The Distinct Psychology of Smartphone Usage

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ABSTRACT

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One of the most important trends in today's marketplace is consumers' increased reliance on smartphones not only as a communication device but also as a central platform for accessing information, entertainment and other consumption activities—the so-called "mobile revolution" (Ackley 2015). While the marketing implications of mobile platforms are receiving emerging attention in the marketing modeling literature (e.g., Danaher et al. 2015; Ghose and Han 2011; Sultan et al. 2009), still very little is known about the consumption psychology of smartphone usage. The purpose of my dissertation is to address this void by examining what is fundamentally different about the psychology of smartphone use. The dissertation consists of two essays examining two complementary components of mobile consumer behavior. In the first essay I focus on clarifying the particular type of relationship that consumers form with their smartphones. Specifically, I advance the hypothesis that smartphones often fulfill the role of "attachment objects" for consumers. That is, smartphones are now used by many consumers in much the same way as pacifiers or security blankets are used by children—which I refer to as the Adult Pacifier Hypothesis. Consistent with this hypothesis, results from two controlled lab experiments show that relative to a comparable device such as one's personal computer, engaging with one's smartphone provides greater comfort as well as faster recovery from a stressful situation, both of which are defining characteristics of attachment objects. A third lab study reveals that, under feelings of stress, people actively seek out and engage with the device over other objects in much

the same way that a child would seek out and engage with his or her pacifier. Also consistent with this hypothesis, a fourth study shows that the drive to use one's smartphone becomes especially pronounced among consumers who have recently quit smoking—that is, consumers who are particularly susceptible to anxiety and stress. In the second essay I document an important consequence of consumers' increased reliance on their smartphones: its impact on user-generated content. Across three field studies and six controlled lab experiments, I find that smartphone usage drives the creation of content that is more emotional, specifically more positively emotional, and potentially more impactful than content generated on PCs. Overall, these findings provide insight into the psychology of the mobile consumer and its downstream marketing implications.

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* = included in a paper currently under second-round review at the *Journal of Marketing Research*

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DEDICATION

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CHAPTER 1
INTRODUCTION

Smartphones have recently been heralded as the "defining technology of the age" (*The Economist* 2015). As of 2014 consumers are officially spending a greater amount of time on their smartphone than any of their other technological devices (Millward Brown 2014), and about 80% of adults worldwide are forecast to own a smartphone within the next few years (*The Economist* 2015). Recent market research studies report that one in five American adults now access the Internet primarily through their smartphone (Pew Research 2015), and the majority of digital media time is now spent on mobile (Comscore 2014).

This shift away from personal computers (PCs) as the dominant online platform represents a major change in consumer behavior, and the industry is increasingly preoccupied with adjusting to the so-called "mobile revolution" (Ackley 2015). Firms are responding by pursuing "mobile-first" digital strategies, wherein mobile users are considered to be the main priority when designing an online experience (*Forbes* 2015). In addition, advertisers are increasingly diverting their ad budgets toward mobile advertising, with $68.7 billion spent in 2015 and a projected $101.4 billion to be spent on mobile advertising in 2016 (eMarketer 2015).

Unsurprisingly, a recent stream of research within the marketing modeling literature has begun to examine the implications of mobile platforms, offering models of mobile marketing effectiveness and browsing behavior. However, there is a dearth behavioral marketing research that examines the psychological aspects of mobile consumption behavior. As consumers continue to use their smartphones in lieu of their other technology, this "mobile revolution" is raising a substantial question for marketers that has yet to be addressed: How is the increasingly pervasive use of the device changing our current understanding of consumer behavior?

In my dissertation I attempt to partially address this gap in the literature by examining what is fundamentally different about the psychology of mobile consumption. Namely, what are the psychological factors that drive the use of smartphones, what are the psychological consequences of using the device, and how does all of this influence consumer behavior on mobile? In most of the studies across the two essays, I sought to compare users' interactions with their smartphone to a comparative device that (1) offers similar functions; (2) is as widely used across the U.S. market; and (3) exhibits a similar rate of daily usage among U.S. consumers. PCs were a natural point of contrast, since smartphones and PCs offer similar communication and browsing capabilities (e.g., email, web-based Internet, applications), exhibit comparable ownership rates in the U.S., with 68% of consumers owning a smartphone and 71% owning a PC (Pew Research 2015), as well as similar average daily usage rates, with users consuming digital media for about 2.8 hours a day on their smartphones and 2.4 hours a day on their PC (KPCB 2015).

In Essay 1 I examine across four studies whether smartphones act as "attachment objects" by testing whether they exhibit the key emotional and behavioral responses identified by attachment theory (e.g., Bowlby 1982). My results show that using one's smartphone does distinctly confer greater comfort and a faster recovery from discomfort due to stress compared to using one's PC (Studies 1-2), and that people actively seek out and engage with their smartphone over other available objects as a means of coping with stress (Studies 3-4). In Essay 2 I examine one important consequence of consumers' increased reliance on their smartphones: its impact on user-generated content. Results of nine studies show that using one's smartphone drives the creation of content that is more emotional – specifically evincing more positive emotion – than using one's PC, and that this greater emotionality is driven by the relative brevity of the content. Moreover, I show that the greater emotionality of smartphone-generated content can also enhance its influence or impactfulness relative to PC-generated content.

In what follows, I first provide a review of the relevant literature for both essays. Next, I report the four studies of Essay 1, demonstrating that smartphones elicit emotional and behavioral responses that are definitionally evoked by attachment objects. After that, I report the nine studies of Essay 2 showing that using one's smartphone drives the creation content that is more emotional, and specifically more positively emotional, than using one's PC, and that content generated on the device may therefore be more impactful. Taken together, my dissertation research provides initial insights into the consumer psychology of smartphone use.

CHAPTER 2
LITERATURE REVIEW

2.1. Typology of the Mobile Marketing Research

A burgeoning stream of research has begun to examine the marketing implications of mobile platforms. Except for recent work by Brasel and Gips (2014) showing that users exhibit greater psychological ownership over products browsed on touchscreen (vs. non-touchscreen) tablet PCs, the vast majority of the related work within marketing has been published on the quantitative side (e.g., Bart, Stephen and Sarvary 2014; Sultan, Rohm and Gao 2009; Xu et al. 2015). This line of research largely focuses on modeling mobile advertising effectiveness (e.g., Andrews et al. 2015) as well as consumer search (e.g., Ghose, Goldfarb and Han 2013) and usage behavior on mobile (e.g., Wang et al. 2015). In the following sections I summarize the major categories of findings within the marketing literature (see Table 1).

2.1.1. Determinants of Mobile Marketing Effectiveness

Location-Based Advertising. Much of the extant research on mobile marketing has focused on location-based mobile advertising (LBA). LBA exists largely in two forms: "pull" advertising, in which consumers actively seek out promotional offers on their mobile devices, and "push" advertising, in which a mobile promotion is sent to the consumer based on relevant user characteristics (e.g., the customer's location or prior search behavior) *without* the user requesting the information. For example, in a paper focusing on the distinction between the two forms of LBA, Unni and Harmon (2007) found that pull LBA is somewhat more effective than push LBA. In general, however, while some papers have examined pull LBA (e.g., Gao, Rau and Salvendy 2009), the vast majority of the research has focused on push LBA (e.g., Andrews et al. 2015; Cheng et al. 2009; Chowdhury et al. 2006; Danaher et al. 2015; Dickenger and Kleijnen 2008; Fong, Fang and Luo 2015; Luo et al. 2014).

One of the main takeaways from this stream of research is that the retailer's physical proximity to the consumer plays a key role in determining the effectiveness of LBA. Specifically, the general finding is that consumers tend to be more responsive to marketing efforts made by retailers that are closer in proximity to them (e.g., Danaher et al. 2015; Luo et al. 2014). Other findings show, for example, that competitive location targeting, in which a focal retailer targets consumers that are proximal to a *competitor's* location, can also increase receptiveness to promotions (Fong et al. 2015). Hui et al. (2013) found that sending real-time mobile promotions to customers in a grocery story can increase the rate of unplanned spending.

Other Determinants. Beyond the effects of retailer proximity on LBA, research has examined additional factors influencing mobile advertising effectiveness. Andrews et al. (2015) examined the effects of users' external environment at the moment they received an LBA, showing that mobile promotions are particularly effective when sent to users in a more crowded environment. Another factor impacting mobile marketing effectiveness is the perceived value associated with the device (see Strom, Vendel and Bredican 2014 for a review). For example, consumers are more open to using mobile services if they perceive the device as containing "emotional value," such as the ability to provide pleasure and enjoyment (Yang and Jolly 2006). Other work has shown that men (vs. women) with higher levels of consumer innovativeness are more open to mobile Internet services (Koenigstorfer and Groeppel-Klein 2012). Looking at the impact of the product itself, Bart et al. (2014) showed that a particular form of mobile advertising called “mobile display ads” is most effective for higher involvement, utilitarian products. Finally, Sultan et al. (2009) found that the extent to which owners customized and personalized their phone was positively related to their willingness to accept mobile marketing efforts. To the extent that device personalization is a signal of a broader emotional attachment to the device, this finding bears specific implications for the studies reported in Essay 1.

2.1.2. Mobile Usage Behavior

Another group of papers within the marketing modeling literature have examined content usage and search behavior on mobile devices. Ghose et al. (2013) found that relative to PCs, the small screen size and keyboard on mobile phones increase the cost of searching for information on the device (e.g., Chae and Kim 2004), resulting in less search behavior overall. Specifically, the authors showed that users browsing on mobile (vs. PC) are more likely to click on links displayed at the top of a search list because of the relative search cost incurred on the device. In the same paper, the authors also found that customers are more likely to click on search results of retail stores that are more proximal to their current location, suggesting that consumers’ physical proximity to a retailer can impact not just their receptivity to LBA but also their *search* behavior on the device. Wang et al. (2015) looked at the change in online shopping behavior before versus after customers adopted a grocery retailer’s mobile app and found, for example, that mobile shopping led to an increase in order rates especially among low-spending customers. Customers were also found to buy more habitually purchased (vs. new) products when shopping on mobile. Looking at shopping behavior on a popular e-commerce website, Xu et al. (2015) examined the extent to which the use of tablets served to complement versus substitute the use of PCs and smartphones. Interestingly, the authors found that tablets tended to serve as a substitute for browsing and shopping on PCs, but actually acted as a *complement* to consumers' shopping activities on smartphones. For example, while it decreased browsing frequency on PCs by nearly 18%, the adoption of tablets actually served to *increase* browsing frequency on smartphones by nearly 40%. Moreover, while users engaged in more casual browsing on tablets, they tended to initiate more directed searches on smartphones. In other words, customers' underlying motivations seemed to vary as a function of whether they were on their smartphone versus another device, which is broadly consistent with my thesis that consumers exhibit a unique relationship with their smartphone relative to comparable electronic devices.

While the papers described above examine content consumption on mobile, much less work within marketing exists on the *generation* of content on the device. One exception is Ghose and Han (2011), who found that the likelihood of generating content on one's mobile device in one time period is negatively correlated with the likelihood of consuming content in another period. The authors postulated that this negative temporal interdependence might be due to resource constraints inherent to mobile (e.g., due to its smaller screen), such that users need to allocate their time spent on the device between generating and consuming content. In an MSI working paper, Lurie and his coauthors find differences in content written on mobile versus PC, and provide conjectures to explain these differences such as the real time nature of mobile relative to PC (the relation between their work and the present research is discussed in Essay 2). In sum, other than these two papers, there is still a dearth of research within mobile marketing on the process of content generation on smartphones.

Finally, in one of the only published papers on the more psychological side of marketing, Brasel and Gips (2014) showed that users incorporate devices with touchscreens (e.g., tablets) into their sense of selves to a greater extent than non-touchscreen devices, thereby amplifying the endowment effect over products browsed on the device. While the paper focuses on differences between PCs and *tablets* (rather than smartphones), this finding provides some support for the idea that consumers form stronger emotional attachments to their smartphones vs. PCs.

2.1.3. Conceptual Models and Literature Reviews

Another set of papers provides literature reviews and conceptual models of mobile marketing. Some of these papers discuss mobile marketing in the context of more traditional marketing, such as Shankar and Balasubramanian (2009) who compared mobile marketing to mass marketing, and identified key research issues such as customer adoption of mobile services, the impact of mobile marketing on customer decision-making and mobile marketing in a cross-cultural context. Shankar et al. (2010) provided a conceptual framework of mobile marketing within the context of retailing and summarized, for example, the different segments of mobile consumers (e.g., “Millenials,” “Concerned Parents”) and marketing strategies that can be implemented by retailers on mobile (e.g., mobile couponing, SMS). Additionally, in a more recent 2015 working paper Lamberton and Stephen offered a critical analysis of the extant academic marketing research on digital, social media and mobile marketing, defining four “eras” across which this research has developed as well as directions for future research.

Outside of the marketing literature, Gerpott and Thomas (2014) provided a literature review on post-adoption mobile Internet usage. For example, the results of a meta-analysis showed that education level and openness to innovation played the greatest role in predicting mobile Internet usage intensity. Strom et al. (2014) provided a literature review on the value of mobile marketing for consumers and retailers, concluding that mobile marketing can increase perceived value for consumers and outcome value for retailers. However, the authors cited limited support for whether mobile marketing increases value over and above alternative marketing efforts.

In sum, while research on mobile marketing has been developing over the past few years, what is still missing is an integrated understanding of the consumer psychology of smartphone use. The aim of my dissertation is to address this gap at least in part by focusing on the psychological aspects of mobile consumer behavior. In the next section, I review two bodies of research related to Essay 1: first, I review a stream of research outside of marketing that examines "smartphone addiction"; next, I review the literature on attachment theory and argue that smartphones exhibit the defining characteristics of attachment objects.

[Insert Table 1]

2.2. Smartphone as Attachment Object (Essay 1)

2.2.1. Smartphone "Addiction"

The topic of excessive smartphone use has been receiving widespread attention across the major media outlets. One of many examples is the coverage of "phantom pocket vibration syndrome," that is, the false sensation that one's smartphone is vibrating as a result of persistent use of the device (e.g., *The Atlantic* 2012, *Telegraph* 2012, *Wired*

2014). A group of psychiatric researchers have even published a proposal to modify the current DSM-V to include a new behavioral dependence called "nomophobia," which is the pathological fear, anxiety or discomfort due to being out of touch with one's mobile phone (Bragazzi and Del Puente 2014).

Outside of marketing, a mostly correlational body of work has emerged on the topic of excessive smartphone usage – or, as it is often loosely referred to in the literature, smartphone "addiction"[1]. It is important to note upfront that smartphone addiction is not formally recognized as a behavioral dependence according to clinical diagnostic criteria (American Psychiatric Association 2013). Instead the term "addiction" is used colloquially throughout much of this body of work to refer to use of the device that is somehow problematic or excessive. Such problematic consequences can include use of the device that hinders productivity (e.g., using one's phone at work), degrades interpersonal interactions (e.g., using one's phone at dinner with a friend), or is generally unsafe (e.g., texting while driving) (e.g., Bianchi and Phillips 2005; Yen et al. 2009). The general finding in this literature is that many consumers indeed report having excessive or "addictive" tendencies with their smartphones – an idea that is broadly consistent with my hypothesis that the device acts as a type of attachment object for consumers.

Before elaborating on the extant findings from this stream of research, it is worthwhile to place the smartphone addiction literature in the context of my research on consumers' reliance on the device as an attachment object. Prior work has described emotional attachment as a precursor or driver of addiction (e.g., Hostetler and Ryabinin 2012). For example, people's emotional attachment patterns have been shown to predict their likelihood of developing addictive tendencies later in life (e.g., Hofler and Kooyman

[1] I use the phrases "excessive smartphone use" and "smartphone addiction" interchangeably.

1996). Research on attachment theory, a literature discussed in the next section, has even argued that a child's emotional attachment to a certain "special" object (e.g., a security blanket or pacifier) can sometimes evolve into an "addiction" to the object (e.g., Bachar et al.1998; Winnicott 1953). In my dissertation I elect to focus on consumers' emotional attachment to their smartphone in the framework of attachment theory rather than addiction per se for two main reasons. First, whereas smartphone addiction focuses on the detrimental relationship some consumers form with their device, I do not want to restrict my investigation solely to the negative aspects of smartphone usage. Second, emotional attachment to smartphones is a more general phenomenon relevant to a broader segment of consumers than is smartphone addiction, which can be understood as a narrower behavioral manifestation of emotional attachment.

In the sections below, I categorize and summarize the main takeaways from the smartphone addiction literature.

Conceptualizations. While many of the papers on excessive smartphone usage use the term "addiction" (e.g., Aoki and Downes 2003; Bragazzi and Puente 2014; Chiu 2014; Hooper and Zhou 2007; James and Drennan 2005; Lapointe et al. 2013), the literature also conceptualizes users' relationships to their mobile devices as:

- **Compulsive behavior**: Impulsive behavior in response to, and providing immediate short-term relief from, negative feelings or stress (e.g., Hooper and Zhou 2007; James and Drennan 2005; Lee et al. 2013)
- **Dependence**: Behavior motivated by the value one places on the substance or the social norms relating to it (e.g., Billieux et al. 2007; Hooper and Zhou 2007; James and Drennan 2005)
- **Habitual**: Automatic behavior in response to an internal or external cue (e.g., Hooper and Zhou 2007; Oulasvierta et al. 2012)
- **Problematic**: Any illegal or dangerous use (e.g., texting while driving) (e.g., Bianchi and Phillips 2005; Leung and Wei 2000; Takao et al. 2009)

Ultimately, these conceptualizations differ in that they use slightly different criteria for categorizing excessive smartphone use. As an example, compulsive behavior is commonly defined as a chronic and repetitive behavior in response to negative events that is very difficult to stop and results in harmful consequences (e.g., O'Guinn and Faber 1989). Compulsive behavior has been linked to addiction, and the two are thought to differ in degree of extremity (e.g., James and Drennan 2005). Both compulsive and addictive behaviors involve an urge to engage in the behavior, mounting tension about engaging in the behavior, denial of negative consequences, and repeated failure in curbing the behavior (e.g., Faber, O'Guinn and Krych 1992; O'Guinn and Faber 1989). However, addiction is distinct in that it also includes the presence of withdrawal (i.e., negative emotions that arise when restricted from engaging in the behavior) and tolerance (i.e., the need to engage in more of the behavior to achieve the same outcome) (e.g., Marlatt et al. 1988; Marks 1990). In line with this, to measure the extent to which people exhibit compulsive behavior Hooper and Zhou (2007) asked participants to indicate the extent to which they agreed with statements such as "Just using my cell phone, no matter what I do with it, makes me feel good", and to measure the degree of "addiction" to the device they used statements such as "I have total control over using my cell phone, I can take it or leave it" (reverse-coded). Importantly, although the papers in this literature differ in their particular conceptualizations of smartphone use, collectively they aim to examine a similar question: Which demographic, psychological, and behavioral factors are correlated with excessive smartphone use? In the subsequent section I review the major findings on the antecedents and consequences that are considered to be associated with smartphone addiction.

Antecedents of Smartphone Addiction. In trying to understand what leads consumers to become "addicted" to their phone, most of the extant research has focused on the user characteristics that tend to correlate with smartphone addiction. For example, one consistent finding is that younger, female consumers are more likely to exhibit addictive behavior towards their smartphone (e.g., Beranuy et al 2009; Bianchi and Phillips 2005; Mok et al. 2014; Walsh et al. 2011). In addition to demographics, psychological traits can also predict smartphone addiction, such as higher trait self-esteem (Bianchi and Phillips 2005; Takao et al. 2009) and higher need to belong (Lapointe et al. 2013; Walsh et al. 2011). People with higher levels of trait anxiety also tend to exhibit greater smartphone addiction (e.g., Billieux et al. 2007; Lapointe et al. 2013; Mok et al. 2014), which is consistent with my prediction that using one's smartphone provides a sense of relief from feelings of discomfort due to stress (H2a tested in Essay 1).

A few papers have also utilized the "uses and gratifications" framework (Katz, Blumler and Gurevitch 1973), which argues that people consume media to fulfill instrumental as well as hedonic goals. In this research, people report that their mobile phone satisfies not only functional needs, such as communicating with work, but also psychological needs, such as the need for sociability and self-expression (Leung and Wei 2000; Wei and Lo 2006). Relatedly, prior work has described the self-expressive benefits of the device as a result of its varied opportunities for personalization (e.g., Walsh and White 2007; Hooper and Zhou 2007).

Finally, a large body of work has conjectured that smartphone addiction is driven by the functionalities afforded by the device. For one, the mobility of the device enables users to carry their smartphones with them virtually anywhere they go, such that the device is “ubiquitously available” (Gao et al. 2009). Relatedly, smartphones allow users to have immediate access to information and social interaction (Aoki and Downes 2003; Leung and Wei 2000; Wei and Lo 2006), as well as “informational rewards” such as news and social media updates (Oulasvierta et al. 2012). As a result of its mobility and the instant access to communication afforded by the device, many users also rely on their smartphones to provide a sense of personal safety in case of emergency, thereby allowing them to avoid potential negative outcomes (e.g., Aoki and Downes 2003; Leung and Wei 2000). These learned associations, such as the feeling of safety associated with the device, is generally consistent with my hypothesis that smartphone usage can increase one’s feelings of comfort (H1 tested in Essay 1). In sum, smartphone addiction has been linked to the functionalities available on the device as well as various psychographic traits (e.g., gender, self-esteem).

Although the idea that people use their smartphone because of its functionalities (e.g., email, social media, games) is highly intuitive, it is important to note that these features are actually available across many other devices such as laptops and tablet PCs. Still, we constantly hear about consumers’ “special relationship” not to their tablet or to their laptop, but to their smartphone in particular. In the present research I argue that the devices’ functionalities alone cannot fully account for consumers’ persistent use of their smartphone. Specifically as I elaborate on below, I propose that smartphones (vs. comparable devices) exhibit a unique combination of properties that are characteristic of attachment objects, such as a pacifier or teddy bear. I therefore propose that the apparent “addiction” to smartphones can at least partly be explained by their role as attachment objects for many consumers. In my dissertation I aim to document evidence that smartphones evoke emotional and behavioral responses definitionally associated with attachment objects, and explore the implications of this phenomenon. Although examining the specific antecedents that drive this emotional attachment is an important undertaking, it is outside the scope of the current research and is instead a question I plan to explore in future work (see Future Research Directions 3.6.2.).

Consequences of Smartphone Addiction. Much of the extant research also focuses on the negative outcomes (i.e., psychological and behavioral correlates) of smartphone addiction. For example, users who demonstrate addictive tendencies with their smartphone also tend to report higher rates of sleep disturbances, depressive symptoms (Thomee, Harenstam, and Hagberg 2011), psychological distress (Beranuy et al. 2009), and lower academic performance (Samaha and Hawi 2016). Additionally, Tang et al. (2017) find that people who report higher levels of smartphone addiction also show more biases in intertemporal choice tasks. When asked to think about being separated from their device, addicted users have also described fears such as social exclusion (e.g., James and Drennan 2005) and have even reported undergoing withdrawal symptoms in the past (e.g., Walsh et al. 2008). In one of the few experimental studies on the topic, Cheever et al. (2014) found that participants separated from their smartphones reported increased feelings of state anxiety over time. Similarly, in another experiment Clayton et al. (2015) found that restricting participants from answering their ringing iPhone while performing a cognitive task resulted in diminished performance on the task, higher reported levels of anxiety and even increased heart rate and blood pressure.

In general, other than the two experimental findings noted above, virtually all of the psychological research on smartphone usage (1) has appeared outside of marketing, (2) is correlational in nature, (3) is based on participants' self-reported mobile usage behaviors, and (4) focuses on the negative aspects of using the device including "addiction". Importantly, to point (3), recent work by Andrews et al. (2015) examined how people's self-reported smartphone usage compares to their actual use of the device, and found that people significantly underestimate the amount that they actually spend on their smartphones. My dissertation contributes to and extends the extant literature by investigating the psychology of smartphone usage using experimental paradigms within a marketing context, and takes a broader perspective by examining consumers' emotional attachment to the device *in general*, rather than addiction per se.

2.2.2. Attachment Theory: Smartphone as an Attachment Object

In Essay 1 I offer a parsimonious hypothesis to conceptualize the disparate findings on smartphone addiction. I argue that many consumers' apparent addiction to the device can be explained in part by the idea that smartphones often fulfill the role of an attachment object—a proposition that I refer to as the Adult Pacifier Hypothesis. In particular, I posit that insight into the consumers' persistent smartphone use can be found in the developmental literature on attachment theory. This literature describes how children form strong emotional attachments to security-enhancing "attachment figures" – usually beginning with their primary caretaker – that help in the development of effective emotional regulation and coping strategies (e.g., Bowlby 1969; Winnicott 1953). As will be elaborated on later, one's drive to maintain close emotional attachments persists into adulthood (e.g., Bowlby 1979).

More specifically, in his seminal work Bowlby (1969; 1982) explained that infants form strong emotional attachments to their primary caregiver as part of the broader evolutionary goal of protection from danger. This attachment develops through associative learning, wherein the child becomes accustomed to the figure providing positive outcomes such as safety and comfort (e.g., Cairns 1966). Such emotional attachments can form not only toward social objects such as a parent, but also toward nonsocial objects such as a pacifier or blanket (e.g., Passman 1977). As an example, an infant may form a strong attachment to his mother because he learns over time that she most reliably responds to his crying. Once the emotional attachment is formed, his mother comes to represent an "attachment figure" that he relies on to increase his feelings of comfort and security when needed. Notably, in moments when this attachment figure is unavailable or unresponsive, the child might seek out a substitutive source of security, such as a familiar blanket or toy, as an alternate means of soothing himself. Over time as the child develops, matures and begins to separate from his parents, he may increasingly rely on this object to fill the security-enhancing role originally fulfilled by his mother, such that the object becomes a "transitional," "comfort," or "attachment object" for the child (Winnicott 1953).

The notion that a possession is an attachment object is in essence a characterization of physical traits and psychological responses associated with the possession. Specifically, the attachment theory literature has identified five major traits that are definitionally associated with attachment objects (see Figure 1), including their physical qualities and the emotional and behavioral responses associated with use of the object:

1. Portable and tactile nature
2. Learned associations of positive outcomes
3. Object increases owner's feeling of comfort
4. Relief from discomfort due to stress
5. Owner becomes distressed when restricted from object

I advance the thesis that smartphones exhibit each of these defining traits. Specifically, in the section below I will (1) describe each of the five major characteristics of attachment objects, (2) cite prior findings from the smartphone addiction literature that are consistent with some of these traits, and (3) propose the three hypotheses tested in Essay 1.

1. Portable and tactile nature

An attachment object tends to contain two key physical traits. First, it is small and lightweight enough so that the child can carry it around for use across various contexts (e.g., Winnicott 1953). For example, a child may carry her pacifier around so that she can derive its soothing properties in case she encounters a stressful situation or environment. Attachment objects also tend to contain a tactile quality, meaning they are primarily used through physical touching (for pacifiers this is referred to as oral-tactile, or primarily used through oral contact) (e.g., Busch et al. 1973; Lehman et al. 1991; Weisberg and Russell 1971). For example, a child might soothe herself by gripping and stroking her blanket, or running her fingers back and forth along the edges of her toy car (e.g., Busch et al. 1973).

Notably, like attachment objects, smartphones are portable and tactile by design. Specifically as "mobile, hand-held devices" smartphones are necessarily (1) portable for use in virtually any context (e.g., Gao et al. 2009) and (2) highly tactile not only due to their "hand-held" nature, but also because consumers must interact with the device tactily through its touch-screen interface. In sum, the idea that smartphones exhibit the key physical properties of attachment objects is fairly straightforward.

2. Learned associations of positive outcomes

Another definitional trait of attachment objects is that the owner must expect the possession to provide certain positive outcomes in a consistent and reliable fashion (e.g., Waters et al. 1991). Similar to the attachment initially formed towards the primary caregiver, attachment to an object develops through associative learning wherein the child becomes accustomed to the object reliably providing certain benefits (e.g., Cairns 1966). For example, a child might notice that her blanket keeps her warm and cozy at night, such that over time she comes to expect her blanket to provide this soothing and calming psychological outcome. Eventually, it is this learned association that will drive the child to reach for her blanket in moments when her attachment figure is unresponsive, as a means of soothing herself and substituting the sense of comfort normally provided by this figure. In sum, to the extent that they expect to derive palliative benefits from engaging with a given object, children will actively seek out the object during moments of psychological discomfort (e.g., a soothing blanket). Over time, continued reliance on the object for this purpose can culminate in the formation of a strong emotional attachment to the object – that is, the object becomes an "attachment object" for the child.

Similarly, I posit that part of the reason consumers form a particularly strong emotional attachment towards their smartphones is that they come to expect the device to produce certain positive outcomes. For one, smartphones act as consumers' primary means of communication, allowing users to interact with virtually whomever they want (e.g., Aoki and Downes 2003; Walsh, White and Young 2010; Wei and Lo 2006). In addition to communication, smartphones also provide users with unbounded access to information and “rewards” such as updates on news and social media (Oulasvierta et al. 2012). Moreover, as noted earlier the portability of the device means that users can derive these benefits, including a feeling of personal safety in case of emergency, at virtually any time and any place (e.g., Gao et al. 2009). Given the range of benefits afforded by the device including an enhanced feeling of security – and as alluded to earlier, the immediacy with which one can derive these benefits due in part to its portability – consumers come to expect their smartphone to provide a unique set of positive outcomes. Thus, the notion that smartphones are associated with positive outcomes makes intuitive sense.

3. Object increases owner’s feeling of comfort

As a child realizes that an object can be consistently relied on to provide certain positive outcomes, this object can soon come to represent a general source of security and comfort for the child (e.g., Bowlby 1969). As a result, over time, engaging with the object can increase the child’s feelings of comfort, relaxation and ease in general (i.e., under neutral circumstances) (e.g., Winnicott 1953). One tangentially related finding in the smartphone addiction literature is that many consumers report using their smartphones as a means of relaxation (Harvard Business Review 2013; Leung and Wei 2000). However, beyond this finding little evidence exists to suggest that smartphones elicit this particular consequence associated with attachment objects. Therefore, this psychological outcome provides the basis for my first hypothesis in Essay 1 (as elaborated on subsequently).

4. Relief from discomfort due to stress

Another psychological outcome elicited by attachment objects is that engaging with the object alleviates feelings of discomfort due to stress. Thus, engaging with an attachment object not only increases the owner's feeling of comfort in general, but is also comforting enough to provide relief from a stressful situation (e.g., Bretherton 1985; Mikulincer and Shaver 2007; Thomson, MacInnis and Park 2005). More specifically, an attachment object must be perceived as being reliably available, responsive, and comforting not just under neutral circumstances but also, importantly, when a threat or stressor is present (e.g., Crowell and Treboux 1995; Waters et al. 1991). This explains why, when distressed, children will actively seek out and engage with their attachment object (e.g., Bretherton 1985).

Consistent with this, findings in the smartphone addiction literature show that people report using their smartphones as a means of escaping daily pressures (Bianchi and Phillips 2005) and reducing negative affect in the short term (Billieux et al. 2007). In addition, higher levels of trait anxiety are correlated with heavier smartphone usage (e.g., Lapointe et al. 2013). These self-report based findings provide tentative evidence that smartphones might indeed provide relief from feelings of discomfort due to stress. As described further in my dissertation, in my second hypothesis I directly examine whether engaging with one's smartphone similarly provides this particular psychological benefit.

5. Owners becomes distressed when restricted from object

Another behavioral response associated with attachment objects is that the owner becomes distressed when separated from the object. For example, when separated from her pacifier, a child can become anxious and react by searching for it, crying, or throwing a temper tantrum (e.g., Bowlby 1969; 1982). As discussed in earlier, two of the only experimental studies on smartphone addiction found that, when restricted from using their smartphones, owners reported increased levels of anxiety (Cheever et al. 2014; Clayton et al. 2015) and even showed elevated blood pressure and heart rate (Clayton et al. 2015). These findings provide compelling experimental evidence that smartphones elicit this particular behavioral response associated with attachment objects.

[Insert Figure 1]

In sum, at present there is clear evidence that smartphones exhibit three of the defining patterns of attachment objects. First, smartphones inherently contain a tactile quality and are portable for use across various contexts, which are the key physical properties of attachment objects. Second, ample evidence shows that users have come to rely on their smartphones to provide a variety of positive outcomes, such as a heightened feeling of safety and instant access to information (e.g., Aoki and Downes 2003; Oulasvierta et al. 2012). Third, recent experimental findings directly demonstrate that users become highly distressed as a result of being restricted from their smartphones (Cheever et al. 2014; Clayton et al. 2015).

The primary objective of Essay 1 is to demonstrate that smartphones elicit the two remaining psychological and behavioral consequences associated with attachment objects. First, if one's smartphone indeed serves as an attachment object, then engaging with the device should provide a distinct feeling of comfort to the owner (relative to comparable devices). Note that smartphone use should not change one's affective state in general, but rather one's feeling of comfort in particular. This leads to hypothesis 1, which is tested in Study 1:

> Hypothesis 1: Holding all else equal, relative to the use of other comparable devices, using one's smartphone will provide a distinct feeling of comfort.

Second, if smartphones act as attachment objects, then using one's smartphone should be comforting enough to also alleviate feelings of discomfort due to stress (relative to comparable devices). This leads to hypothesis 2a, which is tested in Study 2:

> Hypothesis 2a: Holding all else equal, relative to the use of other comparable devices, using one's smartphone will provide greater relief from discomfort due to a stressful situation.

The stress-relieving properties of attachment objects also imply that when owners feel stressed, they will actively seek out and engage with their smartphone over other available objects in order to cope with their stress-induced psychological discomfort. This leads to hypothesis 2b, which is tested in Studies 3 and 4:

> Hypothesis 2b: Under feelings of discomfort due to stress, one will actively seek out and engage with his or her smartphone over other available objects.

In the next section I summarize the literature on adult attachment theory, which lends some support for the notion of an "adult pacifier."

Adult Attachment Theory. Adult attachment theory is guided by the assumption that the same motivational system that drives children's attachment to their primary caregivers also drives interpersonal attachments in adulthood (e.g., Fraley and Shaver 2000; Mikulincer and Shaver 2007). Generally, this theory argues that over the course of development, people expand their sources of security from their primary caregivers to other individuals such as friends and romantic partners (e.g., Hazan and Shaver 1987; Mikulciner and Shaver 2007). Perhaps the most frequently examined topic in adult attachment theory is the extent to which people's interpersonal relationships as adults mirror the type of relationship they had with their parents as children. The research examining this question has largely built on the notion of infants' "attachment styles," which describes individual differences in how children assess and regulate their behavior in response to the accessibility of their attachment figure (e.g., Ainsworth et al. 1978). Although different classifications exist, infant attachment styles have been largely conceptualized in terms of three categories: (a) secure attachment, wherein the child is easily comforted when reunited with a parent; (b) anxious-resistant attachment, wherein the child wants to be comforted but also seeks to punish the parent for being unavailable; and (c) avoidant attachment, wherein the child does not seemed distressed when the parent is unavailable and avoids the parent upon return.

Building on this, much of the adult attachment theory literature has tested for similar attachment styles among adult relationships (e.g., Hazan and Shaver 1987; Fraley and Waller 1998). For example, Brennan, Clark and Shaver (1998) found that, unlike infant attachment styles, attachment styles in adult relationships seem to exist along two major dimensions: attachment-related anxiety, or the degree to which one worries about the responsiveness of others, and attachment-related avoidance, or the extent to which one is open to others. Related work has examined whether people's attachment styles in childhood predict their attachment styles in adulthood (e.g., Feeney and Noller 1990; Fraley 2002), or their selection of romantic partners (e.g., Frazier et al. 1997; Zeifman and Hazan 1997).

While the vast majority of adult attachment theory research has focused on attachments in interpersonal relationships, a small subset of papers has described the psychological security that adults can derive from *non-social* objects (e.g., Erkolahti and Nystrom 2009; Bachar et al. 1998). However, virtually all of this work has conceptualized adults' attachment to non-social objects as dysfunctional behavior symptomatic of a broader clinical disorder. For example, the continued use of one's attachment object through adolescence was shown to be positively associated with the presense of clinical disorders such as OCD (e.g., Nedelisky and Steele 2009) and depression (e.g., Erkolahti and Nystrom 2009; Markt and Johnson 1993).

My findings therefore contribute to the extant adult attachment literature by demonstrating that many adult consumers *commonly* rely on their smartphone as an attachment object. One notable work that is consistent with my thesis is research by Keefer et al. (2012), who examine inanimate objects as a source of psychological security among a "normal" adult population. In three studies the authors find that adults primed to feel uncertain about a close interpersonal relationship (e.g., "my mother was unreliable") subsequently reported greater feelings of attachment to their personal belongings in general (e.g., "I would be helpless without my belongings"), which was mediated by increased "attachment anxiety" (i.e., concern about the reliability of close others). Most importantly, in a paradigm similar to the aforementioned studies on smartphone restriction (Cheever et al. 2014; Clayton et al. 2015), participants in Keefer and colleagues' third study were primed with uncertainty about an interpersonal relationship and were then restricted from using their smartphones while completing a task. Participants primed with uncertainty about an interpersonal relationship (vs. uncertainty about themselves) felt greater separation anxiety from their phones and showed lower persistence on the task. These results converge with those of Cheever et al. (2014) and Clayton et al. (2015), who similarly restricted users from their smartphones and found that it led to increased levels of general anxiety, heart rate and blood pressure, as well as decreased task performance.

In sum, consistent with my thesis, the results of Keefer et al. (2012) suggest that similar to a child turning to an attachment object when a parent is unavailable, “normal” adults may turn to their possessions, including their smartphone, in response to the perceived unavailability of others. My dissertation, however, expands beyond these findings in number of ways. First, Keefer et al.’s findings on the effects of smartphone restriction are very similar to the effects demonstrated by Cheever et al. (2014) and Clayton et al. (2015). Given the already established effects of restriction from the device, in my dissertation I focus on demonstrating that our smartphones’ additionally exhibit the remaining, and more general, psychological and behavioral responses associated with use of the device. Relatedly, while Keefer et al. focus on a highly specific context – people’s willingness to be restricted from their phone when they feel interpersonal uncertainty – I explore the qualities of consumers’ relationship to their smartphone *in general*. Specifically, I demonstrate that engaging with one’s smartphone yields the same psychological and behavioral outcomes as an attachment object across a variety of contexts – under neutral circumstances (Study 1), after different experimental inductions of stress (Studies 2-3), and even under a naturally occurring source of stress due to smoking cessation (Study 4).

2.3. Smartphone Usage as Emotional Expression (Essay 2)

In what follows, I review the literature related to Essay 2, in which I examine whether using one’s smartphone drives the creation of content that is substantively different than using one’s PC, and examine potential downstream consequences.

2.3.1. Content Emotionality due to Emotional Gist

Recent work has shown that compared to larger devices such as PCs, the smaller keyboard and screen available on smartphones increase the physical and cognitive effort of writing on the device (e.g., Raptis et al. 2013). Given the relative difficulty of writing on smartphones (vs. PCs), users should logically tend to write shorter content on the device and retain the most essential or fundamental components of their experience. This idea is consistent with recent work showing that, since it is more effortful to navigate devices with smaller screens, users search through less content when browsing on smartphones versus PCs (Ghose et al. 2013; Raptis et al. 2013).

