlin, Mina W Farag, Aaron R Jensen, Jeffrey S Upperman, and Helen Arbogast. 2018. Heads up, phones down: A pedestrian safety intervention on distracted crosswalk behavior. *Journal of community health* 43 (2018), 810–815. https://doi.org/10.1007/s10900-018-0488-y

[10] Eric P.S. Baumer, Phil Adams, Vera D. Khovanskaya, Tony C. Liao, Madeline E. Smith, Victoria Schwanda Sosik, and Kaiton Williams. 2013. Limiting, Leaving, and (Re)Lapsing: An Exploration of Facebook Non-Use Practices and Experiences. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 3257–3266. https://doi.org/10.1145/2470654.2466446

[11] Diane M Beck and Nilli Lavie. 2005. Look here but ignore what you see: effects of distractors at fixation. *Journal of Experimental Psychology: Human Perception and Performance* 31, 3 (2005), 592. https://doi.org/10.1037/0096-1523.31.3.592

[12] Peter M Bentler. 1995. *EQS structural equations program manual*. Vol. 6. Multivariate software Encino, CA.

[13] Peter M Bentler and Chih-Ping Chou. 1987. Practical issues in structural modeling. *Sociological methods & research* 16, 1 (1987), 78–117. https://doi.org/10.1177/0049124187016001004

[14] Ine Beyens, Eline Frison, and Steven Eggermont. 2016. "I don't want to miss a thing": Adolescents' fear of missing out and its relationship to adolescents' social needs, Facebook use, and Facebook related stress. *Computers in human behavior* 64 (2016), 1–8. https://doi.org/10.1016/j.chb.2016.05.083

[15] Joël Billieux, Martial Van der Linden, and Lucien Rochat. 2008. The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition* 22, 9 (2008), 1195–1210. https://doi.org/10.1002/acp.1429

[16] David Blackwell, Carrie Leaman, Rose Tramposch, Ciera Osborne, and Miriam Liss. 2017. Extraversion, neuroticism, attachment style and fear of missing out as predictors of social media use and addiction. *Personality and Individual Differences* 116 (2017), 69–72. https://doi.org/10.1016/j.paid.2017.04.039

[17] Hubert M Blalock Jr. 1963. Correlated independent variables: The problem of multicollinearity. *Social Forces* 42, 2 (1963), 233–237. https://doi.org/10.2307/2575696

[18] Stoney Brooks. 2015. Does personal social media usage affect efficiency and well-being? *Computers in human behavior* 46 (2015), 26–37. https://doi.org/10.1016/j.chb.2014.12.053

[19] Stoney Brooks, Phil Longstreet, and Christopher Califf. 2017. Social media induced technostress and its impact on internet addiction: A distraction-conflict theory perspective. *AIS Transactions on Human-Computer Interaction* 9, 2 (2017), 99–122. https://aisel.aisnet.org/thci/vol9/iss2/2

[20] U.S. Census Bureau. 2019. 2018: American Community Survey 1-Year Estimates. U.S. Census Bureau.

[21] Barbara M Byrne. 2013. *Structural equation modeling with EQS: Basic concepts, applications, and programming*. Routledge.

[22] Pew Research Center. 2021. Social Media Fact Sheet. https://www.pewresearch.org/internet/fact-sheet/social-media/

[23] Xi-Jing Chang, Fang-Hsin Hsu, En-Chi Liang, Zih-Yun Chiou, Ho-Hsuan Chuang, Fang-Ching Tseng, Yu-Hsin Lin, and Yung-Ju Chang. 2023. Not Merely Deemed as Distraction: Investigating Smartphone Users' Motivations for Notification-Interaction *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 650, 17 pages. https://doi.org/10.1145/3544548.3581146

[24] Ping-Ling Chen and Chih-Wei Pai. 2018. Pedestrian smartphone overuse and inattentional blindness: an observational study in Taipei, Taiwan. *BMC public health* 18, 1 (2018), 1–10. https://doi.org/10.1186/s12889-018-6163-5

