A Field Study of the Determinants of Mobile Advertising Effectiveness

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Abstract

Mobile advertising is one of the fastest-growing advertising formats. In 2011, U.S. advertisers spent approximately $1.2 billion on this form of advertising, and by 2015 global mobile advertising spending is expected to exceed $20 billion. Interestingly, despite the rapid penetration of sophisticated handsets such as smart phones, a growing proportion of mobile advertising spending consists of display advertising, which is known for its limited capacity for the transfer of information. This paper examines why and under what conditions mobile display advertising is effective in increasing consumers’ purchase intentions. We draw on established theories in consumer psychology to identify these conditions and verify our hypotheses in a series of advertising campaign field tests involving 54 U.S. mobile display-advertising campaigns that ran between 2007 and 2010 and involved 27,753 consumers. Our results indicate that mobile display advertising campaigns are effective when they are for products that tend to trigger deliberate thought and consideration, which includes campaigns for higher (versus lower) involvement products, and for products that are seen as more utilitarian (versus more hedonic).
Mobile advertising has become one of the fastest-growing tools for reaching consumers over the last few years. Overall spending on mobile advertising has been growing quickly, rising from $416 million in 2009 to $743 million in 2010 and $1.2 billion in 2011, and is forecasted to reach $4.4 billion by 2015 in the U.S. market alone (eMarketer.com 2011). Globally, mobile advertising spending is expected to reach $20.6 billion by 2015 (Gartner 2011). While only 37% of U.S. marketers surveyed in May 2011 used mobile advertising as one of their communications channels, 58% said that they intended to use mobile advertising in the near future. The popularity of the mobile channel as a way for marketers to reach consumers is expected to continue to increase, fueled by the proliferation of mobile connected devices throughout the world. Thus, there is an increasingly high potential reach for mobile advertising.

Mobile advertising comes in a variety of forms, including display, SMS/text message, location-based, and rich media. Display advertising is the most pervasive, largely because advertisements of this kind are compatible with almost all types of mobile phones currently in use around the world (e.g., smartphones such as iPhone, older smartphones such as Blackberry, and lower-cost feature phones such as many produced by Nokia and Motorola). Of these, mobile banner images displayed on top of the screen in a Wireless Application Protocol (WAP) browser constitute the most common form of such advertising. Recently, this advertising unit has also been embedded in various mobile smartphone applications (apps), affording app developers with another potential source of revenue. Figure 1 shows two examples of mobile display advertisements and their placements in WAP browsers (panel A) and apps (panel B). Interestingly, while the popularity of some other forms of mobile advertising has either exhibited no growth or started to decline (e.g., SMS advertisements), the popularity of mobile display advertising has been steadily increasing. Specifically, the
share of total U.S. mobile advertising held by display is expected to grow from 35% in 2011 to 45% by 2015 (eMarketer.com 2011).

The fast growth of mobile display advertising is somewhat surprising because this advertising format has severe limitations in its ability to engage consumers. Mobile display advertisements occupy a very small portion of an already small screen and can only contain little amounts of information, and consumers are typically “on the move” and therefore exposed many other stimuli. These factors conceivably can severely constrain the effectiveness of mobile display advertising, casting doubt on its ability to have an impact on consumers’ attitudes and behaviors. However, industry studies generally indicate that mobile advertising can be very effective (Pappachen and Manatt 2008) and, as mentioned above, advertisers seem increasingly willing to run mobile display advertising campaigns.

Since the evidence from practice is scant and this form of digital advertising is inherently limited, an important question is when should advertisers use mobile display advertising? Existing research provides little guidance. Formal studies on mobile advertising are rare and have severe limitations both in terms of their methodologies and their scope. In particular, previous studies of mobile advertising effectiveness (Barwise and Strong 2002; Drossos et. al. 2007; Tsang, Ho and Liang 2004) have focused only on SMS advertising, a format that is declining in popularity. While these studies all show a positive effect of SMS advertisements on various stages of consumer decision-making, each set of findings comes from a very limited sample of participants. Moreover, these studies are primarily motivated by pragmatic considerations and therefore provide little insight into the psychological mechanisms that drive mobile advertising effectiveness. For these reasons, existing empirical evidence provides insufficient guidance on the conditions under which mobile advertising is likely to be effective.
Given the dominant share and rising popularity of mobile display advertising, it is important to develop a better understanding of when this type of mobile advertising should be used and why it is likely to be effective under some but not all conditions. Put simply, for which types of products, services, or brands is mobile display advertising most likely to be effective? We address this fundamental question in this paper. To the best of our knowledge, this research is the first extensive empirical study in a field setting involving a relatively large and diverse set of mobile advertising campaigns that addresses this question.

Our approach proceeds in three steps. First, in order to contextualize mobile display advertising relative to other types of digital advertising, we start by introducing a new typology that accommodates technology restrictions. Technology restrictions are particularly relevant to mobile advertising since low bandwidth (Internet speed) and restricted physical space (screen size) are major limitations faced by advertisers that constrain their options with respect to advertising copy, visual richness, and information content. Our typology classifies digital advertising into two types: high-fidelity and low-fidelity. We argue that mobile display advertisements almost always fall into the latter category, which in practice means that advertising messages carry relatively little information and often are low quality, particularly visually. It is therefore somewhat surprising that prior research (including industry studies; e.g., Pappachen and Manatt 2008) finds mobile advertising to be generally very effective.