I posit that the motivation to generate more succinct content on a smartphone (vs. PC) leads users to selectively describe the gist of their experiences, which inclines them to preserve more emotional information. This notion is consistent with the "fuzzy-trace theory" of processing, which argues that one forms multiple mental representations of a given stimulus that range in their level of precision, from low-level details (e.g., exact numerical information) to a "gist" representation that captures the overall meaning or essence of the stimulus (e.g., Reyna 2012; Rivers, Reyna, and Mills 2008). For example, if one learns that choice A can save 100 lives while choice B can save 1,000 lives, the gist representation of this information might be that "choice A saves fewer lives than choice B." Importantly, the gist representation of an experience – that is, the overall meaning one ascribes to it – tends to be based on one's feelings during the experience (e.g., Brainerd and Reyna 1990), which logically is particularly likely in evaluative contexts such as a consumption experience. Consistent with this idea, prior research has shown that when people form an interpretation of a stimulus, the primary dimension of the meaning ascribed to the stimulus is affective in nature (e.g., Osgood 1964). Moreover, other work has found that pressure to reduce the complexity of one's mental representation of an object – i.e., to represent the gist of the object – results in more emotionally polarized evaluations of these stimuli (Paulhus and Lim 1994), presumably because this simpler representation tends to focus on the emotional essence of the target. The notion that a focus on gist increases one's reliance on affect is also consistent with findings showing that, in the context of negotiations, reliance on affect actually triggers a greater focus on the gist of the negotiation (Stephen and Pham 2008). Taken together, these findings converge on the idea that when people are motivated to describe the most fundamental components of information, they tend to focus on their emotional evaluations of that information. Based on this, I propose that since people tend to write shorter content on their smartphone (vs. PC), they selectively describe the essential elements or gist of their experiences, which is often emotionally laden. As a result, I hypothesize that:

> Hypothesis 3a: Content generated on a smartphone will contain greater emotionality than content generated on a PC;
>
> Hypothesis 3b: The greater emotionality of smartphone-generated (vs. PC-generated) content will be driven by the tendency to generate shorter content on the device, focusing writers on the overall gist of the experience under review.

Preliminary support for my main proposition comes from an MSI report by Lurie, Ransbotham, and Liu (2014), who look at customer-generated restaurant reviews from the forum UrbanSpoon (as I do in Study 1) and find that reviews written on mobile devices contain more affective language than those written on PCs. While Lurie and colleagues' findings are consistent with my main proposition, my research contributes beyond this study in several key respects. First, I document the phenomenon not only among UrbanSpoon reviews (Study 1) but also more broadly using additional field data from Twitter (Study 7) and a corporate social media platform (Study 9). Importantly, I go beyond correlational data by conducting four controlled experiments that demonstrate the causal effect of smartphone vs. PC use on content emotionality (Studies 3-6). Moreover, while Lurie et al. (MSI 2014) speculate about the underlying driver of the effect, I provide direct evidence for my proposed explanation. Specifically, these authors conjecture that mobile-generated reviews might be more emotional because they are more likely to be written soon after a consumption experience compared to PC-generated reviews, which are more likely to be written in retrospect. In contrast, I argue that the "real-time" nature of mobile cannot fully account for the phenomenon. I show that smartphone-generated content is still more emotional even after controlling for differences in temporal proximity to the dining experience (in the UrbanSpoon dataset and through controlled experiments), and provide direct experimental evidence in support of my proposed explanation (Study 5).

2.3.2. Valence of Content Emotionality

If content generated on smartphones is indeed more emotional than content generated on PCs, one question that naturally follows is whether this greater emotionality is driven mostly by positive affect or negative affect, or whether it is equally distributed across valences. Two contrasting arguments could be made. One line of reasoning would suggest that the greater emotionality of smartphone-generated content is driven primarily by negative affect. Specifically, due to the relative difficulty of writing on smartphones (e.g., Raptis et al. 2013), there may be a tendency for negative affect arising from the task to transfer onto the content written on the device (Garbarino and Edell 1997).

Additionally, prior work has shown that negative experiences are more motivating than positive ones (e.g., Baumeister et al. 2001). If smartphone-generated content is more emotional because of the "real-time" nature of mobile (as per the conjecture put forth by Lurie et al., MSI 2014), it could be that the types of experiences people are motivated to report on in real time are more negative in nature. As a result, the greater emotionality of smartphone-generated content might be driven mostly by negative affect.

However, another line of reasoning suggests that the effect is driven primarily by positive affect. Findings from the word of mouth (WOM) literature show that online WOM is more positive than negative on average (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004). In fact, a meta-analysis found that positive WOM occurred three times more often than negative WOM, and occurred 3.7 times more often for restaurant reviews in particular (East, Hammond, and Wright 2007). Given that consumers share more positive (vs. negative) content in general, one might expect that any increase in emotionality associated with smartphone use will be driven mostly by positive affect. Relatedly, Berger (2014) argues that positive (vs. negative) WOM is more prevalent because consumers seek opportunities to self-enhance by demonstrating the quality of their choices to others, which predisposes them to share more positive content (e.g., Chung and Darke 2006; Sundaram et al. 1998). Thus, to the extent that people are motivated to self-enhance through WOM, consumers writing shorter content on their smartphones might also be motivated to preserve the aspects of the review that are more self-enhancing, thereby privileging more positive emotional information.

Findings from the fuzzy-trace literature are also consistent with this prediction. When processing information, one's feelings often guide which elements of a stimulus are attended to (e.g., Rivers et al. 2008). Notably, positive (vs. negative) feelings have been shown to lead people to focus on the more global, essential aspects of a stimulus rather than its concrete details (e.g., Gasper and Clore 2002). As a result, people are more likely to form gist-level representations of information under positive affect (Rivers et al. 2008). If, as I propose, consumers tend to focus on the gist of their experiences when writing on the device, smartphone-generated content might also include more positive emotionality. Thus, in light of these findings, I predict that:

> Hypothesis 4: The greater emotionality of smartphone-generated content will be predominantly driven by greater positive (vs. negative) emotionality.

2.3.3. Implications of Content Differences

If relative to PC-generated content smartphone-generated content is indeed more emotional, and specifically more positively emotional, an important question for marketers is whether readers *react* differently to content generated across devices. Specifically, the online word of mouth (eWOM) literature has conceptualized the influence or "impactfulness" of online content in terms of its perceived helpfulness (e.g., Mudambi and Schuff 2010; Schindler and Backart 2012), its effect on sales (e.g., Gopinath et al. 2014; Ghose and Ipeirotis 2011), its popularity or "virality" (e.g., Berger and Schwartz 2011; Milkman and Berger 2012), and its persuasiveness on readers' purchase intentions (e.g., Schellekens, Verlegh, and Smidts 2010). In Essay 2 I focus on two such operationalizations of content impactfulness, namely, persuasiveness or ability to influence readers' behavioral intentions (Study 8), and popularity as measured by the number of "votes" or "likes" given to online posts (Study 9).

Prior work has shown that readers' reactions to eWOM depend on factors such as the characteristics of the reviewer (e.g., Godes and Mayzlin 2009) and the characteristics of the review itself, including its associated numerical rating (e.g., Moe and Trusov 2011) and linguistic characteristics (e.g., Moore 2015). While some of these findings would suggest that smartphone-generated eWOM might be less impactful or persuasive than PC-generated content (e.g., Banerjee and Chua 2014; Wang et al. 2015), other findings suggest that smartphone-generated content would actually be more impactful. For example, prior work has shown that content that is more emotional tends to be more popular or "viral" among online users (e.g., Berger and Milkman 2012; Luminet et al. 2000). To the extent that the emotionality of smartphone-generated content is composed of positive emotionality, Ludwig et al. (2013) find that increasing the proportion of positive emotional language in Amazon reviews led to higher customer conversion rates. Relatedly, Schellekens et al. (2010) show that product reviews containing more positive, abstract language led to greater purchasing intentions among readers of the content. More generally, findings outside of the eWOM literature show that consumers' opinions are especially influenced by texts containing more emotional language (Lau-Gesk and Meyers-Levy 2009). This leads to my fifth hypothesis, which is tested in Studies 8 and 9:

> Hypothesis 5: Due to its heightened emotionality, smartphone-generated content will be more impactful than PC-generated content in terms of persuasiveness and popularity.

CHAPTER 3
ESSAY 1: SMARTPHONE AS THE "ADULT PACIFIER"

3.1. Introduction

In 2015 the amount of time consumers spent on their smartphones jumped to 220 minutes per day, representing a 35% increase in the time spent on the device from 2014 (Yahoo! Insights 2015). In nearly every environment, at almost any time of day, a cursory observation of consumer behavior – whether on the subway, at dinner, in bed, or even while crossing the street – will inevitably find consumers engrossed in their smartphone. As described earlier in the literature review, many consumers even appear to be "addicted" to their smartphones (e.g., Bianchi and Phillips 2005; Bragazzi and Puente 2014). What might account for consumers' persistent increase in smartphone use relative to comparable electronic devices?

The purpose of the first essay of my dissertation is to provide a rigorous investigation into why consumers have such as strong drive to engage with their smartphones. I advance the hypothesis that this phenomenon is driven in part by a general and developmentally primitive psychological mechanism: namely, that smartphones fulfill the role of an "attachment object" or "adult pacifier" for consumers over and above their other technology. Consistent with this Adult Pacifier Hypothesis, I report results from four studies, including three controlled lab experiments and one large correlational study, showing that smartphones elicit the defining emotional and behavioral responses associated with attachment objects.

3.1.1. Overview of Studies

The Adult Pacifier Hypothesis is tested across four studies, including three controlled lab experiments and one large correlational study. In the first two controlled lab experiments (Studies 1-2), I demonstrate that smartphones (vs. laptops) elicit the same emotional and behavioral responses evoked by attachment objects. One defining benefit of attachment objects is that owners feel a heightened sense of comfort after engaging with the possession (e.g., Bowlby 1982). Consistent with this, Study 1 shows that, holding the content consumed across devices constant, engaging with one's smartphone results in a greater feeling of comfort than engaging with one's PC (H1). Another emotional outcome associated with attachment objects is that engaging with the object is comforting enough to alleviate feelings of discomfort due to stress (e.g., Thomson et al. 2005). Study 2 demonstrates that again, holding the content consumed constant, engaging with one's smartphone provides greater relief from a stressful situation than using one's PC (H2a).

In Studies 3 and 4 I further tested for the stress relieving properties of smartphones by examining whether people actively seek out and engage with the device (vs. other available objects) to cope with feelings of stress (H2b). In Study 3 I tested whether participants induced to feel stress were more likely to reach for their smartphones first (before other available stimuli), and show greater engagement with the device, relative to participants who completed a neutral task.

Study 4 builds on the findings of Studies 2 and 3 to test a corollary real world prediction that using one's smartphone will be particularly appealing to consumers who are especially vulnerable to stress – for example, people who have recently quit smoking cigarettes. Research has shown that cigarettes can serve as a source of tension relief for smokers and that, soon after they quit smoking, people crave a substitutive means through which to relieve feelings of stress (e.g., Burr 1984; Sussman and Black 2008). If the recent cessation of smoking is a source of stress and discomfort, people who have recently quit smoking may develop a greater emotional and behavioral attachment to their smartphone as a substitutive source of comfort. In Study 4 I therefore compared smartphone usage patterns among participants who either recently quit smoking cigarettes or who were still smoking at the time. I predicted that the propensity to use one's smartphone would be especially pronounced among consumers who have recently quit smoking relative to consumers who are still currently smoking, which would provide further evidence suggesting that people actively seek out their smartphones due to its tension-relieving properties (H2b). In the following chapters, I report the method, results and discussion of Studies 1 through 4.

3.2. Study 1: The Impact of Smartphone Usage on Consumers' Felt Comfort

As mentioned earlier, one of the primary benefits provided by an attachment object is that owners feel a heightened sense of comfort after engaging with the possession. The purpose of Study 1 was to examine whether smartphone usage increases owners' felt comfort to a greater extent than PC usage. To test this, participants in Study 1 were randomly assigned to browse the same online content either on their smartphone or their laptop, and were asked to indicate their situational feelings at two points in the study: prior to using their assigned device, and after using their device. If consumers indeed perceive their smartphone as an attachment object over and above their comparable devices, then participants assigned to use their smartphone to browse a particular webpage should show a greater increase in their felt level of comfort as a result of using their device relative to participants assigned to use their laptop to browse the same content.

3.2.1. Method

Recruitment. Participants were recruited from the Columbia Business School Behavioral Research Lab (BRL) participant pool through the lab's online recruitment platform. Before signing up for the study, members of the participant pool were told that they must: (1) own both a smartphone and laptop and bring both devices to the study, (2) create a Tumblr account, (3) download the Tumblr mobile application onto their smartphone before arrival. The first criterion ensured that participants could be randomly assigned across the two possible conditions (device: smartphone vs. laptop) without creating a selection bias. The second and third criteria ensured that participants would be able to browse the blog "Things Fitting Perfectly Into Other Things" on the social media site Tumblr, as instructed. This content was chosen for a few key reasons. First, Tumblr is one of the most popular social networking sites in the U.S. (Comscore 2015), which made it a particularly relevant consumption context for testing my hypotheses, and minimized the likelihood of differences in familiarity across participants. Second, the Tumblr site has comparable interfaces across its mobile and web-based formats, which ensured that the browsing experiences did not differ meaningfully across devices (a question was included at the end of study to confirm the comparability of the browsing experience across platforms). Third, "Things Fitting Perfectly Into Other Things" displays simple images of objects fitting into other objects, and includes minimal or no text, such that the content was similarly amenable to browsing on both laptop and mobile devices. Fulfillment of these criteria was verified upon arrival to the study in the lab in order to confirm eligibility for participation.

Design and Procedure. Eighty-seven participants from the Columbia Business School BRL participant pool (66.7% women) participated in a 2 (device: smartphone vs. laptop) × 2 (time: pre-device usage [time 1] vs. post-device usage [time 2]) mixed design, with the first factor being between-subjects and the second factor being within-subject and received the standard compensation for a study of this length in this particular lab ($5). (Three participants were excluded from the data for having brought in tablet PCs instead of laptops.) The dependent measure of interest was the change in participants' felt comfort over time (i.e., from time 1 to time 2). I predicted that participants in the smartphone condition would show a greater increase in their felt comfort from time 1 to time 2 than participants in the laptop condition (H1).

To control for potential distractions posed by the presence of other participants, the study was administered in sessions of a maximum of five participants, with each participant seated in an individual cubicle with at least one empty cubicle on either side of them. To ensure that the presence of the devices would not impact participants' feelings prior to the device manipulation, participants were asked to take out both their smartphone and laptop upon arrival and then place it in the adjacent cubicle so that neither device was in view. Random assigned occurred across sessions, such that all participants were assigned to the same device within each session.

Felt Comfort Measure (Time 1). Participants were told that they would be participating in three (allegedly) unrelated studies that were combined for greater efficiency. In "Study 1: Psychographic Survey I," which was completed with pen and paper, participants were asked to answer a series of questions about themselves. The first set of questions contained demographic measures that served as filler items prior to the actual measure of interest. After the filler items, participants were asked to report their situational feelings by indicating the extent to which they agreed with a total of thirteen statements about "how [they] are currently feeling at this moment." Among the feelings listed (e.g., "I feel excited," "I feel frustrated") were the four items of interest: "I feel relaxed," "I feel calm," "I feel at ease," and "I feel a sense of comfort" (on a 1 = "Not at all" to 7 = "Very much so" scale). Responses to these items ($\alpha = .91$) were averaged to create a felt comfort measure for time 1. (The full list of situational feeling items is provided in Appendix A.)

Device Usage Manipulation. Next, the experimenter collected responses to "Study 1" and provided the instructions for "Study 2: Social Media Survey." In actuality, "Study 2" was used to administer the device manipulation. Participants were instructed to browse a specific social media site either on their smartphone in one condition or on their laptop in the other condition. As noted earlier, to circumvent awareness of the device manipulation, this random assignment occurred across sessions so that participants within a given session were assigned to the same device. To mitigate potential content-specific effects, all participants were asked to browse the same content across conditions. Specifically, participants were directed to the social blogging website Tumblr and were asked to browse the blog "Things Fitting Perfectly Into Other Things." Participants across conditions received the following instructions for "Study 2":

> In the second survey, we are interested in people's assessments of user-generated content such as posts on YouTube, Instagram, Tumblr, etc. You will be asked to browse the Tumblr account 'Things Fitting Perfectly Into Other Things' and evaluate the images posted there.

> Specifically, you will be given 5 minutes to browse this account and look for images that you particularly like.

In the smartphone condition, participants then read the following instructions: “At this time, please take out your <u>smartphone</u> to open the Tumblr mobile application and locate the account ‘Things Fitting Perfectly Into Other Things’ (http://thingsfittingperfectlyintothings.tumblr.com).” In the laptop condition, participants read: “At this time, please take out your <u>laptop</u> to load the Tumblr website and locate the account ‘Things Fitting Perfectly Into Other Things’ (http://thingsfittingperfectlyintothings.tumblr.com).”

Felt Comfort Measure (Time 2). After five minutes had passed, the experimenter instructed participants to stop browsing and handed out the final set of questions. While the alleged purpose of these questions was to gauge participants’ opinions about the Tumblr page, the actual purpose was to measure participants’ felt comfort after using their assigned devices (time 2). Participants were therefore told that before providing their opinions about Tumblr page, “we would like to again ask you how you are feeling at this moment.” Participants then indicated their responses to the same set of items as presented in the alleged “Study 1” (time 1). Responses to the same four measures used for time 1 were averaged into a felt comfort measure for time 2 ($\alpha = .88$).

Next, to reinforce the cover story participants were asked to answer a series of questions about the Tumblr blog. Participants were first asked to “list the title/description of your favorite posts [from the Tumblr blog browsed] and briefly explain why [they] like it.” Two sets of measures were then presented to address possible alternative explanations for the results. To control for potential differences in preexisting familiarity with Tumblr, participants were asked to indicate whether they had a Tumblr account prior to signing up for the study. Another possible concern is that any difference in felt comfort observed might be driven not by the role of smartphones (vs. laptops) as attachment objects, but rather by differences in the browsing experience of the Tumblr site across devices. To address this, participants were next asked to indicate how user-friendly they found the Tumblr application or website, depending on the condition on a 1 ("Not user friendly at all") to 5 ("Very user friendly") scale. Finally, participants completed a set of demographic questions.

3.2.2. Results

Preliminary Analyses. First, an ANOVA of participants' situational feelings at time 1 confirms that there were no differences across conditions prior to the administration of the main treatment (browsing on smartphone vs. PC) (largest $F(1, 85) = 2.70$, *NS*). This finding minimizes the concern that any difference in felt comfort reported below was simply driven by differences in participants' feelings upon arrival to the study. Participants also did not differ across conditions in terms of their familiarity with Tumblr prior to the study, or along any of the demographic variables (largest $\chi^2(1) = 1.37$, *NS*). Additionally, the results reveal no difference in the perceived user-friendliness of the Tumblr site across conditions ($F < 1$). These preliminary findings confirm that the results reported below cannot be explained by differences across conditions in terms of participants' feelings upon arrival to the study, demographic factors, or the perceived user-friendliness of the content consumed.

Main Results. Participants' ratings of felt comfort at times 1 and 2 were submitted to a mixed ANOVA, with time as a within-subject factor and device as a between-subjects factor. The results reveal a main effect of time, such that participants' reported a greater level of felt comfort at time 2 (M = 5.43) than at time 1 on average (M = 4.99; $F(1, 85) = 17.71$, $p < .001$). More importantly, this main effect was qualified by a significant device × time interaction ($F(1, 85) = 7.37$, $p = .01$; see Figure 2). Simple-effects analyses reveal that participants who used their smartphone showed a significant increase in their felt comfort from time 1 (M = 4.93) to time 2 (M = 5.66; $F(1, 43) = 29.78$, $p < .001$), while participants who had used their laptop did not show a significant increase in their felt comfort over time ($M_{\text{Time 1}} = 5.05$ vs. $M_{\text{Time 2}} = 5.21$; $F(1, 42) < 1$, *NS*). Simple-effects analyses in the other direction confirm that while participants did not differ in their felt comfort at time 1 across conditions, participants who had used their smartphone felt greater comfort at time 2 ($M_{\text{Time 2}} = 5.66$) than participants who had used their laptop ($M_{\text{Time 2}} = 5.21$; $F(1,85) = 5.43$, $p = .02$). Taken together, these results support the hypothesis that holding the content consumed constant, users feel greater comfort after engaging with their smartphone relative to a comparable device (H1). Finally, additional analyses confirm no time × device interaction on any of the situational feelings that were unrelated to felt comfort (largest $F(1,85) = 1.86$, *NS*; see Table 2).

[Insert Figure 2]

[Insert Table 2]

3.2.3. Discussion

The results of Study 1 support the proposition that holding all else equal, consumers derive distinctly greater comfort from engaging with their smartphone than with their PC (H1). Thus, relative to a comparable electronic device such as a laptop, smartphones appear to trigger one of the key emotional outcomes associated with attachment objects: an increased feeling of comfort as a result of engaging with the possession. Further, the finding that participants did not differ along any of the other situational feelings across conditions implies that smartphone use does not impact people's affect in general but rather their feeling of comfort in particular, which is central to the argument that smartphones serve as attachment objects. Additional analyses confirm that the main findings cannot be explained by preexisting individual differences across conditions or differences in situational feelings prior to the device manipulation. Since all participants were instructed to browse the same webpage, Study 1 also precludes the possibility that differences in felt comfort were simply driven by the particular content browsed across devices. Finally, the observed differences in felt comfort also cannot be explained by differences in the perceived user-friendliness of the mobile versus PC formats of the content.

In sum, Study 1 provides preliminary evidence that smartphones can serve as a type of attachment object for consumers over and above their other technology, at least with regard to eliciting feelings of comfort. In the next study, I test whether smartphones confer a second defining emotional benefit of attachment objects: providing relief from stress.

3.3. Study 2: Smartphone Usage as Stress Relief

In addition to imparting a feeling of comfort in general, another primary characteristic of attachment objects is that they are comforting enough to provide relief from stressful situations (e.g., Mikulincer and Shaver 2007), which definitionally decrease psychological comfort (e.g., Farr and Seaver 1975). In Study 2 I tested the hypothesis that, holding all else constant, using one's smartphone relieves stress to a greater extent than using one's laptop (H2a). To examine this, participants first underwent a stress induction, and then were randomly assigned to engage either with their smartphone in one condition or with their laptop in another condition. Participants' felt comfort was measured at three points in time during the study: (1) prior to the stress induction, (2) after the stress induction but before device usage, and (3) after using their assigned devices for five minutes. I predicted that after becoming stressed, participants who used their smartphone would show a greater increase in felt comfort – that is, greater recovery from discomfort due to stress – than those who used their laptops.

3.3.1. Stress Induction Pretests

Overview. To increase participants' level of stress in the main study – and thereby decrease their feeling of comfort — I created a stress induction consisting of cognitive tasks administered under time constraints, which is a common method of increasing people's stress level (e.g., Boyes and French 2010; Caciopo et al. 1995; Seery et al. 2004). Three different types of cognitive tasks were selected for the stress induction: a set of GMAT math problems, a set of Remote Associates Test (RAT) items (Mednick and Mednick 1967), and a set of anagrams. It was intended that each problem set in the stress induction, and the problems within each set, would be presented in ascending order of difficulty so that participants would become increasingly stressed throughout each task. Therefore, two pretests were conducted to determine the appropriate stimuli and time constraints for the final stress induction.

To determine the design elements of the second pretest (administered among the same pool of participants as in the main study), an initial pretest was first conducted among participants from the Amazon Mechanical Turk (MTurk) panel. Specifically, the purpose of pretest 1 was to determine (1) the appropriate time constraints to be imposed on the tasks in pretest 2, and (2) the relative difficulty of each task so that they could be presented in increasing order of difficulty in pretest 2. Participants in pretest 1 were randomly assigned to complete one of the three cognitive tasks – the anagram, RAT or math problem set – in order to measure the average amount of time needed to complete each problem within the sets, and were then asked to indicate how difficult they found their assigned task to be. Pretest 2 was then conducted among participants in the BRL pool (as in the main study) to refine the design elements of the final stress induction. More specifically, the first objective of pretest 2 was to gauge the relative difficulty of each task, and each problem within each task, so that the problems and tasks could be ordered in increasing order of difficulty for the main study. The second objective was to confirm whether performing the stress induction tasks under the time constraints chosen based on pretest 1 would decrease participants' felt comfort as intended.

Pretest 1. Pretest 1 consisted of 20 math problems that were randomly selected from an online GMAT practice test, 18 RAT items ranging in difficulty (6 of the problems were categorized as easy, 6 as medium difficulty, and 6 as very difficult; http://www.remote-associates-test.com), and 15 anagrams randomly selected from a set of previously tested anagrams (MacLeod et al. 2002). The two measures of interest for pretest 1 were the (1) average amount of time it took to complete each problem within the tasks, and (2) rated difficulty of each task.

Eighty-six participants from the MTurk panel were randomly assigned to complete one of the three possible problem sets (math, RAT or anagrams). The order of the problems presented in each set was randomized across participants. Participants were allowed to take as much time as they needed to complete the task but were motivated to do the best they could by being informed that:

> [T]hose who correctly solve the greatest number of problems in the shortest amount of time will be entered into a lottery for the chance to win a prize. The lottery will begin about 45 minutes after the survey was originally posted. You should therefore try to correctly answer the questions as quickly as you can.

The amount of time taken to complete each problem was recorded in order to (1) measure the average amount of time necessary to complete each task, which was used to calculate the time constraints for pretest 2, and (2) arrange the problems in pretest 2 in ascending order of the time necessary for completion (e.g., the math problem that took the least amount of time to complete in pretest 1 was presented as the first math problem in pretest 2). After completing their assigned problem set participants were asked to rate how difficult they found the task to be. Responses to four items – "This task was easy" (reverse-coded), "This task was frustrating," "The task was too difficult," and "I was a bit overwhelmed at some points" (answered on a 1 = "Not at all" to 7 = "Very much so" scale) – were averaged to create a measure of task difficulty (α = .83). Thus in addition to arranging the problems within each task based on ascending order of difficulty (i.e., completion time), this measure of task difficulty enabled the tasks to be arranged in ascending order of difficulty in pretest 2.

The results reveal that participants spent an average of 5.75 minutes on the RAT task, 6.77 minutes on the anagram task, and 7.72 minutes on the math task. These times were considerably shortened to set the time constraints for pretest 2. In addition, participants rated the RAT task as the least difficult (M = 4.43), followed by the anagram task (M = 4.86) and finally the math task, which was rated as most difficult (M = 5.59; $F(1,83) = 5.57$, $p = .01$). Based on these two sets of results, in pretest 2 the problem sets were presented in increasing order of rated difficulty, and the problems within each task were presented in ascending order of the amount of time necessary for completion (as elaborated upon below).

Pretest 2. While pretest 1 was conducted amongst MTurk participants, it was important to administer pretest 2 amongst participants from the Columbia BRL pool since the main study was to be conducted amongst this same participant pool. Nineteen participants from the Columbia BRL pool were asked to complete each of the three problem sets under the time constraints chosen based on pretest 1. Specifically, all participants were asked to complete as many of the 18 anagrams as they could within 2 minutes, as many of the 18 RAT item as they could within 2 minutes, and as many of the 20 math problems as they could within 3 minutes (i.e., less than half – half of the time necessary to complete each task in pretest 1). In addition, the three tasks were presented in ascending order of difficulty based on the ratings provided in pretest 1 – the RAT task was presented first, followed by the anagram task, and the math task – and the problems within each task were presented in ascending order according to the amount of time necessary for completion in pretest 1. In order to motivate them to complete the task to the best of their ability, participants were told that those "who are able to solve the most problems correctly within the allotted time will be entered into a lottery for the chance to win a prize." As in pretest 1, the amount of time taken to complete each problem was recorded (a) to refine the time constraints for the main study, and (b) so that the problems could be ordered according to the amount of time necessary for completion in the final stress induction. Once participants had completed all three problem sets, they were asked to indicate how difficult they found each of the tasks to be (1 = "Very easy" to 7 = "Very difficult”). These responses were used in order to arrange the tasks in ascending order of difficulty in the main study. Most importantly, to confirm that the stress induction decreased participants’ felt comfort as intended, participants’ felt comfort was measured at two points during pretest 2: prior to starting the first problem set (time 1), and after completing the last problem set (time 2). Felt comfort was measured by averaging responses to the same items as in Study 1: “I feel relaxed,” “I feel calm,” “I feel at ease,” and “I feel a sense of comfort” (on the same 1 = “Not at all” to 7 = “Very much so” scale) ($\alpha = .97$).

The results show that participants’ felt comfort decreased from time 1 ($M = 5.07$) to time 2 ($M = 3.12$; $F(1, 18)=33.73$, $p < .001$), confirming that the stress induction reduced participants’ felt comfort as intended. An additional analysis shows that participants rated the math task as easiest ($M = 3.95$), the RAT task as second easiest ($M = 4.95$) and the anagram task as most difficult ($M = 5.24$; $F(2, 36) = 10.24$, $p < .001$). The tasks in the final stress induction were ordered in ascending order of difficulty based on these responses.

To present the problems within each task in increasing order of difficulty in the final stress induction, I determined the difficulty of each problem using two criteria. First, the problems completed in pretest 2 were ranked in ascending order of difficulty based on their accuracy rates (e.g., the anagram with the *highest* accuracy rate was ranked first, whereas the anagram with the lowest accuracy rate was ranked eighteenth). Next, the problems were re-ranked in ascending order of difficulty based on the average amount of time necessary for completion (e.g., the anagram that was completed in the *shortest* amount of time was ranked first, and the anagram that was completed in the longest amount of time was ranked eighteenth). The overall difficulty of each problem was judged based on its accuracy ranking relative to its time ranking. For example, the anagram that had the highest accuracy rate (ranked first for accuracy) also happened to take the shortest amount of time to complete (ranked first for time); this anagram was therefore categorized as the least difficult problem and, as a result, was presented as the first problem in the anagram task in the final stress induction. In contrast, the anagram with the lowest accuracy rate (ranked eighteenth for accuracy) took a relatively long amount of time to solve (ranked thirteenth for time) and was presented as the last problem in the anagram task. In order to encourage participants to persist on the task, a few relatively easier problems were interspersed throughout the problems that were otherwise organized in ascending order of difficulty.

Ultimately the final stress induction consisted of 15 (of the 20 pretested) math problems, all of the 18 pretested RAT items, and 18 anagrams (including 15 pretested anagrams as well as 3 new anagrams that were unsolvable). The three tasks were presented in increasing order of difficulty (math, anagrams and RAT) according to the ratings provided by participants in pretest 2, and the problems within each task were organized in ascending order of difficulty based on the criteria described above. (The full list of items comprising the stress induction is reported in Appendix B.) In the main study participants received three minutes per task in order to sufficiently induce a level of stress while keeping the time constraint constant across the tasks. To increase participants' level of stress further, in the main study the experimenter sat behind the participants with a timer that rang loudly when one, two and three minutes had passed during each task.

3.3.2. Main Study Method

Overview, Design, and Predictions. Fifty participants from the same participant pool as in Study 1 (60% women) participated in a 2 (device: smartphone vs. laptop) × 3 (time: pre-stress induction [time 1] vs. post-stress induction/pre-device usage [time 2] vs. post-device usage [time 3]) mixed design, with device as a between-subjects factor and time as a within-subject factor. Participants received $8 for their participation, which is the standard amount of compensation for a study of this length in this particular lab. Before the device manipulation, all participants' felt comfort was lowered using the stress induction described in the prior section, which was common to all participants. Then, as in Study 1, the device manipulation was administered by asking participants to browse the same content either on their smartphone in one condition, or on their laptop in the other condition. The measure of interest was participants' felt comfort, which they reported three times throughout the study: before the stress induction (time 1), after the stress induction/before device usage (time 2), and after device usage (time 3). The change in participants' felt comfort from time 1 to time 2 served as a check of the stress induction. I predicted that all participants would show a significant decrease in felt comfort from time 1 to time 2, and that this effect of the stress induction would not differ across conditions. More importantly, to test for the impact of device usage, the main dependent measure was the change in participants' felt comfort from time 2 to time 3. I predicted that participants in the smartphone condition would show a greater increase in their felt comfort from time 2 to 3 than participants in the laptop condition.

Procedure. As in Study 1, to ensure that the presence of the devices would not impact participants' feelings prior to the device manipulation, upon arrival participants were asked to take out both their smartphone and laptop and place it in the adjacent cubicle so that neither device was in view. To control for potential distractions posed by the presence of other participants, a maximum of two participants were run in an individual session, with each participant seated with his or her back facing the other participant. As in Study 1, random assignment occurred across sessions such that all participants used the same device within a given session.

Participants were led to believe that they were completing two separate studies that had been combined for greater efficiency. Before beginning "Study 1," participants were told that the researcher was first interested in understanding their current state of mind. Participants then indicated their situational feelings on paper using the same measures as in Study 1, including the four items of interest: "I feel relaxed," "I feel calm," "I feel at ease," and "I feel a sense of comfort" (1: "Not at all"; 7: "Very much so" scale). Responses to these four items were averaged into an index of felt comfort for time 1 ($\alpha = .88$).

Next, participants completed "Study 1: Task Performance Study" with pen and paper, which actually served to administer the stress induction. Participants were told that:

> In this study, we are interested in pretesting material for a future survey. Specifically, we are interested in understanding how people deal with various tasks under time constraints. On the following pages you will be presented with three different problem sets and are asked to solve as many problems as you can. Those who correctly solve the greatest number of problems will be entered into a lottery for the chance to win an additional $20. You should therefore try to answer all of the questions correctly and as quickly as you can.

Once participants completed the stress induction, they again provided their responses to the same situational feeling measures including the four items of interest that were averaged into a felt comfort index for time 2 (α = .93). The change in comfort from time 1 to time 2 served as a check of the stress induction.

Next, the device manipulation was administered by asking participants to complete "Study 2: Social Media Survey," which was the same procedure used in Study 1. Specifically, participants received the same instructions to browse the Tumblr page "Things Fitting Perfectly Into Other Things" for five minutes either on their smartphone or on their laptop. Again, this random assignment occurred across sessions, so that all participants within a given session were assigned to the same device. After browsing the content on their assigned device, participants again provided their responses to the same four items of interest that were averaged into an index of felt comfort at time 3 (α = .92). The change in participants' felt comfort from time 2 to time 3 served as a measure of the degree of relief from stress due to device usage.

To reinforce the cover story, participants were asked to answer the same set of questions about the Tumblr blog as in Study 1, which again included the measures of preexisting familiarity with Tumblr and perceived user-friendliness of Tumblr page that were meant to address possible alternative explanations. Participants in Study 2 were also asked to complete three sets of measures that were included to address additional potential explanations. First, to control for the unlikely possibility that, despite random assignment, participants differed in their general smartphone usage behavior, participants indicated the average amount of time they spend on their smartphones per day (on a 1 = "30 minutes" to 9 = "> 4 hours" scale). Second, to preclude the possibility that any effects were driven by differences in the perceived difficulty of the stress induction tasks across conditions, participants were asked to indicate how difficult they found each of the three problem sets to be (on a 1 = “Very easy” to 7 = “Very difficult” scale), as well as how much more time they would have liked to complete the tasks (on a 1 = “50% of the time that was given” to 5 = “150% more time” scale). Third, to ensure that any observed differences across conditions were not driven by differences in engagement in the study, at the end of the study I measured participants’ engagement in the tasks by counting the number of problems attempted on each cognitive task.

3.3.3. Results

Preliminary Analyses. The results of a one-way ANOVA confirm that participants did not differ across conditions in terms of their daily smartphone usage or in their level of engagement (i.e., the number of problems they attempted to solve in the stress induction tasks) (all F-values < 1), which precludes the alternative explanations that differences in felt comfort might be driven by differences in general smartphone proclivity or task engagement across conditions. Next, to check whether participants differed in their feelings upon arrival to the study, their situational feelings at time 1 (prior to the device manipulation) were submitted to an additional one-way ANOVA. The results confirm that participants did not differ in terms of their felt comfort at time 1 ($F < 1$). However, unexpectedly, participants in the smartphone condition indicated that at time 1 they felt marginally more frustrated ($M_{\text{Smartphone}} = 2.6$ vs. $M_{\text{PC}} = 1.88$; $F(1, 48) = 3.96$, $p = .05$) than participants in the PC condition, although additional analyses confirm that the main analysis still holds when controlling for reported frustration at time 1 (reported subsequently).

Stress Induction Checks. To verify that the stress induction decreased participants’ comfort similarly across conditions, the felt comfort measures at time 1 and time 2 were submitted to a mixed ANOVA, with time as a within-subject factor and device as a between-subjects factor. The results reveal the expected main effect of time on comfort, such that participants reported a decrease in their felt comfort from time 1 ($M = 4.91$) to time 2 ($M = 3.45$; $F(1, 48) = 100.81$, $p < .001$) on average. Importantly, this effect was not qualified by a device × time interaction ($F < 1$), which confirms that the stress induction impacted situational feelings similarly across conditions. Additional analyses confirm no difference across conditions in terms of the reported difficulty of each problem set (RAT: $M_{\text{Smartphone}} = 5.04$ vs. $M_{\text{PC}} = 4.6$; Anagrams: $M_{\text{Smartphone}} = 5.88$ vs. $M_{\text{PC}} = 5.76$; GMAT: $M_{\text{Smartphone}} = 4.8$ vs. $M_{\text{PC}} = 4.12$; largest $F(1, 48) = 2.16$, *NS*) or in the additional amount of time participants would have liked in order to complete the tasks ($M_{\text{Smartphone}} = 3.84$ vs. $M_{\text{PC}} = 4.20$; $F(1, 48) = 2.84$, *NS*). Taken together, the results of these checks mitigate the concern that the main findings reported below might have been driven by differences in the effect of the stress induction across conditions.

Stress Relief due to Device Usage. To test the prediction that using one's smartphone provides greater relief from stress than using one's PC, participants' felt comfort at times 1, 2 and 3 were submitted to a mixed ANOVA, with time as a within-subject factor and device as a between-subjects factor. The results reveal a significant main effect of time on felt comfort ($F(2, 96) = 68.60$, $p < .001$). Simple effects analyses confirm that participants reported a decrease in felt comfort from time 1 to time 2 (as reported earlier), followed by an increased feeling of comfort from time 2 to time 3 ($M = 5.02$; $F(1, 48) = 93.48$, $p < .001$).

More importantly, the main effect of time was qualified by a significant device × time interaction ($F(2, 96) = 3.95$, $p < .025$; see Figure 3). As reported earlier, a simple-effects analysis of the change in participants' felt comfort from time 1 to time 2 finds no device × time interaction, confirming that participants across conditions showed a similar decrease in felt comfort due to the stress induction. However, an analysis of participants' felt comfort from time 2 to time 3 does reveal a significant device × time interaction ($F(1, 48) = 5.48$, $p < .025$). As predicted, participants who used their smartphone reported a greater increase in their felt comfort from time 2 to time 3 ($M_{\text{Time 2}} = 3.35$ vs. $M_{\text{Time 3}} = 5.3$; $F(1, 24) = 65.89$, $p < .001$) than participants who used their laptop ($M_{\text{Time 2}} = 3.55$ vs. $M_{\text{Time 3}} = 4.74$; $F(1, 24) = 29.65$, $p < .001$). Thus, whereas participants in the laptop condition reported an average increase of a 1.19 scale point in their felt comfort ratings, participants in the smartphone condition reported an average increase of 1.95 scale points in their felt comfort ratings. It is also worth noting that in the PC condition, participants' level of comfort at time 3 did not differ from their level of comfort at time 1 ($F < 1$), implying that participants recovered to their baseline level of comfort upon arrival to the study after using their PC. In contrast, participants browsing the same content on their smartphone reported significantly greater comfort at time 3 immediately after using the device than they did at time 1 when they first arrived to the study ($F(1, 17) = 6.43$, $p < .025$). Taken together these results support the prediction that using one's smartphone alleviates discomfort to a greater extent than comparable devices (H2b). An additional analysis controlling for participants' feelings of frustration at time 1 shows that the device × time interaction on felt comfort (from time 2 to 3) still holds, although the effect is now marginal ($F(1, 47) = 3.9$, $p < .055$).

Finally, participants' feelings unrelated to felt comfort at times 1, 2 and 3 were also submitted to a mixed ANOVA, with time as a within-subject factor and device as a between-subjects factor. The results reveal a main effect of time on participants' reported anxiety, confidence, satisfaction, happiness, focus, sadness and frustration (smallest $F(2, 96) = 4.79$, $p < .001$; see Table 3). Importantly however, none of these main effects were qualified by a device × time interaction (largest $F(2, 96) = 2.34$, *NS*). This finding is consistent with those of Study 1 and again suggests that it is a feeling of comfort *in particular* that is enhanced due to smartphone usage.