[25] Hoon Choi, Jason Xiong, and Dawn Medlin. 2019. Driving Distractions and Multi-tasking: An Investigative Study. *Journal of Information Systems Applied Research* 12, 3 (2019), 14. http://jisar.org/2019-12/

[26] J Cohen. 1988. *Statistical Power Analysis for the Behavioral Sciences, 2nd Edn. Hillsdale, NJ: Erlbaum.*

[27] Joshua D Cosman and Shaun P Vecera. 2009. Perceptual load modulates attentional capture by abrupt onsets. *Psychonomic bulletin & review* 16, 2 (2009), 404–410. https://doi.org/10.3758/PBR.16.2.404

[28] Deloitte. 2018. 2018 Global Mobile Consumer Survey: US Edition. https://www2.deloitte.com/us/en/pages/technology-media-and-telecommunications/articles/global-mobile-consumer-survey-us-edition.html

[29] Brittany R-L Duff, Gunwoo Yoon, Zongyuan Wang, and George Anghelcev. 2014. Doing it all: An exploratory study of predictors of media multitasking. *Journal of Interactive Advertising* 14, 1 (2014), 11–23. https://doi.org/10.1080/15252019.2014.884480

[30] Jon D Elhai, Jason C Levine, Robert D Dvorak, and Brian J Hall. 2016. Fear of missing out, need for touch, anxiety and depression are related to problematic smartphone use. *Computers in Human Behavior* 63 (2016), 509–516. https://doi.org/10.1016/j.chb.2016.05.079

[31] Jon D Elhai, Haibo Yang, Jianwen Fang, Xuejun Bai, and Brian J Hall. 2020. Depression and anxiety symptoms are related to problematic smartphone use severity in Chinese young adults: Fear of missing out as a mediator. *Addictive behaviors* 101 (2020), 105962. https://doi.org/10.1016/j.addbeh.2019.04.020

[32] Nicole B Ellison, Charles Steinfield, and Cliff Lampe. 2007. The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of computer-mediated communication* 12, 4 (2007), 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.x

[33] Nicole B Ellison, Jessica Vitak, Rebecca Gray, and Cliff Lampe. 2014. Cultivating social resources on social network sites: Facebook relationship maintenance behaviors and their role in social capital processes. *Journal of Computer-Mediated Communication* 19, 4 (2014), 855–870. https://doi.org/10.1111/jcc4.12078

[34] Stacy Eltiti, Denise Wallace, and Elaine Fox. 2005. Selective target processing: Perceptual load or distractor salience? *Perception & psychophysics* 67 (2005), 876–885. https://doi.org/10.3758/bf03193540

[35] Martha J Farah, Kevin D Wilson, Maxwell Drain, and James N Tanaka. 1998. What is "special" about face perception? *Psychological review* 105, 3 (1998), 482. https://doi.org/10.1037/0033-295x.105.3.482

[36] Nicholas Fitz, Kostadin Kushlev, Ranjan Jagannathan, Terrel Lewis, Devang Paliwal, and Dan Ariely. 2019. Batching smartphone notifications can improve well-being. *Computers in Human Behavior* 101 (2019), 84–94. https://doi.org/10.1016/j.chb.2019.07.016

[37] Abraham E Flanigan and Wayne A Babchuk. 2015. Social media as academic quicksand: A phenomenological study of student experiences in and out of the classroom. *Learning and Individual differences* 44 (2015), 40–45. https://doi.org/10.1016/j.lindif.2015.11.003

[38] Sophie Forster and Nilli Lavie. 2009. Harnessing the wandering mind: The role of perceptual load. *Cognition* 111, 3 (2009), 345–355. https://doi.org/10.1016/j.cognition.2009.02.006

[39] J Fox, S Weisberg, B Price, D Adler, D Bates, G Baud-Bovy, B Bolker, et al. 2019. car: Companion to Applied Regression. R package version 3.0-2. *Website https://CRAN. R-project. org/package= car [accessed 17 March 2020]* (2019).