Second, we draw on extant theory and prior empirical research on advertising, persuasion, and consumer information processing to derive a set of hypotheses predicting consumers’ responses to mobile display advertisements. This conceptualization focuses on two widely accepted and general dimensions for classifying products or brands: whether they are more hedonic or more utilitarian (e.g., Dhar and Wertenbroch 2000; Khan, Dhar, and

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1 Hereafter we refer to products, services, or brands simply as “products.”
Wertenbroch 2005), and whether they are higher or lower involvement with respect to consumer judgment and decision-making processes (e.g., Petty, Cacioppo, and Schumann 1983; Zaichkowsky 1985).

Third, we collaborated with a major marketing research agency and their clients (advertisers) to test our hypotheses using a series of field tests that involved 54 different mobile advertising campaigns conducted between mid 2007 and mid 2010 and covered 13 diverse industries. Our data includes individuals’ responses to mobile display advertisements from a nationally representative sample of 27,753 consumers. Each campaign was conducted following standard advertising testing procedures involving random assignment of consumers to either a test group (who were exposed to the campaign’s advertisement) or a control group (who were not exposed to the advertisement).

Empirically, we find substantial heterogeneity in campaign performance, and attempt to explain these differences through our conceptualization focusing on product classification characteristics (hedonic vs. utilitarian; low vs. high involvement). Note that our goal is to show how these product-level characteristics are associated with differences in campaign performance with respect to consumers’ purchase intentions. Although we draw on individual psychological process theories (such as the elaboration likelihood model [ELM]; Petty and Cacioppo 1981) to help develop our predictions, since we are concerned with when managers should expect mobile display advertising campaigns to be more or less effective, we do not formally test underlying individual processes in this paper.²

To preview our results, we find positive advertising treatment effects on consumers’ purchase intentions only for products that are more utilitarian (as opposed to more hedonic) and for which product consideration and purchase decision-making processes are considered to be higher involvement (as opposed to lower involvement). In a number of other conditions,

² For a detailed treatment of the psychological processes associated with how consumers process product information from advertisements, see for example MacInnis, Moorman, and Jaworski (1991).
however, we find either no treatment effects for mobile display advertising or slightly negative effects (i.e., when consumers exposed to an advertisement become less inclined to purchase that product). We also find that these effects on purchase intention are mediated by an increase in consumers’ favorable attitudes towards advertised products. Thus, the current research represents an important step toward helping scholars and managers better understand when mobile display advertising is appropriate and which types of products are best suited for being advertised through this medium.

**Background**

*Related Literature*

Our work is related to two literature streams. The first stream broadly covers advertising effectiveness in the context of digital media. Beyond the limited literature on SMS advertising mentioned earlier, the wider context of digital advertising has gained attention recently among both information systems and marketing scholars. The literature has examined various aspects associated with digital advertising effectiveness and, more generally, effects of media activity on business outcomes such as sales. For example, Goldfarb and Tucker (2011) study determinants of online display advertising effectiveness, Ghose and Yang (2009) examine a similar issue in the domain of online search engine advertising, Danaher, Lee, and Kerbache (2009) consider media mix issues in digital advertising, and Chatterjee, Hoffman, and Novak (2003) model consumer responses to website banner advertisements. In the context of so-called “earned” digital media, recent work has compared the sales response to mentions of a brand in social media to traditional media publicity (Stephen and Galak 2012), explored how online word-of-mouth affects the growth of websites and social networking platforms (Trusov, Bucklin, and Pauwels 2009),
developed economic models of users’ motivations to contribute content on social media platforms such as Twitter (Toubia and Stephen 2012), and analyzed the sales impact of online user-generated product reviews (Dellarocas, Zhang, and Awad 2007). Although studies of mobile media usage and the mobile Internet have also begun to emerge (e.g., Garg and Telang 2011; Ghose and Han 2011; Shim, Park, and Shim 2008), mobile advertising has not received much attention from researchers. In particular, prior research on mobile advertising effectiveness has not considered display advertising and has not examined its effectiveness within the context of a multi-campaign field tests covering a variety of industries and products. Further, prior research has tended to show only cases in which mobile advertisements are effective. While it is possible that mobile advertisements are generally effective in persuading and influencing consumers’ attitudes and behaviors, it is unlikely that their effects are universally positive. Thus, a more general and comprehensive understanding of this increasingly important and popular advertising medium is needed.

The second stream of research is grounded in consumer psychology. In particular, we draw on the ELM (Petty and Cacioppo 1981, 1983) and its application to advertising as a model of how persuasive communications are processed (e.g., Petty, Cacioppo, and Schumann 1983; Petty and Cacioppo 1986). We discuss ELM and related concepts in more detail when we develop our hypotheses below. In addition to the literature on communication persuasion, we also draw on the literature on emotions (in particular the affect-as-information literature; e.g., Avnet, Pham, and Stephen 2012; Greifeneder, Bless, and Pham 2011; Pham, Lee, and Stephen 2012), consumption of hedonic versus utilitarian goods (e.g., Dhar and Wertenbroch 2000; Khan, Dhar, and Wertenbroch 2005), and product involvement (e.g., Zaichkowsky 1985).
Industry Context: Typology Of Digital Advertising Media

We introduce a typology of digital advertising media in Table 1 in which media are classified as either high- or low-fidelity. We use this typology to contextualize mobile display advertising, which largely falls under the low-fidelity type. Note, however, that in the subsequent conceptualization and empirical analysis we focus exclusively on low-fidelity mobile display advertising and do not draw empirical comparisons to other types of digital advertising, many of which have already been studied (see the previous section for examples).