[Insert Figure 3]

[Insert Table 3]

3.3.4. Discussion

The results of Study 2 reveal that, after undergoing stress, participants who engaged with their smartphone showed a greater increase in their felt comfort than participants who browsed the same content on their PC. These findings suggest that in addition to providing a distinct feeling of comfort in general (H1), engaging with one's smartphone can be comforting enough to provide relief after a stressful situation (H2a), which is another defining psychological benefit provided by attachment objects. Importantly, as in Study 1 none of the other situational feelings differed across devices as a function of time, which again implies that smartphone use does not change people's affect in general but rather their felt comfort in particular. Additional analyses confirm that these effects are not driven by differences across conditions in the impact of the stress induction or in the level of involvement during the tasks. The effects also cannot be explained by preexisting differences in situational feelings upon arrival to the study, familiarity with the content browsed, or general smartphone proclivity across conditions. Since the content consumed was held constant, and no differences in the perceived user-friendliness of the content were reported, the impact of smartphone usage also cannot be explained by differences in content differences across conditions.

In sum, the results of Studies 1-2 suggest that relative to comparable devices and holding constant the content consumed, engaging with one's smartphone elicits two defining psychological outcomes associated with the use of attachment objects: it distinctly increases the owner's general feeling of comfort (H1), and is also comforting enough to provide relief from discomfort due to stress (H2a). Given these palliative effects revealed in the first two studies, the purpose of Study 3 was to test whether under feelings of stress, people actually seek their smartphone over other available objects as a means of coping with their stress (H2b), much like a distressed child would seek out a pacifier or security blanket.

3.4. Study 3: Preference for Smartphone Under Stress

As a result of their tension-relieving properties, a related behavioral response elicited by attachment objects is that in moments of stress, the child will actively seek out and engage with the object in order to alleviate feelings of discomfort (e.g., Bretherton 1985). The purpose of the third study was to test whether consumers who feel stressed similarly seek out and engage with their smartphone over other available objects in order to cope with discomfort due to stress (H2b). In Study 3 I therefore manipulated participants' level of stress and then secretly filmed their behavior while they waited for the next part of the study.

If one's smartphone serves as an attachment object as hypothesized, then participants induced to feel high stress should show a stronger drive towards their device than low-stress participants. Moreover, if participants under high stress seek out their smartphone as a means of coping with their discomfort, a corollary prediction is that high-stress participants will also show greater overall engagement with the device (vs. low-stress participants).

3.4.1. Method

Overview and Design. Seventy-six participants were recruited from the Columbia BRL pool and randomly assigned to the conditions of a single factor (stress: high vs. low) between-subjects design and received the standard compensation for a study of this length in this particular lab ($12). The study room was set up so that upon entering, participants walked into a "waiting area" containing: a chair (in the middle of the room); a "clock" on the wall facing the chair with a hidden camera; an ottoman with newspapers to the right of the chair; and a wall to the right of the ottoman separating this waiting area from the "main study area." This main study area contained a chair and table on which participants completed the surveys. The study was run in sessions of one participant at a time so that the dependent measures of interest (i.e., participants' behaviors with their smartphone) would not be impacted by the presence of others.

In the first part of the study (completed in the main study area), participants were asked to report their situational feelings including their felt comfort at time 1 as in the prior studies. Next, as a manipulation of stress, participants were asked to complete a task that either induced stress (high-stress condition) or did not (low-stress condition). After the stress manipulation, participants moved from the main study area to the waiting area and sat alone for ten minutes while they waited for the next part of the study. Critically, during this ten-minute period a hidden camera secretly filmed participants as they waited so that their behavior after the stress manipulation could be recorded. This footage was subsequently coded for the two dependent measures of interest: the extent to which they actively sought out their smartphone, and their overall level of engagement with the device. Once ten minutes had passed the experimenter returned to the room and asked participants to complete the remainder of the study in the main study area, during which felt comfort at time 2, as well as a series of covariates and demographic characteristics, were assessed.

I predicted that high-stress participants would seek out their smartphone more actively than low-stress participants – namely, high-stress participants would be more likely to reach for their phone before any other object, and would reach for their device more quickly. Further, I predicted that high-stress (vs. low-stress) participants would show greater overall engagement with their phone, as manifested in greater amounts of time and sustained attention on the device.

Procedure. Upon arrival to the study, all participants were asked to place their belongings – including their "smartphone and anything else that could be distracting" – in the waiting area, allegedly to avoid disruption while completing the study. This ensured that all participants did not have access to their smartphones prior to the waiting period. After placing their belongings in the waiting area, participants were asked to take a seat in the main study area (on the other side of the wall) and began the first of two surveys that were ostensibly "combined for greater efficiency." First, as in the prior studies participants were asked to complete the same battery of items measuring their situational feelings, including the four items comprising the felt comfort measure at time 1 ($\alpha = .9$).

Next, to manipulate their level of stress participants were randomly assigned to one of two versions of "Survey 1" (adapted from the widely used stress manipulation by Kirschbaum, Pirke and Hellhammer 1993 known as the Trier Social Stress Test; see also Kassam, Koslov and Mendes 2009). In both conditions, participants were given five minutes to complete a writing task. In the high-stress condition, participants were asked to write a speech about why they were the "perfect" candidate for a specific job position and were led to believe that they would subsequently have to recite this speech from memory in front of a camera so that a "video analysis [could] be conducted at a later time." To boost the cover story further, a video camera was placed in the main study area so that it directly faced participants as they completed the task. To provide the cover story for why they would need to sit in the waiting area after the writing task, high-stress participants were told that once five minutes had passed their writing would be handed to "a PhD student in Management and Human Resources (in a separate room in the behavioral lab) who [would] review [their] writing and prepare questions for [them] based on the content of [their] speech"—questions they would supposedly need to respond to later on camera.

In the low-stress condition participants were asked to write for five minutes about what advice they would give to someone who was about to start the same position as described in the high-stress condition. Unlike in the high-stress condition, participants were *not* told that they would need to recite their writing on camera. Correspondingly the video camera (which faced participants in the high-stress condition) was hidden completely out of view in the low-stress condition. As a cover story for why they would be waiting after the writing task, low-stress participants were told that once five minutes had passed their written advice would be handed to “a research assistant (in a separate room in the behavioral lab) who will make sure that [their] writing is legible before transcribing it,” and that they may be asked to clarify what they wrote if their handwriting was hard to read. Thus, unlike in the high-stress condition, participants in the low-stress condition were *not* led to believe that (1) they would present their writing on camera, (2) the content of their writing would be assessed during the waiting period, or (3) they would need to respond to questions about their writing on camera.

After participants wrote for five minutes the experimenter indicated that time was up and asked them to sit in the waiting area for “about ten minutes,” supposedly while a research assistant transcribed their writing (low-stress condition), or while a PhD student evaluated their writing and came up with questions for them to subsequently answer on camera (high-stress condition). Participants were then led to the waiting area on the other side of the wall and, after they sat down, the experimenter left the room and began a ten-minute timer.

Critically, during this ten-minute period a hidden camera (hidden in a wall clock facing participants) secretly filmed participants as they waited. It is important to note that during this time, in addition to their smartphone participants also had at their disposal any other belongings that they brought with them to the study (e.g., book bag, laptop), as well as the option of engaging with “novel” stimuli. Specifically, to provide a more conservative test of my hypothesis, two newspapers (*The New York Times* and *Wall Street Journal*) were also intentionally placed on an ottoman beside participants’ chair in the waiting area. After the study was complete, two independent coders who were blind to both condition and hypothesis coded the video footage for four behaviors comprising the two dependent measures of interest: the extent to which they actively sought out their phone, operationalized as (a) whether the first object engaged was their smartphone (vs. another object), and (b) the time elapsed before they first reached for their phone (if at all); and their overall level of engagement with the device, operationalized as the (a) quantity of engagement (i.e., proportion of time spent on the device) and (b) degree of sustained attention on the device (i.e., average amount of time per interaction with the device, as well as the maximum amount of continued time spent on the device relative to total waiting time). The coders also coded the footage for the following behaviors: number of distinct interactions with their smartphone; the number of discrete actions initiated (e.g., using their phone, reading a newspaper, then using their phone again would be coded as three discrete actions); and number of unique objects they engaged with (e.g., in the previous example two unique objects would be coded). I predicted that high-stress (vs. low-stress) participants would show a stronger drive toward their phone – as manifested in (a) a greater likelihood of reaching for their phone first before other objects, and (b) shorter time elapsed before reaching for the device – and would demonstrate greater overall engagement with the device – as manifested in (a) higher engagement quantity (i.e., greater proportion of time spent on the device), and (b) more sustained attention on the device (i.e., greater maximum amount of continuous time spent on the device, and greater average amount of time per interaction with the device). The interrater reliability for all behaviors coded is reported in Table 4.

Once the ten-minute waiting period was over the experimenter returned to the room and led participants back to the main area to finish the remainder of the study. To measure their felt comfort at time 2 ($\alpha = .94$), those in the low-stress condition were simply asked to indicate how they were feeling at that moment as in the prior studies, while those in the high-stress condition were told that, before presenting their speech on camera, the experimenter was first interested in understanding how they were feeling at this moment. High-stress participants also responded to three filler questions before indicating their situational feelings: “Have you ever been on a job interview before?” (“Yes” or “No”), “Do you have experience with public speaking?” and “How prepared and ready do you feel to present your speech?” (both on a 1 = “Not at all” to 7 = “Very much so” scale). The change in felt comfort from time 1 to time 2 served as a potential check of the stress manipulation, with the caveat that if most high-stress participants use their smartphone as expected between time 1 and 2, given the findings of Study 2 it is possible that use of the device might serve to dampen the effect of the stress induction on felt comfort.

Next, participants were asked to complete an allegedly unrelated survey titled “Survey 2: Consumption Behavior Study,” which was used to measure several covariates and address potential alternative explanations. Upon presenting Survey 2 to the high-stress participants, the experimenter explained that for the sake of time they would actually *not* be asked to present their speech, and would instead just complete the last part of the study. In “Survey 2” participants were first asked to indicate the extent to which they agreed with three statements measuring their emotional attachment to their phone: “I feel emotionally attached to my smartphone,” “To me, using my smartphone provides a source of comfort,” and “I think of my smartphone MOSTLY as a work device” (reverse-coded), in addition to two filler statements (“I use my smartphone to distract myself” and “I use my smartphone to alleviate boredom”) (on a 1 = “Not at all” to 7 = “Very much so" scale). Responses to the three relevant items were averaged into an index of smartphone attachment (α = .70). Next participants were asked three factual questions about their current smartphone: how many hours they spend on their smartphone in a given day (on a 1 = "30 minutes" to 9 = ">4 hrs." scale); how long they have owned their current smartphone (open-ended); and whether they brought their smartphone to the study ("Yes" or "No", with "No" serving as a basis for exclusion from the study)[2]. Participants then responded to three behavioral questions about their smartphone: how much they paid for the case/cover on their smartphone if they had one (open-ended); how much they would need to be paid to be restricted from their phone for 24 hours (open-ended); and how upset they would be if they inadvertently left their phone at home for a day (on a 1 = "Not upset at all" to 7 = "Very upset" scale). All of these measures allowed me to partially address the possibility that despite random assignment, any effects reported below might be driven by differences in participants' general relationship with their device. However, one caveat is that since these subjective (vs. fact-based) measures were taken *after* the waiting period – during which participants may have used their smartphones – these self-reported measures of emotional attachment may not accurately reflect participants' actual preexisting attachment to the device.

If the predicted effects arise, another possible explanation is that high-stress (vs. low-stress) participants showed a stronger drive toward their smartphone not because it is an attachment object per se but because they specifically wanted to make social contact as a means of coping with their stress, which is a functionality that happens to be

[2] Participants were also asked to indicate whether they brought their laptops with them to the study. 47.2% of participants in the high-stress condition, and 37.1% in the low stress condition, reported bringing their laptops to the study, with a chi-square analysis confirming no differences across conditions ($\chi^2(1) = 0.74$, *NS*).

available on the device. To address this, I asked all participants to indicate what they were doing on their smartphone the "last time [they] used the device" (open-ended) so that I could test whether this differed between high-stress and low-stress participants who used their phone during the waiting period. Responses to this question were subsequently categorized as one of six activities: (1) replying to or writing a message; (2) checking for new messages/emails; (3) consuming content (e.g., browsing one's newsfeed on Facebook, reading an article); (4) checking logistical information (e.g., time, location of study); (5) more than one activity *including* replying to/writing a message; or (6) other. (For the subsequent analysis, the first and fifth categories were coded as 1 for "initiating direct social contact," with all other activities coded as 0.) Finally, participants answered a set of demographic questions and were then debriefed about the purpose of the study.

3.4.2. Results

Preliminary Analyses. A preliminary analysis confirmed that participants did not differ across conditions in terms of any of the demographic measures (all p-values > .25) and, importantly, also did not differ in terms of the number of hours spent on the device, the length of time they owned the device or any of the behavioral measures of smartphone attachment (e.g., price of smartphone cover) (all F-values < 1). To the extent that they accurately reflected participants' pre-experimental relationship to the device and were not significantly affected by the treatment and/or the potential use of the device during the waiting period, the results also find no differences in participants' preexisting emotional attachment to the device across conditions ($F < 1$). Additionally, participants did not differ upon arrival in terms of their felt comfort or any of the other situational feelings measured at time 1 (largest $F(1, 69) = 1.81$, *NS*). These findings mitigate the concern that any differences reported below were driven by some preexisting differences in participants' behavioral or emotional relationship to their phone, or in their situational feelings upon arrival. Finally, five participants were excluded from the data for indicating that they did not bring their smartphone with them to the study, leaving 71 participants for analysis (69% women).

Stress Manipulation Check. To examine whether the stress induction worked as intended, participants' felt comfort at time 1 and time 2 were submitted to a mixed ANOVA with time as a within-subject factor and condition as a between-subjects factor. The results show a time × stress level interaction ($F(1, 69) = 14.09$, $p < .001$), such that participants in the low-stress condition showed an increase in felt comfort over time ($M_{T1} = 4.28$ vs. $M_{T2} = 4.71$; $F(1, 34) = 6.92$, $p < .015$), while participants in the high-stress condition showed a decrease in felt comfort from time 1 ($M = 4.11$) to time 2 ($M = 3.42$; $F(1, 35) = 7.79$, $p = .008$), as expected. A simple-effects analysis in the other direction showed no difference in comfort at time 1 as reported above, but that at time 2, low-stress participants reported significantly greater comfort than high-stress participants ($F(1, 69) = 18.3$, $p < .001$). The same mixed ANOVA analysis confirmed no time × stress level interaction on any of the other situational feelings unrelated to felt comfort (largest $F(1, 69) = 1.38$, *NS*) other than on confidence ($F(1, 45) = 4.92$, $p < .05$), such that low-stress participants did not report a change in confidence from time 1 ($M = 4.51$) to time 2 ($M = 4.66$; $F(1, 34) = 1.49$, *NS*), whereas high-stress participants reported a directional decrease in confidence from time 1 ($M = 4.72$) to time 2 ($M = 4.36$; $F(1, 25) = 2.08$, $p < .11$). The directional decrease in confidence among high-stress participants is unsurprising given that at time 1 these participants were unaware of the alleged speech they would “need” to present, whereas at time 2 they believed that they were about to present their speech on-camera and be evaluated.

Next, looking at differences in felt comfort only among the subset of participants who used their smartphone at some point during the waiting period (N = 47), the results again reveal a time × stress level interaction ($F(1, 45) = 8.44$, $p = .006$). Participants in the low-stress condition again reported a significant increase in their felt comfort from time 1 ($M = 4.29$) to time 2 ($M = 4.87$; $F(1, 20) = 9.35$, $p = .006$), whereas for high-stress participants the previously significant decrease in comfort now became directional ($M_{\text{Time 1}} = 4.06$ vs. $M_{\text{Time 2}} = 3.54$; $F(1, 25) = 2.92$, $p = .1$). As alluded to earlier, the fact this latter result was only directionally significant among high-stress participants who used their smartphone is not that surprising given the palliative effects of smartphone usage revealed in Study 2[3]. The results of a simple-effects analysis from the opposite direction again showed no differences in felt comfort at time 1 ($F < 1$) but that low-stress participants reported significantly greater comfort than high-stress participants at time 2 ($F(1, 45) = 10.25$, $p = .003$). Finally, the same mixed ANOVA analysis again found no time × stress level interaction on any of the other situational feelings unrelated to comfort other than confidence ($F(1, 45) = 4.92$, $p < .035$), showing that low-stress participants now reported a significant increase in confidence from time 1 ($M = 4.43$) to time 2 ($M = 4.76$; $F(1, 20) = 5.39$, $p < .035$), whereas high-stress participants again reported a directional decrease in confidence from time 1 ($M = 4.96$) to time 2 ($M = 4.58$; $F(1, 25) = 2.08$, $p = .16$). Taken together, these results confirm that the stress manipulation

[3] Specifically, as will be reported in the subsequent sections, most high-stress participants had engaged with their smartphones between time 1 (upon arrival) and time 2 (immediately after the waiting period). It is therefore possible that use of the device during the waiting period served to dampen the negative effect of the stress induction on felt comfort over time.

generally impacted participants' felt comfort in the intended direction across conditions (and that smartphone use seemed to again exhibit the comfort-enhancing effects observed in Study 2).

Strength of Drive Towards Smartphone. To test whether high-stress participants showed a stronger drive towards their smartphone than low-stress participants, I tested (a) whether they were more likely to reach for their smartphone first (before any other objects), and (b) whether they were faster to reach for the device. As in the previous section, these analyses were conducted first for all participants, and then only for the subset of participants who used their phone at *some point* during the study.

(a) Whether Reached for Smartphone First. A preliminary chi-square test of independence found that high-stress participants were as likely to engage with their phone at *some* point during the waiting period (72.2%) as low-stress participants (60%; $\chi^2(1)$ = 1.19, *NS*; see Table 4 for all frequencies, means, and interrater reliabilities). More importantly, to test the hypothesis that owners actively seek out their smartphone over other available objects under feelings of stress (H2b), I next ran a chi-square test of independence comparing the frequency of engaging with one's smartphone first (before any other object) between the low- and high-stress conditions. As predicted, participants in the high-stress condition were significantly more likely to engage with their smartphone *first* (63.9%) relative to participants in the low-stress condition (34.3%; $\chi^2(1)$ = 5.13, p < .015). Next, I ran the same analysis among only participants who engaged with their phone at *some point* during the waiting period (a total of 26 high-stress and 21 low-stress participants). Even among the participants who used their phone at some point during the study, those in the high-stress condition were still more likely to

reach for their smartphone first (88.5%) than those in the low-stress condition (57.1%; $\chi^2(1) = 5.99$, $p < .015$; see Table 4). This pattern of results is consistent with my thesis that under feelings of stress, consumers seek out and prefer their smartphone to other objects, much like a distressed child would seek out their pacifier (H2b).

(b) Time Elapsed Before Reaching for Smartphone. In addition to examining whether high-stress participants were more likely to reach for their phone before any other object, a conceptually related question is whether they were also faster to reach for the device than low-stress participants. A Poisson regression with stress-level as a predictor (high-stress coded as 1, low-stress coded as 0) and number of seconds before first reaching for the device as a dependent measure revealed that, as expected, high-stress participants who used their smartphone were also faster to reach for the device (M = 23.9 seconds) than low-stress participants who used their phone (M = 89.69 seconds; $\beta = -1.32$, $p < .001$)[4]. This pattern of results provides further support for the thesis that people show a strong drive toward their smartphone in moments of stress (H2b).

Level of Smartphone Engagement. Next, I examined whether high-stress (vs. low-stress) participants showed greater overall engagement with their smartphone, which was operationalized in two ways: (a) quantity of engagement, measured by the proportion of the waiting time spent on one's phone; and (b) degree of sustained attention on the device, measured by the maximum amount of continuous time spent on the device (relative to total waiting time) as well as the average amount of time spent per interaction with the device. Again, these analyses were conducted first for all participants, and then only for the subset of participants who used their phone at some point during the study.

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[4] Although the means are reported in seconds in the text for ease of interpretation, in all Poisson and binomial logit regressions reported the dependent measure was transformed into a count variable by converting seconds into milliseconds.

(a) Quantity of Engagement. To test for differences in the proportion of time spent on the device, I conducted a binomial logit regression that included stress-level as a predictor (high-stress coded as 1, low-stress coded as 0), the number of seconds spent on the device as the dependent measure (i.e., the number of events occurring in a trial) and the total number of seconds during the waiting period as the number of trials. As predicted, the results show that high-stress participants spent a significantly greater proportion of time on their smartphones (M = 51.3%) than low-stress participants (M = 31.3%; β = .36, $p < .001$). The same analysis conducted only among participants who engaged with their phone at *some point* during the waiting period revealed a similar pattern of results (M_{High} = 71% vs. M_{Low}= 52.1%; β = .16, $p < .001$; see Table 4). These findings therefore support the idea that, when stressed, consumers will not only be driven towards their smartphones, but will also engage more intensely with the device as a means of comforting themselves (H2b).

(b) Degree of Sustained Attention. First, a similar binomial logit regression as reported above with the maximum amount of continuous time spent on the device (relative to total waiting time) as the dependent measure revealed that, as expected, high-stress participants spent a significantly greater maximum proportion of continuous time on their smartphone than did low-stress participants (M_{High} = 49.3% vs. M_{Low}= 30.7%; β = .76, $p < .001$). The results of the same analysis conducted only among those who engaged with their smartphone at some point during the study showed a similar pattern of results, such that high-stress participants who used their phone spent a greater proportion of continuous time on the device than did low-stress participants who used their phone (M_{High} = 68.3% vs. M_{Low} = 51.2%; β = .72, $p < .001$; see Table 4).

Next, I conducted a Poisson regression with stress level as a predictor and the amount of time spent per interaction with the device as a dependent measure. The results show that, as predicted, high-stress participants spent significantly more time per interaction with the device on average (M = 299.32 seconds per interaction) than low-stress participants (M = 165.54 seconds; $\beta = .59$, $p < .001$). An additional analysis confirms no differences in terms of the total number of interactions with the device across conditions ($F < 1$). A similar pattern of results emerged for the same Poisson regression conducted only among participants who used their device at some point during the waiting period, such that high-stress participants who used their phones spent more time per interaction with the device (M = 414.44 seconds per interaction) than low-stress participants who used their phone (M = 275.91 seconds; $\beta = .41$, $p < .001$). Again, no differences were revealed across conditions in terms of the total number of interactions with the device ($F(1, 45) = 1.1$, *NS*; see Table 4). Taken together, these results converge on the notion that much like children sustain their attention on their pacifier or security blanket in moments of stress, people who feel high (vs. low) stress exert more sustained attention on their smartphone in particular.

Other Behaviors. To enrich my understanding of the phenomenon, I also tested for differences in the number of discrete actions initiated and the number of unique objects engaged across conditions. While the results reveal no differences in the numbers of unique objects engaged or distinct interactions initiated (largest $F(1, 69) = 1.15$, *NS*), the same analysis conducted only among participants who used their smartphone showed that low-stress participants who used their phone engaged with a marginally greater number of unique objects ($M_{High} = 1.42$ vs. $M_{Low} = 1.81$; $F(1, 45) = 3.31$, $p < .08$) and initiated a marginally greater number of distinct actions than did high-stress participants who used their phone ($\mathrm{M_{High}}$ = 1.79 vs. $\mathrm{M_{Low}}$ = 3.71; F(1, 45) = 3.66, $p < .065$). In other words, low-stress participants who used their phone seemed to shift their attention across slightly more objects and actions than high-stress who used the device, which is consistent with my earlier findings showing that high-stress participants demonstrated more sustained attention on their phone in particular.

[Insert Table 4]

Desire for Social Contact as Alternative Explanation. One possible alternative explanation is that high-stress participants sought out their smartphone not for its palliative effects per se but because they desired the social contact facilitated by the device (e.g., writing a text message to a friend). If this was the case, then high-stress participants who used their phone during the waiting period should have been more likely to engage in direct social contact (vs. a different activity) than participants who engaged with their phone in the low-stress condition. However, the results of a chi-square test of independence show that high-stress participants were as likely to make social contact on their phone during the waiting period (34.6%) as low-stress participants who had used the device (38.1%; $\chi^2(1)$ = 0.06, *NS*), thereby mitigating concerns about this alternative explanation.

3.4.3. Discussion

One classic finding in attachment theory is that, in moments of stress, children actively seek out and engage with their attachment object over other available objects as a means of alleviating their discomfort (e.g., Bretherton 1985). Consistent with this, in Study 3 participants induced to feel high stress showed a stronger drive toward their smartphone, and engaged with the device more intensely, than participants who completed a low-stress task. Specifically, relative to those in the low-stress condition, participants in the high-stress condition were more likely to seek out their smartphone first over other objects at their disposal – including any other belongings they brought with them to the study as well as "novel" stimuli (two newspapers placed next to their seat) – and were similarly faster to reach for the device. Even among only the participants who used their smartphone at some point during the waiting period, high-stress participants were still more likely to reach for the device first, and did so more quickly, than low-stress participants who used their phone.

In addition to exhibiting a stronger drive towards their phone, high-stress (vs. low-stress) participants also demonstrated greater overall engagement with the device as manifested in a greater proportion of time spent on their phone (i.e., engagement quantity) and more sustained attention on the device. Consistent with this latter finding, low-stress participants who did use their smartphone also divided their attention across a slightly greater number of objects and interactions in general relative high-stress participants who used the device, which again converges on the idea that in moments of stress, consumers may turn to and focus their attention on their smartphone in particular.

Finally, these effects cannot be explained by differences in participants' situational feelings upon arrival, self-reported general attachment to their smartphones, or demographic factors across conditions. The results also cannot be accounted for by differences in the desire for social contact across conditions. Instead, in combination with the stress-relieving effects uncovered in Study 2 (H2a), the results of Study 3 support the thesis that consumers actively seek out and engage with their smartphone during times of stress because of its palliative properties (H2b).

3.5. Study 4: Smoking Cessation and Smartphone Attachment

The purpose of Study 4 was to provide a corollary test of the Adult Pacifier Hypothesis in the real world. A large body of research on cigarette cessation has identified stress as a major factor contributing to relapse (e.g., Shiffman 1985; Wynd 1992). Specifically, ex-smokers who encounter stress often seek out other resources to substitute for the palliative effects of smoking such as increasing their consumption of food or other substances, known as "substitutive behaviors" (e.g., Sussman and Black 2008; Zweben 1987). Failure to do so often results in relapse (e.g., Burr 1984; Pomerleau and Pomerleau 1987). If smartphones indeed contain stress-relieving properties (H2a-b), then relative to those still currently smoking, consumers who have recently quit smoking should show greater reliance on smartphone usage as a type of substitutive behavior.

To test this prediction, in Study 4 I sampled a large population of current smokers as well as ex-smokers and measured their emotional and behavioral attachment to smoking (i.e., smoking propensity) as well as their emotional and behavioral attachment to the use of their smartphone (i.e., smartphone usage propensity). I predicted that among *ex*-smokers, the *more* emotionally and behaviorally attached they used to be smoking, the *more* attached they would be to their smartphone since quitting. In contrast, this effect would not hold among *current* smokers since they do not need a substitutive behavior to replace cigarettes. This pattern of results would provide further support for the hypothesis that people actively seek out their smartphone for its stress-relieving effects much like a smoker would seek out a cigarette, or a child would seek out a pacifier (H2b).

3.5.1. Method

Design and Overview. Under the guise of a study on how cigarette smoking impacts consumers' behaviors and lifestyle, 879 participants from the MTurk panel were recruited on the basis that they were either current cigarette smokers or ex-smokers who quit smoking over the past twelve months (48.6%). After indicating their smoking status, participants responded to a set of questions about their smoking propensity (i.e., their emotional and behavioral attachment to smoking), followed by a series of questions about their consumption propensity across three additional domains: food, alcohol and smartphone use. Specifically, in order to provide a more precise understanding of the possible effects of smoking cessation on smartphone use, I also measured the change in other behaviors that could also theoretically be connected with recent smoking cessation and, perhaps, smartphone use: the consumption of food and alcohol. These questions were not intended to diagnose "addictive" behaviors in a clinical sense (i.e., whether the necessary diagnostic criteria for clinical dependence were met) but rather to more generally measure participants' propensity for consumption in each domain (these measures are described in the subsequent section and are reported in Appendix C). Current smokers were asked to describe their behaviors across domains "over the past year (in the last 12 months)." In contrast, ex-smokers completed a version of the survey that asked the same set of questions about their "previous smoking behavior," and then asked about their behaviors across the other domains with respect to the time "since [they] quit smoking."

Procedure. Participants first answered a set of questions about their current or prior smoking propensity. Responses to these items were used to calculate the main predictor of interest: for ex-smokers, their prior smoking propensity, and for current smokers, their smoking propensity over the past year. Participants then answered two additional sets of questions about their food and alcohol consumption patterns, which were used to measure their eating propensity and drinking propensity, respectively (again, "since [they] quit smoking" for ex-smokers, and "over the past year" for current smokers). These two sets of questions served both as filler items as well as control variables. Next, to measure the main dependent variable – for ex-smokers, their smartphone usage propensity since quitting, and for current smokers, their smartphone usage propensity over the past year – participants responded to a set of questions about their smartphone-related behaviors.

Finally, a number of additional measures were included to control for factors that could influence participants' likelihood of quitting smoking or relapsing. First, two factors that are commonly associated with smoking relapse are high trait neuroticism and low trait perseverance (e.g., Terracciano and Costa 2004). Participants therefore completed the neuroticism subscale of the Big Five Inventory (John and Srivastava 1999) as well as the perseverance subscale of the UPPS Impulsive Behavior Scale (Whiteside and Lynam 2001). (Both of these measures were completed on a 1 to 5 scale, with higher scores indicating higher levels of neuroticism and perseverance, respectively.)

Consumption Propensity Measures. To construct the consumption propensity measures, a variety of items were selected from scales measuring addiction to tobacco (e.g., Etter 2005; Fagerström 1978), food (Gearhardt, Corbin and Brownell 2009) and alcohol (Skinner and Allen 1982). The items measuring the smartphone usage propensity were adapted from "smartphone addiction" scales (e.g., Bianchi and Phillips 2005) as well as the aforementioned (and better validated) cigarette smoking scales. As noted earlier, the purpose of these measures was not to diagnose disordered behaviors in a clinical sense but rather to more generally measure participants' propensity for consumption in each domain. A number of the questions were selected to be comparable across the domains; for example, participants indicated whether they had increased their consumption of food, alcohol as well as smartphone use, respectively.

To create the consumption propensity measures for each group of smokers, I calculated a standardized sum across all relevant measures in each domain. For each participant a given measure was standardized by subtracting the average value of the measure and dividing by its standard deviation. The measure of (current/prior) smoking propensity was calculated as the standardized sum of the following six measures that captured both their emotional and behavioral attachment to smoking: (1) the total number of cigarettes smoked in a typical day; (2) the total number of years they smoked; (3) the number of previous attempts they had made at quitting; (4) the type of smoker they considered themselves to be (1 = "Non-smoker" to 5 = "Heavy smoker"); (5) an index of six items measuring their smoking engagement (e.g., "I enjoy[ed] the physical sensation of lighting and handling a cigarette," "I worry [worried] that smoking was bad for my health but still continue[d] to smoke" on a 1 = "Strongly disagree" to 7 = "Strongly agree" scale) (current smokers: $\alpha = .78$; ex-smokers: $\alpha = .86$); and (6) how often they craved a cigarette this past week (1 = "Never" to 5 = "All the time") (current smokers: $\alpha = .70$; ex-smokers: $\alpha = .71$). A higher score on this index was interpreted as a greater emotional and behavioral attachment to smoking (over the past year/previously). To measure a potential moderator for the effects among ex-smokers, this group of participants was also asked how long ago they quit smoking (1 = "A few days ago" to 11 = "2 or more years ago").

The measure of smartphone usage propensity (over the past year/since quitting) was similarly calculated as the standardized sum of the following four measures capturing participants' emotional and behavioral attachment to the device: (1) the total number of times they used their phone in a typical day; (2) the extent to which the time spent on their smartphone had increased (over the past year/since quitting) (1 = "Not true at all" to 5 = "Very true"); (3) six items measuring their emotional relationship to the device (e.g., "When I'm tense or upset, using my smartphone helps me relax," "I feel more comfortable with my smartphone in my hand" on a 1 = "Strongly disagree" to 7 = "Strongly agree" scale) (current smokers: $\alpha = .9$; ex-smokers: $\alpha = .9$); and (4) an item measuring how they felt towards their smartphone (1 = "I feel fine about my smartphone" to 5 = "I love my smartphone") (current smokers: $\alpha = .70$; ex-smokers: $\alpha = .62$). A higher score on this index was interpreted as a greater emotional and behavioral attachment to one's smartphone (over the past year/since quitting). The full survey instrument for the smoking propensity and smartphone propensity measures, as well as for the eating propensity (current smokers: $\alpha = .76$; ex-smokers: $\alpha = .83$) and drinking propensity measures (current smokers: $\alpha = .76$; ex-smokers: $\alpha = .80$), are reported in Appendix C.

I predicted that among ex-smokers, the greater their prior smoking propensity had been, the greater their smartphone usage propensity would be since quitting. In contrast, among current smokers, smoking propensity over the past year would not predict their smartphone usage propensity over that same time period.

Finally, it is important to note that although they are similar, the propensity items presented to ex-smokers were measured on somewhat different scales than those presented to current smokers (i.e., prior vs. current smoking propensity, consumption propensity since quitting vs. over the past year). Therefore, for the main results reported below I conducted two separate sets of regression analyses – one for current smokers and one for ex-smokers[5].

3.5.2. Results

Preliminary Analyses. A preliminary analysis shows that participants did not differ in their levels of trait neuroticism or trait perseverance across the smoking status groups or any of the other demographic variables (all F-values < 1; see Table 5 for sample characteristics). An additional analysis also reveals an unsurprising negative relationship between age and smartphone usage propensity ($\beta = -.06$, $p < .001$, $R^2 = .06$), whereby younger adults were more emotionally and behaviorally attached to their smartphones than older adults on average[6]. Moreover, a one-way ANOVA shows that current smokers were older (M = 35.36 years old) than ex-smokers on average (M = 33.29 years old; $F(1, 871) = 8.54$, $p < .005$; see Table 5). To accommodate for differences in age across the samples, I report two sets of analyses below: one set that does not control for the age of the respondents, and a second set that does.

[Insert Table 5]

[5] To the extent that one is comfortable comparing the slopes of these two groups given the use of distinct measurement scales, I also ran a regression model with smoking status (current vs. ex-smoker), smoking propensity (averaged across groups), and their interaction as predictors, and smartphone usage propensity (averaged across groups) as the dependent measure. The results show a significant smoking status × smoking propensity interaction ($\beta = .08$, $p = .003$, $R^2 = .01$), confirming a conceptually similar pattern of results as the ones reported in the main text.

[6] The negative relationship between age and smartphone usage propensity also held when analyzed for ex-smokers ($\beta = -.04$, $p = .01$, $R^2 = .02$) and current smokers ($\beta = -.08$, $p < .001$, $R^2 = .10$) separately.

Effects on Smartphone Usage Propensity. To test my main prediction I regressed participants' smoking propensity on their smartphone usage propensity, running separate regression models for current and ex-smokers. For current smokers, smartphone usage propensity over the past year was regressed on their smoking propensity over that same time period. As expected, the results reveal a non-significant relationship between current smokers' smoking propensity over the past year and their smartphone usage propensity over that time period (β = -.08, t(451) = -1.83, p <.075, R^2 =.009; see Figure 4a). Although non-significant, this directionally negative relationship suggests that the more attached people were to smoking over the past year, the directionally less attached they were to their smartphone over that time period, which is broadly consistent with my thesis that one's smartphone can be used as a substitute for the palliative effects of cigarettes.

Next, for ex-smokers, smartphone usage propensity since quitting was regressed on their prior smoking propensity. As predicted, the results show a negative relationship between prior smoking propensity and smartphone usage propensity since quitting (β = .07, t(426) = 1.94, p = .05, R^2 =.009; see Figure 4b), such that the more emotionally and behaviorally attached people used to be to smoking, the more attached they have been to their smartphone since quitting. These findings support my thesis that, as a result of their stress-relieving properties, people may seek out their smartphone (H2b) to replace the alleviating function of cigarettes.

[Insert Figure 4a-d]

Effects on Consumption Propensity in Other Domains. To get a better understanding of the processes at work, I analyzed the effects of participants' smoking propensity on their consumption propensity in other domains that could be related either to the main dependent variable (smartphone usage propensity) and/or the their propensity to smoke – namely, the consumption of food and alcohol. First, a regression with (current/prior) smoking propensity as the predictor and drinking propensity (over the past year/since quitting) as the dependent measure was conducted separately for each group. For current smokers the results show no relationship between their smoking propensity over the past year and their propensity to consume alcohol over that same time period ($\beta = .002$, $t(451) = .06$, $p < .955$, $R^2 = .00$). Similarly, ex-smokers showed no relationship between their prior smoking propensity and their propensity to consume alcohol since quitting ($\beta = -.02$, $t(426) = -.29$, $p < .75$, $R^2 = .00$). This pattern of results suggests that ex-smokers might not rely on alcohol to compensate for the palliative effects of smoking. These results also mitigate concerns about the potential alternative explanation that smoking cessation increases attachment not to one's smartphone in particular, but rather to pleasurable things in general.

Next, similar regressions were run for each group with eating propensity (over the past year/since quitting) as the dependent measure. The results show that for current smokers, there was no relationship between their propensity to smoke over the past year and their propensity to eat over that same time period ($\beta = .02$, $t(451) = .43$, $p < .67$, $R^2 = .00$). However, for ex-smokers, the higher their prior propensity to smoke, the higher their propensity to eat since quitting ($\beta = .22$, $t(426) = 5.14$, $p < .001$, $R^2 = .06$). This pattern of results is unsurprising given that eating is one of the most common means of coping with stress after smoking cessation (e.g., Sussman and Black 2008).

Controlling for Consumption Propensity in Other Domains. Next, I examined the relationship between smoking propensity and smartphone usage propensity while controlling for participants' drinking propensity. For current smokers, the results show no effect of the covariate ($\beta = .05$, $t(450) = 1.02$, $p < .65$) and again find a non-significant (and directionally negative) relationship between smoking propensity over the past year and smartphone propensity over that same time period ($\beta = -.08$, $t(450) = -1.83$, $p < .07$, Overall model fit: $R^2 = .01$). For ex-smokers, the results do find a positive relationship between the covariate and dependent measure ($\beta = .11$, $t(425) = 2.98$, $p = .003$), suggesting that people who increase their smartphone use since quitting also tend to consume more alcohol over the same time period. More importantly, the findings confirm that the positive relationship between prior smoking propensity and smartphone usage propensity since quitting still holds after controlling for drinking propensity ($\beta = .07$, $t(245) = 2$, $p < .05$, Overall model fit: $R^2 = .03$). Taken together, this pattern of results again suggests that consumers may not rely on alcohol in the same way as they may rely on their smartphones after the cessation of smoking.

Next, the same regression analyses were conducted that instead included eating propensity as a covariate. Among current smokers, the regression results show a positive relationship between the covariate and dependent measure, such that the greater the eating propensity over the past year, the greater the smartphone usage propensity over that same time period ($\beta = .18$, $t(450) = 4.07$, $p < .001$). After controlling for eating propensity the results now find a marginally significant (rather than directional) negative relationship between smoking propensity over the past year and smartphone propensity over that same time period ($\beta = -.08$, $t(450) = -1.94$, $p < .055$, Overall model fit: $R^2 =$

.04), such that the more attached people were to smoking over the past year, the less attached they were to their smartphone over that same time period. Again, this particular finding points to a potential compensatory relationship between smoking and smartphone use, which is consistent with my overall thesis.

Among ex-smokers, the results also reveal a positive relationship between the covariate and dependent measure such that the greater the eating propensity since quitting, the greater the smartphone usage propensity over that time period ($\beta = .25$, $t(425) = 6.26$, $p < .001$). However, after controlling for eating propensity since quitting, prior smoking propensity no longer predicted smartphone usage propensity since quitting ($\beta = .02$, $t(425) = .46$, $p < .65$, Overall model fit: $R^2 = .09$). This pattern of results is discussed further in the discussion section of this study.