[40] Héctor Fuster, Ander Chamarro, and Ursula Oberst. 2017. Fear of Missing Out, online social networking and mobile phone addiction: A latent profile approach. *Aloma: Revista de Psicologia, Ciències de l'Educació i de l'Esport* 35, 1 (2017), 22–30. https://doi.org/10.51698/aloma.2017.35.1.22-30

[41] Benjamin Gardner, Charles Abraham, Phillippa Lally, and Gert-Jan de Bruijn. 2012. Towards parsimony in habit measurement: Testing the convergent and predictive validity of an automaticity subscale of the Self-Report Habit Index. *International Journal of Behavioral Nutrition and Physical Activity* 9, 1 (2012), 1–12. https://doi.org/10.1186/1479-5868-9-102

[42] Adam Gazzaley and Larry D Rosen. 2016. *The distracted mind: Ancient brains in a high-tech world*. Mit Press.

[43] Hüseyin Ugur Genç and Aykut Coskun. 2020. Designing for social interaction in the age of excessive smartphone Use. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13. https://doi.org/10.1145/3313831.3376492

[44] Natasha Gupta and Julia D Irwin. 2016. In-class distractions: The role of Facebook and the primary learning task. *Computers in Human Behavior* 55 (2016), 1165–1178. https://doi.org/10.1016/j.chb.2014.10.022

[45] Young Wook Ha, Jimin Kim, Christian Fernando Libaque-Saenz, Younghoon Chang, and Myeong-Cheol Park. 2015. Use and gratifications of mobile SNSs: Facebook and KakaoTalk in Korea. *Telematics and Informatics* 32, 3 (2015), 425–438. https://doi.org/10.1016/j.tele.2014.10.006

[46] Maxi Heitmayer and Saadi Lahlou. 2021. Why are smartphones disruptive? An empirical study of smartphone use in real-life contexts. *Computers in Human Behavior* 116 (2021), 106637. https://doi.org/10.1016/j.chb.2020.106637

[47] Clayton Hickey and Wieske Van Zoest. 2012. Reward creates oculomotor salience. *Current Biology* 22, 7 (2012), R219–R220. https://doi.org/10.1016/j.cub.2012.02.007

[48] Alexis Hiniker, Shwetak N Patel, Tadayoshi Kohno, and Julie A Kientz. 2016. Why would you do that? predicting the uses and gratifications behind smartphone-usage behaviors. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 634–645. https://doi.org/10.1145/2971648.2971762

[49] Yoori Hwang, HyoungJee Kim, and Se-Hoon Jeong. 2014. Why do media users multitask?: Motives for general, medium-specific, and content-specific types of multitasking. *Computers in Human Behavior* 36 (2014), 542–548. https://doi.org/10.1016/j.chb.2014.04.040

[50] Se-Hoon Jeong and Martin Fishbein. 2007. Predictors of multitasking with media: Media factors and audience factors. *Media Psychology* 10, 3 (2007), 364–384. https://doi.org/10.1080/15213260701532948

[51] Elihu Katz. 1974. *Utilization of mass communication by the individual*. Sage, 19–32.

[52] David A Kenny. 2015. Measuring model fit. https://davidakenny.net/cm/fit.htm

[53] Matthew A Killingsworth and Daniel T Gilbert. 2010. A wandering mind is an unhappy mind. *Science* 330, 6006 (2010), 932–932. https://doi.org/10.1126/science.1192439

[54] Inyeop Kim, Hwarang Goh, Nematjon Narziev, Youngtae Noh, and Uichin Lee. 2020. Understanding user contexts and coping strategies for context-aware phone distraction management system design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (2020), 1–33. https://doi.org/10.1145/3432213

[55] Jaejeung Kim, Joonyoung Park, Hyunsoo Lee, Minsam Ko, and Uichin Lee. 2019. LocknType: Lockout task intervention for discouraging smartphone app use. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–12. https://doi.org/10.1145/3290605.3300927

[56] Seongho Kim. 2015. ppcor: an R package for a fast calculation to semi-partial correlation coefficients. *Communications for statistical applications and methods* 22, 6 (2015), 665. https://doi.org/10.5351/CSAM.2015.22.6.665

[57] Michaela Klauck, Yusuke Sugano, and Andreas Bulling. 2017. Noticeable or Distractive? A Design Space for Gaze-Contingent User Interface Notifications. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI EA '17)*. Association for Computing Machinery, New York, NY, USA, 1779–1786. https://doi.org/10.1145/3027063.3053085

[58] Rex B Kline. 2023. *Principles and practice of structural equation modeling*. Guilford publications.