[INSERT TABLE 1 ABOUT HERE]

We borrow the concept of “fidelity” from literature in computer science and engineering where fidelity refers to a property of prototypes, websites, and images. For example, low-fidelity prototypes in engineering have generally limited functionality and are relatively low quality. Low-fidelity prototypes are often static and lack interactivity. A low-fidelity prototype of a website design could be as simple as a pencil-and-paper sketch of how a website should look and its basic functions (cf. Rudd, Stern, and Isensee 1996). In contrast, high-fidelity prototypes are much more thoroughly developed and “fleshed out,” and therefore tend to be more realistic and detailed, feature a higher degree of functionality and interactivity, and are generally of better quality. Importantly, low-fidelity prototypes tend to convey limited information, whereas high-fidelity prototypes offer more extensive information.

Adapted to the context of digital advertising, low- versus high-fidelity refers to how much information can be feasibly conveyed through a particular medium, the medium’s level of quality in presenting that information, and aspects associated with the consumer experience such as the degree to which the medium is interactive. Examples of high-fidelity digital advertising media include rich media advertisements such as video-based interstitials
or interactive display or banner advertisements, advertisements that are based on Flash or HTML5 technologies, and other types of media that are highly interactive and are able to present relevant information to consumers in a high-quality dynamic format. In contrast, low-fidelity digital advertising media include advertisements that are fully text based (e.g., Google Adwords), contain low-resolution and static images (e.g., basic website display banners), or a combination of text and images in a static, non-interactive, and size-constrained format (e.g., Facebook advertisements). In the domain of mobile advertising, the vast majority of options managers currently have at their disposal fall into the low-fidelity category. For example, SMS advertisements only contain text. MMS advertisements contain images but are still very basic. Advertisements on smartphones with higher-resolution screens can be high-fidelity, such as advertisements on Apple’s iOS devices published through the iAd platform (e.g., advertisements can feature video, high-quality images, and be interactive). However, a more common mobile advertising unit, including on current-model smartphones, is the mobile display advertisement, which is another example of a low-fidelity advertisement.

While high-fidelity digital advertisements are more frequently used on websites, they are less common on mobile devices due to technology restrictions. Even though many mobile devices have the ability to access the Internet via high-speed connections (e.g., Wi-Fi), often their connections rely on mobile Internet technologies such as 3G and 4G networks. These Internet connections have limited bandwidth and, therefore, limit what advertisers can realistically do with rich media, particularly with respect to streaming video and other dynamic interactive elements.

Another important aspect that limits the widespread use of high-fidelity advertising in mobile channels is screen size. With the exception of tablet devices (e.g., iPad), most mobile connected devices have relatively small screens. This simply means that advertisers cannot fit
as much content or information into an advertisement, even if it occupies the whole screen (which is rare, particularly with mobile display advertisements). Finally, some mobile device platforms and operating systems make rich-media and interactive advertisements difficult or impossible to implement. For example, while Flash has been a de facto standard for interactive advertisements on mobile websites, this software is not allowed on Apple’s iOS platform (i.e., iPhone and iPad). Moreover, given the heterogeneity in types of mobile devices and those devices’ technical capabilities, advertisers often prefer to use simpler, low-fidelity advertising media in mobile channels to ensure the compatibility of their advertisements with as many devices and networks as possible, increasing an advertisement’s potential reach. Taken together, these factors make it likely that the low-fidelity type of mobile advertising will remain highly popular in the foreseeable future.

**Conceptual Development and Hypotheses**

*Persuasion in Communication and Information Processing*

Despite their apparent inferiority, low-fidelity mobile advertisements of various types have been shown in prior research to be effective in influencing consumers’ attitudes and behaviors (e.g., Barwise and Strong 2002; Drossos et al. 2007; Pappachen and Manatt 2008). Although we argue below that low-fidelity mobile display advertisements are likely to be effective only under specific conditions, previous findings imply that this type of advertising unit at least has the potential to be persuasive.

Marketers and psychologists have studied advertising effectiveness and consumer responses to advertising for decades. In the psychology literature, a classic model of persuasion in communication is the ELM (Petty and Cacioppo 1981, 1983). The ELM is an information-processing model of how individuals’ attitudes are formed or changed in
response to potentially persuasive stimuli such as advertisements. The ELM postulates two routes through which persuasion can occur: the central route and the peripheral route.\(^3\) Persuasion through the central route implies that consumers deliberately process message-relevant information. In contrast, in the case of the peripheral route attitudes are determined by environmental cues and not the message or information itself. Individuals process information in a more cognitive manner under the central route, which in the mobile display advertising case would mean that they pay attention to the content of the advertisement and thoughtfully consider it (i.e., with a high “elaboration likelihood” and thus a high degree of cognitive elaboration). On the other hand, individuals rely more on affective evaluation of stimuli under the peripheral route. In fact, the literature on affect-as-information suggests that a person’s current affective state (i.e., mood) or their feelings toward a stimulus could themselves be peripheral cues (cf. Avnet et al. 2012; Pham et al. 2012; Schwarz, Bless, and Bohner 1991).