Moderation by Recency of Smoking Cessation. If ex-smokers indeed rely on their smartphone to compensate for the tension-relieving effects of cigarettes, the relationship between people's prior attachment to smoking and their attachment to their phone since quitting should logically be especially pronounced for those most susceptible to stress: people who quit smoking most recently. To examine this, I ran a regression for ex-smokers with their prior smoking propensity, how recently they quit smoking (with higher scores indicating greater recency), and their interaction as predictors, and their smartphone usage propensity since quitting as a dependent measure. First, the results now show a directionally positive relationship between prior smoking propensity and smartphone usage propensity since quitting ($\beta = .07$, $t(424) = 1.84$, $p < .07$) and find a non-significant relationship between cessation recency and smartphone usage propensity ($\beta = .03$, $t(424) = .73$, $p < .465$). Most importantly, the results show a prior smoking propensity × cessation recency interaction (β = .03, t(424) = 2.1, p < .04, Overall model fit: R^2 = .02) such that the relationship between people's prior attachment to smoking and their attachment to their smartphone since quitting was stronger for those who quit more recently.

To present this result more clearly I discretized recency of smoking cessation into terciles (people who quit: a few days ago–1 month ago; 1.5–6 months ago; or 6.5 months–2 or more years ago). Next, for each group (i.e., tercile) of ex-smokers I regressed their prior smoking propensity on their smartphone usage propensity since quitting. The results confirm that this relationship is well pronounced for people who quit smoking within the past month (β = .2, t(156) = 3.73, p < .001, R^2 = .08), but becomes non-significant the further back in time people quit ($\beta_{1.5-6\text{ mo.}}$ = .03, t(160) = .44, p <.665, R^2 = .001, and $\beta_{6.5\text{mo.}-2\text{yr.}}$ = -.05, t(106) = -.59, p < .56, R^2 = .003; see Figures 5a-c). These results suggest that the ex-smokers who show the strongest attachment to their smartphones since quitting are those with the greatest need for stress relief – namely, those who quit smoking most recently. Next, I report the results for the same set of analyses while also including age as covariate.

[Insert Figures 5a-f]

Effects on Smartphone Usage Propensity Controlling for Age. To account for the aforementioned differences in age across the samples, I tested whether my main predictions still held after controlling for participants' age. For current smokers, the results show a negative relationship between age and the dependent measure, such that younger smokers unsurprisingly showed greater attachment to their smartphone over the past year than older smokers (β = -.09, t(443) = -6.87, p < .001). More importantly, after controlling for age, the relationship between smoking propensity over the past year and smartphone propensity over that same time period remained non-significant (and became weaker) for current smokers (β = .05, t(443) = 1.08, *p* < .285, Overall model fit: R^2 = .11; see Figure 4c). For ex-smokers, the results similarly find an effect of age such that younger ex-smokers showed greater attachment to their smartphone since quitting than older ex-smokers (β = -.06, t(424) = -3.79, *p* < .001). More importantly, the results confirm that the positive relationship between prior smoking propensity and smartphone usage propensity since quitting still holds after controlling for participants' age (β = .13, t(424) = 3.39, *p* = .001, Overall model fit: R^2 = .04; see Figure 4d). Taken together, these findings provide further support for the thesis that consumers seek out their smartphone to substitute the alleviating function of cigarettes (H2b) (even after accounting for differences in age).

Effects on Consumption Propensity in Other Domains Controlling for Age. To test for the effects of smoking propensity on eating and drinking propensity, the same analyses reported earlier were conducted while also controlling for participants' age. In terms of drinking propensity, for current smokers the results show no effect of age (β = -.003, t(443) = -.25, *p* < .81), and again find no relationship between smoking propensity over the past year and the propensity to consume alcohol over that same time period (β = .000, t(443) = .003, *p* < .999, Overall model fit: R^2 = .00). Similarly, ex-smokers showed no relationship between the covariate and the dependent measure (β = .006, t(424) = .3, *p* < .77), and again showed no relationship between prior smoking propensity and their propensity to consume alcohol since quitting (β = -.02, t(424) = -.39, *p* < .7, Overall model fit: R^2 = .00). Taken together, these results replicate those reported in the prior set of analyses, and again suggest that consumers might not rely on alcohol as a substitute for smoking.

Next, similar regressions controlling for age were run for each group with eating propensity (over the past year/since quitting) as the dependent measure. For current smokers, the results show that younger smokers reported greater eating propensity over the past year than older smokers (β = -.05, t(443) = -.37, $p < .001$). Unlike in the first set of analyses, the results now show a significantly positive relationship between current smokers' smoking propensity over the past year and their eating propensity over that same time period (β = .11, t(443) = 2.32, $p < .025$, Overall model fit: $R^2 = .043$). Thus, whereas in the original analysis this relationship was non-significant, after controlling for age the results now find that the more attached people were to smoking over the past year, the more attached they were to eating over that same time period. For ex-smokers, the results find no relationship between age and dependent measure (β = .01, t(424) = .51, $p < .61$), but do confirm that, as in the original set of analyses, the higher the prior propensity to smoke, the higher the propensity to eat since quitting (β = .21, t(424) = 4.43, $p < .001$, Overall model fit: $R^2 = .06$). In sum, whereas for current smokers the (previously non-significant) relationship between smoking and eating propensity becomes significantly positive after controlling for age, for ex-smokers the positive relationship between the prior propensity to smoke and the propensity to eat since quitting is robust across analyses. These findings are discussed further in the discussion section of this study.

Controlling for Age and Consumption Propensity in Other Domains. I next examined the relationship between smoking propensity and smartphone usage propensity while controlling for both drinking propensity and age. For current smokers, the results show a negative relationship between age and the dependent measure (β = -.09, t(442) = -6.85, *p* < .001) and, as reported in the earlier analysis, no effect of drinking propensity on smartphone usage propensity (β = .03, t(442) = .73, *p* < .47). More importantly, the results again find a non-significant relationship between smoking propensity over the past year and smartphone propensity over that same time period for current smokers (β = .05, t(442) = 1.08, *p* < .285, Overall model fit: R^2 = .11). For ex-smokers the results similarly show that younger ex-smokers were more likely to be attached to their smartphones than older ex-smokers (β = -.06, t(423) = -3.87, *p* < .001), and as in the first analysis reveal that the greater the drinking propensity since quitting, the greater the smartphone propensity over the same time period (β = .11, t(423) = 3.09, *p* = .002). Most importantly, the results confirm that the positive relationship between prior smoking propensity and smartphone usage propensity since quitting still holds after controlling for both drinking propensity and age (β = .14, t(423) = 3.48, *p* < .001, Overall model fit: R^2 = .06). Thus, for both samples, controlling for participants' drinking propensity *and* age did not change the nature of the relationship between smoking and smartphone usage propensity reported in the first set of analyses.

Next, the same regression analyses were conducted that included age and eating propensity as covariates. Among current smokers, the results show an unsurprising negative relationship between age and smartphone usage propensity over the past year (β = -.08, t(442) = -6.23, *p* < .001). As reported in the initial set of analyses, the results again find that the greater the eating propensity over the past year, the greater the smartphone usage propensity over that same time period (β = .16, t(442) = 3.59, *p* < .001). More importantly, the findings again reveal a non-significant relationship between smoking propensity over the past year and smartphone usage propensity over that same time period, even after controlling for both covariates ($\beta = .03$, $t(442) = 0.69$, $p < .5$, Overall model fit: $R^2 = .13$).

Among ex-smokers, the results similarly reveal that younger ex-smokers were more attached to their smartphones since quitting than older ex-smokers ($\beta = -.06$, $t(423) = -4.13$, $p < .001$), and that, as reported in the first analysis, the greater the eating propensity since quitting, the greater the smartphone usage propensity over that time period ($\beta = .25$, $t(423) = 6.49$, $p < .001$). Notably, whereas controlling *only* for eating propensity since quitting in the initial analysis mitigated the positive relationship between smoking and smartphone usage propensity for ex-smokers, this significantly positive relationship reemerged after age was included as a second covariate in the model ($\beta = .08$, $t(423) = 2.11$, $p < .04$, Overall model fit: $R^2 = .12$). Again, this pattern of results is discussed further in the discussion section of this study.

Moderation by Recency of Smoking Cessation Controlling for Age. Finally I tested whether, after controlling for the age of ex-smokers, the recency of smoking cessation still moderated the relationship between prior smoking propensity and smartphone usage propensity since quitting. The results show an expected negative relationship between age and smartphone usage propensity since quitting ($\beta = -.06$, $t(422) = -3.8$, $p < .001$), and now reveal a stronger positive relationship between prior smoking propensity and smartphone usage propensity since quitting ($\beta = .13$, $t(422) = 3.32$, $p = .001$). In addition, while marginally significant in the original analysis, the results now find a non-significant relationship between cessation recency and smartphone usage propensity (β = .05, t(422) = 1.2, *p* = .23). Most importantly, the results still reveal a prior smoking propensity × cessation recency interaction after controlling for age (β = .02, t(422) = 1.91, *p* < .06, Overall model fit: R^2 = .05), although now marginally significant. Thus, the relationship between people's prior attachment to smoking and their attachment to their smartphone since quitting was (marginally) still stronger for those who quit more recently, even after controlling for age.

As in the original analysis, I next discretized recency of smoking cessation into terciles (people who quit: a few days ago–1 month ago; 1.5–6 months ago; or 6.5 months–2 or more years ago) and, for each tercile, regressed prior smoking propensity on smartphone usage propensity since quitting while controlling for age. The results confirm that the relationship between prior smoking propensity and smartphone usage propensity since quitting was still well pronounced for people who quit within the past month (β = .22, t(154) = 3.85, t(154) = 3.85, *p* < .001*,* R^2= .09), and became less pronounced the further back in time people quit ($\beta_{1.5-6\text{ mo.}}$ = .09, t(159) = 1.43, *p* < .16*,* R^2 = .03, and $\beta_{6.5\text{mo.}-2\text{yr.}}$ = .05, t(105) =.61, *p* < .55*,* R^2 = .08; see Figures 5d-f). As in the previous analyses, these findings again suggest that the ex-smokers who are potentially most susceptible to stress – namely, those who quit smoking more recently – are the ones who show the strongest attachment to their smartphone since quitting.

3.5.3. Discussion

Study 4 shows that the more emotionally and behaviorally attached ex-smokers used to be to smoking, the more attached they have been to their smartphone since quitting, whereas a comparable relationship does not hold for current smokers. Interestingly, the relationship between prior smoking propensity and smartphone usage propensity since quitting was especially pronounced for the ex-smokers who quit most recently – that it is, those who presumably have the greatest need to substitute for the palliative effects previously provided by cigarettes. Taken together, these findings converge on the idea that consumers who quit smoking might seek out their smartphone as a compensatory means of coping with stress (H2a-b).

A second set of analyses confirms that the relationship between smoking propensity and smartphone use propensity for current and ex-smokers still holds after accommodating for differences in age across the two samples. While the main results of interest were robust across analyses, two minor differences emerged. First, whereas for current smokers the original analysis found no relationship between smoking propensity and eating propensity over the past year, after controlling for age this relationship became significantly positive, which may be due to the relationship between current smokers' age and eating propensity over the past year (β = -.04, t(444) = -2.99, p = .003, R^2=.02), and/or the relationship between their age and smoking propensity over the past year (β = .13, t(444) = 10.4, $p < .001$, R^2=.44).

Second, and more relevant to the main predictions, the results from the first set of analyses showed that the key relationship of interest among ex-smokers – namely, the positive relationship between their prior smoking propensity and their smartphone usage propensity since quitting – was mitigated after controlling for participants' eating propensity since quitting. This pattern of results would suggest that food and smartphones might play almost substitutable roles for ex-smokers. However, after controlling for ex-smokers' eating propensity *and* age in the second set of analyses, the significantly positive relationship between prior smoking propensity and smartphone usage propensity since quitting reemerges. This latter finding would instead suggest that eating and smartphone use serve as similar but *non*-substitutable forms of stress relief for ex-smokers. In light of the heterogeneity in age revealed across the samples, I believe that the second series of analyses (controlling for age) indicate the more precise set of results. Consistent with this last set of findings, additional results across the two sets of analyses show that prior smoking propensity positively predicted ex-smokers' propensity to eat since quitting (as it did for their smartphone use propensity), which is consistent with the well-established finding that people who quit smoking use food to compensate for the stress-relief previously provided by cigarettes (e.g., Sussman and Black 2008). Given that prior attachment to smoking was positively related to ex-smokers' attachments to both eating *and* smartphone use since quitting, one interpretation of these results is that ex-smokers rely on food and their phone in similar (but not identical) ways to compensate for the stress relief that used to be achieved through smoking. On the other hand, no relationship was found between ex-smokers' prior smoking propensity and their drinking propensity since quitting, and controlling for drinking propensity did not change any key patterns of results, which suggests that alcohol might not contain the properties that commonly underlie cigarette, smartphone and food consumption.

In sum, consistent with the results of Study 3, the findings of Study 4 provide further support for the hypothesis that to alleviate stress, consumers may seek out and engage with their smartphone in the same way that a smoker would a cigarette, or a child would a pacifier (H2b).

3.6. Essay 1 General Discussion

The results across the four studies of Essay 1, including three lab studies and one large correlational study, provide convergent evidence for the thesis that smartphones often serve as an attachment object for many consumers. Findings from two lab studies (Studies 1-2) show that smartphones elicit two key psychological consequences associated with attachment objects to a greater extent than a comparable device providing the same information. Specifically, relative to engaging with one's laptop and holding the content consumed constant, engaging with one's smartphone (1) distinctly increases felt comfort (H1), and (2) provides greater relief from feelings of discomfort due to stress (H2a). Moreover, across both studies device usage did not impact any of the other types of emotional feelings, suggesting that rather than a change in affect in general, smartphone use impacts one's sense of comfort in particular, which is critical to the notion that the device acts as an attachment object.

Building off of the palliative effects revealed in the first two studies, Studies 3-4 show that smartphones also elicit a behavioral response definitionally evoked by attachment objects: namely, that children actively seek out and engage with their attachment object in moments of stress due to its stress-relieving properties (H2b). Consistent with this, the third lab study (Study 3) shows that participants under high stress exhibited a stronger drive towards their smartphone over other available objects, and engaged with the device more intensely, than participants who completed a low-stress task. Finally, lending real world support for my hypothesis, a large correlational study (Study 4) finds that consumers' emotional and behavioral attachment to their smartphone is especially pronounced among those particularly susceptible to stress:

people who recently quit smoking (vs. current smokers). Taken together, these findings suggest that smartphones might indeed act as an "adult pacifier" for many consumers.

3.6.1. Contributions of the Current Research

Although some research within the marketing modeling literature has begun to examine the implications of mobile platforms (e.g., Bart et al. 2014; Ghose et al. 2013), there is a surprising dearth of research on the psychological aspects of mobile consumer behavior. The psychological research that does exist has been conducted outside of marketing and focuses on "smartphone addiction" in particular, primarily describing the psychographic factors associated with excessive use of the device (e.g., Bianchi and Phillips 2005; Walsh et al. 2011). In Essay 1 I investigated the particular nature of consumers' relationship with their smartphone across three controlled lab experiments, and have provided direct experimental evidence that the device can serve as an attachment object for many consumers (Studies 1-3). This idea is further supported by the results of a large correlational study conducted amongst ex-smokers and current smokers (Study 4).

Notably, my results also show that using one's smartphone can confer *positive* emotional benefits, demonstrating that the consequences of smartphone use are not solely negative as the research on "smartphone addiction" might suggest. Specifically, as discussed earlier, the extant literature on smartphone addiction largely focuses on the negative outcomes associated with excessive use of the device, such as heightened psychological distress (Beranuy et al. 2009), sleep disturbances (Thomee et al. 2011), and anxiety (e.g., Cheever et al. 2014). In contrast, my research suggests that at times many consumers actually rely on their smartphone to provide a set of *positive* emotional outcomes, namely, a heightened feeling of comfort and relief from stress.

More specifically, I propose that insight into the psychology of smartphone use can be found in the developmental research on attachment theory. I advance the proposition that engaging with one's smartphone can elicit the same psychological and behavioral responses as a pacifier or security blanket would for a child. Consistent with this Adult Pacifier Hypothesis, I show that engaging with one's smartphone confers a greater feeling of comfort and faster recovery from stress relative to comparable devices, and that, in moments of stress, people actively seek out their smartphone over other available objects – all of which are defining characteristics of attachment objects.

It is important to note that the attachment theory literature focuses on the relationship *young children* form towards their possessions (e.g., Bowlby 1982). While a body of research exists on *adult* attachment theory, the vast majority of this work focuses on the interpersonal attachments adults form to other people, such as a significant other or close friend (e.g., Crowell and Treboux 1995; Hazan and Shaver 1987). The few papers that do exist on non-social objects mostly describe adults' attachment to their possessions as part of a clinical disorder such as depression or OCD (e.g., Nedelisky and Steele 2009; see Keefer et al. 2012 for one exception). The results of Essay 1 therefore contribute to these bodies of research by demonstrating that adults may *commonly* rely on their smartphone to provide the psychological benefits that a pacifier confers to a child.

Finally, given my Adult Pacifier Hypothesis, one question that naturally follows is whether adults similarly relied on attachment objects *before* the introduction of the smartphone. Anecdotally, one can think of a number of possessions that may provide psychological comfort and security for some adults, such as a lucky charm, rabbit's foot or prayer beads. Consistent with this, nine years before the introduction of the iPhone Bachar et al. (1998) found that 22 percent of *normal* adolescents still relied on their attachment object from childhood. My research suggests that, whereas in the past attachment objects might have been more idiosyncratic across individuals (e.g., special keychain, childhood teddy bear), today smartphones are becoming an increasingly universal attachment object for consumers.

These results also bear important practical implications for firms. Over the past few years, marketers have been responding to the "mobile revolution" by diverting more of their budgets to mobile advertising (eMarketer 2015) and attempting to pursue "mobile-first" digital strategies (Forbes 2015). As consumers continue to increase the use of their smartphones in lieu of other devices, firms must endeavor to develop a richer understanding of the consumer psychology of smartphone use. The findings of Essay 1 provide insight into this psychology by shedding light on the unique emotional mindset that consumers undergo while on the device. For one, smartphone brands and carriers can integrate the notion of the "adult pacifier" into their advertising campaigns. Whereas mobile phone companies focus their persuasive messaging almost exclusively on features available on the device (e.g., battery life, display resolution), my findings suggest that marketers should additionally emphasize the psychological feeling of comfort and reassurance that comes with having one's smartphone in hand. To the extent that people are more open to processing information when in a relaxed state (see Pham, Hung, and Gorn 2011), retailers could also leverage this insight by investing more aggressively in beacons and other technology that enable them to reach customers on their smartphones in-store. My findings could also potentially help explain why mobile advertising is often more effective than web-based advertising (Miratech 2012) – specifically, this could be not just because of the location-based targeting capabilities available on the device, but also because messaging is more emotionally persuasive when read on one's smartphone.

3.6.2. Future Research Directions

The studies of Essay 1 provide convergent evidence that smartphones elicit the behavioral and psychological consequences associated with attachment objects. After establishing that smartphones can indeed act as an attachment object for many consumers, in my future work I plan to focus on the particular antecedents that makes smartphones particularly amenable to becoming attachment objects. For example, to what extent do the available functionalities drive consumers' attachment to the device? To test this, in a future study I plan to randomly assign participants to either engage with a smartphone or laptop, and also randomly assign them to engage with their own device or an identical device belonging to the experimenter. Specifically I will rent an iPhone 6 and a 13" Macbook Pro as the experimental devices, and recruit participants on the basis that they own each of these particular models, which they will be required to bring to the study. I predict that participants who use their own smartphone will show a greater increase in comfort than participants engaging with a *functionally identical* phone belonging to the lab, whereas this difference will be less pronounced for laptops. This pattern of results would suggest that consumers are attached to their smartphone per se, over and above the functionalities available on the device (vs. PCs). This prediction is based on a classic attachment theory finding that children show a strong preference for their own security blanket relative to an otherwise identical blanket belonging to someone else (e.g., Hood and Bloom 2008; Weisberg and Russell 1971).

Additionally, as noted earlier I believe that smartphones are amenable to becoming attachment objects because of their functionalities *in combination* with two physical properties definitional of attachment objects: their tactile nature, and portability for use across various contexts. To investigate this idea, I plan to compare how users interact with their smartphones relative to another comparable device containing some similar physical properties: tablets PCs (e.g., iPads). Specifically, in a future study I will randomly assign participants to use either their smartphone, laptop or tablet, holding the content consumed constant, and measure how they feel before and after using their device. On the one hand, similar to smartphones but unlike PCs, tablets contain a highly tactile nature. On the other hand, similar to PCs, tablets are not nearly as portable as smartphones. Building on this, I predict that holding the content consumed constant, tablets will increase participants' felt comfort to a greater extent than PCs, but to a lesser extent than smartphones.

Finally, I am also interested in testing the downstream consequences of the effects documented in this essay. For example, do consumers' emotional attachments to their smartphones lead them to be more receptive to advertising on the device (vs. other devices)? Are certain types of advertising messages (e.g., emotional vs. cognitive content) more effective on smartphones relative to other devices? These are questions that I additionally plan to investigate in my future stream of research.

CHAPTER 4
ESSAY 2: SMARTPHONE USAGE AS EMOTIONAL EXPRESSION

4.1. Introduction

The past decade has seen the production of an unprecedented amount of user-generated content, such as online customer reviews and social media content. According to one market research study (Deloitte 2016), 81% of consumers utilize user-generated content in forming their purchase decisions. As consumers continue to rely on online reviews and social media content created by other customers, while also sharing their own experiences online, firms and marketers are responding by pursuing various “digital listening” efforts to monitor customer opinions. For example, a growing number of companies are using software to track opinions expressed on social media (e.g., Crimson Hexagon) in an attempt to better understand consumer experiences and identify online content that could be particularly influential.

Meanwhile, marketers are also adjusting to one of the biggest transitions in recent years – the so-called “mobile revolution” (Ackley 2015). Consumers are now spending a greater amount of time on their smartphone than any of their other technological devices (Comscore 2015), and 80% of adults worldwide are forecast to own a smartphone within the next few years (*The Economist* 2015). Recent market research studies report that one in five American adults accesses the Internet primarily through their smartphone (Pew Research 2015), and the majority of digital media time is now spent on mobile (Comscore 2014). This shift away from personal computers (PCs) as the dominant online platform represents a major change in consumer behavior, and in response firms are increasingly pursuing “mobile first” marketing strategies. As an illustration of this, marketers are now spending more on mobile advertising than on web-based advertising worldwide, with more than $100 billion spent on mobile advertising in 2016 alone (eMarketer 2014).

Because the creation of massive amounts of user-generated content has coincided with the "mobile revolution," an ensuing trend has recently emerged: 67% of owners now use their smartphones to share content online (Pew Research 2015). As consumers create more and more content online, while also shifting their digital activities away from PCs toward smartphones, firms are faced with an important question: Are smartphones simply an additional platform for creating user-generated content, or is the device actually changing the nature of the content being generated? In Essay 2 I examine this question.

The main purpose of Essay 2 is to demonstrate that smartphone (vs. PC) use is altering the nature of user-generated content, and to shed light on the underlying driver of this effect. My results consistently indicate a fundamental difference in the content produced across devices – namely, that content generated on smartphones is generally more emotional, specifically containing more positive emotionality, than PC-generated content. In this research I use the term "emotionality" to refer to language conveying affective information (e.g., Berger and Milkman 2012; Ludwig et al. 2013), such as "love," "disgust," "reassuring," and "embarrassed." I distinguish general emotionality from the valence of the emotionality – namely, positive vs. negative emotionality – and investigate these two issues separately. A second corollary objective is to examine how differences in content emotionality change the overall impact of user-generated content. My results show that smartphone-generated (vs. PC-generated) content is more impactful in terms of its persuasiveness and overall popularity, and that these differences are to an extent driven by the greater emotionality of smartphone-generated content. I demonstrate these effects in a series of nine experimental and field studies. In the next section, I provide a summary of my predictions as well as a general description of the studies reported in Essay 2.

4.1.1. Overview of Studies

I predict that content generated on a smartphone will be generally more emotional than PC-generated content (H3a), and that this difference will be driven by a heightened tendency to describe the gist of one's experience while writing on the device (H3b). I also predict that the greater emotionality of smartphone-generated content will be mostly comprised of positive (vs. negative) affect (H4). Finally, I predict that as a result of its greater emotionality, smartphone-generated content will be more impactful than PC-generated content in terms of the persuasiveness and popularity of the content (H5). Consistent with recent calls for greater practical relevance of academic marketing research (Inman 2012; Pham 2013), I test these hypotheses across nine experimental and field studies. Specifically, three of these are field studies – using data from a popular online restaurant review forum (Study 1), one of largest social media networks (Study 7), and a corporate social media platform (Study 9) – and the remaining six studies are controlled experiments (Studies 2-6 and 8). Across the studies (other than Studies 2 and 8), I conduct text analyses using natural language processing software to assess differences in the amount of emotional language contained in smartphone-generated vs. PC-generated content. Significant differences in the proportion of emotional words indicate cross-device differences in content emotionality.

Specifically, Study 1 establishes the existence of the basic phenomena in the marketplace by capitalizing on field data from a popular online customer review forum. This study documents the propositions that user-generated content written on smartphones contains greater emotionality in general and more positive emotionality in particular than content generated on PCs. The results also provide initial evidence that differences in emotionality are driven by the length of the content. Study 2 shows that the emotionality measured through text analysis in Study 1 also holds in terms of subjective reader perceptions of the content.

Next I demonstrate the causal effect of smartphone vs. PC use on content emotionality across four controlled experiments, and provide further support for the proposed explanation for the effect. Studies 3 and 4 show that participants assigned to use their smartphones to write a review – of a recent restaurant experience in Study 3, or of a particular on-campus dining hall in Study 4 – produced content that contained greater emotionality, and specifically greater positive emotionality, than participants assigned to use their PCs. Across these studies I also provide consistent evidence that the greater emotionality of smartphone-generated content is mediated by the relative brevity of the content, which serves as a proxy for the tendency to focus on the gist of one's experience. Study 5 directly tests the proposed explanation for differences in emotionality, showing that the effect is attenuated when the length of the content is held constant across devices. Study 6 refines the boundaries of the observed differences in valence, demonstrating that content written on smartphones (vs. PCs) still contains more positive emotionality even when all participants were instructed to review an explicitly positive experience, but that no differences in negativity are revealed when participants were assigned to review a negative experience. In the second field study (Study 7), I show that all of the observed effects generalize to user-generated content posted on Twitter, thereby demonstrating that the phenomena extend beyond the domain of online customer reviews.

Focusing on the fifth hypothesis, the final two studies demonstrate that smartphone-generated content can be more impactful than PC-generated content in terms of its persuasiveness (Study 8) and overall popularity (Study 9). Study 8 shows that participants expressed greater interest in trying restaurants described in smartphone-generated reviews vs. PC-generated reviews, and that this effect was driven by the greater perceived emotionality of the content. Finally, the third field study (Study 9) shows that, to an extent, cross-device content differences may still hold in a corporate social media platform, and that smartphone-generated content received more "votes" than PC-generated content.

4.2. Study 1 – Field Study: Differences in Content Across Devices

The purpose of the first study was to establish the existence of the basic phenomenon and demonstrate the effects in a real marketplace context (see Inman 2012; Pham 2013). As a primary setting for testing my hypotheses, I focus on online restaurant reviews, a particularly relevant consumer context. Specifically, I analyze customer-generated reviews from UrbanSpoon.com, which was a popular restaurant information and recommendation service at the time of data collection (and has since been acquired by the recommendation service Zomato). This was also the data source explored by Lurie et al. (MSI 2014). UrbanSpoon provides a uniquely pertinent setting for my research because it contained a device label indicating whether reviews were written on mobile devices (vs. PCs), with traffic split roughly in half between mobile and web-based users.

In 2011 alone the company saw 28 million visits per month, with its traffic consisting of 10 million monthly visits from mobile devices (TechCrunch 2012). The relative equivalence of traffic across devices therefore allows for a meaningful exploration of differences in content generated on smartphones as compared to PCs. I predicted that (a) smartphone-generated content would be more emotional than PC-generated content, (b) this greater emotionality would be predominantly positive (rather than negative), and (c) this greater emotionality would be driven by a tendency to generate shorter content on the device.

4.2.1. Data

At the time that the data were extracted, UrbanSpoon had a database of more than 300,000 restaurants and operated across the United States as well as in five other English-speaking countries. In keeping with repeated calls for greater evidence of replicability of findings in consumer research (Pham 2013) and in the social sciences in general (Open Science Collaboration 2012), I tested the reliability of our findings across different markets by including two replication datasets.

The first replication set contained reviews of New York City (NYC) restaurants, for which 39,980 reviews were extracted from 2011 through 2014 across 9,270 restaurants from the UrbanSpoon website (with the technical help of a colleague). Of the total reviews in the first replication set, 23,365 posts were written from PCs and 16,615 posts were written from smartphones (41.6%). The second replication set contained reviews of restaurants in Portland, Oregon, which was selected because of its distance from New York (East Coast vs. Pacific Northwest) as well as its smaller population size (2013 population in Portland: 609,456 vs. New York: 8.41 million). 29,082 UrbanSpoon reviews were extracted from 2010 through 2014 across 3,924 restaurants in Portland. Of the total reviews in the second replication set, 16,281 posts were written from PCs and 12,801 posts were written from smartphones (44%). Across both cities, each review contained the text of the review, the name of the restaurant reviewed, the date on which it was posted, and the device from which it was posted (mobile vs. PC).

4.2.2. Method

Content Analysis. In order to test for differences in content emotionality, I conducted text-based content analyses on the posts. Specifically, throughout the studies reported, content was coded using the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker et al. 2015). A tool for applied natural language processing, LIWC has been used to analyze many types of texts, including online texts such as blog posts, instant messages, and customer reviews (e.g., Cohn, Mehl, and Pennebaker 2004; Ludwig et al. 2013; Slatcher and Pennebaker 2006).

Since my research focuses on increased emotionality due to smartphone use, I tested for cross-device differences in the "affective processes" linguistic category, which consists of 1,393 words classified by human coders as emotional (e.g., "love," "nice," "cried"). This linguistic category is composed of two subcategories: one for positive emotional words (620 words; e.g., "happy"), another for negative emotional words (744 words; e.g., "hurt"). I also added a third subcategory: a remaining set of words coded as neither positive nor negative that I categorized as "neutral emotional words" (e.g., "basic"). The first dependent variable of interest was the proportion of emotional words in the content (i.e., the sum across the three subcategories). The other main dependent variables of interest encompassed the emotional-valence subcategories: the proportions of positive, negative, and neutral emotional words.

Finally, I note that throughout this essay I use the word count of the reviews (i.e., review length) as a proxy for the degree to which consumers described the overall gist of their experiences. Specifically, I interpret a lower word count (i.e., shorter review) as pointing to a greater focus on the overall gist of an experience.

4.2.3. Results

Content Emotionality and Emotional Valence. To test for differences in content emotionality across devices, I ran a mixed ANOVA with device (smartphone vs. PC) and replication city (New York vs. Portland) as between-subjects factors and type of emotion (positive, negative, and neutral) as a within-subject factor[7]. The results confirm a non-significant device × type of emotion × replication city interaction ($F(2, 138116) = 1.56$, *NS*; see Table 6 for means), indicating that the effects reported below are robust across geographical markets. I therefore report the results collapsed across the replication sets hereafter. Next, a main effect of type of emotion ($F(2, 138116) = 49619.351$, $p < .001$) reveals that consumers used a greater proportion of positive emotional words ($M = 8.87\%$) than negative emotional words ($M = 1.39\%$; $F(1, 69058) = 41179.88$, $p < .001$) and neutral words ($M = 0.34\%$; $F(1, 69058) = 70591.75$, $p < .001$). These findings are

[7] Tests of normality (a Kolmogorov-Smirnov test for studies with at least 50 participants per condition, and a Shapiro-Wilks test for studies with less than 50 participants per condition) were conducted for the seven studies with proportion-based dependent measures. The results across these studies indicated that the proportions of emotional and positive emotional words deviated from a normal distribution for smartphone-generated and PC-generated content. However, after performing an arcsine square root transformation on these measures, the results of additional mixed ANOVAs confirm that the pattern of results reported is robust across analyses. The only exceptions are that, after the transformation, the results are no longer significant for Study 9, and the effect of device type on positivity falls from $p < .05$ to $p < .09$ in Study 4.

thus consistent with the greater incidence of positive content in online WOM shown in prior work (e.g., East et al. 2007).

More importantly, the results reveal a main effect of device on the overall emotionality of the reviews, such that reviews written on smartphones contained a greater proportion of emotional words (M = 12.77%) than reviews written on PCs (M = 8.43%; $F(1, 69058) = 4256.45$, $p < .001$). This finding supports my main thesis that relative to content generated on PCs, content written on smartphones is more emotional (H3a).

In regard to differences in the valence of this emotionality, the results identify a significant device × type of emotion interaction ($F(2, 138116) = 2188.594$, $p < .001$). Simple effect tests reveal that smartphone-generated content contained a greater proportion of positive emotional words (M = 10.72%) than did PC-generated content (M = 7.02%; $F(1, 69058) = 3334.972$, $p < .001$). Relative to PC-generated content, smartphone-generated content also included a greater proportion of neutral emotional words ($M_{\text{Smartphone}} = 0.42\%$ vs. $M_{\text{PC}} = 0.27\%$; $F(1, 69058) = 211.95$, $p < .001$) and negative emotional words ($M_{\text{Smartphone}} = 1.64\%$ vs. $M_{\text{PC}} = 1.14\%$; $F(1, 69058) = 324.32$, $p < .001$). However, proportions of neutral and negative emotional words were much lower across devices. These results indicate that the greater emotionality of smartphone-generated content is predominantly driven by greater positive affect (H4).

Mediating Effect of Brevity. To test the proposition that the greater emotionality of smartphone-generated content is driven by the tendency to focus on the gist of one's experiences (H3b), I used the word count of the reviews as a proxy for the focus on gist (with lower word count pointing to a greater emphasis on gist). A one-way ANOVA with device as a between-subjects factor and word count as the dependent measure confirmed that smartphone-generated reviews were significantly shorter (M = 35.47 words) than PC-generated reviews (M = 88.64 words; $F(1, 69058) = 8488.34$, $p < .001$). To test for mediation, I used Preacher and Hayes' (2004) bootstrapping technique (PROCESS-Model 4) with 95% confidence intervals using 1,000 resamples. The results reveal an indirect effect ($\beta = .74$, SE = .01, 95% CI = [.72, .77]), confirming that the effect of device on content emotionality is partially mediated by the length of the reviews (with briefer reviews resulting in more emotional content). These results are consistent with my proposition that, since users tend to produce shorter content on their smartphones (vs. PCs), they tend to describe the overall gist of their evaluations, thereby privileging the inclusion of more emotional content (H3b).

Temporal Proximity as an Alternative Explanation. Although the results of the mediation analysis are consistent with the proposed explanation, a potential alternative account for the results is that smartphone-generated reviews are more emotional simply because, as speculated by Lurie et al. (MSI 2014), they are more likely to be written shortly after a consumption experience, whereas PC-generated reviews are more likely to be written in retrospect. In other words, consumers writing reviews on their smartphones might use more emotional language because they write the reviews in real time, which would render their feelings more salient or "hot" (e.g., Metcalfe and Jacobs 1998; Metcalfe and Mischel 1999).

Examining this, I first found that smartphone-generated reviews included a *smaller* proportion of present-focused words compared to PC-generated reviews. However, smartphone-generated reviews also contained a smaller proportion of past-focused words (see Table 6). To investigate this further, I conducted a mixed ANCOVA using the same factors as in the main analysis while also controlling for the temporal markers in the reviews: namely, the proportions of present-focused, past-focused, and future-focused words. After controlling for temporal markers in the content, I determined that smartphone-generated content still contained a greater proportion of emotional words than PC-generated content on average (LS-means: $M_{\text{Smartphone}}$ = 12.47% vs. M_{PC} = 8.67%; F(1, 69055) = 3570.17, *p* < .001). The results again revealed a device × type of emotion interaction (F(2, 69055) = 1684.06, *p* < .001) such that smartphone-generated reviews still included a greater proportion of positive emotional words (LS-means: $M_{\text{Smartphone}}$ = 10.42% vs. M_{PC} = 7.26%; F(1, 69055) = 2689.32, *p* < .001), negative emotional words (LS-means: $M_{\text{Smartphone}}$ = 1.64% vs. M_{PC} = 1.13%; F(1, 69055) = 341.56, *p* < .001), and neutral emotional words (LS-means: $M_{\text{Smartphone}}$ = 0.4% vs. M_{PC} = 0.28%; F(1, 69055) = 144.14, *p* < .001). These effects also hold for the New York and Portland replication sets when analyzed separately.

The findings that smartphone-generated reviews included a smaller proportion of present-focused words, and that the effects of interest still hold when controlling for temporal markers provide evidence against the alternative explanation that smartphone-generated reviews are more emotional simply because they are more likely to be written during the restaurant experience (vs. PC-generated reviews). As an additional robustness check, I used a different method to control for variations in time elapsed between the dining experience and the creation of the review. Specifically, I created "temporal conditions" that attempted to equate the reviews across devices in terms of the proximity to the consumption experience (see Table 6). For example, in one analysis, I only analyzed posts that contained the phrase "last night" (N = 736). As a check, this subset of posts shows that PC-generated content still contains a greater proportion of past-focused words ($M_{Smartphone}$ = 8.09% vs. M_{PC} = 9.35%; $F(1, 732) = 17.87$, $p < .001$), but that there are no longer differences in the proportion of present-focused words ($F < 1$).

The results confirm that even among this subset of reviews, smartphone-generated content still contained a greater proportion of emotional words than PC-generated content ($M_{Smartphone}$ = 8.09% vs. M_{PC} = 6.58%; $F(1, 732) = 20.6$, $p < .001$). A significant device × type of emotion interaction finds that relative to PC-generated reviews, smartphone-generated reviews still consisted of a greater proportion of positive emotional words ($M_{Smartphone}$ = 6.69% vs. M_{PC} = 5.26%; $F(1, 732) = 16.74$, $p < .001$). The reviews no longer differed in the proportions of negative emotional words or neutral emotional words (largest $F(1, 732) = 1.82$, *NS*). Taken together, these results provide suggestive evidence that the greater emotionality of smartphone-generated content is not simply driven by differences across devices in temporal proximity to the experience. I provide further evidence in Study 3, where this possibility is ruled out through a controlled lab experiment.

[Insert Table 6]

Given the correlational nature of this data, it is possible that the observed differences in content emotionality are influenced by a respondent self-selection bias. To explore this, I conducted a repeated measures t-test among the 909 unique users in the dataset who had used both their mobile and PC devices at least once to post reviews on UrbanSpoon. The results confirm that the reported effects of device on content emotionality ($M_{Smartphone}$ = 11.2% vs. M_{PC} = 8.55%; $t(908) = 9.80$, $p < .001$) and positive emotionality ($M_{Smartphone}$ = 9.83% vs. M_{PC} = 7.49%; $t(908) = 8.63$, $p < .001$)

still hold. Thus, controlling for individual-level factors that may underlie self-selection does not affect the results.

4.2.4. Discussion

The results of Study 1 provide initial marketplace evidence for my prediction that smartphone use promotes the creation of more emotional content (H3a), and particularly more positive emotional content (H4), relative to the use of a PC. This pattern of results is robust across bicoastal US markets, and still holds after controlling for potential differences in temporal proximity between the writing of the review and the restaurant experience, which mitigates the possibility that smartphone-generated content is more emotional simply because of the "real-time" nature of smartphones (vs. PCs). Instead, the results of a mediation analysis are consistent with the proposition that the greater emotionality of smartphone-generated content is largely driven by consumers' tendency to focus on the gist of their experiences on the device, and thus preserve the most essential – and often more emotional - information about their consumption experiences (H3b).

One caveat of Study 1 is that I used text analysis software to examine a particular measure of emotionality—the proportion of emotional words in the text. Although this measure has the benefit of being grounded in prior literature (e.g., Ludwig et al. 2013; Slatcher and Pennebaker 2006), use of this objective linguistic metric begs the question of whether the observed content differences are actually *perceived* by other consumers when reading the reviews. In Study 2 I test whether these results replicate with human coders.