[59] Minsam Ko, Seungwoo Choi, Koji Yatani, and Uichin Lee. 2016. Lock n' LoL: Group-Based Limiting Assistance App to Mitigate Smartphone Distractions in Group Activities *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 998–1010. https://doi.org/10.1145/2858036.2858568

[60] Alexander Kowarik and Matthias Templ. 2016. Imputation with the R Package VIM. *Journal of statistical software* 74 (2016), 1–16. https://doi.org/10.18637/jss.v074.i07

[61] Tuomo Kujala. 2013. Browsing the information highway while driving: three in-vehicle touch screen scrolling methods and driver distraction. *Personal and ubiquitous computing* 17 (2013), 815–823. https://doi.org/10.1007/s00779-012-0517-2

[62] Mirjam Lanzer, Ina Koniakowsky, Mark Colley, and Martin Baumann. 2023. Interaction Effects of Pedestrian Behavior, Smartphone Distraction and External Communication of Automated Vehicles on Crossing and Gaze Behavior *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 768, 18 pages. https://doi.org/10.1145/3544548.3581303

[63] Robert LaRose. 2010. The problem of media habits. *Communication Theory* 20, 2 (2010), 194–222. https://doi.org/10.1111/j.1468-2885.2010.01360.x

[64] Nilli Lavie. 1995. Perceptual load as a necessary condition for selective attention. *Journal of Experimental Psychology: Human perception and performance* 21, 3 (1995), 451. https://doi.org/10.1037//0096-1523.21.3.451

[65] Nilli Lavie, Diane M Beck, and Nikos Konstantinou. 2014. Blinded by the load: attention, awareness and the role of perceptual load. *Philosophical Transactions of the Royal Society B: Biological Sciences* 369, 1641 (2014), 20130205. https://doi.org/10.1098/rstb.2013.0205

[66] N Lavie and S Cox. 1997. On the efficiency of attentional selection: Efficient visual search results in inefficient rejection of distraction. *Psychological Science* 8 (1997), 395–398. https://doi.org/10.1111/j.1467-9280.1997.tb00432.x

[67] Nilli Lavie and Polly Dalton. 2014. Load theory of attention and cognitive control. *The Oxford handbook of attention* (2014), 56–75.

[68] Nilli Lavie, Aleksandra Hirst, Jan W De Fockert, and Essi Viding. 2004. Load theory of selective attention and cognitive control. *Journal of experimental psychology: General* 133, 3 (2004), 339. https://doi.org/10.1037/0096-3445.133.3.339

[69] Chei Sian Lee and Long Ma. 2012. News sharing in social media: The effect of gratifications and prior experience. *Computers in human behavior* 28, 2 (2012), 331–339. https://doi.org/10.1016/j.chb.2011.10.002

[70] Sangwon Lee and Moonhee Cho. 2011. Social media use in a mobile broadband environment: Examination of determinants of Twitter and Facebook use. *International Journal of Mobile Marketing* 6, 2 (2011), 71–87.

[71] Laura E Levine, Bradley M Waite, and Laura L Bowman. 2012. Mobile media use, multitasking and distractibility. *International Journal of Cyber Behavior, Psychology and Learning (IJCBPL)* 2, 3 (2012), 15–29. https://doi.org/DOI:10.4018/ijcbpl.2012070102

[72] Christophe Leys, Marie Delacre, Youri L Mora, Daniël Lakens, and Christophe Ley. 2019. How to classify, detect, and manage univariate and multivariate outliers, with emphasis on pre-registration. *International Review of Social Psychology* 32, 1 (2019). https://doi.org/10.5334/irsp.289

[73] Sohye Lim and Hongjin Shim. 2016. Who multitasks on smartphones? Smartphone multitaskers' motivations and personality traits. *Cyberpsychology, Behavior, and Social Networking* 19, 3 (2016), 223–227. https://doi.org/10.1089/cyber.2015.0225