Because the information they contain is presented in a lower quality manner, low-fidelity mobile display advertisements are less likely to be processed through the central route. This opens up the possibility that these types of advertisements are instead processed through the peripheral route. Peripheral-route processing could translate into paying less direct attention to the content of the advertisement and relying more on other cues that are not contained within the advertisement itself and therefore less likely to be controlled by the advertiser (i.e., with a low “elaboration likelihood” and thus a low degree of cognitive elaboration). This may be problematic from an advertiser’s point of view. In a low-fidelity environment the quality of available information is lower and may be distorted or less fluent. Accordingly, there is likely to be an increased risk of consumers misunderstanding an advertisement presented in such an environment, not paying sufficient attention to it, or

\(^3\) Related “dual process” models in psychology postulate information processing and responding to stimuli as following either a more cognitive, systematic, and reason-based process versus a more affective, heuristic-based, and intuitive process (e.g., Chaiken 1980; Epstein and Pacini 1999).
becoming influenced by tangential (and largely irrelevant) cues. Put simply, consumers may draw unintended conclusions (if they draw any conclusions at all).

Moreover, the peripheral cues that influence consumers under the peripheral route to persuasion may negatively affect their attitudes and intentions. For example, a low-fidelity advertisement for an airline when processed along the peripheral route could cue memories of ruined vacations due to delayed flights and lost baggage, which may result in a consumer’s attitude toward the advertised airline becoming less positive (or more negative). This would be less likely under the central route, since information contained in the advertisement itself (e.g., “We have a 99% on-time departure record”) would be thoughtfully processed and directly linked to the consumer’s attitude. Another example is low-fidelity advertisements for movies. Under peripheral-route processing a movie advertisement with low image quality may result in a consumer (unconsciously) expecting the movie itself to be of low quality, whereas such an association would be less likely under central-route processing.

Given the risks described above, we only expect low-fidelity mobile advertisements to more likely to have a positive effect on consumer attitudes and purchase intentions when they are processed through the central route. Two determinants of which route an individual takes are processing elaboration ability and processing motivation (Petty and Cacioppo 1979, 1986).

Processing ability refers to the relative ease or difficulty of elaborating on a stimulus when processing its information. This may be an individual difference, but can also be associated with certain product types or characteristics. Processing ability can also be more generally associated with the presence or absence of distractions external to the stimulus or distortion associated with the processing of the stimulus itself. For example, the environmental cues that are attended to under peripheral-route processing but are not in fact central to the task at hand may be a source of distortion or distraction that lowers processing
elaboration ability, thus lowering elaboration likelihood and making central-route processing less likely to occur (Petty, Ostrom and Brock 1981).

Processing motivation refers to the extent to which a person is motivated to engage in effortful processing of a stimulus. When consumers are highly motivated they are expected to have higher elaboration likelihood and will process through the central route. The advertisement itself is unlikely to provide high processing ability or high processing motivation in the case of low-fidelity mobile display advertising. Certain product characteristics, however, may promote processing motivation and enhance processing ability, and thus potentially increase the likelihood that the central route is taken, and thus affect the nature and extent of persuasion.

**Hypothesis Development**

We now develop a set of specific hypotheses that draw on the above-described literature to predict conditions under which low-fidelity mobile display advertisements are expected to be more effective in increasing consumers’ purchase intentions and favorable attitudes towards products. Note that we shift our focus to product-level characteristics that map to the theoretical dimensions outlined above, instead of building a fully individual-level theory. This is for two important reasons. First, the goal of this research is to examine which types of products lend themselves more to mobile display advertising. While individual-level process explanations help to establish our predictions, they are drawn from prior research and are therefore not directly tested within the scope of our research question. Second, our field-test data from multiple campaigns featuring products that vary on theoretically and practically meaningful dimensions at the product level unfortunately does not allow for detailed individual-level psychological process testing (which we leave for future research).

**Processing ability and product type.** We first consider a product characteristic associated with the consumer having a higher or lower processing ability: whether the
product is more utilitarian or more hedonic (product type). Utilitarian products tend to be instrumental and functional, whereas hedonic products are associated with experiential consumption, pleasure, excitement, and fun (Dhar and Wertenbroch 2000; Holbrook and Hirschman 1982; Khan, Dhar, and Wertenbroch 2005). Because of their functional nature, utilitarian products are more likely to be processed in a deliberative, thoughtful, and cognitive manner. Importantly, when thinking about utilitarian products, consumers are less likely to be distracted by thoughts not central to the evaluation of the product (cf. Petty et al. 1981). Further, since utilitarian products tend to be more functional and used for achieving instrumental goals (Khan et al. 2005), consumers tend to find it easier to imagine consuming the product and deriving value from consumption. Thus, consumers are expected to have higher processing ability when considering utilitarian products. Hedonic products, on the other hand, lend themselves more to affective and heuristic-based processing (Pham 1998). Further, they are often more experiential in nature and tend to be judged in a holistic manner (Pham 2007). These aspects tend to make it more difficult to imagine oneself consuming and deriving value from hedonic products, and also make it harder to avoid judgments being distorted by peripheral cues. Thus, hedonic products are expected to be associated with lower processing ability. These arguments suggest that utilitarian (hedonic) products are associated more with the central (peripheral) route (Geuens et al. 2010).