4.3. Study 2: Perceived Emotionality of Content

The text analysis software used in Study 1 assumes that it is the proportion (rather the raw number) of emotional words that determines the degree of emotionality in the text. While this is indeed the common practice in analyses using the LIWC natural language processing tool (e.g., Berger and Milkman 2012; Ludwig et al. 2013), it is still possible that reviews containing different total word counts (i.e., longer vs. shorter reviews) but comparable numbers of emotional words actually convey similar degrees of perceived emotionality to readers. To test whether my results are specific to the LIWC (2015) dictionary and the proportion-based measures it provides, in Study 2 I presented a set of UrbanSpoon restaurant reviews from Study 1 to a separate group of participants and asked them to rate how emotional, positive, and negative they perceived each review to be. Unbeknownst to them, half of the presented reviews had been written by UrbanSpoon users on smartphones, and half had been written on PCs. This allowed me to test whether the effects observed in Study 1 using the proportion-based measures of emotionality provided by the text analysis software hold in terms of subjective reader perceptions, independent of any knowledge of the originating device.

4.3.1. Method

Overview and Design. Two hundred and eighteen respondents from the MTurk panel (50.9% women) participated in the study, in which the originating device of the review (smartphone vs. PC) was manipulated within-subject. Each participant was presented with a set of UrbanSpoon reviews – half of which had been written by customers on smartphones and the other half of which had been written on PCs – and were asked to rate each review along a number of dimensions (without knowledge of the originating device). To mitigate potential review-specific effects, each participant received a random selection of two smartphone-generated and two PC-generated UrbanSpoon reviews. Prior to the main experiment, fifty smartphone-generated reviews and fifty PC-generated reviews were selected from the UrbanSpoon reviews in Study 1 to be representative of content that consumers would actually write on smartphones and PCs. Specifically, an analysis prior to the main study confirmed that the fifty smartphone-generated and fifty PC-generated reviews in Study 2 did not differ from the smartphone-generated and PC-generated reviews in Study 1 in terms of word count and the proportions of emotional, positive emotional, negative emotional, and neutral emotional words. (For the comparison of the content characteristics of the subset of reviews used in Study 2 vs. the characteristics of the reviews in Study 1, see Table 7.)

[Insert Table 7]

Procedure and Measures. Participants were presented with a set of four randomly selected UrbanSpoon reviews (two generated via smartphone and two generated via PC) and were asked to evaluate each review. Participants were not aware that there were any differences in originating device. To measure the perceived emotionality of the content, participants were asked to indicate the extent to which they agreed with three statements on a seven-point scale (1 = "Not true at all" to 7 = "Very true"): "When I read this review, I can sense how the writer felt emotionally," "This review is analytical" (reverse-coded), and "This review is unemotional" (reverse-coded). Responses to these three items were averaged to create an index of perceived emotionality ($\alpha = .59$). To measure the perceived positivity of the content, participants were asked to rate the extent to which three discrete emotions (selected from Shaver et al. 1987) were reflected in the review (on a scale of 1 = “Not true at all” to 7 = “Very true”): positivity, happiness, and excitement. Responses to these three items were averaged to create an index of perceived positivity (α = .92). I also measured the degree to which negativity, anger, and disgust were expressed in the reviews, which were averaged to calculate an index of perceived negativity (α = .94).

4.3.2. Results

To test my predictions, I ran a repeated measures ANOVA with originating device as the within-subject factor and perceived emotionality, perceived positivity, and perceived negativity as the dependent measures. Consistent with the results of Study 1, the results reveal a main effect of originating device, such that smartphone-generated reviews were perceived as more emotional (M = 5.02) than PC-generated reviews (M = 4.35; $F(1, 435) = 77.21$, $p < .001$). Smartphone-generated reviews were also rated as more positive (M = 4.62) than PC-generated content (M = 3.99; $F(1, 435) = 24.75$, $p < .001$). Finally, consistent with the findings of Study 1, participants did not report differences in perceived negativity across the reviews ($M_{\text{Smartphone}} = 2.67$ vs. $M_{\text{PC}} = 2.65$; $F < 1$). Taken together, these results offer convergent evidence for the effects observed in Study 1.

4.3.3. Discussion

The results of Study 2 demonstrates that the pattern of results observed in the first field study is robust not just across geographical markets, but also across objective as well as subjective measures of emotionality and emotional valence. These results therefore confirm that the effects observed in Study 1 are not merely an artifact of the proportion-based measures of emotionality and emotional valence provided by the text analysis tool, but instead are also perceptible to customers who may be reading the reviews. Further, since participants were not informed about whether the reviews had been written by other customers on smartphones or PCs, these findings suggests that participants in Study 2 were responding to *inherent* differences in the content itself. Although the findings of Studies 1 and 2 are consistent, these results are essentially correlational. In Study 3 I examine whether the observed effects hold in a controlled experimental setting in which participants are randomly assigned to write reviews from their smartphones vs. PCs.

4.4. Study 3: The Causal Effect of Smartphone Usage on Content Emotionality (Restaurant Study)

The purpose of the third study was to provide direct experimental evidence for the effects observed in Study 1. I therefore randomly assigned participants in Study 3 to write a review of their most recent dining experience on either their smartphone or their PC. The experimental setting of this study thus allowed me to test for content differences across devices while circumventing potential issues of self-selection or temporal proximity that might have been faced in Study 1. I predicted that, even when written by participants who were randomly assigned to a device, reviews generated on smartphones would contain greater emotionality (H3a), and specifically greater positive emotionality (H4), than reviews written on PCs. Moreover, I predicted that the effect of smartphone use on increased content emotionality would again be driven by the tendency to generate shorter content on the device (H3b).

4.4.1. Method

Under the guise of pretesting material for a future study, 384 US-based participants from the MTurk panel were asked to write a review of a recent restaurant experience. Specifically, participants were randomly assigned to one of two conditions: a treatment condition in which they were asked to use their smartphone to write the review, or a control condition in which they were asked to use their PC to write the review. To ensure that participants were using the devices to which they were assigned, two device checks were included in the study. First, a self-reported verification question asked participants to confirm that they were using their assigned device. Second, and more importantly, an unobservable check was embedded throughout the survey that recorded the brand and model of the device being used to complete the study. Based on the results of the checks, 15 participants were excluded for having falsely reported using their assigned devices. After removing these reviews from the dataset, 369 responses remained for analysis (49.3% women).

To justify asking participants to use their randomly assigned device, the study presented the following cover story in the smartphone (*PC*) condition:

> We have asked you to complete this study on your smartphone *(PC)* because we need to determine whether our surveys are appropriately optimized for mobile devices *(personal computing devices)*. Therefore, in order to participate in this research, YOU MUST BE VIEWING THIS SURVEY ON YOUR SMARTPHONE *(PC)*.

After agreeing to participate, participants were presented with a link and were asked either to copy it to their smartphone or follow it on their PC, depending on the condition.

The link led participants to an external page in which they were to write their review. The page contained an empty text box with the following instructions: “In the space below, please write a review of a restaurant experience (1 paragraph). Specifically, please think of a restaurant that you visited at least one month ago but within the past year." Restricting the range of possible dates allowed me to mitigate potential differences in the recency of the reported experiences across conditions. Participants were then asked to write the name of the restaurant, their review of the restaurant, and to indicate approximately when the restaurant experience occurred (on a scale of 1 = "A little over a month ago" to 5 = "10 months – 1 year ago").

After completing their review, participants were redirected to a final page where they were asked a series of demographic questions. Additionally, to address the unlikely possibility that, despite random assignment, differences in content emotionality might be driven by preexisting differences in online review behavior, participants were asked to indicate the extent to which they agreed with the following statements: "I often post reviews of restaurants online (e.g. on Yelp)," "I often post reviews of products online (e.g. on Amazon)," "I often use my smartphone to post reviews online," and "I often use my PC to post reviews online" (on a 1 = "Not true at all" to 5 = "Very true" scale). Responses to these four items were averaged into an index of online review behavior (α = .84).

4.4.2. Results

Preliminary Analyses. Two sets of findings confirm that Study 3 effectively removed any potential differences across devices in terms of temporal proximity to the dining experience. First, participants across conditions did not differ in terms of the reported recency of the restaurant experiences they had reviewed ($M_{Smartphone}$ = 1.46 vs. M_{PC} = 1.61; $F(1, 367) = 2.01$, *NS*). Moreover, unlike in Study 1, the reviews contained no differences in the proportion of past-tense ($M_{Smartphone}$ = 5.39% vs. M_{PC} = 6.29%; $F(1, 367) = 1.52$, *NS*) or present-tense words across devices ($M_{Smartphone}$ = 6.53% vs. M_{PC} = 6.64%; $F(1, 367) = .03$, *NS*).

Unexpectedly, despite random assignment participants in the smartphone condition were somewhat younger ($M_{Smartphone}$ = 31.3 years old vs. M_{PC} = 37.3; $F(1, 367) = 17.32$, $p < .001$) and engaged more frequently in online review behavior than those in the PC condition ($M_{Smartphone}$ = 2.31 vs. M_{PC} = 1.89; $F(1, 367) = 11.88$, $p < .001$). However, additional analyses (reported in the subsequent section) confirm that the main results still hold after controlling for participants' age as well as online review behavior.

Content Emotionality and Emotional Valence. To test for differences in content emotionality across conditions, I ran a mixed ANOVA with device as a between-subjects factor and type of emotion as a within-subject factor. First, as in the prior studies, I found a main effect of type of emotion ($F(2, 734) = 423.52$, $p < .001$) such that on average participants used a greater proportion of positive emotional words (M = 8.94%) than negative emotional words (M = 0.81%; $F(1, 368) = 444.7$, $p < .001$) and neutral emotional words (M = 0.42%; $F(1, 368) = 541.71$, $p < .001$). More importantly, a significant main effect of device reveals that, as predicted, participants who wrote the review on their smartphone used a greater proportion of emotional words (M = 11.88%) than participants who wrote the review on their PC (M = 8.47%; $F(1, 367) = 21.37$, $p < .001$). An additional analysis confirms that this effect still holds after controlling for participants' age and online review behavior ($F(1, 365) = 22.22$, $p < .001$). These findings closely replicate the results of Studies 1-2, thereby providing further support for H3a.

In regard to differences in valence, the results reveal a significant device × type of emotion interaction ($F(2, 734) = 15.5$, $p < .001$). As expected, a simple effects test shows that smartphone-generated content contained a significantly greater proportion of positive emotional words (M = 10.55%) than PC-generated reviews (M = 7.33%; $F(1, 367) = 18.7$, $p < .001$). Relative to PC-generated content, smartphone-generated content also included a greater proportion of negative emotional words ($M_{Smartphone}$ = 1.03% vs. M_{PC} = 0.6%; $F(1, 367) = 4.22$, $p < .05$). However, as in Study 1 the proportion of negative emotional words was much lower across devices**.** Finally, the reviews no longer differed in the proportion of neutral emotional words across devices ($F(1, 367) = 3.14$, *NS*). This pattern of results provides further support for the prediction that relative to PC-generated content, the greater emotionality of smartphone-generated content is predominantly driven by positive emotionality (H4).

Mediating Effect of Brevity. As in Study 1, smartphone-generated reviews contained fewer words (M = 41.1 words) than reviews written on PCs (M = 58.7 words; $F(1, 367) = 18.17$, $p < .001$). A formal mediation test using Preacher and Hayes' (2004) bootstrapping technique (PROCESS-Model 4) with 95% confidence interval using 1,000 resamples reveals a significant indirect effect ($\beta = .72$, SE = .16, 95% CI = [.45, 1.08]), showing that the effect of device on content emotionality is partially mediated by the length of the reviews (with briefer reviews resulting in more emotional content). These results again suggest that the greater emotionality of smartphone-generated content is driven by a tendency to express the gist of one's experience on the device (H3b).

4.4.3. Discussion

Consistent with the results of the first two studies, Study 3 shows that participants who were randomly assigned to write reviews on their smartphones generated content that was more emotional, and specifically more positively emotional, than those who were assigned to write on their PCs. Unlike the correlational results of Study 1, these results demonstrate a causal impact of smartphone usage on increased content emotionality and positivity, thereby ruling out the possibility that the observed effects were driven by differences in temporal proximity to the consumption experience or self-selection bias across devices. In addition, the results of a mediation analysis again suggest that the increased emotionality of smartphone-generated content is driven by the tendency to focus on the gist of one's experiences.

Although Study 3 indicates a causal effect of device use on content emotionality and positive emotionality, another possible alternative explanation for the findings is that writing on one's smartphone somehow prompts the user to recall experiences that are more emotional and positive than writing on one's PC. In other words, differences in content may be driven not by the tendency to generate shorter content but rather by the tendency to recall different types of experiences on the device altogether. In Study 4 I address this potential alternative explanation.

4.5. Study 4: The Causal Effect of Smartphone Usage on Content Emotionality (Cafeteria Study)

The purpose of the fourth study was to provide further experimental evidence that smartphone (vs. PC) usage increases the emotionality and positivity of user-generated content. An additional aim of Study 4 was to control for the possibility that using a smartphone prompts users to recall experiences that are more emotional and positive than using a PC. In light of these objectives, in addition to randomly assigning participants to write a review on their smartphone or their PC, in Study 4 I instructed all participants (who were undergraduate students) to write a review of the same type of experience – their most recent dining experience at the on-campus dining hall. This procedure allowed me to hold the "restaurant" under review constant across conditions as well as effectively randomize the recency of the experience, which further addresses potential differences in temporal proximity.

I predicted that even when (a) randomly assigning participants to a device, and (b) instructing them to review the same type of experience, content generated on smartphones would still be more emotional, and more positively emotional, than PC-generated content. I also predicted that this greater emotionality would again be driven by the tendency to generate shorter content on the device.

4.5.1. Method

Under the guise of a study on students' opinions of university services, 71 participants from the Columbia Business School BRL were instructed to write a review of a particular dining experience. Specifically, participants were asked to write a review of their most recent dining experience at the main on-campus dining hall. Since the dining hall exclusively serves undergraduate students, participants were recruited on the basis that they were currently enrolled as an undergraduate student at the university.

Participants were randomly assigned to one of two conditions: a treatment condition in which they were asked to use their smartphone to write the review, or a control condition in which they were asked to use their PC to write the review. Since I was specifying the topic of their review, to preserve ecological validity I sent the survey to participants via email so that they could complete the review at their preferred location and time (within a window of a few hours). Since I expected the majority of participants to begin the survey on their personal computers, a potential confound was that participants in the PC condition could begin the survey immediately, whereas participants in the smartphone condition would have to copy the link from their PC to their smartphone before beginning. To avoid this issue, participants received two sequential emails before beginning the study. The first email provided the cover story for asking participants to use their randomly assigned device and contained the following information:

> We are interested in students' experiences with various services offered by the university. In particular, in this study we are interested in your consumption experiences at [the main campus] dining hall. In order to ensure that our surveys are optimized for mobile devices (*personal computing devices*), we ask that you complete this study on your smartphone (*PC*). In a few minutes you will be receiving an email from the experimenter that contains a link to this survey. We ask that you open this link on your smartphone (*PC*). If you do not complete this survey on your smartphone (*PC*), you cannot be compensated.

The second email contained the survey link and was sent several minutes after the first email so that participants had a sufficient amount of time to prepare their assigned device. To confirm that participants were using the devices to which they were assigned, as in Study 3 an unobservable check was embedded throughout the survey that recorded the brand and model of the device being used to complete the study. Based on the results of the check, one participant was excluded for not having used the assigned device. In addition, two participants were excluded for having failed an attention check. After removing these reviews from the dataset, 68 responses remained for analysis (75% women).

The link led participants to an external page where they were instructed to write a review of their most recent experience at the campus dining hall. They were also asked to indicate approximately when the experience occurred on an eight-point scale (1 = "Today" to 8 = "4 or more weeks ago"), which allowed me to further control for potential differences in temporal proximity of the experience across conditions.

After completing their review, participants were redirected to the final set of questions. To control for potential differences in general affinity for the dining hall, I asked participants to indicate: "In general, how much do you enjoy eating at [the main campus] dining hall?" (1 = "I do not enjoy it at all" to 5 = "I enjoy it very much"). To control for potential preexisting differences in online review behavior, participants were asked to indicate the extent to which they agreed with the following statements: "I often post reviews of restaurants online (e.g., on Yelp)," "I often use my smartphone to post reviews online," and "I often use my PC to post reviews online" (1 = "Not true at all" to 5 = "Very true"). Responses to these three items were averaged into an index of online review behavior ($\alpha = .72$). Finally, I asked participants to indicate where they had completed the study to control for potential location effects, and then to answer a series of demographic questions.

4.5.2. Results

Preliminary Analyses. There were no differences across conditions in terms of participants' preexisting online review behavior, affinity for the dining hall, or any demographic measures (largest $F(1, 66) = 2.32$, *NS*). As in Study 3, the reviews did not differ in the proportions of present-focused or past-focused words (all F-values < 1) across devices. Participants in the PC condition unexpectedly reported that their experience at the dining hall was more recent than those in the smartphone condition ($M_{Smartphone}$ = 4.68 vs. M_{PC} = 3.53; $F(1, 66) = 3.97$, $p = .05$). Nevertheless, additional analyses confirm that the results reported below persist after controlling for the timing of the experience.

Content Emotionality and Emotional Valence. To test for differences in content emotionality, I ran a mixed ANOVA with device as a between-subjects factor and type of emotion as a within-subject factor. First, as in the prior studies, I found a main effect of type of emotion ($F(2, 132) = 67.51$, $p < .001$) such that on average participants used a greater proportion of positive emotional words (M = 6.94%) than negative emotional words (M = 0.91%; $F(1, 66) = 63.76$, $p < .001$) and neutral emotional words (M = 0.27%; $F(1, 66) = 87.32$, $p < .001$).

More importantly, there was a main effect of device such that participants who wrote a review on their smartphone used a greater proportion of emotional words (M = 10.12%) than did participants who wrote on their PC (M = 6.13%; $F(1, 66) = 5.95$, $p < .02$). Additional analyses show that this effect remains after controlling for the recency of the experience reviewed, as well as the location in which the study was completed (smallest $F(1, 65) = 5.38$, $p < .03$). This pattern of results therefore replicates the findings of the previous studies, and further demonstrates that smartphone (vs. PC) use indeed has a causal impact on increased content emotionality (H3a).

In regard to differences in valence, the results reveal a marginally significant device × type of emotion interaction ($F(2, 132) = 2.53$, $p < .085$). A simple effects test shows that smartphone-generated content contained a significantly greater proportion of positive emotional words (M = 8.43%) than PC-generated reviews (M = 5.45%; F(1, 66)

= 4.36, $p < .05$). The reviews did not differ in the proportion of neutral emotional words and, unlike in the prior studies, no longer differed in the proportion of negative emotional words across devices (largest $F(1, 66) = 1.24$, *NS*). As in Studies 1-3, this pattern of results supports the prediction that the greater emotionality of smartphone-generated content is predominantly driven by positive emotionality (H4). Finally, additional analyses show that after controlling for the recency of the experience as well as the location in which the study was completed, the device × type of emotion interaction becomes significant (smallest $F(1, 65) = 3.1$, $p < .05$).

Mediating Effect of Brevity. First, as in the prior studies, smartphone-generated content contained fewer words than PC-generated content on average ($M_{\text{Smartphone}}$ = 23.44 words vs. M_{PC} = 39.82 words; $F(1, 66) = 11.2$, $p = .001$). A formal mediation test using Preacher and Hayes' (2004) bootstrapping technique (PROCESS-Model 4) with 95% confidence intervals using 1,000 resamples reveals a significant indirect effect (β = 1.03, SE = .36, 95% CI = [.5, 1.96]). The results indicate that the effect of device on content emotionality is fully mediated by the length of the reviews, which is again consistent with my proposition that the heightened emotionality of smartphone-generated content is driven by a greater tendency to limit the review to the gist of one's experience (H3b).

4.5.3. Discussion

Consistent with the results of the previous studies, Study 4 shows that participants who were randomly assigned to write a review on their smartphone generated content that was more emotional, and specifically more positively emotional, than those who were assigned to write a review on their PC. As in Study 3, the results of this controlled experiment demonstrate the causal impact of smartphone usage on content emotionality (H3a) and positive emotionality (H4), circumventing potential issues of self-selection that might have been present in the first field study. Since all participants wrote a review of the same type of dining experience, the results of Study 4 also further minimize the concern that the observed effects are driven by differences in the types of dining experiences reviewed across devices.

Instead, the results of a mediation analysis again show that the greater emotionality of smartphone-generated content was driven by the tendency to review experiences more succinctly on the device. This finding is again consistent with my thesis that, since users limit their review to the gist of their experiences when writing on their smartphones (vs. PCs), they tend to describe the more essential, and often more emotional, elements of their experiences (H4). In Study 5 I provide direct experimental evidence for this proposed explanation.

4.6. Study 5: Manipulating the Propensity to Rely on Gist

The purpose of Study 5 was to directly test my proposed explanation for the greater emotionality of smartphone-generated content. In addition to randomly assigning participants to a device, in Study 5 I randomly assigned them to write either a short review or a long review. If smartphone-generated content is more emotional because users generate shorter content on the device thereby encouraging a reliance on gist, then (1) restricting participants to shorter reviews on their PC than they typically would write should *increase* the emotionality of PC-generated content, whereas (2) forcing participants to write longer reviews than they usually do on their smartphone should *decrease* the emotionality of smartphone-generated content.

4.6.1. Method

Overview and Design. One hundred and thirty-three participants from the MTurk panel (62.4% women) were randomly assigned to the conditions of a 2 (device: smartphone vs. PC) × 2 (review length: short vs. long) between-subjects design. Similar to Studies 3-4, participants were asked to write a review of their most recent experience at a sit-down restaurant, and they were randomly assigned to do so either on their smartphone or PC. To determine the particular number of words to be written in each review-length condition, I referenced the average word count of the smartphone-generated ($M = 23.44$ words) and PC-generated reviews ($M = 39.82$ words) written by participants in Study 4. Based on this, participants in Study 5 were randomly assigned to write a review that either contained exactly 20 words (as was typical of a smartphone-generated review in Study 4) or exactly 40 words (as was typical of a PC-generated review in Study 4).

I predicted that participants using their smartphone to write a "standard" short review would use a greater proportion of emotional words than those using their PCs to write a "standard" long review, thereby replicating my prior findings. More importantly, I predicted that participants using their PC to write a short review would use (1) a *greater* proportion of emotional words than participants writing a "standard" long review on their PC, and (2) a *similar* proportion of emotional words as participants writing a "standard" short review on their smartphone. Similarly, participants using their smartphone to write a long review would use (1) a *lower* proportion of emotional words than participants writing a "standard" short review on their smartphone, and (2) a *similar* proportion of emotional words as participants writing a "standard" long review on their PC.

Procedure and Measures. As in Study 4, Study 5 was conducted in two sequential parts in order to provide participants the opportunity to prepare their assigned devices. To administer the device manipulation, the first email notified participants that they would shortly be receiving the survey link and that they must prepare their smartphone (vs. PC) to complete the survey. To ensure that participants used their assigned device, I again embedded an unobservable check that recorded the brand and model of the device being used. The survey link was sent in the second email, at which point participants used their assigned device to begin the "Restaurant Experiences Survey." To manipulate review length, I presented the following instructions to participants in the short (vs. *long*) condition:

> In this market research, we are interested in consumers' experiences with various services. Please take a moment to recall your most recent experience at a sit-down restaurant. In the space below, please write a review of the restaurant in light of this experience. Your review must contain exactly 20 (*40*) words. A word counter (below the text box) will indicate how many words you have written. You will not be able to submit your review unless it contains 20 (*40*) words.

To enforce the assigned word count, a webpage was programmed that contained two key features: first, it displayed a counter indicating how many words had been written; second, it restricted reviews from being submitted until they contained the assigned word count.

4.6.2. Results

To test my proposed explanation for the greater emotionality of smartphone-generated content, I ran a mixed ANOVA with device and review length as between-subjects factors and type of emotion as a within-subject factor[8]. A planned contrast

[8] The results of a preliminary analysis confirm that participants did not differ across conditions in terms of general online review behavior, propensity to eat at restaurants or any of the demographic variables (largest $F(1, 129) = 3.55$, *NS*).

showed that, consistent with my prior studies, short reviews written on smartphones contained a greater proportion of emotional words (M = 11.07%) than long reviews written on PCs (M = 8.14%; $F(1, 129) = 7.3$, $p < .01$), thereby replicating my previous results. However, unlike in the previous studies, there was no longer a main effect of device ($F < 1$). Instead, there was a main effect of review length showing that relative to long reviews, short reviews contained a greater proportion of emotional words (M_{Short}= 11.48% vs. M_{Long} = 7.95%; $F(1, 129) = 21.18$, $p < .001$). Finally, there was no device × review length interaction ($F < 1$).

Importantly, among PC-generated reviews, short reviews contained a greater proportion of emotional words ($F(1, 129) = 13.93$, $p < .001$) relative to long reviews. Similarly, among smartphone-generated reviews, short reviews contained a greater proportion of emotional words ($F(1, 129) = 8.15$, $p = .005$) relative to long reviews. Viewed from a different perspective, among the short reviews, the results indicate no differences between smartphone-generated and PC-generated content in the proportion of emotional words ($M_{Smartphone}$= 11.07% vs. M_{PC} = 11.89%; $F < 1$). Similarly, among the long reviews, smartphone-generated content and PC-generated content contained a comparable proportion of emotional words ($M_{Smartphone}$ = 7.76% vs. M_{PC} = 8.14%; $F < 1$; see Table 8)[9]. Taken together, these results provide further support for the proposition that smartphone-generated content is more emotional because users tend to describe the overall essence of their experiences in lieu of more detailed information.

[Insert Table 8]

[9] The pattern of results reported for the proportion of emotional words also holds for the proportion of positive emotional words, showing again that the greater emotionality of smartphone-generated content is predominantly driven by positive affect (see Table 8).

4.6.3. Discussion

Study 5 shows that restricting users to shorter reviews than they normally would write on their PC – and thereby encouraging a greater focus on gist – drives the creation of *more* emotional content, while leading users to write longer reviews than they typically would on their smartphone drives the creation of *less* emotional content. In other words, the observed differences in content can be attenuated by holding constant the length of the reviews across devices. In combination with the results of the mediation analyses across my prior studies, these findings support the proposition that the greater emotionality of reviews written on smartphones (vs. PCs) is driven by the tendency of smartphone users to concisely report the gist of their experiences (H3b). Next, in Study 6 I investigate differences in valence more directly.

4.7. Study 6: Testing for Differences in Emotional Valence

Across my studies I find that the greater emotionality of smartphone-generated content is driven primarily by positive emotionality. This finding is broadly consistent with the greater incidence of positive (vs. negative) eWOM shown across the WOM literature (e.g., Chevalier and Mayzlin 2006; East et al. 2007). This pattern of results is also consistent with prior findings in the fuzzy-trace literature showing that gist-level processing of a stimulus is often associated with positive (rather than negative) affect (e.g., Gasper and Clore 2002; Rivers et al. 2008). Nevertheless, it is possible that the reason I did not find systematic differences in negative emotionality in my studies is that the proportions of negative emotional words were generally low across devices, which may be due to a censoring of the types of experiences that consumers choose to write about in restaurant reviews.

To obtain a more powerful test of differences in valence, in Study 6 participants were randomly assigned to review a positive dining experience, a negative dining experience, or their most recent dining experience, in addition to being randomly assigned to a device type. If smartphones enhance positive emotions in particular, then smartphone-generated reviews of positive experiences should contain greater positivity than the same type of reviews written on PC. However, if smartphones enhance all feelings indiscriminately, then I should additionally find that reviews of negative experiences contain greater negativity when written on smartphones (vs. PCs).

4.7.1. Method

Under the guise of a study on customer opinions on restaurant experiences, 119 participants (72.3% women) from the Columbia Business School BRL were randomly assigned to the conditions of a 2 (device: smartphone vs. PC) × 3 (experience valence: negative vs. positive vs. control) between-subjects design. For the device manipulation, participants were randomly assigned to write a review either on their smartphone or their PC. To manipulate the valence of the experience, I randomly assigned participants to write a review of a negative restaurant experience in one condition, a positive restaurant experience in a second condition, or their most recent dining experience in a third condition.

I followed a similar procedure as in Studies 4 and 5, implementing the study in two sequential parts and providing the cover story that I was interested in consumers' opinions of restaurant experiences. Upon opening the survey link, participants in the positive-experience (negative-experience) condition received the following instructions:

> Please take a moment to think about a sit-down restaurant at which you have had a positive (*negative*) experience. In the space below, please write a review of this restaurant in light of this positive (*negative*) experience.

Participants in the control condition were told to recall their most recent experience at a sit-down restaurant and to write a review in light of this experience (as in Study 5). As a check of the experience-valence manipulation, participants were also asked to rate the restaurant on a scale of 1 to 5 stars. After completing their reviews, participants indicated how often they eat at restaurants in general (1 = "Less than once a week" to 5 = "2-3 times a day, every day") and where they completed the study, and responded to the same online review behavior ($\alpha = .73$) and demographic questions as in Study 4.

4.7.2. Results

Preliminary Analyses. As a check of the experience-valence manipulation, I conducted a mixed ANOVA of the numerical restaurant ratings with device and experience-valence as between-subjects factors, and type of emotion as a within-subject factor. The results revealed a main effect of experience-valence on restaurant ratings ($F(2, 113) = 68.5$, $p < .001$), confirming that positive experiences elicited higher numerical ratings ($M = 4.47$) relative to negative experiences ($M = 2.13$; $F(1, 112) = 129.60$, $p < .001$) and experiences in the control condition ($M = 3.85$; $F(1, 112) = 10.90$, $p < .001$). This effect was not qualified by a device × experience-valence interaction ($F(1,113) = 1.31$, *NS*), which mitigates any concern that smartphone use somehow prompts users to recall experiences that are more positive than PC use does.

Valence of Content Emotionality. To test for differences in emotional valence, I ran a mixed ANOVA with device and experience-valence as between-subjects factors, and type of emotion as a within-subject factor. Consistent with the results of the previous studies, results again showed that reviews written on smartphones contained a greater proportion of emotional words on average (M = 12.23%) relative to reviews written on PCs (M = 8.45%; $F(1, 113) = 7.67$, $p = .007$)[10]. This effect was not qualified by a device × experience-valence interaction ($F < 1$; see Table 9 for means), showing that the greater emotionality of smartphone-generated content did not vary according to the particular valence of the experience assigned[11].

Next, the results reveal an experience-valence × type of emotion interaction ($F(4, 226) = 9.09$, $p < .001$). As expected, the positive-experience reviews contained a significantly greater proportion of positive emotional words than the negative-experience reviews, as well as a directionally greater proportion than the recent reviews; and negative-experience reviews contained a greater proportion of negative emotional words than the positive-experience reviews, as well as the reviews in the control condition (see Table 9 for means).

Most importantly, the results do not show a device × experience-valence × type of emotion interaction ($F(4, 226) = 1.23$, *NS*). Among the reviews in the control condition, smartphone-generated content contained a greater proportion of positive emotional words (M = 10.69%) than PC-generated reviews (M = 6.33%; $F(1, 113) = 4.41$, $p < .04$). No differences were revealed in the proportions of negative or neutral emotional words across devices for the control-condition reviews (all F-values < 1; see Table 9). This pattern of findings replicates the content differences observed in Study 5, where

[10] A mediation analysis confirms that smartphone-generated content contained fewer words (M = 28.88) than PC-generated content (M = 43.53; $F(1,113) = 10.77$, $p = .001$) and that the length of the reviews fully mediated the effect of device on emotionality ($\beta = .98$, SE = .33, 95% CI = [.43, 1.77]).

[11] A preliminary analysis confirms no differences across conditions in terms of general online review behavior or any of the demographic measures (largest $F(2, 113) = 2.44$). The results show a main effect of valence on the general tendency to dine at restaurants ($F(2, 113) = 3.13$, $p < .05$), but an analysis confirms that the main results still hold after controlling for general dining tendency.

participants were similarly asked to review their most recent dining experience (i.e., no valence was assigned).

In the positive-experience condition, smartphone-generated content again contained a greater proportion of positive emotional words (M = 13.41%) than PC-generated reviews (M = 8.97%; $F(1, 113) = 4.06$, $p < .05$; see Table 9). No differences across devices were found in the proportions of negative or neutral emotional words in this condition (largest $F(1, 113) = 3.16$, *NS*; see Table 9). In other words, even when participants were explicitly instructed to write a review of a positive experience, those writing on their smartphones still generated content that was more positively emotional than those writing on their PCs.

In contrast, in the negative-experience condition, the results showed no differences across devices in the proportions of positive emotional or neutral emotional words (all F-values < 1). Importantly, the results also reveal no significant differences in the proportion of negative emotional words across devices ($M_{\text{Smartphone}} = 4.19\%$ vs. $M_{\text{PC}} = 2.74\%$; $F(1, 113) = 1.92$, *NS*; see Table 9). This finding suggests that smartphone use does not accentuate all types of feelings (including negative feelings), but rather positive feelings in particular.

[Insert Table 9]

4.7.3. Discussion

The findings of Study 6 provide further insight into differences in emotional valence across devices. Content written on smartphones (vs. PCs) was found to contain a greater proportion of positive emotional words not only among reviews of recent experiences as in Study 5, but also among reviews of explicitly positive experiences. This finding is inconsistent with the alternative explanation that smartphone-generated content is more positive because users are somehow more likely to recall positive experiences on a smartphone (vs. PC). Among reviews of negative experiences, there was no difference in positive emotionality, as one would expect, but importantly there was also no difference in negative emotionality across devices. These findings suggest that smartphone use does not indiscriminately accentuate any type of feeling in general but rather positive emotions in particular (although apparently not enough to temper the negativity associated with aversive experiences) (H4).

4.8. Study 7 – Field Study: Testing for Differences Among Twitter Content

Whereas all previously reported studies examined the basic phenomenon in the context of online restaurant reviews, in the second field study I test for the phenomenon with content posted on Twitter, one of the largest and most popular online social networks. Testing for my effects among Twitter posts ("Tweets") allowed me to examine whether the observed findings are unique to customer-generated reviews on restaurant-specific websites or generalize to a broader online context. In addition, whereas in my previous studies the user-generated content was effectively unrestricted in its length (other than Studies 3 and 5), Tweets are constrained to a maximum of 140 characters. Given this restriction, this platform thus provides a more conservative test of my thesis.

4.8.1. Data

To test the generalizability of my findings to other contexts without altering too many variables at the same time, a set of Tweets in which users referenced a restaurant was scraped. To ensure that I could collect a sufficient amount of Tweets, I elected to scrape Tweets that referenced any of the following major national restaurant chains:

Applebee's, Chili's, Olive Garden, and Red Lobster. Twitter users indicate that they are referencing a particular topic by accompanying the topic with a "hashtag" (e.g., "#OliveGarden"). Any Tweets containing a hashtag for one of the four restaurants was scraped over a two-week period in December 2015, resulting in 4,853 unique Tweets. The final dataset included 1,335 Tweets that had been posted from PCs and 3,518 posted from smartphones (72.49%).

4.8.2. Results

Content Emotionality and Emotional Valence. To test for differences in emotionality, I ran a mixed ANOVA with device as a between-subjects factor and type of emotion as a within-subject factor. Again, the results reveal a main effect of device (F(1, 4851) = 109.78, $p < .001$), such that Tweets posted from smartphones contained a greater proportion of emotional words (M = 6.99%) relative to Tweets posted from PCs (M = 4.8%). This finding suggests that the greater emotionality of smartphone-generated content observed in my other studies generalizes to the broader domain of general social media content (H3a).

The results additionally revealed a main effect of type of emotion (F(2, 9702) = 1151.24, $p < .001$), such that Tweets contained a greater proportion of positive emotional words on average (M = 4.45%) relative to the proportions of negative emotional words (1.43%) and neutral emotional words (M = .01%). Importantly, this effect was qualified by a device × type of emotion interaction (F(4, 9702) = 31.76, $p < .001$). Smartphone-generated Tweets contained a greater proportion of positive emotional words (M = 5.21%) than PC-generated Tweets (M = 3.7%; F(1, 4851) = 66.89, $p < .001$). While no differences were found in the proportion of neutral emotional words (F(1, 4851) = 1.04, *NS*), smartphone-generated Tweets contained a greater proportion of negative emotional words than PC-generated Tweets ($M_{Smartphone}$ = 1.76% vs. M_{PC} = 1.1%; F(1, 4851) = 27.84, *p* < .001), although as in Studies 1 and 3 the means were quite low. Finally, all the results reported above still hold when controlling for the particular restaurant mentioned in the Tweet. These findings are consistent with the results of the prior studies reported in this paper, providing further evidence that the greater emotionality of smartphone-generated content is primarily driven by positive emotionality (H4) – even in the domain of social media content.

Mediating Effect of Brevity. The results of an ANOVA revealed a main effect of device on the word count of the Tweets (F(2, 1981) = 40.90, *p* < .001), such that smartphone-generated Tweets contained fewer words (M = 15.03 words) than PC-generated content (M = 18.12 words; F(1, 4851) = 288.32, *p* < .001). A formal mediation test using Preacher and Hayes' (2004) bootstrapping technique (PROCESS-Model 4) with 95% confidence intervals using 1,000 resamples reveals a significant indirect effect (β = .19, SE = .03, 95% CI = [.13, .27]). The results show that the effect of device on the emotionality of this particular content was partially mediated by word count, which again served as a proxy for a focus on gist. These results therefore suggest that the proposed explanation for the phenomenon holds even for Twitter content (H3b).

4.8.3. Discussion

The results of the second field study show that the greater emotionality, and positive emotionality, of smartphone-generated content extends to other domains of user-generated content, in this case, Twitter content. Moreover, even with content that is tightly bounded in length, the greater emotionality of smartphone-generated content is still driven by the tendency to generate shorter content on the device, thus encouraging a reliance on gist. These results suggest that the findings observed across Studies 1-6 generalize to other domains of user-generated content.

4.9. Study 8: Downstream Consequences of Content Emotionality

While the first seven studies demonstrate that smartphone-generated content is more emotional, and especially more positively emotional, than PC-generated content, the main purpose of the present study was to examine the downstream consequences of these differences. Specifically, Study 8 tests whether smartphone-generated reviews are more impactful than PC-generated reviews in terms of readers' behavioral intentions, and whether this persuasiveness is indeed driven by the heightened emotionality of the content (H5). Similar to the paradigm used in Study 2, participants in the present study were shown a set of restaurant reviews that had been previously written by participants in Study 3. Half of the reviews presented had been written on smartphones, while the other half had been written on PCs. After reading each review, participants were asked to rate how emotional they found the review to be, as well as their interest in trying the restaurant described in the review. These measures allow me to examine whether (1) readers of reviews actually perceive differences in content, thus potentially providing convergent validity to the results of Study 2, (2) smartphone-generated content is more *persuasive* than PC-generated content, and (3) this persuasiveness is driven by the perceived emotionality of smartphone-generated content.

Should content generated on smartphones indeed be more impactful than content generated on PCs in terms of behavioral intentions, an additional objective of Study 8 was to refine the exact interpretation of such a downstream effect. Because an increasing number of online review forums, such as TripAdvisor and UrbanSpoon (the latter examined in Study 1), explicitly mention whether a review was written on a mobile device (e.g., "written via mobile"), it is possible that smartphone-generated content is more impactful simply because readers are aware of the originating device. For example, perhaps consumers share a naïve theory that smartphone-generated reviews are more spontaneous and veridical than PC-generated reviews. To test the possibility that smartphone-generated content is more impactful not because of the content itself but rather because of readers' knowledge of the originating device, I randomly assigned participants to one of two conditions: In one condition, participants were notified of the originating device for each review, while in the other condition participants were not provided with this information.

If differences in content impact are driven by consumers' naïve theories about the originating devices, then smartphone-generated content should be more persuasive than PC-generated content only when consumers are *aware* of the originating devices. In contrast, if smartphone-generated reviews are more impactful because of their inherently heightened emotionality (H5), then this effect should hold regardless of whether users are aware of the originating devices. Moreover, H5 predicts that the perceived emotionality of the review should mediate the effect of the originating device on review impact.