[74] Luis E Llerena, Kathy V Aronow, Jana Macleod, Michael Bard, Steven Salzman, Wendy Greene, Adil Haider, and Alex Schupper. 2015. An evidence-based review: distracted driver. *Journal of trauma and acute care surgery* 78, 1 (2015), 147–152. https://doi.org/10.1097/TA.0000000000000487

[75] Ulrik Lyngs, Kai Lukoff, Petr Slovak, Reuben Binns, Adam Slack, Michael Inzlicht, Max Van Kleek, and Nigel Shadbolt. 2019. Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–18. https://doi.org/10.1145/3290605.3300361

[76] Ulrik Lyngs, Kai Lukoff, Petr Slovak, William Seymour, Helena Webb, Marina Jirotka, Jun Zhao, Max Van Kleek, and Nigel Shadbolt. 2020. 'I Just Want to Hack Myself to Not Get Distracted': Evaluating Design Interventions for Self-Control on Facebook *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3313831.3376672

[77] James SP Macdonald and Nilli Lavie. 2008. Load induced blindness. *Journal of Experimental Psychology: Human Perception and Performance* 34, 5 (2008), 1078. https://doi.org/10.1037/0096-1523.34.5.1078

[78] James SP Macdonald and Nilli Lavie. 2011. Visual perceptual load induces inattentional deafness. *Attention, Perception, & Psychophysics* 73 (2011), 1780–1789. https://doi.org/10.3758/s13414-011-0144-4

[79] David P MacKinnon, Jennifer L Krull, and Chondra M Lockwood. 2000. Equivalence of the mediation, confounding and suppression effect. *Prevention science* 1 (2000), 173–181. https://doi.org/10.1023/a:1026595011371

[80] Brandon T McDaniel and Sarah M Coyne. 2016. "Technoference": The interference of technology in couple relationships and implications for women's personal and relational well-being. *Psychology of Popular Media Culture* 5, 1 (2016), 85. https://doi.org/10.1037/ppm0000065

[81] Lisa J Merlo, Amanda M Stone, and Alex Bibbey. 2013. Measuring problematic mobile phone use: Development and preliminary psychometric properties of the PUMP scale. *Journal of addiction* 2013 (2013). https://doi.org/10.1155/2013/912807

[82] Jinyoung Min. 2017. Effects of the use of social network sites on task performance: Toward a sustainable performance in a distracting work environment. *Sustainability* 9, 12 (2017), 2270. https://doi.org/10.3390/su9122270

[83] Katharine Molloy, Timothy D Griffiths, Maria Chait, and Nilli Lavie. 2015. Inattentional deafness: visual load leads to time-specific suppression of auditory evoked responses. *Journal of Neuroscience* 35, 49 (2015), 16046–16054. https://doi.org/10.1523/JNEUROSCI.2931-15.2015

[84] Katharine Molloy, Nilli Lavie, and Maria Chait. 2019. Auditory figure-ground segregation is impaired by high visual load. *Journal of Neuroscience* 39, 9 (2019), 1699–1708. https://doi.org/10.1523/JNEUROSCI.2518-18.2018

[85] Peter R Monge and Noshir S Contractor. 2003. *Theories of communication networks*. Oxford University Press, USA.

[86] Alberto Monge Roffarello and Luigi De Russis. 2019. The race towards digital wellbeing: Issues and opportunities. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–14. https://doi.org/10.1145/3290605.3300616

[87] Jeffrey RW Mounts and Brandon E Gavett. 2004. The role of salience in localized attentional interference. *Vision research* 44, 13 (2004), 1575–1588. https://doi.org/10.1016/j.visres.2004.01.015

[88] Hermann J Müller and Patrick M Rabbitt. 1989. Reflexive and voluntary orienting of visual attention: time course of activation and resistance to interruption. *Journal of Experimental psychology: Human perception and performance* 15, 2 (1989), 315. https://doi.org/10.1037//0096-1523.15.2.315