In an advertising context, a consumer presented with an advertisement for a utilitarian product has a better ability to directly scrutinize the message’s arguments. This is harder when considering advertisements for hedonic products, since hedonic products lend themselves more to intuitive or “gut feeling” assessments relying on peripheral cues and heuristics. Thus, compared to hedonic products, the ability to process advertisements for utilitarian products is expected to be higher. Elaboration is therefore more likely, and consequently it is likely that utilitarian products will be processed through the central route.
and hedonic products through the peripheral route. Importantly, this also means that low-fidelity advertisements for utilitarian products are less susceptible to being misunderstood or otherwise erroneously processed. Thus, low-fidelity mobile display advertisements are more likely to have a positive effect on consumers’ attitudes such as purchase intent for utilitarian products than for hedonic products. Stated formally:

**Hypothesis 1:** After exposure to a mobile display advertisement, consumers’ increases in purchase intent will be larger for utilitarian products than for hedonic products.

*Processing motivation and product involvement.* Previous research on advertisement processing motivation shows that higher processing motivation increases the likelihood of central-route processing and increases the extent to which an advertisement impacts purchase intent (Mackenzie and Spreng 1992). In other words, when a consumer is exposed to an advertisement and is highly motivated to process it his/her resulting attitudes should be less affected by peripheral cues, s/he should be less likely to use heuristic-based processing, and s/he should be less influenced by feelings-based inferences. Psychologists have identified personal relevance as one of the most important variables affecting the motivation to process a persuasive message (Petty and Cacioppo 1979). Higher personal relevance means that a product is intrinsically important (Sherif and Hovland 1961) and is expected to have significant consequences for one’s life (Apsler and Sears 1968). In consumer behavior this is often referred to as a product being higher involvement because greater personal relevance and intrinsic importance imply that a consumer will engage in a higher level of effortful processing when considering such a product or information associated with that product (e.g., an advertisement).
Higher-involvement products (or advertisements for higher-involvement products) therefore will generally be examined in greater detail and considered with greater care, in large part because they are more personally relevant (Celsi and Olson 1988). Conversely, consumers will not focus on lower-involvement products with as much detail or care. Put simply, processing motivation is expected to be higher (lower) for advertisements for products that are higher (lower) involvement. Consequently, it is likely that higher-involvement products will be processed through the central route and lower-involvement products will be processed through the peripheral route (Petty, Cacioppo, and Schumann 1983). As with utilitarian products, this means that low-fidelity mobile display advertisements for higher-involvement products will also be less susceptible to being misunderstood or otherwise erroneously processed. Low-fidelity mobile display advertisements are therefore more likely to have positive effect on purchase intent when they are for higher-involvement products than when they are for lower-involvement products. Stated formally:

**Hypothesis 2:** After exposure to a mobile display advertisement, consumers’ increases in purchase intent will be larger for higher-involvement products than for lower-involvement products.

*Processing ability and processing motivation.* Both processing ability and processing motivation affect how a stimulus is processed. Even if a consumer is highly motivated to process an advertisement (i.e., for a higher-involvement product), it may be difficult for them to do this—and take the central route to persuasion—unless they simultaneously have a higher processing ability (i.e., the product type is utilitarian). Thus, we expect low-fidelity mobile display advertisements to be most persuasive for products that promote higher
processing motivation and higher processing ability. This implies a product type \( \times \) product involvement interaction such that the advertising effect is highest when both processing motivation and processing ability are higher. In our setting this corresponds to a utilitarian, higher-involvement product. Stated formally:

**Hypothesis 3:** After exposure to a mobile display advertisement, consumers’ increases in purchase intent will be largest for utilitarian, higher-involvement products (i.e., a positive interaction between product type and involvement).

**Recent advertising exposure.** The timing of the placement of an advertisement that is part of a larger multi-channel campaign\(^4\) may also affect processing and persuasion. This is related to whether a consumer recalls being recently exposed to advertising for a given product. The effect of recent advertising exposure on the process through which a subsequent advertisement is evaluated and the resultant effect on purchase intent, however, is unclear. For instance, consumers who have not recently been exposed to an advertisement for a product may have higher motivation to process an advertisement when they see it (for the first time) because it is novel. On the other hand, these consumers may have lower processing ability because they are inherently less familiar with the product due to not having a prior, recent opportunity to consider and evaluate that product in response to an advertising exposure. These potential processes imply opposite predictions for the effect of recent advertising exposure on the current advertising effect on purchase intent. However, following the ELM we expect processing motivation to be marginally more important than processing ability. That is, we should find that not having been recently exposed to an advertisement for a product increases the impact of the current exposure on purchase intent. Stated formally:

\(^4\)Mobile channels are rarely the only channel used in a campaign.
**Hypothesis 4:** After exposure to a mobile display advertisement, consumers’ increases in purchase intent will be larger when the consumer has not recently been exposed to advertisements for that product.

The mediating role of favorable attitudes towards products. The above four hypotheses predict how product type and involvement affect purchase intentions. Since this research is most concerned with the effectiveness of mobile display advertisements in lifting consumers’ actual purchase intentions instead of affecting other related attitudes that may be less closely associated with tangible sales-related outcomes, our conceptualization necessarily considers purchase intent as the primary dependent variable. However, our data also allows us to test whether these predicted effects are mediated by favorable product attitudes. We expect this to be the case. Stated formally:

**Hypothesis 5:** The hypothesized effects of product type and product involvement on purchase intent will be mediated by an increase in favorable attitude toward the advertised product.