4.9.1. Method

Overview and Design. One hundred and thirty-five respondents from the MTurk panel (54.1% women) participated in a 2 (originating device of review: smartphone vs. PC) × 2 (device knowledge: device-indicator vs. no-indicator) × 2 (review set: A vs. B) mixed design, with the last two factors manipulated between-subjects. Participants were presented with six restaurant reviews—half of which had been written on smartphones, and the other half on PCs—and were asked to rate each review along a number of dimensions.

Originating Device of Reviews. All reviews presented for evaluation were selected from the actual reviews written by participants in Study 3. Of the six reviews presented to each participant, three had been written via smartphones, and the other three reviews had been written via PCs. That is, the originating device of the reviews varied within-subject as in Study 2 (rather than between-subjects as in Studies 3-6). To mitigate potential review-specific effects, two different sets of six reviews (replication set A vs. B) were created. Participants were randomly assigned to rate one of these two sets of reviews. Further, to ensure that the reviews were accurately representative of content that consumers would actually write on smartphones or PCs, the reviews were selected such that the average content characteristics of the smartphone-generated (PC-generated) reviews in each replication set fell within +/-15% of the average word count and emotionality ratings of the smartphone-generated (PC-generated) reviews that were written in Study 3 (all content characteristics are reported in Table 10).

[Insert Table 10]

Knowledge of Originating Device. In addition to the particular set of reviews presented to participants, knowledge of the originating device was manipulated between-subjects. In the device-indicator condition, each review was accompanied by a label indicating whether it had been written on a smartphone (“written on mobile device”) or PC (“written on desktop/laptop”). In contrast, in the no-indicator condition there were no such labels presented with the reviews.

Procedure and Measures. Participants were presented with a set of six reviews and asked to evaluate each review, as well as the restaurant described in the review. To ensure that they were focusing on the content of the review itself, participants were instructed to assume that they enjoyed the particular type of cuisine described in each review.

To measure the perceived emotionality of the content, participants were asked to indicate the extent to which they agreed with two statements: “This review is passionate” and “This review is emotional” (1 = “Not true at all” to 7 = “Very true”). Responses to these two items were averaged ($\alpha = .85$) to create an index of perceived emotionality. Then, as a marketing-relevant measure of impact, participants were asked to indicate their behavioral intentions toward the target by responding to the following statement: “Based on this review, I would be interested in trying this restaurant” (1 = “Not true at all” to 7 = “Very true”).

Finally, as background measures of individual differences in online review behavior, participants were asked to indicate the extent to which they agreed with the following statements: “I often post reviews of restaurants online (e.g. on Yelp),” “I often read online restaurant reviews,” “I often use my smartphone to post reviews online,” and “I often use my PC to post reviews online” (1 = “Not true at all” to 5 = “Very true”). Responses to these four items were averaged into an index of active online review engagement ($\alpha = .77$). Finally, participants answered a series of demographic questions.

4.9.2. Results

Preliminary Analyses. Preliminary analyses indicated no differences in preexistent online review behavior or any of the demographic variables across conditions (largest $F(1, 131) = 3.53$). These preliminary findings rule out the possibility that the main findings reported below could be driven by preexistent differences across conditions.

Perceived Emotionality. I first ran a mixed-model regression (controlling for subject effects) in which the dependent measure was perceived emotionality, and the predictors were the originating device as the within-subject factor (1: smartphone, -1: PC), device knowledge as the between-subjects factor (1: indicator, -1: no indicator), and their interaction. As predicted, the results reveal a main effect of actual originating device, such that smartphone-generated reviews were perceived as more emotional ($M = 4.93$) than PC-generated reviews ($M = 4.22$; $\beta = .81$, $p < .001$). These results show that smartphone-generated reviews contain greater emotionality not only in terms of objective language use (Studies 1, 3-7), but also in terms of subjective reader perceptions, thereby replicating the findings of Study 2.

Importantly, the analysis did not reveal an interaction between originating device and device knowledge on perceived emotionality ($\beta = .2$, *NS*; see Figure 6), indicating that the perceived emotionality of smartphone-generated (vs. PC-generated) content did not differ as a function of device knowledge. These findings suggests that consumers perceive the increased emotionality of smartphone-generated reviews *regardless* of whether they are aware of the device on which the reviews were written. Therefore, the higher perceived emotionality of smartphone-generated reviews is inherent to the content of the reviews themselves, rather than their perceived origins.

To test the robustness of the main findings, I ran an additional mixed-model regression in which the particular set of reviews (i.e., review set A or B) was included as an additional predictor. The results show no three-way interaction on perceived emotionality, which mitigates concerns that the observed effects were driven by the particular set of reviews presented to participants.

[Insert Figures 6 and 7 here]

Behavioral Intentions. To test for differences in content impact, I ran a mixed-model regression (controlling for subject effects) with behavioral intentions as the dependent measure, and originating device (within-subject), device knowledge (between-subjects), and their interaction as predictors. The results show that participants expressed greater intention to try restaurants described in smartphone-generated reviews (M = 5.21) than restaurants described in PC-generated reviews (M = 4.80; $\beta = .48$, $p < .001$; see Table 11), which is consistent with my hypothesis that smartphone-generated content is more impactful than content generated on PCs (H5). (Recall from the previous studies that the increase in emotionality of smartphone-generated reviews is mainly driven by positive emotionality.)

Importantly, the results do not show an originating device × device knowledge interaction on behavioral intention ($\beta = -.17$, NS; see Figure 7), which demonstrates that smartphone-generated content is more impactful than PC-generated content regardless of whether originating device information is provided.

To test the robustness of the results, I ran another mixed-model regression that included the replication review set as an additional factor. As expected, the results did not reveal a three-way interaction, which again suggests that the observed effects were not contingent on the particular set of reviews shown to participants.

[Insert Table 11]

Mediating Effect of Perceived Emotionality. Next, I tested the prediction that perceived content emotionality mediates the effect of originating device on behavioral intention. As in the prior studies, to test for mediation I used Preacher and Hayes' (2004) bootstrapping technique (PROCESS-Model 4) with 95% confidence intervals using 1,000 resamples. The results show a significant indirect effect ($\beta = .12$, $SE = .02$, 95% CI = [.08, .17]), revealing that the perceived emotionality of the reviews fully mediated the effect of originating device on behavioral intentions. These results support the thesis that greater emotionality drives the heightened persuasiveness of smartphone-generated content relative to PC-generated content (H5).

4.9.3. Discussion

Study 8 expands upon the prior studies in two ways. First, as in Study 2 the results provide additional evidence that smartphone usage drives the creation of more emotional content not just in terms of objective linguistic metrics but also in terms of subjective perceptions of emotionality, thereby further supporting H3a. Second, Study 8 extends the prior findings by showing that the greater emotionality of smartphone-generated content yields downstream consequences in terms of overall persuasive impact. Specifically, smartphone-generated reviews were shown to trigger higher behavioral intentions relative to PC-generated reviews. This greater impact is not an artifact of the mere knowledge of the originating devices. Instead, the results of a mediation analysis reveal that the effect of smartphone usage on behavioral intentions was mediated by the greater perceived emotionality of smartphone-generated content. These results thus support the hypothesis that, relative to content created on PCs, content created on smartphones can be more impactful because of its heightened emotionality (H5).

All of the studies reported so far have demonstrated the hypothesized effects in the context of restaurants – looking either at customer-generated restaurant reviews (Studies 1-6), or Tweets related to restaurants (Study 7). One potential concern is that restaurant reviews are premised on consumer evaluations, which are often determined by emotional reactions (e.g., Zajonc 1981). Relatedly, users' motivations for posting and reading restaurant reviews are primarily hedonic, which has also been shown to increase reliance on affect (Adaval 2001; Holbrook and Hirschman 1982; Pham 1998). Thus, it is possible that the effects observed thus far might only arise among user-generated content that is primarily hedonic and evaluative. To address this issue, I conducted a final field study involving a completely different domain of user-generated content.

4.10. Study 9 – Field Study: Testing for Effects Among Corporate Social Media Content

The studies reported so far demonstrate the predicted effects among online restaurant reviews – content that is primarily hedonic, evaluative, and generated by consumers. Although the results were found to be robust across restaurant-related content on Twitter (Study 7), in the final field study I investigated whether the phenomena generalize to an even more distinct domain of user-generated content. Specifically, in the third field study I tested for the effects in an online context that is not consumer-based and in which the motives, both of the poster and of the reader, are not primarily hedonic or evaluative – a corporate social media platform.

For Study 9, I obtained field data from a large community of start-ups that agreed to share content from its internal social network. At the time (April–October 2014), this community consisted of about 15,000 members, all of whom had access to the network.

Similar to Facebook, the newsfeed of this social network provided a platform for members to not only generate content but also consume and respond to content posted by other users. The type of posts present in the data varied greatly, ranging from inquiries about programming advice, to advertisements for recreational sports teams, to music suggestions. Thus, the various types of content posted in this social network allowed my hypotheses to be tested in a complementary setting to that of restaurant reviews.

Importantly, this social network contained two particularly relevant features for the present research. First, as with UrbanSpoon, the network existed in both web-based and mobile formats, which allowed me to test whether the content differences found among restaurant reviews (Studies 1–8) extends to other forms of user-generated content. Second, the network included a feature that allowed users to "vote" for content posted on the newsfeed by clicking on a button, akin to the "like" feature available on Facebook or the "thumbs up" feature on YouTube. Thus, the number of votes given to each post in the data allowed me to measure the impact of smartphone-generated vs. PC-generated content in terms of its popularity among users.

4.10.1. Data

The dataset contained 1,420 posts ranging from April 1st, 2014, through October 17th, 2014. Of these posts, 340 were written on smartphone devices and 1,080 were written on PCs. Some of the posts were work-related, including job recruitment postings and events happening in the office. Other posts were not work-related, consisting instead of very simple content (e.g., "Happy Monday!"), content from other websites (e.g., links to articles with commentary), or more socially directed posts such as invitations to go camping that weekend.

Each post from the network contained the content of the post, the date on which it was posted, the device from which it was posted[12], and the number of votes the post received. Sixteen posts (all of which were written from PCs) were excluded from the data because they only contained an image and were thus not amenable to text-based content analysis. Ultimately, 1,404 posts (24% smartphone) remained for analysis.

4.10.2. Results

Content Emotionality and Emotional Valence. To test for differences in content emotionality across devices, I ran a mixed ANOVA with device as a between-subjects factor and type of emotion as a within-subject factor[13]. The results reveal a main effect of device such that, as predicted, smartphone-generated content contained a greater proportion of emotional words than PC-generated content ($M_{Smartphone}$ = 6.87% vs. M_{PC} = 5.80%; $F(1, 1402) = 6.97$, $p = .01$). This finding is consistent with H3a and therefore suggests that the results of Studies 1–8 may generalize across different types of user-generated content (i.e., restaurant-related content as well as corporate social media content).

The results additionally revealed a main effect of type of emotion ($F(2, 2804) = 677.85$, $p < .001$), such that posts contained a greater proportion of positive emotional words on average (M = 5.77%) relative to the proportions of negative emotional words (0.54%) and neutral emotional words (M = .03%). Importantly, this effect was qualified by a device × type of emotion interaction ($F(2, 2804) = 4.24$, $p < .02$). Smartphone-

[12] At the time, the device from which the content was posted was not visible to users of the network.
[13] As noted in footnote #7, a Kolmogorov-Smirnov test showed that the assumption of normality was violated among the proportion-based measures in Study 9. Moreover, after performing an arcsine square root transformation on these measures, the results of a mixed ANOVA no longer found significant differences in the proportion of emotional or positive emotional words across devices. Therefore, any proportion-based results reported in Study 9 should be interpreted with caution.

generated posts again contained a greater proportion of positive emotional words (M = 6.23%) than PC-generated posts (M = 5.3%; $F(1, 1402) = 5.45$, $p = .02$). There were no differences in the proportion of neutral emotional words or negative emotional words across devices (largest $F(1, 1402) = 1.24$, *NS*). These results, emerging in the context of a corporate social media platform, are consistent with the previous findings that the greater emotionality of smartphone-generated content is primarily driven by positive emotionality (H4).

Content Popularity. To test for differences in the impact of content in terms of popularity, I submitted the number of votes given to the posts to an ANOVA. The results reveal that smartphone-generated posts received more votes (M = 4.69 votes) than posts generated on PCs (M = 2.79 votes; $F(1, 1402) = 78.46$, $p < .001$). This finding supports my prediction that smartphone-generated content is more impactful than PC-generated content (H5) and thereby suggests a robustness of the effect observed in Study 8 across different domains. As will be reported in the next section, this result still holds when controlling for the word count of the posts ($F(1, 1401) = 74.60$, $p = .00$), which mitigates concern that favorability toward smartphone-generated content (vs. PC-generated content) is driven by the brevity of the post rather than the content itself.

Serial Mediation Analysis. First, it is worth noting that as in the prior studies, smartphone-generated content on this platform contained fewer words (M = 22.49 words) than PC-generated content (M = 39.28 words; $F(1, 1402) = 47.2$, $p < .001$), and that a meditation analysis using Preacher and Hayes' (2004) bootstrapping technique (PROCESS-Model 4) with 95% confidence intervals using 1,000 resamples again found that the greater emotionality of smartphone-generated content was partially mediated by the relative brevity of the content (β = .1; SE = .03; 95% CI = [.06, .16]). These findings therefore suggest that even on a corporate social media platform, the greater emotionality of smartphone-generated content is partly due to tendency to create shorter content on the device (H3b).

Next, I tested whether differences in content brevity across devices led to differences in emotionality that in turn led to differences in popularity (i.e., number of votes) (H5). To examine this I used a conditional indirect effect analysis (Hayes 2013, Model 6) to test whether the effect of device on the number of votes is mediated first, by word count (serving as a proxy for focus on gist) and second, by content emotionality. The results show that the indirect pathway from device to votes through emotionality was significant (β = .02, SE = .01, 95% CI = [.002, .054]), thereby replicating the mediation analysis results of Study 8. As noted in the previous section, the indirect pathway from device to votes through word count was not significant. Most importantly, the results reveal that the indirect effect of the hypothesized serial mediation pathway is significant (device→word count→emotionality→number of votes) (β = .005; SE = .002; 95% CI = [.001, .01]). Taken together, these results are consistent with the thesis that relative to PC-generated content, smartphone-generated content is more emotional due to its relative brevity (H3b) and that, because of this heightened emotionality, smartphone-generated content may ultimately be more influential (H5).

4.10.3. Discussion

The final field study suggests that the main findings may hold not only in the more hedonic, evaluative consumer setting of online restaurant reviews (Studies 1–7) and in the broader social media context of restaurant-related posts on Twitter (Study 8), but also among content in a corporate social network that is neither primarily hedonic nor inherently evaluative. However, as noted in earlier footnotes, results for the Kolmogorov-Smirnov test for normality indicated that the proportions of emotional words deviated significantly from a normal distribution for smartphone-generated ($D(340) = .23$, $p < .001$) and PC-generated content ($D(1072) = .15$, $p < .001$), as did the proportions of positive emotional words (smartphone: $D(340) = .25$, $p < .001$; PC: ($D(1072) = .17$, $p < .001$). Moreover, after performing an arcsine square root transformation on these proportion-based measures, the same ANOVAs no longer yielded the differences reported in Study 9 (all F-values < 1). Therefore, the cross-device differences in the proportions of emotional and positive emotional words reported in Study 9 should be interpreted with caution.

To the extent that one is comfortable drawing inferences from the results, the findings of the third field study are at least consistent with those of Studies 1–8, suggesting that (a) smartphone-generated content is more emotional, and especially more positively emotional, than PC-generated content (H3a, H4), and (b) the greater emotionality of smartphone-generated content is driven by the tendency to generate shorter content on the device (H3b), which I interpret as a propensity to focus on the gist of one's experiences. Consistent with Study 8, the results of this final field study show that smartphone-generated content is more popular than PC-generated content as manifested in a greater number of votes, and that this impactfulness may be driven by its heightened emotionality (H5).

It is also worth noting that although information about the originating device was available to me as a researcher in the dataset, the actual users of the social network in

Study 9 were provided no indication of whether posts had been written on PCs or smartphone devices. Since members were unaware of the originating device, the results of the present study converge with those of Study 8 in showing that smartphone-generated content is more influential not because of some naïve theories about the use of smartphones relative to PCs, but potentially because of differences in the content itself.

4.11. Essay 2 General Discussion

The rapid proliferation of smartphones and the progression of the "mobile revolution" have shifted consumers' digital media engagement away from PC toward smartphones. As mobile continues to replace the PC as the central hub of consumers' digital activities (Comscore 2014), one significant consequence is that consumers are increasingly using their smartphones to generate online content such as restaurant reviews and social media postings (Pew Research 2015). Firms and advertisers have therefore become preoccupied with adjusting to these changes, as evidenced by increasing efforts to monitor online consumer opinions (e.g., Crimson Hexagon) as well as a greater focus on mobile-first digital strategies (e.g., *Fast Company* 2013; *Forbes* 2015). As these trends persist, it is clear that marketers must gain a deeper understanding of how online content created on smartphones differs from content created on PCs.

Essay 2 employs a multi-method approach—including three field studies and six controlled experiments—to investigate the unique consequences of smartphone use for content generation. Two key finding emerge across my studies. First, relative to content generated on PCs, content generated on smartphones (which is understandably shorter) contains greater emotionality (H3a), specifically evincing greater positive emotionality (H4). It is worth noting that among the 90 linguistic categories measured by the LIWC text analysis software, it was only these three categories (word count, emotionality, and positive emotionality) that systematically differed across types of device in my studies. This pattern of results holds in a field study examining online restaurant reviews (Study 1), among restaurant reviews written by participants in experimental settings (Studies 3-6), in a second field study examining social media content (Study 7) and, to an extent[14], in a third field study examining content in a corporate social network (Study 9). Moreover, this effect holds when using measures based on objective linguistic standards (Studies 1, 3-7, 9) as well as consumers' subjective perceptions of emotionality (Studies 2 and 8).

My results also provide insight into the underlying explanation for the greater emotionality of smartphone-generated content. Across all relevant studies I consistently find that the difference in emotionality across devices is driven by differences in the brevity of the content, which supports the thesis that because consumers using their smartphone (vs. PC) generate shorter content on the device, this focuses them on the overall essence of the experiences they describe and thus privileges the inclusion of emotional content (e.g., Brainerd and Reyna 1990) (H3b). In Study 5 I provide additional empirical support for this explanation by showing that differences in emotionality dissipate when the length of the review – and thus the propensity to focus on gist – is held constant across devices. The findings also counter the alternative explanation that smartphone-generated content is more emotional simply because of the "real-time" nature of mobile (vs. PC) communication.

[14] Given the violation of normality and lack of robustness across analyses in Study 9.

Second, results across two studies show that smartphone-generated content can be more influential than PC-generated content in terms of its persuasiveness (Study 8) as well as its popularity among other users (Study 9). This effect emerges for online restaurant reviews within an experimental setting, as manifested in higher behavioral intention (Study 8), as well as in field data from a corporate social network, as seen in the number of votes given to posts in a corporate social network (Study 9). Further, the results of mediation analyses in Study 8 and, to an extent, Study 9, show that smartphone-generated content can be more impactful than PC-generated content as a result of its heightened emotionality (H5). In sum, the results of Essay 2 shows that generating content on one's smartphone drives the creation of more emotional, more positively emotional—and thus potentially more influential—user-generated content.

4.11.1. Contributions of the Current Research

While the vast majority of mobile marketing research has focused on the *consumption* of content on mobile, such as users' search behavior (e.g., Ghose et al. 2013; Wang et al. 2015) and receptiveness to mobile marketing efforts on the device (e.g., Andrews et al. 2015; Danaher et al. 2015), very few papers have examined the *generation* of content on smartphones. One exception is work by Ghose and Han (2011) who find that users are less likely to generate content on their mobile devices in one time period if they had consumed content on the device in the preceding period. The findings of Essay 2 therefore contribute to the extant mobile marketing literature by demonstrating that the use of smartphones (vs. PCs) is actually *changing* the process of content generation by leading to the creation of content that is (understandably) shorter and thereby enhancing the emotionality, and specifically positive emotionality, of user-generated content.

In addition, a substantial body of work exists on the topic of online word of mouth (eWOM), which has largely focused on the influence or impact of eWOM, such as its perceived helpfulness (e.g., Ghose and Ipeirotis 2011), virality (e.g., Berger and Milkman 2012), and effect on sales (e.g., Godes and Mayzlin 2009). However, much less work exists on the factors that influence the *type* of content shared in WOM. One such paper argues that the type of content shared in WOM is determined by one's motivation to share the content in the first place, and that when people generate WOM as a means of emotional regulation, this drives them to share more emotionally laden content (Berger 2014).

Berger and Iyengar (2013) examine how the medium through which WOM is transmitted – in their case, oral vs. written WOM – impacts the type of content shared. They argue that because written WOM is more asynchronous, people can take the time to edit and refine their WOM, which leads them to share more interesting content with others. My work extends these findings by showing that, even within the mode of written communication, the use of different media can change the type of content shared in WOM. Specifically, because using the device encourages consumers to generate shorter content, smartphones (vs. PCs) result in eWOM that is more emotional in nature.

In terms of practical insights, the differences in content generated on smartphones versus PCs bear important implications for marketers concerned with the effects of eWOM. For example, the heightened emotionality of smartphone-generated content implies that content created on the device might provide firms with more diagnostic and accurate accounts of consumers' experiences (e.g., Bird et al. 2002; Fazio 1995). As such, firms seeking to gain a better understanding of customers' true experiences and opinions may want to encourage these consumers to generate online content on their smartphones. Moreover, as discussed in the literature review, while some of findings from the eWOM literature would suggest that smartphone-generated eWOM might be less impactful than PC-generated content (e.g., Banerjee and Chua 2014), other findings would suggest that smartphone-generated content would actually be more impactful (e.g., Berger and Milkman 2012; Luminet et al. 2000). For example, Ludwig et al. (2013) show that reviews with greater positive emotionality led to higher customer conversion rates. Notably, the results of Study 6 show that smartphones use enhances positive emotionality in particular (versus other feelings such as negative affect), suggesting that content generated on the device may indeed be more persuasive than content generated on PCs.

Indeed, direct support for this notion comes from the two final studies, which suggest that, due to its heightened emotionality, smartphone-generated content can be more impactful in terms of readers' behavioral intentions (Study 8), and potentially more popular (Study 9) than PC-generated content. Further, my results show these differences in impact hold regardless of whether users are provided with originating device information as on sites such as UrbanSpoon and TripAdvisor (Studies 8-9). Taken together, these findings suggest that firms could benefit from marketing efforts that encourage customers to generate content on their smartphones, such as offering customers software applications (i.e., mobile apps) that facilitate posting from the device. My results also imply that attaining data on which device was used to generate eWOM may be critical in helping firms identify the content that may be most influential – namely, smartphone-generated content.

4.11.2. Future Research Directions

My findings provide a basis for several research avenues. To further isolate the locus of the effects, future research could examine how content generated on other devices such as tablet PCs compares to smartphone-generated and PC-generated content. Additionally, in the present work I use a measure of the mediating process (i.e., word count) that, while theoretically correlated with the focus on gist, is not a direct measure of the gist itself (for which at present there is no precise linguistic category in LIWC). It is worth noting that, to the extent that my proxy is imperfectly correlated with the theoretical mediator, my mediation estimates are likely to be conservative, given that imperfect measurement of a process will logically attenuate the ability of the measure to capture genuine variation. Nevertheless, in future work I would like to examine more direct measures of the focus on gist. For example, I would like to test whether instructing participants who are writing reviews on their PCs to describe the gist of their experience will lead to the creation of content that is similarly as emotional as smartphone-generated content written under normal circumstances.

Relatedly, other complementary explanations for the effects observed here could also be explored. For example, in light of the findings in Essay 1 showing that consumers often form strong emotional attachments to their smartphones over and above their other devices, it might be the case that engaging with their smartphone puts consumers in a more emotional mindset, thus increasing the emotionality of content generated on the device. This explanation might also help explain the greater positive emotionality of content generated on smartphones (vs. PCs). To test this I would like to examine whether generating content on *someone else's* smartphone (vs. one's own device) attenuates the greater emotionality of smartphone-generated versus PC-generated content.

Another question worthy of future investigation is whether there are substantive differences across devices not just in terms of valence, but also in terms of the discrete emotions expressed (e.g., Raghunathan and Pham 1999). While theoretically interesting, I believe this question is outside the scope of the present research for two reasons. First, my perusal of the results for the related categories available in LIWC (anxiety, anger, and sadness) reveals that there were very few instances of variation in discrete emotional categories across devices. Second, the types of discrete emotions expressed in customer-generated content are likely to be highly specific across contexts. Given that in Essay 2 I largely focus on one particular context (restaurant reviews), it is yet to be determined whether broad generalizations could be extracted from any in-depth analysis of discrete emotions at this point. Finally, in addition to exploring variation in discrete emotions, future work could identify boundary conditions under which focusing on the overall essence of an experience does *not* increase content emotionality. For instance, given prior findings suggesting that affect is less engaged in utilitarian contexts (Pham 1998), it is possible that a review of utilitarian products (e.g., a review of a refrigerator) does not exhibit the same phenomena.

CHAPTER 5
CONCLUSION

In recent years, marketers have largely focused their mobile strategies around the unique functionalities available on smartphones, such as leveraging location-based information to target customers in real-time. However, as consumers continue to rely on their smartphone as the central hub for accessing information, entertainment and other consumption activities, it is critical that firms and academics alike develop a deeper understanding of the psychology underlying use of the device. While a recent body of work within the marketing modeling literature has emerged on the implications of mobile platforms (e.g., Andrews et al. 2015; Bart et al. 2014), there is still very little marketing research that examines the psychological elements of mobile consumption behavior.

In an attempt to partially address this gap in the literature, I investigate two complementary components of mobile consumer behavior across the two essays of my dissertation. Essay 1 clarifies the particular type of relationship that many consumers form with their smartphones. The results show that beyond the negatively valenced consequences of smartphone "addiction" discussed in prior work (e.g., Bianchi and Phillips 2005; Walsh et al. 2011), smartphones can also serve as a type of "adult pacifier" for many consumers, conferring psychological and emotional *benefits* that are definitional of attachment objects. As such, my findings suggest that smartphones can often represent a rich emotional object for many consumers, fulfilling needs that very few other objects can fulfill in adulthood. Essay 2 shows that the use of one's smartphone relative to a comparable device drives the creation of more emotional, more positively emotional, and potentially more impactful user-generated content. These results therefore suggest that smartphones are not simply providing an additional platform for customers to consume and generate user-generated content. Instead, it seems that use of the device is actually altering the very nature of the content itself.

Taken together, the results of my dissertation suggest that in order to develop a comprehensive understanding of the consumer psychology of smartphone use, it is critical to consider and investigate the device beyond just its functional value.

TABLES (ESSAY 1)

Table 1
Mobile Marketing Literature Main Findings

Authors	Journal	Design	Main findings
Andrews, Luo, Fang and Ghose (2015)	*Marketing Science*	Field study; modeling	Commuters in crowded (vs. non-crowded) train were more likely to make a purchase in response to a mobile offer.
Andrews, Goehring, Hui, Pancras and Thornswood (2016)	*Journal of Interactive Marketing*	Conceptual framework and research directions	Mobile promotions (e.g., m-coupons) meant to drive specific consumer behavior in the short-term, whereas mobile advertising (e.g., banner ad with brand name displayed) strives to influence brand attitudes and build brand equity in the long term.
Bart, Stephen and Sarvary (2014)	*Journal of Marketing Research*	Field study; modeling	Mobile display ads (MDAs) are most effective for higher (vs. lower) involvement, utilitarian (vs. hedonic) products.
Bellman, Potter, Treleaven-Hassard, Robinson and Varan (2011)	*Personal and Ubiquitous Computing*	Experimental	Uses a pre-test/post-test experimental design to determine whether using popular mobile phone apps affects brand attitude and brand purchase intention. Branded apps are found to be more persuasive, increasing interest in the brand and its product category, especially for apps with an informational style (e.g. explaining how the brand can solve a particular problem for the customer) versus experiential game-like apps, which were less successful because they focus attention on the phone (vs. the brand).
Brasel and Gips (2014)	*Journal of Consumer Psychology*	Experimental	Touchscreen (vs. non-touchscreen) devices elicit greater sense of psychological ownership, and thus enhances the endowment effect, for products browsed on the device.
Cheng, Blankson, Wang and Chen (2009)	*International Journal of Advertising*	Field study	Randomly assigned participants in the field to rate 1 of 4 types of mobile advertising (MMS, SMS, email, e-advertising). Identified 3 categories of attitudes towards mobile advertising (i.e. users perceive it as informative, entertaining or irritating). Attitudes are generally more positive towards MMS and e-advertising relative to email and SMS advertising.
Chowdhury, Parvin, Weitenberner and Becker (2006)	*International Journal of Mobile Marketing*	Conceptual framework; survey-based; modeling	Credibility of mobile ads most strongly predicted receptiveness to SMS-based advertising. Ads with pleasant content and appropriate information can overcome annoyance elicited by ads.
Danaher, Smith, Ranasinghe, and Danaher (2015)	*Journal of Marketing Research*	Field study; modeling	Redemption of m-coupons is more likely if retailer is more proximal, it is sent in the morning, it is a snack food coupon, it has a higher face value (bigger discount) and it has a shorter expiration date.
Dickenger and Kleijnen (2008)	*Journal of Interactive Marketing*	Survey-based	Consumers attitudes towards m-coupons predicted by perceived effort of redeeming the coupon; fear of "mobile spam" decreased perceived control regarding SMS-based ads. These effects were enhanced for value-seeking (vs. other) consumers.

Fong, Fang and Luo (2015)	*Journal of Marketing Research*	Field study; modeling	Competitive location-based advertising (i.e. targeting consumers near a competitor's location) yielded increases returns to deep discounts, while targeting at the focal retail location yielded decreasing returns.
Gao, Rau and Salvendy (2009)	*International Journal of Human-Computer Interaction*	Experimental	Perceived "interactivity" of mobile advertisement – which is determined by the degree to which users feel they can choose the content and timing of the ad – predicts attitude towards the advertisement.
Gerpott and Thomas (2014)	*Telecommunications Policy*	Literature review	Provide literature review on post-adoption mobile Internet usage. Results of a meta-analysis show, for example, that education level and openness to innovation had the largest effect sizes in predicting mobile Internet usage intensity.
Ghose, Goldfarb and Han (2013)	*Information Systems Research*	Field study; modeling	Relative to PCs, the small screen size and keyboard on mobile phones increase the cost of searching for information on the device, resulting in less search behavior overall. Specifically, the authors showed that users browsing on mobile (vs. PC) are more likely to click on links displayed at the top of a search list because of the relative search cost incurred on mobile. In addition, customers are more likely to click on search results of stores that are more proximal to their current location (suggesting that consumers' physical proximity to a retailer can also impact their *search* behavior on the device).
Ghose and Han (2011)	*Management Science*	Field study; modeling	Find negative temporal interdependence between content generation and content usage on mobile; the authors conjecture that this is due to users' need to allocate resources while on the device. Specifically, content usage is especially less likely following a content generation in the prior session. Users are also more likely to use (vs. generate) content while traveling. In addition, users' social network has a stronger positive effect on content usage than generation.
Goh, Chu and Wu (2015)	*Journal of Interactive Marketing*	Natural experiment; modeling	Compare spatial (in relation to their proximity to the automotive show location) and temporal (before vs. after launch of mobile campaign for the automotive show) effects on mobile search behavior and advertising response. They find for example that users' receptiveness to the ad campaign is positively related to their breadth and depth of search about the show being advertised.
Hui, Inman, Huang and Suher (2013)	*Journal of Marketing*	Field study; modeling	Targeted mobile promotions aimed at increasing in-store path length (i.e. increasing wandering off of planned traveling path) can increase unplanned spending.
Jung, Umyarov, Bapna and Ramaprasad (2014)	*Thirty Fifth International Conference on Information Systems*	Modeling	Using propensity score matching, they find that users who moved from web-based to mobile versions of an online dating website showed greater engagement on the website.
Koenigstorfer and Groeppel-Klein (2012)	*Marketing Letters*	Quasi-experimental	Gave participants the choice of using mobile internet vs. non-internet media; then measured personality traits via survey. Find, for example, that men (vs. women) with higher levels of consumer innovativeness are more open to mobile Internet services.
Lamberton and Stephen (2015)	*Working paper*	Critical analysis and future research directions	Provide critical analysis of prior academic marketing research on digital, social media and mobile marketing, identifying only two extant marketing papers on mobile marketing theory development (by Andrews et al. 2015 and Danaher et al. 2015). They also set agenda for future

			research.
Lariviere, Joosten, Malthousem van Birgelen, Aksoy, Kunz and Huang (2013)	*Journal of Service Management*	Conceptual framework	This paper synthesizes insights from the extant value literature has focused on either the customer's or the firm's perspective, but rarely both, to describe the potential "value fusion" that can arise from mobile devices.
Luo, Andrews, Fang and Wei (2014)	*Management Science*	Field experiment; modeling	Find that temporal and location-based targeting of SMS-based ads (for movie ticket discounts) are effective as individual strategies. For proximal customers, targeting on the same day increases purchase likelihood more than sending two-days before. For non-proximal customers, targeting one day before increases purchase likelihood relative to targeting same day and two days before. Based on survey responses, sending SMSs closer in time and location are assumed to create more concrete mental construal and thus increase involvement and purchase intent.
Lurie, Ransbotham and Liu (2014)	*Working paper*	Modeling	Find that mobile (vs. PC) Urbanspoon postings are, for example, shorter, more emotional, more negative, more present-focused and less socially-oriented, and offer conjectures for why these differences arise.
Lurie, Berger, Chen, Li, Liu, Mason, Muir, Packard, Pancras, Schlosser, Sun and Venkatesan (2016)	*Working paper*	Conceptual framework and research directions	Identify research questions, the types of data that empirical researchers should seek to gather, and the ways in which this data may be analyzed, to gain better understanding of the role of mobility in the marketplace.
Molitor, Reichhart, Spann and Ghose (2014)	*Working paper*	Randomized field experiment	Mobile coupon redemption is higher the closer you are to the story, and the higher it's displayed on the screen, conditional on the type of offer it is.
Munoz-Leiva, Climent-Climent and Liebana-Cabanillas (2016)	*Spanish Journal of Marketing*	Survey; modeling	Develop a technology acceptance model and find that users' willingness to accept mobile banking apps is determined by the perceived intended use of the app.
Shankar and Balasubramanian (2009)	*Journal of Interactive Marketing*	Literature review; conceptual framework	Compared mobile marketing to mass marketing, and identified key research issues such as customer adoption of mobile services, the impact of mobile marketing on customer decision-making and mobile marketing in a global context.
Shankar, Venkatesh, Hofacker and Naik (2010)	*Journal of Interactive Marketing*	Conceptual framework	Provided a conceptual framework of mobile marketing within the context of retailing and summarized, for example, the different segments of mobile consumers (e.g., Millenials, Concerned Parents) and marketing strategies that can be implemented by retailers on mobile (e.g., mobile couponing, SMS).
Strom and Vendel (2014)	*Journal of Retailing and Consumer Services*	Literature review	Provided a literature review on the value of mobile marketing for consumers and retailers, concluding that mobile marketing can increase perceived value for consumers and outcome value for retailers. However, the authors cited limited support for whether mobile marketing increases value over and above alternative marketing efforts.
Sultan and Rohm (2005)	*MIT Sloan Management Review*	Interview-based	Examine ways in which mobile marketing differs from traditional approaches; identify when and how a company should pursue mobile marketing strategies.
Sultan and Rohm (2008)	*MIT Sloan Management Review*	Survey-based	Across US and Pakistan, that factors such as usage characteristics (e.g., using mobile for instrumental and hedonic purposes) predict consumer acceptance of mobile marketing. Within the US, personal attachment to the device also predicts acceptance.

Sultan, Rohm and Gao (2009)	*Journal of Interactive Marketing*	Conceptual model	Using the "uses and gratifications" framework, developed conceptual model of antecedents predicting behavioral intent in response to mobile marketing (in US and Pakistan). They find, for example, that the degree to which consumers are personally attached to their phones – as measured by the degree to which they customize and personalize their devices – predicted acceptance of mobile marketing.
Tsang, Ho and Liang (2004)	*International Journal of Electronic Commerce*	Instrument development; survey-based	Develop instrument for measuring attitudes towards mobile advertising.
Unni and Harmon (2007)	*Journal of Interactive Advertising*	Experimental	Find that pull LBA was slightly more effective than push LBA.
Wang, Malthouse and Krishnmaurthi (2015)	*Journal of Retailing*	Natural experiment; Modeling	Look at the change in shopping behavior over time due to the adoption of a grocery retailer's mobile app. For example, they find that mobile shopping (m-shopping) increases customers' order rate over time, especially for low-spending customers, and that people tended to shop for more habitual (vs. new) products on mobile.
Wu, Shu-Hua and Kang-Ping (2016)	*Telematics and Informatics*	Survey-based	They find that three traits of smartphone users' – their "core self evaluation," online consumer conformity and social identity -- each increase users' positive emotions, which increases their level of trust in mobile apps and thus heightens their intention to buy paid the apps.
Xu, Chan, Ghose and Han (2015)	*Management Science*	Natural experiment; modeling	Quantify the impact of tablet adoption on an e-commerce site (Alibaba) and examine the extent to which tablets serve as a complement or substitute for smartphone and PC channels. Find that tablets tend to serve as a substitute for browsing/shopping on PCs, but *complement* shopping activities on smartphones. For example, the adoption of tablets was found to increase browsing frequency on smartphones by nearly 40% but decreased browsing frequency on PCs by nearly 18%. Additionally, while users seem to be engaging in more casual browsing on tablets, they seem to make more directed searches from their smartphones.
Yang and Jolly (2006)	*International Journal of Mobile Marketing*	Modeling	Using "uses and gratifications" framework, find that perceived emotional and functional value of mobile predicted behavioral intentions to use mobile services.