[89] Matthias M Müller, Søren K Andersen, and Andreas Keil. 2008. Time course of competition for visual processing resources between emotional pictures and foreground task. *Cerebral Cortex* 18, 8 (2008), 1892–1899. https://doi.org/10.1093/cercor/bhm215

[90] Jaap Munneke, Artem V Belopolsky, and Jan Theeuwes. 2016. Distractors associated with reward break through the focus of attention. *Attention, Perception, & Psychophysics* 78 (2016), 2213–2225. https://doi.org/10.3758/s13414-016-1075-x

[91] Gillian Murphy and Ciara M Greene. 2017. The elephant in the road: auditory perceptual load affects driver perception and awareness. *Applied Cognitive Psychology* 31, 2 (2017), 258–263. https://doi.org/10.1002/acp.3311

[92] Gillian Murphy, John A Groeger, and Ciara M Greene. 2016. Twenty years of load theory—Where are we now, and where should we go next? *Psychonomic bulletin & review* 23 (2016), 1316–1340. https://doi.org/10.3758/s13423-015-0982-5

[93] Jack L Nasar and Derek Troyer. 2013. Pedestrian injuries due to mobile phone use in public places. *Accident Analysis & Prevention* 57 (2013), 91–95. https://doi.org/10.1016/j.aap.2013.03.021

[94] Ursula Oberst, Elisa Wegmann, Benjamin Stodt, Matthias Brand, and Andrés Chamarro. 2017. Negative consequences from heavy social networking in adolescents: The mediating role of fear of missing out. *Journal of adolescence* 55 (2017), 51–60. https://doi.org/10.1016/j.adolescence.2016.12.008

[95] Adiba Orzikulova, Hyunsung Cho, Hye-Young Chung, Hwajung Hong, Uichin Lee, and Sung-Ju Lee. 2023. FinerMe: Examining App-level and Feature-level Interventions to Regulate Mobile Social Media Use. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW2 (2023), 1–30. https://doi.org/10.1145/3610065

[96] Antti Oulasvirta, Tye Rattenbury, Lingyi Ma, and Eeva Raita. 2012. Habits make smartphone use more pervasive. *Personal and Ubiquitous computing* 16 (2012), 105–114. https://doi.org/10.1007/s00779-011-0412-2

[97] Luiz Pessoa. 2015. Multiple influences of reward on perception and attention. *Visual cognition* 23, 1-2 (2015), 272–290. https://doi.org/0.1080/13506285.2014.974729

[98] Kristopher J Preacher and Donna L Coffman. 2006. Computing power and minimum sample size for RMSEA [Computer software]. http://quantpsy.org/

[99] Andrew K Przybylski, Kou Murayama, Cody R DeHaan, and Valerie Gladwell. 2013. Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in human behavior* 29, 4 (2013), 1841–1848. https://doi.org/10.1016/j.chb.2013.02.014

[100] Aditya Kumar Purohit, Kristoffer Bergram, Louis Barclay, Valéry Bezençon, and Adrian Holzer. 2023. Starving the Newsfeed for Social Media Detox: Effects of Strict and Self-regulated Facebook Newsfeed Diets. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16. https://doi.org/10.1145/3544548.3581187

[101] Anabel Quan-Haase and Alyson L Young. 2010. Uses and gratifications of social media: A comparison of Facebook and instant messaging. *Bulletin of science, technology & society* 30, 5 (2010), 350–361. https://doi.org/10.1177/0270467610380009

[102] R R Core Team et al. 2013. R: A language and environment for statistical computing. (2013).

[103] Dana Raveh and Nilli Lavie. 2015. Load-induced inattentional deafness. *Attention, Perception, & Psychophysics* 77 (2015), 483–492. https://doi.org/10.3758/s13414-014-0776-2

[104] William Revelle et al. 2018. psych: Procedures for psychological, psychometric, and personality research.