**Data and Methodology**

**Mobile Advertising Field Test Data**

Our data are from a large market research agency that specializes in measuring the effectiveness of digital advertising, including mobile display advertisements. The data cover 54 mobile display advertising campaigns that the agency worked on with their clients between July 2007 and June 2010. The 54 campaigns include brands from 13 different industries (e.g., consumer packaged goods, entertainment, financial services, health care).\(^5\)

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\(^5\) For confidentiality reasons cannot disclose the names of the brands. Most brands were large and well known.
The agency worked with mobile advertising networks and mobile service providers to place their clients’ low-fidelity mobile advertisements on specific mobile (WAP) webpages on consumers’ mobile devices. Across the 54 campaigns, 27,753 individuals participated in these field tests.

Each campaign was run as a standard advertising testing field study.\(^6\) This meant that participants who browsed to one of the many mobile webpages in the advertising network were randomly assigned to one of two conditions: (i) exposed, where an advertisement was displayed on their screen, or (ii) control, where they were not exposed to an advertisement. In total, 14,457 (52.09\%) participants were assigned to the exposed condition, and 13,296 (47.91\%) participants were assigned to the control condition. Neither the agency, their clients, nor we had control over the types of webpages and content contexts in which the test advertisements were displayed (these were determined by the advertising network, usually by an automatic allocation algorithm). In both conditions, the webpage also included a prominently placed banner the same size as the advertisement in the exposed condition that invited participants to complete a short survey. An example is shown in Figure 2.

Note that, like previous research in marketing using standard advertising testing data (e.g., Goldfarb and Tucker 2011), we did not control who participated in these campaigns. All participants were recruited via the survey invitation that appeared when browsing the mobile webpages. Our findings therefore reflect the stated preferences of those consumers who were willing to answer the survey questions. The marketing research agency and their advertising network partners perform multiple checks to ensure the general national representativeness of survey participants and based on conversations with the agency staff

\(^6\) This approach is identical to advertising effectiveness testing procedures used in other digital advertising media, such as webpage display advertising (e.g., Goldfarb and Tucker 2011).
responsible for these campaigns we are confident that the participant samples were representative of the general population of U.S. adult consumers and mobile phone users.

The short survey measured (i) favorable attitude towards the product ("How would you describe your overall opinion of brand?" 1 = very unfavorable, 5 = very favorable), (ii) purchase intent ("Next time you are looking to purchase product category, how likely are you to purchase brand?" 1 = very unlikely, 5 = very likely), \(^7\) and (iii) whether or not participants had been recently (prior 30 days) exposed to advertising for the focal product (yes/no). No other participant data were available.

Various summary statistics for the campaigns are reported in Table 2. The mean number of participants per campaign was 513.94 (SD = 554.87) and the mean campaign length, which was the number of days the advertisement in the exposed condition was displayed and the product-specific purchase intent measurement was undertaken, was 54.80 days (SD = 32.79). As mentioned above, a variety of industries were represented in this set of campaigns. The most represented industry was consumer-packaged goods (33.33% of campaigns), followed by financial services (16.67%) and automotive (12.96%). The majority of the campaigns were for products (85.19%, vs. services), business-to-consumer brands (96.30%, vs. business-to-business), and for existing products or brand extensions (92.59%, vs. new products).

[INSERT TABLE 2 ABOUT HERE]

**Data Analysis Methodology**

*Classification of products by type and involvement.* To test our hypotheses we first classified each campaign on the two dimensions of product involvement (higher vs. lower) and product type (hedonic vs. utilitarian). This was done in two ways. First, the marketing

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7 Note that this measure of purchase intent was not specific to any type of retail channel.
research agency provided us with campaign-level data that classified each campaign’s product as either higher or lower involvement. For product type, we carefully examined each campaign’s product and judged it as either more hedonic or more utilitarian, following Strahilevitz and Myers (1998) and Dhar and Wertenbroch (2000).\(^8\)

Second, we recruited members of a large online panel to validate our classification. For each campaign, 19 or 20 respondents (M = 19.80, SD = .41) were presented with the product/brand name,\(^9\) the definitions of utilitarian and hedonic items used by Dhar and Wertenbroch (2000), a nine-point bipolar scale for product type (1 = mostly hedonic, 9 = mostly utilitarian), and five items on five-point Likert scales (1 = strongly disagree, 5 = strongly agree) designed to measure product involvement ($\alpha = .86$; e.g., “Deciding whether to purchase product is an important decision” and “Whether or not product turns out to be good would matter a lot to me”). The five items were averaged to form a single measure of involvement for each respondent. We used these data to confirm the validity of the product involvement classification (provided by the agency) and the product type classification (determined by us using detailed proprietary campaign information). To do this we estimated two random effects logit models (with campaign random effects). The first model regressed our binary measure of product type on the respondents’ ratings of how hedonic/utilitarian each product was. The second model regressed the agency-provided binary measure of product involvement on respondents’ ratings of involvement. Both models confirmed our classifications’ validities by showing strong positive relationships between the predictors and the binary dependent variables (product type $p < .01$; product involvement $p < .001$).

This two-stage procedure resulted in a $2\times2$ campaign classification. We report the distributions of campaigns and participants across these cells in Table 3, and the exposed versus control condition sizes

\(^8\) We also took into account how each product was framed/positioned when making these judgments. 
\(^9\) The proprietary nature of the data meant that we could not make detailed information available to respondents.
for each cell in Table 4. Since these were field tests we did not expect these distributions to be uniform.