TABLES (ESSAY 1)

Table 2
Study 1 Means (and Standard Errors) of Other Situational Feelings as a Function of Device and Time

Feeling:	Mobile		PC	
	Time 1	Time 2	Time 1	Time 2
Anxious	2.75 (SE=.26)	2.32 (SE=.21)	3.02 (SE=.27)	2.30 (SE=.21)
Confident	5.30 (SE=.18)	5.16 (SE=.18)	4.98 (SE=.18)	5.05 (SE=.18)
Satisfied	5.09 (SE=.20)	5.25 (SE=.17)	5.02 (SE=.20)	5.09 (SE=.18)
Bored	2.66 (SE=.23)	2.86 (SE=.25)	3.19 (SE=.20)	3.37 (SE=.25)
Happy	4.82 (SE=.17)	4.96 (SE=.16)	4.88 (SE=.17)	4.81 (SE=.16)
Focused	5.07 (SE=.21)	5.02 (SE=.21)	4.84 (SE=.21)	4.81 (SE=.21)
Excited	3.71 (SE=.21)	4.00 (SE=.23)	3.81 (SE=.21)	3.65 (SE=.23)
Sad	1.86 (SE=.17)	1.66 (SE=.18)	2.07 (SE=.21)	1.80 (SE=.19)
Frustrated	2.27 (SE=.21)	1.80 (SE=.19)	2.47 (SE=.21)	2.05 (SE=.20)

TABLES (ESSAY 1)

Table 3
Study 2 Means (and Standard Errors) of Other Situational Feelings as a Function of Device and Time

Feeling:	Mobile			PC		
	Time 1	Time 2	Time 3	Time 1	Time 2	Time 3
Anxious	3.52 (SE=.30)	4.52 (SE=.30)	2.56 (SE=.23)	3.04 (SE=.30)	3.52 (SE=.30)	2.52 (SE=.23)
Confident	5.04 (SE=.29)	3.24 (SE=.23)	4.40 (SE=.24)	4.56 (SE=.29)	3.20 (SE=.23)	4.00 (SE=.24)
Satisfied	4.88 (SE=.29)	2.88 (SE=.23)	4.72 (SE=.25)	4.76 (SE=.29)	2.96 (SE=.23)	4.60 (SE=.25)
Bored	2.72 (SE=.28)	2.56 (SE=.28)	3.08 (SE=.34)	2.76 (SE=.28)	2.72 (SE=.28)	2.88 (SE=.34)
Happy	4.88 (SE=.25)	3.44 (SE=.26)	4.60 (SE=.24)	4.72 (SE=.25)	3.48 (SE=.26)	4.20 (SE=.24)
Focused	5.16 (SE=.33)	4.36 (SE=.31)	4.32 (SE=.24)	4.72 (SE=.33)	4.52 (SE=.31)	4.08 (SE=.24)
Excited	3.76 (SE=.30)	3.40 (SE=.30)	3.80 (SE=.26)	3.40 (SE=.30)	3.00 (SE=.30)	3.16 (SE=.26)
Sad	2.20 (SE=.24)	2.68 (SE=.29)	2.04 (SE=.22)	1.88 (SE=.24)	3.08 (SE=.29)	2.00 (SE=.22)
Frustrated	2.60 (SE=.26)	4.16 (SE=.36)	2.20 (SE=.23)	1.88 (SE=.26)	3.88 (SE=.36)	2.36 (SE=.23)

TABLES (ESSAY 1)

Table 4
Study 3 Frequencies, Means, and Interrater Reliabilities for all Behaviors During the Waiting Period

	Inter-rater reliability	All participants (N=71)			Used smartphone at some point (N=47)		
		Low stress (n=35)	High stress (n=36)	p-value	Low stress (n=21)	High stress (n=26)	p-value
Used smartphone at some point	α = .98*	60%	72.2%	$p = .28$			
Likelihood of reaching for phone 1st	α = .93*	34.3%	63.9%	$p = .013$	57.1%	88.5%	$p = .014$
Time until 1st reached for smartphone	α = .99				89.69 sec	23.9 sec	$p < .001$
Proportion of time spent on phone	α = .97	31.3%	51.3%	$p < .001$	52.1%	71%	$p < .001$
Maximum continuous amount of time spent on phone relative to waiting time (*sustained attention*)	α = .95	30.7%	49.3%	$p < .001$	51.2%	68.3%	$p < .001$
Average time per interaction with phone (*sustained attention*)	α = .96	165.54 sec	299.32 sec	$p < .001$	275.91 sec	414.44 sec	$p < .001$
Number of interactions with phone	α = .89*	0.89	0.92	$p = .88$	1.48	1.27	$p = .3$
Number of unique objects engaged	α = .90*	1.37	1.19	$p = .35$	1.81	1.42	$p = .076$
Number of distinct interactions	α = .89*	1.89	1.53	$p = .29$	2.67	1.89	$p = .062$

* Means reported in Table 4 were calculated after two coders (blind to both condition and hypothesis) reconciled the measures they had originally disagreed on. Cronbach's alphas reported in the table reflect the interrater reliability *prior* to reconciliation of measures.

TABLES (ESSAY 1)

Table 5
Study 4 Sample Characteristics Across Samples

	Current smokers (N=452)	**Ex-smokers** (N=427)
Age	35.36 years old	33.29 years old
Gender	Male (57%)	Male (55.5%)
Education	4-year degree (34.4%)	4-year degree (32.2%)
Marital status	Never married (49.9%)	Never married (51.6%)
Ethnicity	Caucasian (82.1%)	Caucasian (78%)
Trait neuroticism	2.58	2.53
Trait perseverance	3.88	3.91

TABLES (ESSAY 2)

Table 6
Study 1 Replication Sets and Temporal Condition Results: Content Characteristic Means (and Standard Errors) Across Devices (N=69,062)

Dependent Measure	Replication 1 (New York) (N=39,980)		Replication 2 (Portland) (N=29,082)		Controlling for Temporal Markers (Past-, Present- and Future-Focused Words)		Temporal Condition 1: "Last Night" (N=736)		Temporal Condition 2: "Tonight" (N=546)	
Type of Emotion:	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC
Proportion of Emotional Words	12.95% (SE= .07)	8.56% (SE= .06)	12.59% (SE= .07)	8.29% (SE= .07)	12.47% (SE= .05)	8.67% (SE= .04)	8.09% (SE= .30)	6.58% (SE= .14)	8.65% (SE= .31)	6.64% (SE= .21)
Proportion of Positive Emotional Words	10.93% (SE= .07)	7.17% (SE= .06)	10.50% (SE= .07)	6.87% (SE= .06)	10.42% (SE= .05)	7.26% (SE= .04)	6.69% (SE= 0.32)	5.26% (SE= .15)	6.97% (SE= .32)	5.18% (SE= .22)
Proportion of Negative Emotional Words	1.67% (SE= .03)	1.16% (SE= .02)	1.60% (SE= .03)	1.12% (SE= .03)	1.64% (SE= .02)	1.13% (SE= .02)	1.28% (SE= .14)	1.14% (SE= .06)	1.41% (SE= .13)	1.26% (SE= .08)
Proportion of Neutral Emotional Words	0.35% (SE= .01)	0.23% (SE= .01)	0.49% (SE= .01)	0.30% (SE= .01)	0.40% (SE= .01)	0.28% (SE= .01)	0.12% (SE= .04)	0.19% (SE= .02)	0.27% (SE= .06)	0.20% (SE= .04)
Other content characteristics	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC
Word Count	33.96 (SE= .56)	84.13 (SE= .47)	36.98 (SE= .68)	93.15 (SE= .60)	36.24 (SE= .43)	88.10 (SE= .37)	72.75 (SE= 12.13)	161.33 (SE= 5.62)	69.03 (SE= 10.17)	164.53 (SE= 6.80)
Proportion of Past-Focused Words	4.57% (SE= .04)	5.19% (SE= .03)	4.51% (SE= .04)	5.08% (SE= .04)			9.35% (SE= .27)	8.09% (SE= .13)	7.93% (SE= .29)	7.59% (SE= .19)
Proportion of Present-Focused Words	7.58% (SE= .05)	8.24% (SE= .04)	8.00% (SE= .05)	8.75% (SE= .05)			5.81% (SE= .14)	5.64% (SE= .29)	6.07% (SE= .29)	6.68% (SE= .20)
Proportion of Future-Focused Words	0.74% (SE= .01)	0.87% (SE= .01)	0.95% (SE= .02)	0.94% (SE= .01)			1.00% (SE= .05)	0.80% (SE= .10)	3.78% (SE= .20)	2.27% (SE= .13)

TABLES (ESSAY 2)

Table 7
Mean Sample Characteristics of the Study 1 Reviews that Were Used in Study 2

Means:	Smartphone			PC		
	Study 2 (N=50)	Study 1 (N=29,558)	*p*-value	Study 2 (N=50)	Study 1 (N=39,504)	*p*-value
Word Count	39.98	35.47	*p* = .31	86.6	88.62	*p* = .82
Proportion of Emotional Words	12.94%	12.77%	*p* = .92	8.79%	8.43%	*p* = .69
Proportion of Positive Emotional Words	10.80%	10.71%	*p* = .96	6.77%	7.02%	*p* = .69
Proportion of Negative Emotional Words	1.80%	1.64%	*p* =.76	1.74%	1.14%	*p* = .23
Proportion of Neutral Emotional Words	0.34%	0.42%	*p* =.66	0.27%	0.27%	*p* = .999

TABLES (ESSAY 2)

Table 8
Study 5 Means (and Standard Errors) as a Function of Review Length and Device
(N=133)

Dependent Measure	Short Reviews (N=65)		Long Reviews (N=68)	
	Smartphone	PC	Smartphone	PC
Proportion of Emotional Words	11.07% (SE=0.83)	11.89% (SE=0.72)	7.76% (SE=0.81)	8.14% (SE=0.70)
Proportion of Positive Emotional Words	9.29% (SE=0.83)	10.95% (SE=0.72)	6.12% (SE=0.82)	6.92% (SE=0.70)
Proportion of Negative Emotional Words	0.71% (SE=0.35)	0.41% (SE=0.30)	1.29% (SE=0.34)	0.77% (SE=0.30)
Proportion of Neutral Emotional Words	1.07% (SE=0.30)	0.54% (SE=0.26)	0.35% (SE=0.29)	0.45% (SE=0.25)

TABLES (ESSAY 2)

Table 9
Study 6 Means (and Standard Errors) as a Function of Experience-Valence and Device (N=135)

Dependent Measure	Positive Experience (N=32)		Negative Experience (N=41)		Control Condition (N=46)	
Type of Emotion:	Smartphone	PC	Smartphone	PC	Smartphone	PC
Proportion of Emotional Words	14.65% (SE=1.69)	9.54% (SE=1.57)	9.36% (SE=1.84)	7.94% (SE=1.84)	12.66% (SE=1.57)	7.86% (SE=1.50)
Proportion of Positive Emotional Words	13.41% (SE=1.61)	8.97% (SE=1.50)	5.17% (SE=1.76)	5.20% (SE=1.76)	10.69% (SE=1.50)	6.33% (SE=1.44)
Proportion of Negative Emotional Words	0.39% (SE=0.68)	0.33% (SE=0.63)	4.19% (SE=0.74)	2.74% (SE=0.74)	1.58% (SE=0.63)	1.27% (SE=0.61)
Proportion of Neutral Emotional Words	0.86% (SE=0.26)	0.24% (SE=0.24)	0.00% (SE=0.28)	0.00% (SE=0.28)	0.39% (SE=0.24)	0.26% (SE=0.23)

TABLES (ESSAY 2)

Table 10
Mean Sample Characteristics of the Study 3 Reviews that Were Used in Study 8

	Study 3 (N=369)		Study 8							
Measure	Mobile	PC	Mobile				PC			
			Set A (N=70)	*p*-value	Set B (N=65)	*p*-value	Set A (N=70)	*p*-value	Set B (N=65)	*p*-value
Word Count	41.1 (SD= 25.7)	58.7 (SD= 35.2)	39.7 (SD= 10.69)	*p* = .84	41.7 (SD= 22.2)	*p* =.97	56.3 (SD= 10.7)	*p* =.74	56.7 (SD= 11.0)	*p* = .68
Proportion of Emotional Words	12.40% (SD= 9.36)	8.56% (SD= 5.13)	11.78% (SD= 2.82)	*p* = .74	11.91% (SD= 1.23)	*p* =.56	8.39% (SD= 4.9)	*p* =.96	8.48% (SD= .72)	*p* = .87

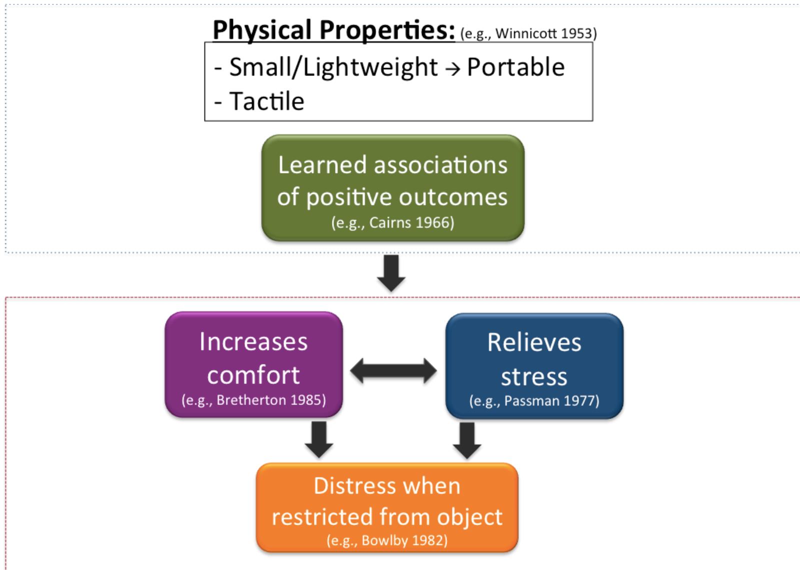
TABLES (ESSAY 2)

Table 11
Study 8 Means (and Standard Errors) as a Function of Originating Device and Device Knowledge (N=135)

Dependent Measure	Device-Indicator (N=71)		No-Indicator (N=64)	
	Smartphone	PC	Smartphone	PC
Perceived Emotionality	4.97 (SE=.14)	4.17 (SE=.14)	4.88 (SE=.14)	4.28 (SE=.14)
Behavioral Intention	5.11 (SE=.13)	4.81 (SE=.12)	5.31 (SE=.14)	4.79 (SE=.13)

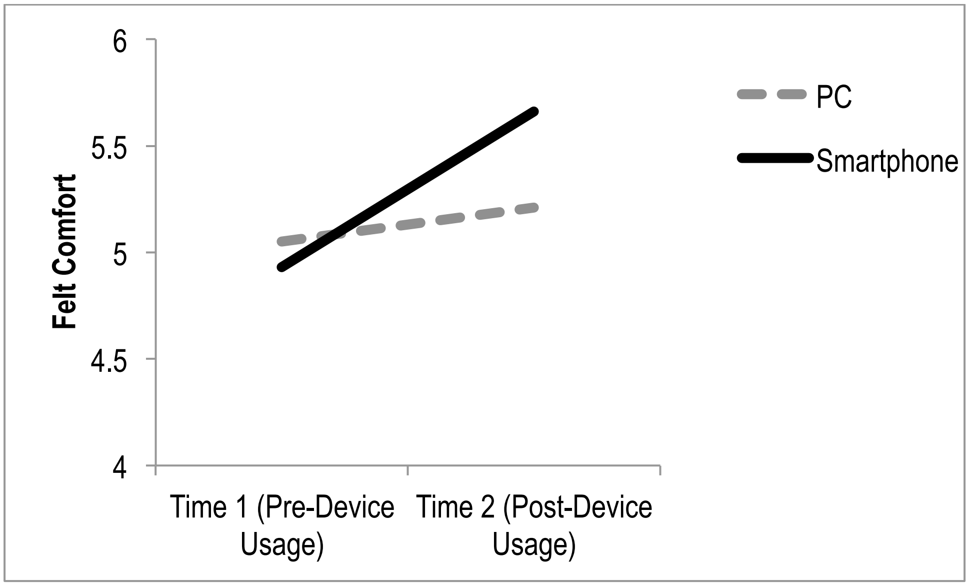
FIGURES (ESSAY 1)

Figure 1
Key Properties of Attachment Objects



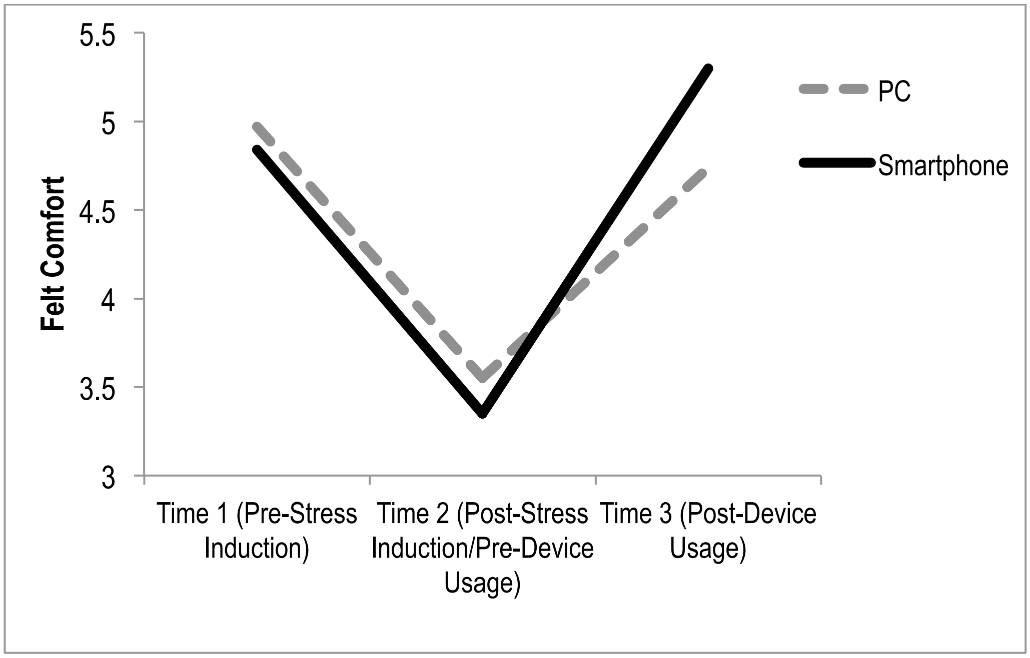
FIGURES (ESSAY 1)

Figure 2
Change in Felt Comfort Over Time as a Function of Device in Study 1



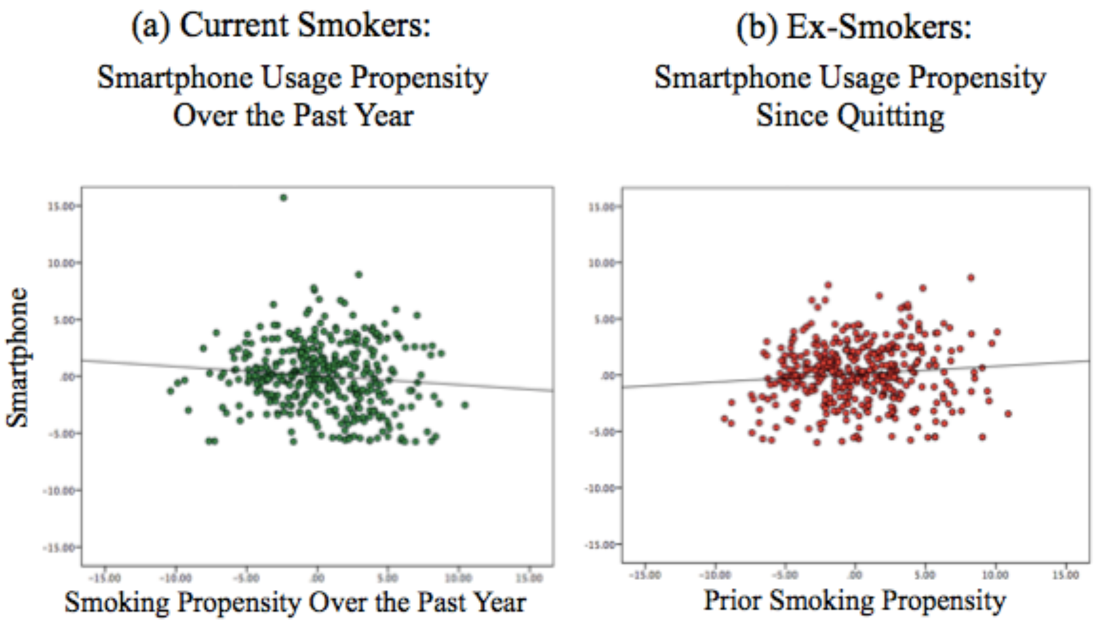
FIGURES (ESSAY 1)

Figure 3
Change in Felt Comfort Over Time as a Function of Device in Study 2



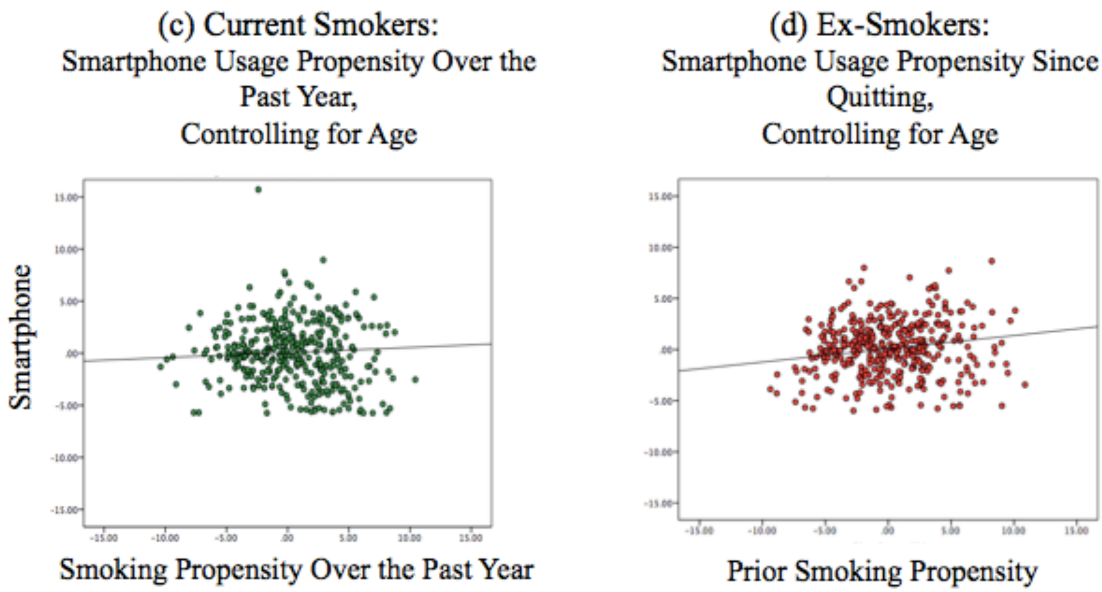
FIGURES (ESSAY 1)

Figures 4a-b
Smartphone Usage Propensity as a Function of Smoking Propensity for Current Smokers and Ex-Smokers in Study 4



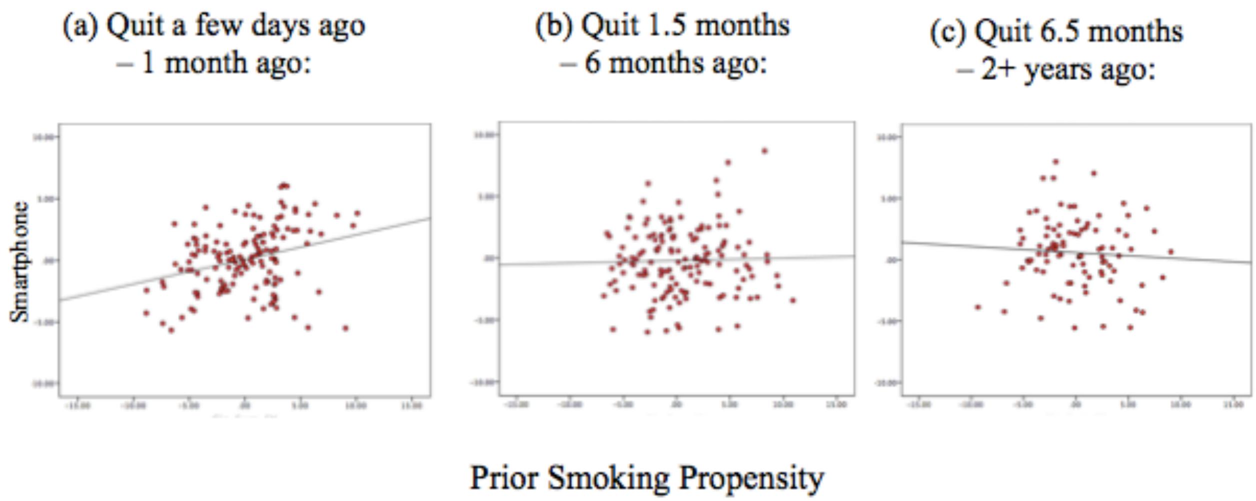
FIGURES (ESSAY 1)

Figures 4c-d
Smartphone Usage Propensity as a Function of Smoking Propensity for Current Smokers and Ex-Smokers, Controlling for Age in Study 4

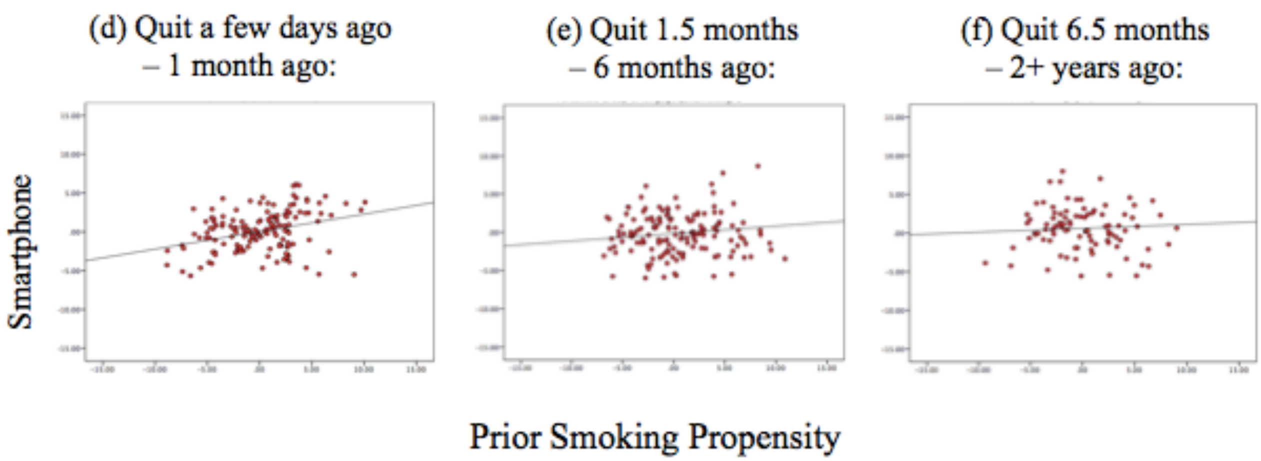


FIGURES (ESSAY 1)

Figures 5a-c
Relationship Between Smartphone Usage Propensity Since Quitting and Prior Smoking Propensity as a Function of Cessation Recency in Study 4

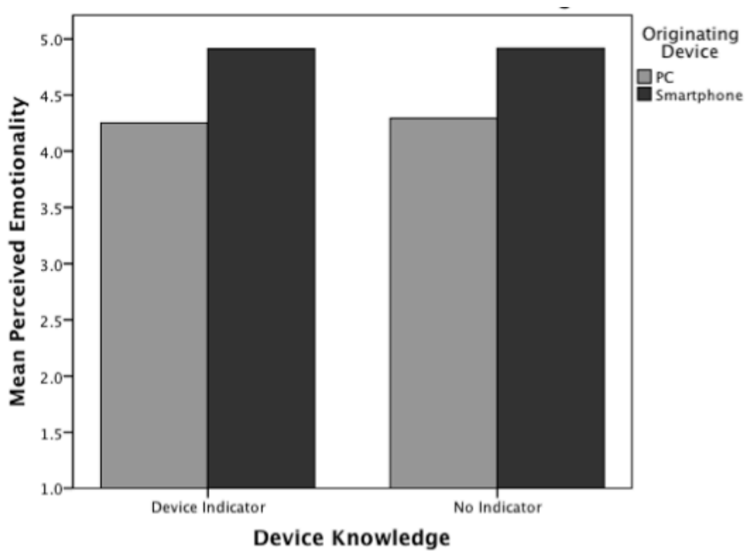


Figures 5d-f
Relationship Between Smartphone Usage Propensity Since Quitting and Prior Smoking Propensity as a Function of Cessation Recency, Controlling for Age in Study 4



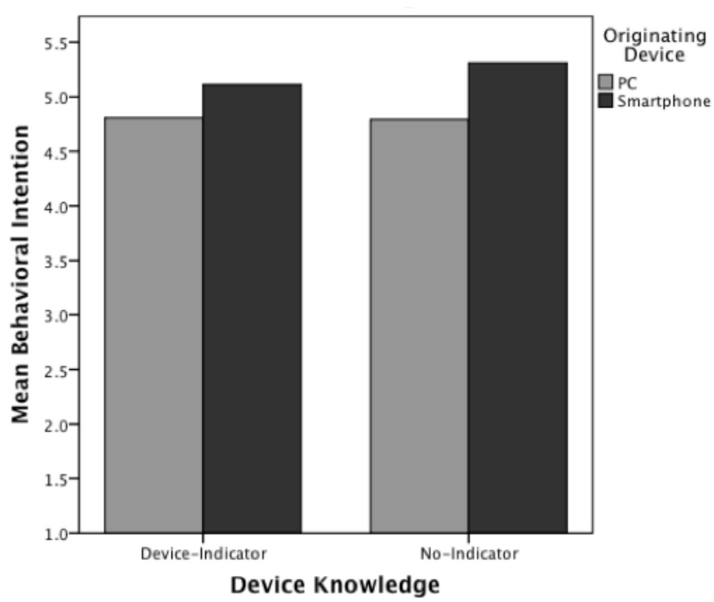
FIGURES (ESSAY 2)

Figure 6
Perceived Emotionality as a Function of Originating Device and Device Knowledge in Study 8



FIGURES (ESSAY 1)

Figure 7
Behavioral Intention as a Function of Originating Device and Device Knowledge in Study 8



REFERENCES

Ackley, Matt (2015), “Quantifying the Mobile Revolution: Mobile Advertising Progress in 2014,” *Search Engine Land* (March 18) (accessed May 15, 2015), [available at: http://searchengineland.com/quantifying-mobile-revolution-2014-benchmark-mobile-advertising-progress-216696].

Adaval, Rashmi (2001), “Sometimes It Just Feels Right: The Differential Weighting of Affect-Consistent and Affect-Inconsistent Product Information,” *Journal of Consumer Research*, 28 (June), 1–17.

Ainsworth, Mary D. S., Mary C. Blehar, Everett Waters, and Sally N. Wall (1978), *Patterns of Attachment: Assessed in the Strange Situation and at Home.* Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Andrews, Michelle, Xueming Luo, Zheng Fang, and Anindya Ghose, (2015) “Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness,” *Marketing Science*, 35 (2), 218–33.

Andrews, Michelle, Jody Goehring, Sam Hui, Joseph Pancras, and Lance Thornswood (2016), "Mobile Promotions: A Framework and Research Priorities," *Journal of Interactive Marketing,* 34, 15–24.

Andrews, Sally, Heather Shaw, and Lukasz Piwek (2015), “Beyond Self-Report: Tools to Compare Estimated and Real-World Smartphone Use,” *PLoS ONE,* 10 (10), 1–9.

Aoki, Kumiko and Edward J. Downes (2003), “An Analysis of Young People’s Use of and Attitudes Toward Cell Phones,” *Telematics and Informatics*, 20 (4), 349–64.

Bachar, Eytan, Laura Canetti, Esti Galilee-Weisstub, Atara Kaplan-DeNour, and Arieh Y. Shalev (1998), "Childhood vs. Adolescence Transitional Object Attachment, and its Relation to Mental Health and Parental Bonding," *Child Psychiatry and Human Development,* 28 (3), 149–67.

Banerjee, Snehasish and Alton YK Chua (2014), "A Study of Manipulative and Authentic Negative Reviews," in *Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication*, ACM.

Bart, Yakov, Andrew T. Stephen, and Miklos Sarvary (2014), “Which Products Are Best Suited to Mobile Advertising? A Field Study of Mobile Display Advertising Effects on Consumer Attitudes and Intentions,” *Journal of Marketing Research*, 51 (3), 270–85.

Baumeister, Roy F., Ellen Bratslavsky, Catrin Finkenauer, and Kathleen D. Vohs (2001), "Bad is Stronger than Good," *Review of General Psychology,* 5 (4), 323–70.

Bellman, Steven, Robert F. Potter, Shiree Treleaven-Hassard, Jennifer A. Robinson, and Duane Varan (2011), "The Effectiveness of Branded Mobile Phone Apps," *Journal of Interactive Marketing*, 25 (4), 191–200.

Beranuy, Marta, Ursula Oberst, Xavier Carbonell, and Ander Chamarro (2009), "Problematic Internet and Mobile Phone Use and Clinical Symptoms in College Students: The Role of Emotional Intelligence," *Computers in Human Behavior,* 25 (5), 1182–7.

Berger, Jonah (2014), "Word of Mouth and Interpersonal Communication: A Review and Directions for Future Research," *Journal of Consumer Psychology,* 24 (4), 586–607.

Berger, Jonah and Eric M. Schwartz (2011), "What drives immediate and ongoing word of mouth?," *Journal of Marketing Research*, *48*(5), 869-80.

Berger, Jonah and Raghuram Iyengar (2013), "Communication Channels and Word of Mouth: How the Medium Shapes the Message," *Journal of Consumer Research,* 40 (3), 567–79.

Bianchi, Adriana and James G. Phillips (2005), "Psychological Predictors of Problem Mobile Phone Use," *CyberPsychology & Behavior,* 8 (1)*,* 39–51.

Billieux, Joel, Martial Van der Linden, Mathieu d'Acremont, Grazia Ceschi, and Ariane Zermatten (2007), "Does Impulsivity Relate to Perceived Dependence on and Actual Use of the Mobile Phone?," *Applied Cognitive Psychology,* 21 (4), 527–38.

Bird, Helen, Sue Franklin, and David Howard (2002), "'Little Words'—Not Really: Function and Content Words in Normal and Aphasic Speech," *Journal of Neurolinguistics,* 15 (3-5), 209–37.

Bowlby, John (1979), *The Making and Breaking of Affectional Bonds.* New York: Routledge.

Bowlby, John (1969), *Attachment and Loss*: *Vol. 1*. New York: Basic Books.

Bowlby, John (1982), "Attachment and Loss: Retrospect and Prospect," *American Journal of Orthopsychiatry* 52 (4), 664–78.

Boyes, Mark E. and Davina J. French (2010), "Neuroticism, Stress, and Coping in the Context of an Anagram-Solving Task," *Personality and Individual Differences,* 49, 380–5.

Bragazzi, Nicola L. and Giovanni Del Puente (2014), "A Proposal for Including Nomophobia in the New DSM-V," *Psychology and Behavior Management,* 7, 155–60.

Brainerd, Charles J. and Valerie F. Reyna (1990), "Gist is the Grist: Fuzzy-Trace Theory and the New Intuitionism," *Developmental Review,* 10 (1), 3–47.

Brasel, S. Adam and James Gips (2014), "Tablets, Touchscreens, and Touchpads: How Varying Touch Interfaces Trigger Psychological Ownership and Endowment," *Journal of Consumer Psychology*, 24 (2), 226–33.

Brennan, Kelly A., Catherine L. Clark, and Phillip R. Shaver, (1998) "Self-Report Measurement of Adult Romantic Attachment: An Integrative Overview," in J. A. Simpson & W. S. Rholes (Eds.), Attachment Theory and Close Relationships, New York: Guilford Press, 46–76.

Bretherton, Inge (1985), "Attachment Theory: Retrospect and Prospect," *Monographs of the Society for Research in Child Development*, 50 (1/2), 3–35.

Burr, Ralph G. (1984), "Smoking Among US Navy Enlisted Men: Some Contributing Factors," *Psychological Reports,* 54 (1), 287–94.

Busch, Fred, Humberto Nagera, Judith McKnight, and Guillermo Pezzarossi (1973), "Primary Transitional Objects," *Journal of the American Academy of Child Psychiatry* 12 (2), 193–214.

Cacioppo, John T., William B. Malarkey, Janice K. Kiecolt-Glaser, Bert N. Uchino, Sandra A. Sgoutas-Emch, John F. Sheridan, Gary G. Berntson, and Ronald Glaser (1995), "Heterogeneity in Neuroendocrine and Immune Responses to Brief Psychological Stressors as a Function of Autonomic Cardiac Activation," *Psychosomatic Medicine*, 57, 154–64.

Cairns, Robert B. (1966), "Attachment Behavior of Mammals," *Psychological Review*, 73 (5), 409–26.

Chae Minee and Jinwoo Kim (2004), "Do Size and Structure Matter to Mobile Users? An Empirical Study of the Effects of Screen Size, Information Structure, and Task Complexity on User Activities with Standard Web Phones," Behaviour & Information Technology, 23 (3), 165–181.

Cheever, Nancy A., Larry D. Rosen, L. Mark Carrier, and Amber Chavez (2014), "Out of Sight is Not Out of Mind: The Impact of Restricting Wireless Mobile Device Use on Anxiety Levels Among Low, Moderate and High Users," *Computers in Human Behavior,* 37, 290–7.

Cheng, Julian Ming-Sung, Charles Blankson, Edward Shih-Tse Wang, and Lily Shui-Lien Chen (2009), "Consumer Attitudes and Interactive Digital Advertising," *International Journal of Advertising,* 28 (3), 501–25.

Chevalier, Judith A., and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research,* 43 (3), 345–54.

Chiu, Shao-I (2014), "The Relationship Between Life Stress and Smartphone Addiction on Taiwanese University Student: A Mediation Model of Learning Self-Efficacy and Social Self-Efficacy," *Computers in Human Behavior,* 34, 49–57.

Chowdhury, Humayun Kabir, Nargis Parvin, Christian Weitenberner, and Michael Becker (2006), "Consumer Attitude Toward Mobile Advertising in an Emerging Market: An Empirical Study," *International Journal of Mobile Marketing*, 1 (2), 33–41.

Chung, Cindy MY and Peter R. Darke (2006), "The Consumer as Advocate: Self-Relevance, Culture, and Word-of-Mouth," *Marketing Letters,* 17 (4), 269–79.

Clayton, Russell B., Glenn Leshner, and Anthony Almond (2015), "The Extended iSelf: The Impact of iPhone Separation on Cognition, Emotion, and Physiology," *Journal of Computer-Mediated Communication,* 20 (2), 119–35.

Cohn, Michael A., Matthias R. Mehl, and James W. Pennebaker (2004), "Linguistic Indicators of Psychological Change After September 11, 2001," *Psychological Science*, 15 (10), 687–93.

comScore (2014), "The US Mobile App Report" (August 21) (accessed June 10, 2015), [available at: https://www.comscore.com/Insights/Presentations-and-Whitepapers/2014/The-US-Mobile-App-Report].

comScore (2015), "US Digital Future in Focus 2015" (March 26) (accessed April 20, 2015), [available at: https://www.comscore.com/Insights/Presentations-and-Whitepapers/2015/2015-US-Digital-Future-in-Focus].

Crowell, Judith A. and Dominique Treboux (1995), "A Review of Adult Attachment Measures: Implications for Theory and Research," *Social Development*, 4, 294–327.

Danaher, Peter J., Michael S. Smith, Kulan Ranasinghe, and Tracey S. Danaher (2015), "Where, When and How Long: Factors that Influence the Redemption of Mobile Phone Coupons," *Journal of Marketing Research*, 52 (5), 710–25.

Deloitte (2016), "On the Couch: Understanding Consumer Shopping Behavior," Deloitte University Press (accessed December 20, 2015), [available at: https://dupress.deloitte.com/dup-us-en/industry/retail-distribution/understanding-consumer-behavior-shopping-trends.html].

Dickinger, Astrid, and Mirella Kleijnen (2008), "Coupons Going Wireless: Determinants of Consumer Intentions to Redeem Mobile Coupons," *Journal of Interactive Marketing,* 22 (3), 23–39.

eMarketer (2014), "Advertisers Will Spend Nearly $600 Billion Worldwide in 2015" (December 10) (accessed January 5, 2015), [available at http://www.emarketer.com/Articles/Print.aspx?R=1011691].

eMarketer (2015), "Trends for 2016: Six Predictions for What Will Happen," (December 2015), [available at http://www.emarketer.com/Article/Trends-2016-Six-Predictions-What-Will-Happen/1013335].

East, Robert, Kathy Hammond, and Malcolm Wright (2007), "The Relative Incidence of Positive and Negative Word of Mouth: A Multi-Category Study," *International Journal of Research in Marketing,* 24 (2), 175–84.

Erkolahti, Ritva and Marjaana Nyström (2009), "The Prevalence of Transitional Object use in Adolescence: Is There a Connection Between the Existence of a Transitional Object and Depressive Symptoms?," *European Child & Adolescent Psychiatry,* 18 (7), 400–6.

Etter, Jean-François (2005), "A Comparison of the Content-, Construct-and Predictive Validity of the Cigarette Dependence Scale and the Fagerström Test for Nicotine Dependence," *Drug and Alcohol Dependence,* 77 (3), 259–68.

Fagerström, Karl-Olov (1978), "Measuring Degree of Physical Dependence to Tobacco Smoking with Reference to Individualization of Treatment," *Addictive Behaviors,* 3 (3), 235–41.

Farr, James L. and W. Burleigh Seaver (1975), "Stress and Discomfort in Psychological Research," *American Psychologist*, 30 (7), 770–3.

Fast Company (2013), "What Does Mobile Phone Mean to You?," (December 2013) [available at http://www.fastcompany.com/3022187/mobilizing/what-does-mobile-first-mean-to-you].

Fazio, Russell H. (1995), "Attitudes as Object-Evaluation Associations: Determinants, Consequences, and Correlates of Attitude Accessibility," in *Attitude Strength: Antecedents and Consequences*, Vol. 4, Richard E. Petty and Jon A. Krosnick, eds. Mahwah, NJ: Psychology Press, 247–82.

Feeney, Judith A. and Patricia Noller (1990), "Attachment Style as a Predictor of Adult Romantic Relationships," *Journal of Personality and Social Psychology*, 58 (2), 281–91.