[105] Larry Rosen, Louis M Carrier, Aimee Miller, Jeffrey Rokkum, and Abraham Ruiz. 2016. Sleeping with technology: cognitive, affective, and technology usage predictors of sleep problems among college students. *Sleep health* 2, 1 (2016), 49–56. https://doi.org/10.1016/j.sleh.2015.11.003

[106] Larry D Rosen, L Mark Carrier, and Nancy A Cheever. 2013. Facebook and texting made me do it: Media-induced task-switching while studying. *Computers in Human Behavior* 29, 3 (2013), 948–958. https://doi.org/10.1016/j.chb.2012.12.001

[107] Alan M Rubin. 1984. Ritualized and instrumental television viewing. *Journal of communication* (1984). https://doi.org/10.1111/j.1460-2466.1984.tb02174.x

[108] Alan M Rubin. 1993. Audience activity and media use. *Communications Monographs* 60, 1 (1993), 98–105. https://doi.org/10.1080/03637759309376300

[109] Thomas E Ruggiero. 2000. Uses and gratifications theory in the 21st century. *Mass communication & society* 3, 1 (2000), 3–37. https://doi.org/10.1207/S15327825MCS0301_02

[110] Brendan J Russo, Emmanuel James, Cristopher Y Aguilar, and Edward J Smaglik. 2018. Pedestrian behavior at signalized intersection crosswalks: Observational study of factors associated with distracted walking, pedestrian violations, and walking speed. *Transportation research record* 2672, 35 (2018), 1–12. https://doi.org/10.1177/0361198118759949

[111] Alireza Sahami Shirazi, Niels Henze, Tilman Dingler, Martin Pielot, Dominik Weber, and Albrecht Schmidt. 2014. Large-scale assessment of mobile notifications. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 3055–3064. https://doi.org/10.1145/2556288.2557189

[112] Mohammad Salehan and Arash Negahban. 2013. Social networking on smartphones: When mobile phones become addictive. *Computers in human behavior* 29, 6 (2013), 2632–2639. https://doi.org/10.1016/j.chb.2013.07.003

[113] Lauren L Saling and James G Phillips. 2007. Automatic behaviour: efficient not mindless. *Brain research bulletin* 73, 1-3 (2007), 1–20. https://doi.org/10.1016/j.brainresbull.2007.02.009

[114] Sarita Yardi Schoenebeck. 2014. Giving up Twitter for Lent: how and why we take breaks from social media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 773–782. https://doi.org/10.1145/2556288.2556983

[115] Mary Ann Schroeder, Janice Lander, and Stacey Levine-Silverman. 1990. Diagnosing and dealing with multicollinearity. *Western journal of nursing research* 12, 2 (1990), 175–187. https://doi.org/10.1177/019394599001200204

[116] David C Schwebel, Leslie A McClure, and Bryan E Porter. 2017. Experiential exposure to texting and walking in virtual reality: A randomized trial to reduce distracted pedestrian behavior. *Accident Analysis & Prevention* 102 (2017), 116–122. https://doi.org/10.1016/j.aap.2017.02.026

[117] David C Schwebel, Despina Stavrinos, Katherine W Byington, Tiffany Davis, Elizabeth E O'Neal, and Desiree De Jong. 2012. Distraction and pedestrian safety: how talking on the phone, texting, and listening to music impact crossing the street. *Accident Analysis & Prevention* 45 (2012), 266–271. https://doi.org/10.1016/j.aap.2011.07.011

[118] Claire M Segijn, Shili Xiong, and Brittany RL Duff. 2019. Manipulating and measuring media multitasking: Implications of previous research and guidelines for future research. *Communication Methods and Measures* 13, 2 (2019), 83–101. https://doi.org/10.1080/19312458.2018.1555797

[119] Daniel J Simons and Melinda S Jensen. 2009. The effects of individual differences and task difficulty on inattentional blindness. *Psychonomic Bulletin & Review* 16 (2009), 398–403. https://doi.org/10.3758/PBR.16.2.398

[120] Andrew D Smock, Nicole B Ellison, Cliff Lampe, and Donghee Yvette Wohn. 2011. Facebook as a toolkit: A uses and gratification approach to unbundling feature use. *Computers in human behavior* 27, 6 (2011), 2322–2329. https://doi.org/10.1016/j.chb.2011.07.011