[INSERT TABLES 3 AND 4 ABOUT HERE]

**Main analysis.** We treated each participant as the unit of analysis. We estimated the average treatment effect for exposed versus control on purchase intent, specifically focusing on how both the sign and size of the effect varied according to (i) whether the participant had recent exposure to advertising for the focal product (yes, no), (ii) product involvement (high, low), and (iii) product type (hedonic, utilitarian). For this we estimated a random effects linear model to regress purchase intent on main effects for product type (utilitarian = 1, hedonic = -1), product involvement (high = 1, low = -1), recent exposure (yes = 1, no = -1), treatment condition (exposed = 1, control = -1), and all two-, three-, and four-way interactions. We also included fixed effects (dummy variables) for industry, year, whether the advertised product was new or existing/extension, whether the product was an actual product or a service, and whether the product was business-to-consumer or business-to-business, as well as a covariate for campaign length (in days).\(^\text{10}\) A campaign random effect captured heterogeneity across campaigns.\(^\text{11}\)

### Results

**Hypothesis Tests**

Results from the random effects linear model are reported in Table 5, where we report estimates from two nested models. The first model is a full model including all effects, including those of the control variables (e.g., fixed effects for industry and year). The second

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\(^\text{10}\) We also considered campaign year as a moderator of the effects of interest (e.g., treatment effects may have varied across years). We tested this with year interactions but found no evidence of significant variation in effects by year.

\(^\text{11}\) An alternative is to include campaign fixed effects instead of a random effect. Results are robust to this variation.
model estimated only the main and interaction effects for the four variables of interest and not the control variables’ effects. Although the fit of the second model is slightly better, we base our findings on the full model. In any case, the effects required for testing our hypotheses did not differ in terms of sign, size, or significance.

[HYPOTHESES 1 TO 4.][1] We first turn our attention to testing hypotheses 1 to 4 by focusing on the estimated means for purchase intent and treatment effects (differences in the estimated means between exposed and control conditions). A significant positive (negative) treatment effect indicates that the average purchase intent was significantly higher (lower) for exposed participants than control participants. Table 6 lists the estimated means and treatment effects broken down by product type and involvement.

Hypothesis 1 predicted a larger positive treatment effect for purchase intent for utilitarian products than for hedonic products. This implies a significant positive utilitarian × exposed interaction in Table 5, which was the case (b = .03, t = 2.87, p < .01). Hence, the model’s results support this prediction. Specifically, when the campaign was for a utilitarian product, the mean purchase intent in the exposed condition was 3.09 versus 3.00 in the control condition. This difference was significant (∆ = .09, F(1, 50) = 13.89, p < .001). The treatment effect when the campaign was for a hedonic product was not significant (M_{exposed} = 2.51, M_{control} = 2.55; ∆ = -.04, F(1, 50) = 1.00, p = .32).

Hypothesis 2 predicted a larger positive treatment effect for purchase intent for higher-involvement products than for lower-involvement products. This implies a significant positive involvement × exposed interaction in Table 5, which was found (b = .03, t = 3.13, p < .01). Accordingly, this hypothesis is also supported. Specifically, when the campaign was for a higher-involvement product, the mean purchase intent in the exposed condition was 2.59 versus 2.50 in the control condition. This difference was significant (∆ = .09, F(1, 50) =
7.07, \( p = .01 \)). On the other hand, the treatment effect when the campaign was for a lower-involvement product was marginally significant and negative (\( M_{\text{exposed}} = 3.01, M_{\text{control}} = 3.05; \Delta = -.04, F(1, 50) = 2.77, p = .10 \)).

Hypothesis 3 proposed an interaction between product type and product involvement with respect to the exposed-versus-control treatment effect. Support for this hypothesis was also found: the utilitarian × involvement × exposed interaction in Table 5 was significant (\( b = .03, t = 2.88, p < .01 \)). To further examine this interaction we examined the estimated means and treatment effects. The only combination of type and involvement that resulted in a significant treatment effect was in campaigns for higher-involvement utilitarian products (\( M_{\text{exposed}} = 2.98, M_{\text{control}} = 2.76; \Delta = .22, F(1, 50) = 40.80, p < .001 \)). The treatment effects in the other three cells were not significant (all \( p > .20 \)).

Hypothesis 4 considered the effect of having been recently exposed to advertisements for the focal product, predicting a larger treatment effect on purchase intent when participants had not experienced (or did not recall) recent exposure. This hypothesis was also supported. The recent exposure × exposed interaction in Table 5 was significant and negative (\( b = -.04, t = -4.15, p < .001 \)). Specifically, when the participants recalled recent exposure the mean purchase intent in the exposed condition was 3.05 versus 3.11 in the control condition. This difference was only marginally significant (\( \Delta = -.06, F(1, 50) = 3.05, p = .09 \)). However, when participants did not recall recent exposure the mean purchase intent in the exposed condition was 2.55 versus 2.44 in the control condition, and the difference was highly significant (\( \Delta = .11, F(1, 50) = 24.03, p < .001 \)).

*Hypothesis 5: favorability toward product as a mediator.* The above results are based on the dependent variable of purchase intent since it is the main focus of our research question and managerially most interesting. However, it is also worth understanding the effects of product type and involvement on purchase intent in greater detail. As predicted by
hypothesis 5, it is conceivable that these product characteristics affect purchase intent through attitudes, particularly how favorable or unfavorable a consumer is toward the advertised product. We tested this hypothesis using standard mediation analysis. First, we regressed favorability on the same set of predictors in the full models used for testing hypotheses 1 to 4. The effects corresponding to hypotheses 1 to 3 were significant and in the same direction: utilitarian × exposed ($b = .03, t = 3.33, p < .001$), involvement × exposed ($b = .02, t = 2.83, p < .01$), utilitarian × involvement × exposed ($b = .03, t = 3.82, p < .001$). The effect for hypothesis 4—recent exposure × exposed—was not significant ($p = .99$).