Fong, Nathan M., Zheng Fang, and Xueming Luo (2015), "Geo-Conquesting: Competitive Locational Targeting of Mobile Promotions," *Journal of Marketing Research*, 52 (5), 726–35.

Forbes (2015), "Mobile First: What Does It Really Mean?," *Forbes* (April 10) (accessed July 3, 2015), [available at: http://www.forbes.com/sites/benkepes/2015/04/10/mobile-first-what-does-it-really-mean/].

Fraley, Chris R. (2000), “Attachment Stability From Infancy to Adulthood: Meta-Analysis and Dynamic Modeling of Developmental Mechanisms,” Personality and Social Psychology Review, 6 (2), 123-51.

Fraley, R. Chris, Niels G. Waller, and Kelly A. Brennan (2000), “An Item Response Theory Analysis of Self-Report Measures of Adult Attachment,” *Journal of Personality and Social Psychology*, 78, 350–65.

Gao, Qin, Pei-Luen Patrick Rau, and Gavriel Salvendy (2009), "Perception of Interactivity: Affects of Four Key Variables in Mobile Advertising," *International Journal of Human-Computer Interaction,* 25 (6), 479–505.

Garbarino, Ellen C. and Julie A. Edell (1997), "Cognitive Effort, Affect, and Choice," *Journal of Consumer Research,* 24 (2), 147–58.

Gasper, Karen and Gerald L. Clore (2002), "Attending to the Big Picture: Mood and Global Versus Local Processing of Visual Information," *Psychological Science,* 13 (1), 34–40.

Gearhardt, Ashley N., William R. Corbin, and Kelly D. Brownell (2009), "Preliminary Validation of the Yale Food Addiction Scale," *Appetite,* 52 (2), 430–36.

Gerpott, Torsten J. and Sandra Thomas (2014), "Empirical Research on Mobile Internet Usage: A Meta-Analysis of the Literature," *Telecommunications Policy,* 38 (3), 291–310.

Ghose, Anindya, Avi Goldfarb, and Sang-Pil Han (2013), “How is the Mobile Internet Different? Search Costs and Local Activities,” *Information Systems Research,* 24 (3), 613–31.

Ghose, Anindya and Sang-Pil Han (2011), “An Empirical Analysis of User Content Generation and Usage Behavior on the Mobile Internet,” *Management Science*, 57 (9), 1671–91.

Ghose, Anindya and Panagiotis G. Ipeirotis (2011), "Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics," *IEEE Transactions on Knowledge and Data Engineering,* 23 (10), 1498–512.

Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science,* 23 (4), 545–60.

Godes, David and Dina Mayzlin (2009), "Firm-Created Word-of-Mouth Communication: Evidence from a Field Test," *Marketing Science,* 28 (4), 721–39.

Goh, Khim-Yong, Junhong Chu and Jing Wu (2015), "Mobile Advertising: An Empirical Study of Temporal and Spatial Differences in Search Behavior and Advertising Response," *Journal of Interactive Marketing,* 30, 34–45.

Harvard Business Review (2013), “Cracking the Mobile Advertising Code,” (September 2013) [available at https://hbr.org/2013/09/cracking-the-mobile-advertisin/].

Hayes, Andrew F. (2013), *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York: Guilford Press.

Hazan, Cindy and Phillip Shaver (1987), "Romantic Love Conceptualized as an Attachment Process," *Journal of Personality and Social Psychology,* 52 (3), 511–24.

Höfler, Dagmar Zimmer and Martien Kooyman (1996), "Attachment Transition, Addiction and Therapeutic Bonding—An Integrative Approach," *Journal of Substance Abuse Treatment,* 13 (6), 511–19.

Holbrook, Morris B. and Elizabeth C. Hirschman (1982), “The Experiential Aspect of Consumption: Consumer Fantasies, Feelings and Fun,” *Journal of Consumer Research*, 9 (2), 132–40.

Hood, Bruce M., and Paul Bloom (2008), "Children Prefer Certain Individuals Over Perfect Duplicates," *Cognition,* 106 (1), 455–62.

Hooper, Val and You Zhou (2007), “Addictive, Dependent, Compulsive? A Study of Mobile Phone Usage,” in *20th Bled eConference eMergence: Merging and Emerging Technologies, Processes, and Institutions*, Slovenia (June 4-6).

Hostetler, Caroline M. and Andrey E. Ryabinin (2012), "Love and Addiction: The Devil is in the Differences: A Commentary on ‘The Behavioral, Anatomical and Pharmacological Parallels Between Social Attachment, Love and Addiction’," *Psychopharmacology,* 224 (1), 27–9.

Hui, Sam K., J. Jeffrey Inman, Yanliu Huang, and Jacob Suher (2013), "The Effect of In-Store Travel Distance on Unplanned Spending: Applications to Mobile Promotion Strategies," *Journal of Marketing,* 77 (2), 1–16.

Inman, J. Jeffrey (2012), ACR Presidential Address, presented at the Association for Consumer Research North American Conference (Vancouver, CA).

James, Diana and Judy Drennan (2005), "Exploring Addictive Consumption of Mobile Phone Technology," *Australian and New Zealand Marketing Academy Conference,* Perth, Australia.

John, Oliver P. and Sanjay Srivastava (1999), "The Big Five Trait Taxonomy: History, Measurement, and Theoretical Perspectives," in L. A. Pervin & O. P. John (Eds.), *Handbook of Personality: Theory and Research* (Vol. 2). New York: Guilford Press, 102–138.

Jung, Umyarov, Bapna and Ramaprasad (2014), “Mobile as a Channel: Evidence from Online Dating,” *Thirty Fifth International Conference on Information Systems*, Auckland, New Zealand.

Kassam, Karim S., Katrina Koslov, and Wendy Berry Mendes (2009), "Decisions Under Distress: Stress Profiles Influence Anchoring and Adjustment," *Psychological Science,* 20 (11), 139–49.

Katz, Elihu, Jay G. Blumler, and Michael Gurevitch (1973), "Uses and Gratifications Research," *Public Opinion Quarterly*, 509–23.

Keefer, Lucas A., Mark J. Landau, Zachary K. Rothschild, and Daniel Sullivan (2012), "Attachment to Objects as Compensation for Close Others' Perceived Unreliability," *Journal of Experimental Social Psychology,* 48 (4), 912–7.

Kirschbaum, Clemens, K-M. Pirke, and Dirk H. Hellhammer (1993), "The ‘Trier Social Stress Test’–A Tool for Investigating Psychobiological Stress Responses in a Laboratory Setting," *Neuropsychobiology,* 28 (1-2), 76–81.

Koenigstorfer, Joerg and Andrea Groeppel-Klein (2012), "Consumer Acceptance of the Mobile Internet," *Marketing Letters,* 23 (4), 917–28.

KPCB (2015), “2015 Internet Trends Report,” (May 2015) [available at http://www.kpcb.com/blog/2015-internet-trends].

Lamberton, Cait Poynor and Andrew T. Stephen (2015), "Taking Stock of the Digital Revolution: A Critical Analysis and Agenda for Digital, Social Media, and Mobile Marketing Research," *Saïd Business School WP,* 16.

Lapointe, Liette, Camille Boudreau-Pinsonneault, and Isaac Vaghefi (2013), "Is Smartphone Usage Truly Smart? A Qualitative Investigation of IT Addictive Behaviors," in *System Sciences (HICSS),46th Hawaii International Conference on*, 1063–72.

Lariviere, Bart, Herm Joosten, Edward C. Malthouse, Marcel van Birgelen, Pelin Aksoy, Werner H. Kunz, and Ming-Hui Huang (2013), "Value Fusion: The Blending of Consumer and Firm Value in the Distinct Context of Mobile Technologies and Social Media," *Journal of Service Management*, 24 (3), 268–93.

Lau-Gesk, Loraine and Joan Meyers-Levy (2009), "Emotional Persuasion: When the Valence Versus the Resource Demands of Emotions Influence Consumers' Attitudes," *Journal of Consumer Research*, 36 (4), 585–99.

Lee, Yu-Kang, Chun-Tuan Chang, You Lin, and Zhao-Hong Cheng (2013), "The Dark Side of Smartphone Usage: Psychological Traits, Compulsive Behavior and Technostress," *Computers in Human Behavior,* 31, 373–83.

Lehman, Elyse Brauch, Susanne A. Denham, Margo H. Moser and Sally L. Reeves (1992), "Soft Object and Pacifier Attachments in Young Children: The Role of Security of Attachment to the Mother," *Journal of Child Psychology and Psychiatry,* 33 (7), 1205–15.

Leung, Louis, and Ran Wei (2000), "More Than Just Talk on the Move: Uses and Gratifications of the Cellular Phone," *Journalism & Mass Communication Quarterly,* 77 (2), 308–20.

Ludwig, Stephan, Ko de Ruyter, Mike Friedman, Elisabeth C. Brüggen, Martin Wetzels, and Gerard Pfann (2013), "More Than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates," *Journal of Marketing*, 77 (January), 87–103.

Luminet IV, Olivier, Patrick Bouts, Frédérique Delie, Antony SR Manstead, and Bernard Rimé (2000), "Social Sharing of Emotion Following Exposure to a Negatively Valenced Situation," *Cognition & Emotion*, 14 (5), 661–88.

Luo, Xueming, Michelle Andrews, Zheng Fang, and Chee Wei Phang (2014), "Mobile Targeting," *Management Science,* 60 (7), 1738–756.

Lurie, Nicholas H., Jonah Berger, Zoey Chen, Beibei Li, Hongju Liu, Charlotte H. Mason, David M. Muir, Grant Packard, Joseph Pancras, Ann Schlosser, Baohong Sun and Raj Venkatesan (2016), "Everywhere and at all times: Mobility, Consumer Decision Making, and Choice," Working Paper, SSRN.

Lurie, Nicholas H., Sam Ransbotham, and Hongju Liu (2014), "The Characteristics and Perceived Value of Mobile Word of Mouth," Working paper 14-109, Marketing Science Institute Working Paper Series 2014.

Marlatt, G. Alan, John S. Baer, Dennis M. Donovan, and Daniel R. Kivlahan (1988). "Addictive Behaviors: Etiology and Treatment," *Annual Review of Psychology,* 39 (1), 223–52.

MacLeod, Colin, Elizabeth Rutherford, Lyn Campbell, Greg Ebsworthy, and Lin Holker (2012), "Selective Attention and Emotional Vulnerability: Assessing the Causal Basis of Their Association Through the Experimental Manipulation of Attentional Bias," *Journal of Abnormal Psychology,* 111(1), 107.

Markt, Charla and Martin Johnson (1993), "Transitional Objects, Pre-sleep Rituals, and Psychopathology," *Child Psychiatry and Human Development,* 23 (3), 161–73.

Mednick, Sarnoff A. and Martha T. Mednick (1967), *Examiner's Manual, Remote Associates Test: College and Adult Forms 1 and 2*, Houghton Mifflin.

Metcalfe, Janet and Walter Mischel (1999), "A Hot/Cool-System Analysis of Delay of Gratification: Dynamics of Willpower," *Psychological Review*, 106 (1), 3–19.

Metcalfe, Janet and W. Jake Jacobs (1998), "Emotional Memory: The Effects of Stress on 'Cool' and 'Hot' Memory Systems," in *Psychology of Learning and Motivation*, Vol. 38, Douglas L. Medin, ed. Academic Press, 187–222.

Mikulincer, Mario and Phillip R. Shaver (2007),"Boosting Attachment Security to Promote Mental Health, Prosocial Values, and Inter-Group Tolerance," *Psychological Inquiry* , 18 (3), 139–56.

Milkman, Katherine L. and Jonah Berger (2012), "What Makes Online Content Viral?," *Journal of Marketing,* 49 (2), 192–205.

Millward Brown (2014), "Millward Brown AdReaction: Marketing in a Multiscreen World," in *MSI Conference "The Future of Marketing in a Multi-Channel & Multi-Screen World"* (May 15-16).

Miratech (2012), "Google ads are even more effective on smartphones." [available at: http://miratech.com/google-ads-are-even-more-effective-on-smartphones.html].

Moe, Wendy W., and Michael Trusov (2011), "The Value of Social Dynamics in Online Product Ratings Forums," *Journal of Marketing Research,* 48 (3), 444–56.

Mok, Jung-Yeon, Sam-Wook Choi, Dai-Jin Kim, Jung-Seok Choi, Jaewon Lee, Heejune Ahn, Eun-Jeung Choi, and Won-Young Song (2014), "Latent Class Analysis on Internet and Smartphone Addiction in College Students," *Neuropsychiatric Disease and Treatment,* 10, 817–28.

Molitor, Dominik, Philipp Reichhart, Martin Spann, and Anindya Ghose (2016), "Measuring the Effectiveness of Location-Based Pull Advertising: A Randomized Field Experiment," Working Paper, SSRN.

Moore, Sarah G. (2015), "Attitude Predictability and Helpfulness in Online Reviews: The Role of Explained Actions and Reactions," *Journal of Consumer Research* 42 (1), 30–44.

Mudambi, Susan M. and David Schuff (2010), "What Makes a Helpful Review? A Study of Customer Reviews on Amazon.com," *MIS Quarterly*, 34 (1), 185–200.

Muñoz-Leiva, F., Climent-Climent, S., and Liébana-Cabanillas, F. (2017), "Determinants of Intention to use the Mobile Banking Apps: An Extension of the Classic TAM Model," *Spanish Journal of Marketing-ESIC*, (January).

Nedelisky, Anna and Miriam Steele (2009), "Attachment to People and to Objects in Obsessive-Compulsive Disorder: An Exploratory Comparison of Hoarders and Non-Hoarders," *Attachment & Human Development,* 11 (4), 365–83.

O'Guinn, Thomas C. and Ronald J. Faber (1989), "Compulsive Buying: A

Phenomenological Exploration,” *Journal of Consumer Research*, 16 (2), 147–57.

Open Science Collaboration (2012), “An Open, Large-Scale, Collaborative Effort to Estimate the Reproducibility of Psychological Science,” *Perspectives on Psychological Science*, 7 (6), 657–60.

Osgood, Charles E. (1964), "Semantic Differential Technique in the Comparative Study of Cultures," *American Anthropologist,* 66 (3), 171–200

Oulasvirta, Antti, Tye Rattenbury, Lingyi Ma, and Eeva Raita (2012), "Habits Make Smartphone Use More Pervasive," *Personal and Ubiquitous Computing,* 16 (1), 105–14.

Passman, Richard H. (1977), "Providing Attachment Objects to Facilitate Learning and Reduce Distress: Effects of Mothers and Security Blankets," *Developmental Psychology,* 13 (1), 25–8.

Paulhus, Delroy L. and David T.K. Lim (1994), “Arousal and Evaluative Extremity in Social Judgment: A Dynamic Complexity Model,” *European Journal of Social Psychology*, 24, 89–9.

Pennebaker, James W., Ryan L. Boyd, Kayla Jordan, and Kate Blackburn (2015), *LIWC 2015: Linguistic Inquiry and Word Count* [available at http://www.liwc.net/].

Pew Research Center (2015), “US Smartphone Use in 2015,” Pew Research Center: Internet, Science & Tech (April 2015) (accessed May 5, 2015), [available at http://www.pewinternet.org/2015/04/01/us-smartphone-use-in-2015/].

Pham, Michel T. (1998), “Representativeness, Relevance, and the Use of Feelings in Decision Making," *Journal of Consumer Research*, 25 (September), 144–59.

Pham, Michel T. (2013), “The Seven Sins of Consumer Psychology,” *Journal of Consumer Psychology*, 23 (October), 411–23.

Pham, Michel T., Iris W. Hung, and Gerald J. Gorn (2011), "Relaxation Increases Monetary Valuations," *Journal of Marketing Research,* 48 (5), 814–26.

Pomerleau, Cynthia S. and Ovide F. Pomerleau (1987), "The Effects of a Psychological Stressor on Cigarette Smoking and Subsequent Behavioral and Physiological Responses," *Psychophysiology,* 24 (3), 278–85.

Preacher, Kristopher J. and Andrew F. Hayes (2004), “SPSS and SAS Procedures for Estimating Indirect Effects in Simple Mediation Models,” *Behavior Research Methods, Instruments, and Computers*, 36 (4), 717–31.

Raghunathan, Rajagopal and Michel Tuan Pham (1999), "All Negative Moods are not Equal: Motivational Influences of Anxiety and Sadness on Decision Making," *Organizational Behavior and Human Decision Processes,* 79 (1), 56–77.

Raptis, Dimitrios, Nikolaos Tselios, Jesper Kjeldskov, and Mikael B. Skov (2013), "Does Size Matter? Investigating the Impact of Mobile Phone Screen Size on Users' Perceived Usability, Effectiveness and Efficiency," in *Proceedings of the 15th International Conference on Human-Computer Interaction with Mobile Devices and Services*, ACM (August 27-30).

Reyna, Valerie F (2012), "A New Intuitionism: Meaning, Memory, and Development in Fuzzy-Trace Theory," *Judgment and Decision Making,* 7 (3), 332–59.

Rivers, Susan E., Valerie F. Reyna, and Britain Mills (2008), "Risk Taking Under the Influence: A Fuzzy-Trace Theory of Emotion in Adolescence," *Developmental Review,* 28 (1), 107–44.

Samaha, Maya and Nazir S. Hawi (2016), "Relationships Among Smartphone Addiction, Stress, Academic Performance, and Satisfaction with Life," *Computers in Human Behavior,* 57, 321–5.

Schellekens, Gaby AC, Peeter WJ Verlegh, and Ale Smidts (2010), "Language Abstraction in Word of Mouth," *Journal of Consumer Research,* 37 (2), 207–23.

Schindler, Robert M. and Barbara Bickart (2012), "Perceived Helpfulness of Online Consumer Reviews: The Role of Message Content and Style," *Journal of Consumer Behaviour,* 11 (3), 234–43.

Seery, Mark D., Jim Blascovich, Max Weisbuch, and S. Brooke Vick (2004), "The Relationship Between Self-Esteem Level, Self-Esteem Stability, and Cardiovascular Reactions to Performance Feedback," *Journal of Personality and Social Psychology,* 87 (1), 133–45.

Shankar, Venkatesh and Sridhar Balasubramanian (2009), "Mobile Marketing: A Synthesis and Prognosis," *Journal of Interactive Marketing,* 23 (2), 118–29.

Shankar, Venkatesh, Alladi Venkatesh, Charles Hofacker, and Prasad Naik (2010), "Mobile Marketing in the Retailing Environment: Current Insights and Future Research Avenues," *Journal of Interactive Marketing,* 24 (2), 111–20.

Skinner, Harvey A. and Barbara A. Allen (1982), “Alcohol Dependence Syndrome: Measurement and Validation,” *Journal of Abnormal Psychology,* 91, 199–209.

Slatcher, Richard B. and James W. Pennebaker (2006), "How Do I Love Thee? Let Me Count the Words," *Psychological Science,* 17 (8), 660–64.

Stephen, Andrew T. and Michel T. Pham (2008), “On Feelings as a Heuristic for Making Offers in Ultimatum Negotiations,” *Psychological Science,* 19 (10), 1051–8.

Ström, Roger, Martin Vendel, and John Bredican (2014), "Mobile Marketing: A Literature Review on its Value for Consumers and Retailers," *Journal of Retailing and Consumer Services,* 21 (6), 1001–12.

Sultan, Fareena, Andrew J. Rohm, and Tao Tony Gao (2009), "Factors Influencing Consumer Acceptance of Mobile Marketing: A Two-Country Study of Youth Markets," *Journal of Interactive Marketing,* 23 (4), 308–20.

Sussman, Steve and David S. Black (2008), "Substitute Addiction: A Concern for Researchers and Practitioners," *Journal of Drug Education*, 38 (2), 167–80.

Takao, Motoharu, Susumu Takahashi, and Masayoshi Kitamura (2009), "Addictive Personality and Problematic Mobile Phone Use," *CyberPsychology & Behavior,* 12 (5), 501–7.

Tang, Zixuan, Huijun Zhang, An Yan, and Chen Qu (2017), "Time is Money: The Decision Making of Smartphone High Users in Gain and Loss Intertemporal Choice," *Frontiers in Psychology*, 1–12.

TechCrunch (2012), “UrbanSpoon: Traffic Up 80% in 2011, Mobile Growth Faster than Web” (accessed September 2014), [available at http://techcrunch.com/2012/02/07/urbanspoon-traffic-up-80-in-2011-mobile-growth-faster-than-web/].

Telegraph (2012), “Obsessive Smart Phone Users Hear 'Phantom Vibrations',” (2012) [available at http://www.telegraph.co.uk/news/science/science-news/9007294/Obsessive-smart-phone-users-hear-phantom-vibrations.html].

Terracciano, Antonio and Paul T. Costa (2004), “Smoking and the Five-Factor Model of Personality,” *Addiction,* 99 (4), 472–81.

The Atlantic (2012), “The Cigarette of this Century,” (June 2012) [available at http://www.theatlantic.com/technology/archive/2012/06/the-cigarette-of-this-century/258092/].

The Economist (2015), “The Truly Personal Computer” (accessed Feb. 28, 2015), [available at http://www.economist.com/news/briefing/21645131-smartphone-defining-technology-age-truly-personal-computer].

Thomée, Sara, Annika Härenstam, and Mats Hagberg (2011), "Mobile Phone Use and Stress, Sleep Disturbances, and Symptoms of Depression Among Young Adults: A Prospective Cohort Study," *BMC PublicHJealth,* 11:66, 1–11.

Thomson, Matthew, Deborah J. MacInnis, and C. Whan Park (2005), "The Ties That Bind: Measuring the Strength of Consumers' Emotional Attachments to Brands," *Journal of Consumer Psychology,* 15 (1), 77–91.

Tsang, Melody M., Shu-Chun Ho, and Ting-Peng Liang (2004), "Consumer Attitudes Toward Mobile Advertising: An Empirical Study," *International Journal of Electronic Commerce,* 8 (3), 65–78.

Unni, Ramaprasad and Robert Harmon (2007), "Perceived Effectiveness of Push vs. Pull Mobile Location Based Advertising," *Journal of Interactive Advertising,* 7 (2) 28–40.

Walsh, Shari P. and Katherine M. White (2007), "Me, My Mobile, and I: The Role of Self-and Prototypical Identity Influences in the Prediction of Mobile Phone Behavior," *Journal of Applied Social Psychology,* 37 (10), 2405–34.

Walsh, Shari P., Katherine M. White, and Ross M. Young (2008), "Over-Connected? A Qualitative Exploration of the Relationship Between Australian Youth and their Mobile Phones," *Journal of Adolescence,* 31 (1), 77–92.

Walsh, Shari P., Katherine Marie White, and Ross McD Young (2010), "Needing to Connect: The Effect of Self and Others on Young People's Involvement With their Mobile Phones," *Australian Journal of Psychology,* 62 (4), 194–203.

Walsh, Shari P., Katherine M. White, Stephen Cox, and Ross McD Young (2011), "Keeping in Constant Touch: The Predictors of Young Australians' Mobile Phone Involvement," *Computers in Human Behavior*, 27 (1), 333–42.

Wang, Rebecca Jen-Hui, Edward C. Malthouse, and Lakshman Krishnamurthi (2015), "On the Go: How Mobile Shopping Affects Customer Purchase Behavior," *Journal of Retailing,* 91 (2), 217–34.

Waters, Everett, Kiyomi Kondo-Ikemura, German Posada, and John E. Richters (1991), "Learning to Love," in *Self Processes and Development: The Minnesota Symposium in Child Development*, 217–55.

Wei, Ran and Ven-Hwei Lo (2006), "Staying Connected While on the Move Cell Phone Use and Social Connectedness," *New Media & Society,* 8 (1), 53–72.

Weisberg, Paul and James E. Russell (1971), "Proximity and Interactional Behavior of Young Children to Their 'Security Blankets'," *Child Development*, 1575-9.

Whiteside, Stephen P. and Donald R. Lynam (2001), "The Five Factor Model and Impulsivity: Using a Structural Model of Personality to Understand Impulsivity," *Personality and Individual Differences,* 30 (4), 669–89.

Wired (2014), “What’s Up With That? Phantom Cellphone Vibrations,” (September 2014) [available at http://www.wired.com/2014/09/whats-phantom-cellphone-vibrations/].

Winnicott, D. W. (1953), “Transitional Objects and Transitional Phenomena,” *International Journal of Psycho-Analysis*, 34, 89–97.

Wu, Jyh-Jeng, Chien Shu-Hua, and Liu Kang-Ping (2016), "Why Should I Pay? Exploring the Determinants Influencing Smartphone Users’ Intentions to Download Paid App," *Telematics and Informatics*, (December).

Xu, Kaiquan, Jason Chan, Anindya Ghose, and Sang Pil Han (2016), "Battle of the channels: The Impact of Tablets on Digital Commerce," *Management Science*, 124.

Yahoo! Insights (2015), “Media, Productivity & Emojis Give Mobile Another Stunning Growth Year” (January 2016) [available at http://flurrymobile.tumblr.com/post/136677391508/stateofmobile2015].

Yang, Kiseol, and Laura D. Jolly (2006), “Value-Added Mobile Data Services: The Antecedent Effects of Consumer Value on Using Mobile Data Services,” *International Journal of Mobile Marketing,* 1(2), 11–7.

Zajonc, Robert B. (1980), “Feeling and Thinking: Preferences Need No Inferences,” *American Psychologist*, February, 35 (2), 151–75.

Zeifman, Debra and Hazan, Cindy (1997), *Attachment: The Bond in Pair-Bonds,* in J. A. Simpson & D. T. Kenrick (Eds.), Evolutionary Social Psychology, Mahwah, NJ: Erlbaum, 237–63.

Zweben, Joan Ellen (1987), "Eating Disorders and Substance Abuse," *Journal of Psychoactive Drugs,* 19 (2), 181–92.

APPENDIX A
Situational Feelings Measures (Studies 1-3)

Indicate the extent to which you agree with each of the following statements *right now:*

	1-Not at all	2	3	4	5	6	7-Very much so
I feel relaxed	○	○	○	○	○	○	○
I feel calm	○	○	○	○	○	○	○
I feel at ease	○	○	○	○	○	○	○
I feel anxious	○	○	○	○	○	○	○
I feel confident	○	○	○	○	○	○	○
I feel satisfied	○	○	○	○	○	○	○
I feel bored	○	○	○	○	○	○	○
I feel happy	○	○	○	○	○	○	○
I feel focused	○	○	○	○	○	○	○
I feel a sense of comfort	○	○	○	○	○	○	○
I feel excited	○	○	○	○	○	○	○
I feel sad	○	○	○	○	○	○	○
I feel frustrated	○	○	○	○	○	○	○

APPENDIX B
Stress Induction Stimuli (Study 2) – GMAT Questions

Problem Set #1: "Mathematical Ability"

This task is a test of people's mathematical ability.

On the following page you will be presented with a total of 15 math questions. Participants who are able to solve the most problems correctly within the allotted time will be entered into a lottery for the chance to win a prize.

You will have 3 minutes to solve as many problems as you can. An alarm will go off once every minute to indicate that 1 minute, 2 minutes and 3 minutes have passed. Once 3 minutes have passed, you are required to turn this problem set face down and wait to receive the next problem set.

Now that you have read the instructions, please (1) write your post-it number at the top of this page and (2) raise your hand to indicate that you are ready to begin.

DO NOT TURN TO THE NEXT PAGE UNTIL THE EXPERIMENTER TELLS YOU TO BEGIN.

APPENDIX B
Stress Induction Stimuli (Study 2) – GMAT Questions

1. Of the following, which is greater than ½ ?
   A. 2/5
   B. 4/7
   C. 4/9
   D. 5/11
   E. 6/13

2. If an object travels at five feet per second, how many feet does it travel in one hour?
   A. 30
   B. 300
   C. 720
   D. 1800
   E. 18000

3. What is the average (arithmetic mean) of all the multiples of ten from 10 to 190 inclusive?
   A. 90
   B. 95
   C. 100
   D. 105
   E. 110

4. A cubical block of metal weighs 6 pounds. How much will another cube of the same metal weigh if its sides are twice as long?
   A. 48
   B. 32
   C. 24
   D. 18
   E. 12

5. In a class of 78 students 41 are taking French, 22 are taking German. Of the students taking French or German, 9 are taking both courses. How many students are not enrolled in either course?
   A. 6
   B. 15
   C. 24
   D. 33
   E. 54

6. A straight fence is to be constructed from posts 6 inches wide and separated by lengths of chain 5 feet long. If a certain fence begins and ends with a

post, which of the following could **not** be the length of the fence in feet? (12 inches = 1 foot)

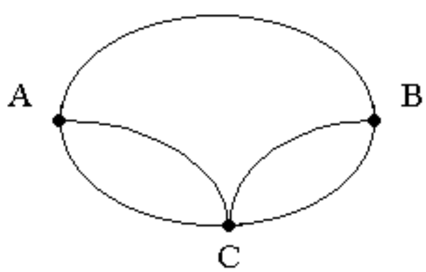
A. 17
B. 28
C. 35
D. 39
E. 50

7. $(\sqrt{2} - \sqrt{3})^2 =$

A. $5 - 2\sqrt{6}$
B. $5 - \sqrt{6}$
C. $1 - 2\sqrt{6}$
D. $1 - \sqrt{2}$
E. 1

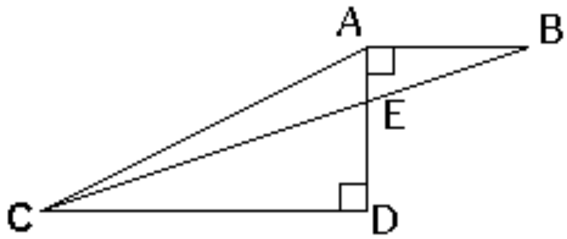
8. $2^{30} + 2^{30} + 2^{30} + 2^{30} =$

A. 8^{120}
B. 8^{30}
C. 2^{32}
D. 2^{30}
E. 2^{26}

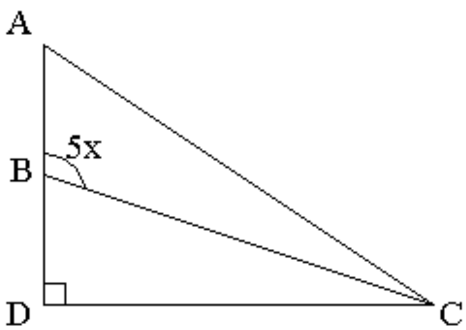


9. Amy has to visit towns B and C in any order. The roads connecting these towns with her home are shown on the diagram. How many different routes can she take starting from A and returning to A, going through both B and C (but not more than once through each) and not travelling any road twice on the same trip?

A. 10
B. 8
C. 6
D. 4
E. 2



10. In the figure above AD = 4, AB = 3 and CD = 9. What is the area of triangle AEC ?
    A. 18
    B. 13.5
    C. 9
    D. 4.5
    E. 3



11. Which of the following could be a value of x, in the diagram above?
    A. 10
    B. 20
    C. 40
    D. 50
    E. any of the above

12. Helpers are needed to prepare for the fete. Each helper can make either 2 large cakes per hour, or 35 small cakes per hour. The kitchen is available for 3 hours and 20 large cakes and 700 small cakes are needed. How many helpers are required?
    A. 10
    B. 15
    C. 20
    D. 25
    E. 30

13. Jo's collection contains US, Indian and British stamps. If the ratio of US to Indian stamps is 5 to 2 and the ratio of Indian to British stamps is 5 to 1,

what is the ratio of US to British stamps?

A. 5 : 1
B. 10 : 5
C. 15 : 2
D. 20 : 2
E. 25 : 2

14. A 3 by 4 rectangle is inscribed in circle. What is the circumference of the circle?
    A. 2.5π
    B. 3π
    C. 5π
    D. 4π
    E. 10π

15. Two sets of 4 consecutive positive integers have exactly one integer in common. The sum of the integers in the set with greater numbers is how much greater than the sum of the integers in the other set?
    A. 4
    B. 7
    C. 8
    D. 12
    E. it cannot be determined from the information given.

APPENDIX B
Stress Induction Stimuli (Study 2) – RAT Items

Problem Set 2: "Reasoning Ability"

This task is a test of people's reasoning ability.

On the following page, you will be shown a total of 18 questions. Each question contains three words and asks you to think of the one word that these three words have in common.

For example, if the three words are, "[Cottage] [Swiss] [Cake]," you would try to think of the word "Cheese."

"Cheese" is related to "Cottage" (the expression "Cottage Cheese"), to "Swiss" ("Swiss Cheese"), and to "Cake" ("Cheese Cake").

Participants who are able to solve the most problems correctly within the allotted time will be entered into a lottery for the chance to win a prize.

You will have 3 minutes to solve as many problems as you can. An alarm will go off once every minute to indicate that 1 minute, 2 minutes and 3 minutes have passed. Once 3 minutes have passed, you are required to turn this problem set face down and wait to receive the next problem set.

Now that you have read the instructions, please (1) write your post-it number at the top of this page and (2) raise your hand to indicate that you are ready to begin.

DO NOT TURN TO THE NEXT PAGE UNTIL THE EXPERIMENTER TELLS YOU TO BEGIN.

Cream Skate Water :

Aid Rubber Wagon :

Safety Cushion Point :

Cast Side Jump :

Light Birthday Stick :

Skunk Kings Boiled :

Master Toss Finger :

Flake Mobile Cone :

Chamber Staff Box :

Fox Man Peep :

Blank List Mate :

Shopping Washer Picture :

Pie Luck Belly :

Type Ghost Screen :

Blood Music Cheese :

Bass Complex Sleep :

Sea Home Car :

APPENDIX B
Stress Induction Stimuli (Study 2) – Anagram Items

Problem Set 3: "Anagrams"

This is the final set of problems. On the following page you will be presented with a series of anagrams, which are words whose letters are scrambled. When you have unscrambled the letters to form the word, type the solution into the space provided. Below is an example of an anagram:

Example anagram

SMOM

Solution:
Moms

There are 18 anagrams in total. You will have 3 minutes to solve as many problems as you can. Participants who are able to solve the most problems correctly within the allotted time will be entered into a lottery for the chance to win a prize.

You will have 3 minutes to solve as many problems as you can. An alarm will go off once every minute to indicate that 1 minute, 2 minutes and 3 minutes have passed. Once 3 minutes have passed, you are required to turn this problem set face down and wait to receive the next problem set.

Now that you have read the instructions, please (1) write your post-it number at the top of this page and (2) raise your hand to indicate that you are ready to begin.

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APPENDIX B
Stress Induction Stimuli (Study 2) – Anagram Items

UGARS

MHNUA

HREAFTS

ITWHEG

THGRUOH

COMEPR

CEENRYEGM

RISECET

KDNITE

OIRUPMTPM

TYIHEASR

ACLADIR

AIPTLRA

VETIIFUG

PPSORALO

TRNTHEGS

OSLURDEH

AINNTRTSO

APPENDIX C
Consumption Propensity Measures – Ex-Smokers Version (Study 4)

I. Smoking Propensity Measures

1. In total, how many years did you smoke? (Please provide the number of years in numerical response only, e.g. 0.5 [i.e. for 6 months] or 10 [i.e. for 10 years])
2. Over this time period, how many times did you attempt to quit smoking? (Please provide the number of years in numerical response only, e.g. 0 or 5)
3. What type of smoker did you consider yourself to be?
   - Non-smoker
   - Social smoker
   - Light smoker
   - Moderate smoker
   - Heavy smoker
4. Please estimate how many cigarettes you smoked during the following time periods during a typical day (in numerical response only, e.g. 0 or 3):
   - 6:00 AM - 9:00 AM
   - 9:00 AM – Noon
   - Noon - 3:00 PM
   - 3:00 PM - 6:00 PM
   - 6:00 PM - 9:00 PM
   - 9:00 PM - Midnight
   - Midnight - 3:00 AM
   - 3:00 AM - 6:00 AM
5. Over the past week (in the past 7 days), how often did you find yourself craving a cigarette?
   - Never
   - Rarely
   - Sometimes
   - Most of the time
   - All the time
6. Please indicate the extent to which you agree with the statements below: When I was smoking cigarettes: (1 - Strongly Disagree to 7 - Strongly Agree)
   1. When I hadn't smoked in a while, I started craving a cigarette
   2. I enjoyed the physical sensation of lighting and handling a cigarette
   3. I automatically had a cigarette at certain times or activities, such as after meals
   4. I worried that smoking was bad for my health but still continued to smoke
   5. The biggest reason I couldn't stop smoking was because I was addicted
   6. My friends thought of me as a smoker

APPENDIX C
Consumption Propensity Measures – Ex-Smokers Version (Study 4)

II. Eating Propensity Measures

1. What type of diet do you consider yourself to have since you've quit smoking?
    - 1-Very Healthy
    - Moderately Healthy
    - 3-Somewhat Healthy
    - Moderately Unhealthy
    - 5-Very Unhealthy (i.e. I eat lots of junk food)
2. Please indicate the extent to which you agree with the statements below about your eating habits **since you quit smoking**: (1 - Strongly Disagree to 7 - Strongly Agree)
    - I find myself consuming certain foods even though I am no longer hungry
    - When I start eating certain foods I end up eating more than I had planned
    - My behavior with respect to food and eating causes me significant distress
    - I often feel sluggish or fatigued from over-eating
3. **Indicate the extent to which you agree with the statements below:** Since I quit smoking, I have started eating more junk food.
    - 1-Not true at all
    - 2
    - 3-Somewhat
    - 4
    - 5-Very true
4. **Indicate the extent to which you agree with the statements below:** Since I quit smoking, I have started eating more in general.
    - 1-Not true at all
    - 2
    - 3-Somewhat
    - 4
    - 5-Very true

APPENDIX C
Consumption Propensity Measures – Ex-Smokers Version (Study 4)

III. Drinking Propensity Measures

1. How often have you had any kind of alcoholic drink since you've quit smoking?
    - Never
    - Monthly or less
    - 2 - 4 times a month
    - 2 - 3 times a week
    - 4 - 5 times a week
    - 6 or more times a week
2. Since you've quit smoking **how many drinks do you have on a typical day of drinking?**
    - 1 - 2 drinks
    - 3 - 4 drinks
    - 5 - 6 drinks
    - 7 - 9 drinks
    - 10 or more drinks
3. In total, how many years have you been drinking alcohol? (Please provide the number of years in numerical response only, e.g. 0.5 [i.e. for 6 months] or 7 [i.e. for 7 years]).
4. Please indicate the extent to which you agree with the statements below about drinking alcohol **since you've quit smoking**: (1 - Strongly Disagree to 7 - Strongly Agree)
    - When I'm depressed I drink to feel better
    - When I drink I often lose track of how much alcohol I'm consuming
    - I have tried to cut down on my drinking and failed
    - I usually cannot stop drinking after taking 1 to 2 drinks

APPENDIX C
Consumption Propensity Measures – Ex-Smokers Version (Study 4)

IV. Smartphone Usage Propensity Measures

1. How do you feel about your current smartphone?
    - 1-I feel fine about my smartphone
    - 2
    - 3
    - 4
    - 5-I love my smartphone
2. Please estimate <u>how many times you use your smartphone during the following time periods</u> during a typical day **since you quit smoking** (in numerical response only, e.g. 0 or 3):
    - 6:00 AM - 9:00 AM
    - 9:00 AM – Noon
    - Noon - 3:00 PM
    - 3:00 PM - 6:00 PM
    - 6:00 PM - 9:00 PM
    - 9:00 PM - Midnight
    - Midnight - 3:00 AM
    - 3:00 AM - 6:00 AM
3. Please indicate the extent to which you agree with the statements below about <u>your smartphone use since you've quit smoking</u>: (1 - Strongly Disagree to 7 - Strongly Agree)
    - When I run out of battery it's almost unbearable until I recharge my smartphone
    - When I'm tense or upset, using my smartphone helps me relax
    - Using my phone helps me deal with an overly stimulating environment
    - Using my phone helps me feel comfortable in social situations
    - When I see other people using their phones I want to use my phone
    - I feel more comfortable with my smartphone in my hand
4. **<u>Indicate the extent to which you agree with the statement below</u>:** Since I quit smoking, the time I spend on my smartphone has increased.
    - 1-Not true at all
    - 2
    - 3-Somewhat
    - 4
    - 5-Very true