[121] Despina Stavrinos, Caitlin N Pope, Jiabin Shen, and David C Schwebel. 2018. Distracted walking, bicycling, and driving: Systematic review and meta-analysis of mobile technology and youth crash risk. *Child development* 89, 1 (2018), 118–128. https://doi.org/10.1111/cdev.12827

[122] Charles Steinfield, Nicole B Ellison, and Cliff Lampe. 2008. Social capital, self-esteem, and use of online social network sites: A longitudinal analysis. *Journal of applied developmental psychology* 29, 6 (2008), 434–445. https://doi.org/10.1016/j.appdev.2008.07.002

[123] Christine J Syrek, Jana Kühnel, Tim Vahle-Hinz, and Jessica De Bloom. 2018. Share, like, twitter, and connect: Ecological momentary assessment to examine the relationship between non-work social media use at work and work engagement. *Work & Stress* 32, 3 (2018), 209–227. https://doi.org/10.1080/02678373.2017.1367736

[124] Jan Theeuwes. 1991. Exogenous and endogenous control of attention: The effect of visual onsets and offsets. *Perception & psychophysics* 49, 1 (1991), 83–90. https://doi.org/10.3758/bf03211619

[125] Jan Theeuwes and Artem V Belopolsky. 2012. Reward grabs the eye: Oculomotor capture by rewarding stimuli. *Vision research* 74 (2012), 80–85. https://doi.org/10.1016/j.visres.2012.07.024

[126] Bas Verplanken and Wendy Wood. 2006. Interventions to break and create consumer habits. *Journal of public policy & marketing* 25, 1 (2006), 90–103. https://doi.org/10.1509/jppm.25.1.90

[127] Zheng Wang, John M Tchernev, and Tyler Solloway. 2012. A dynamic longitudinal examination of social media use, needs, and gratifications among college students. *Computers in human behavior* 28, 5 (2012), 1829–1839. https://doi.org/10.1016/j.chb.2012.05.001

[128] Dominik Weber, Alexandra Voit, and Niels Henze. 2018. Notification log: An open-source framework for notification research on mobile devices. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*. 1271–1278. https://doi.org/10.1145/3267305.3274118

[129] Dominik Weber, Alexandra Voit, Huy Viet Le, and Niels Henze. 2016. Notification Dashboard: Enabling Reflection on Mobile Notifications. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (Florence, Italy) *(MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 936–941. https://doi.org/10.1145/2957265.2962660

[130] Anita Whiting and David Williams. 2013. Why people use social media: a uses and gratifications approach. *Qualitative market research: an international journal* 16, 4 (2013), 362–369. https://doi.org/10.1108/QMR-06-2013-0041

[131] Hadley Wickham. 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org

[132] Claire A Wolniewicz, Mojisola F Tiamiyu, Justin W Weeks, and Jon D Elhai. 2018. Problematic smartphone use and relations with negative affect, fear of missing out, and fear of negative and positive evaluation. *Psychiatry research* 262 (2018), 618–623. https://doi.org/10.1016/j.psychres.2017.09.058

[133] Steven Yantis and John Jonides. 1990. Abrupt visual onsets and selective attention: voluntary versus automatic allocation. *Journal of Experimental Psychology: Human perception and performance* 16, 1 (1990), 121. https://doi.org/10.1037//0096-1523.16.1.121

[134] Kristie L Young, Paul M Salmon, and Miranda Cornelissen. 2013. Missing links? The effects of distraction on driver situation awareness. *Safety science* 56 (2013), 36–43. https://doi.org/10.1016/j.ssci.2012.11.004

[135] Richard Young, Sean Seaman, and Li Hsieh. 2016. The dimensional model of driver demand: visual-manual tasks. *SAE International journal of transportation safety* 4, 1 (2016), 33–71. https://doi.org/10.4271/2016-01-1423

[136] Michael Zehetleitner, Anja Isabel Koch, Harriet Goschy, and Hermann Joseph Müller. 2013. Salience-based selection: Attentional capture by distractors less salient than the target. *PLoS One* 8, 1 (2013), e52595. https://doi.org/10.1371/journal.pone.0052595