Second, we estimated the full model with purchase intent as the dependent variable with favorability as an additional predictor and expected its effect to be positive and significant and the effects corresponding to hypotheses 1 to 3 to be non-significant. This was the case: the effect of favorability was positive and significant ($b = .73, t = 120.92, p < .001$), and the utilitarian × exposed ($p = .25$), involvement × exposed ($p = .08$), and utilitarian × involvement × exposed ($p = .43$) effects on purchase intent became non-significant. The recent exposure × exposed effect remained negative and significant ($p < .001$).

These results provide partial support for hypothesis 5. We find that the effects of product type and involvement (separately and jointly) on purchase intent are mediated by favorability. In other words, these two product characteristics operate by affecting how positively or negatively consumers perceive products, which in turn impacts their purchase intentions. The effect in hypothesis 4 related to recent exposure to advertising, however, does not appear to be mediated by favorability and instead directly affects purchase intent. This makes sense since a lack of previous recent exposure to a product is unlikely to make a

---

12 We repeated this mediation analysis using indirect-effect bootstrap methods (Hayes 2009) and found consistent results. Indirect effects on purchase intent mediated by favorability were significant for utilitarian × exposed (95% C.I.: .02 to .04), involvement × exposed (95% C.I.: .01 to .03), and utilitarian × involvement × exposed (95% C.I.: .02 to .04), but not significant for recent exposure × exposed (95% C.I.: -.02 to .01).
consumer more or less favorable toward that product, although it could make them directly more interested in purchasing it (for the reasons outlined earlier in relation to hypothesis 4).

Robustness Checks

To check the robustness of the main findings (hypotheses 1 to 4) we estimated three additional random effects models, which are reported in Table 7. We based these models on different functional forms that correspond to recoding/transformation of the purchase intent dependent variable. First, we transformed purchase intent into a binary variable with 1 being equal to purchase intent = 5 (“very likely”) and 0 otherwise, and estimated a random effects binary logit model (“Binary Logit 1”). Second, we transformed purchase intent into a binary variable with 1 being equal to purchase intent ≥ 4 (“likely” or “very likely”) and again estimated a random effects binary logit model (“Binary Logit 2”). Third, we treated purchase intent as a discrete, ordinal variable instead of as a continuous variable and estimated a random effects ordered logit model (“Ordered Logit”).

[INSERT TABLE 7 ABOUT HERE]

Generally, the results derived from these models are largely consistent with those reported above for hypotheses 1 to 4. Hypotheses 2 and 4 are again supported under all three different model specifications. For hypothesis 1, we find support in Binary Logit 2 and Ordered Logit models, but not in Binary Logit 1 (although the sign is correct, the parameter does not reach significance). For hypothesis 3, we find support in Binary Logit 1 and Ordered Logit models, but not in Binary Logit 2 (once again, the sign is consistent but not significant). Importantly, we find complete support for hypotheses 1 to 4 in the ordered logit model, which is the least restrictive specification since purchase intent was used as measured. In both binary logit models purchase intent was dichotomized according to an arbitrary threshold,
which is more restrictive. Thus, we are confident that our results are robust to variations in model specification.

Discussion

Summary of Main Findings and Implications for Theory

This paper examined the ability of 54 low-fidelity mobile display advertising campaigns to affect consumers’ levels of purchase intent for advertised brands and products using a series of standard advertising field tests involving 27,753 consumers who were randomly assigned to either an exposed or a control condition. Two theoretically and managerially important campaign characteristics were considered—whether the product was more hedonic or more utilitarian and whether the product was higher or lower involvement—as well as whether participants recalled recent exposure to advertising for the focal product. Using these data and product classifications we tested a set of hypotheses derived from prior research on advertising, persuasion, and psychological information processing that predicted conditions under which low-fidelity mobile display advertisements would be effective. Our results suggest that product type and product involvement are indeed important factors that affect whether mobile advertisement exposure increases an individual’s purchase intent for an advertised product. Consistent with our conceptualization, the strongest positive impact of mobile display advertising on purchase intent appears to be found when high-involvement, utilitarian products are advertised. Moreover, it appears that the primary effects of interest operate by enhancing favorability toward products.

Despite strong managerial interest in and substantial spending on mobile display advertising, it is interesting that only under quite specific conditions are such advertisements found to be effective in increasing consumers’ purchase intentions (and favorability). In fact,
in our results the average treatment effect (main effect of exposed) was not significant (purchase intent model $p = .33$; favorability model $p = .38$). This means that, on average, the tested campaigns were not effective based on these criteria. However, there is substantial heterogeneity in the effectiveness of campaigns. Figure 3 plots the distributions of average campaign effectiveness for favorability (panel A) and purchase intent (panel B). These were computed for each campaign by taking the difference between measured favorability or purchase intent for exposed participants and for control participants. Both histograms show substantial variation in effectiveness across campaigns, with some campaigns having clearly negative effectiveness, others having clearly positive effectiveness, and many clustered around the zero point. This variation in effectiveness is at least partly explained by the variables in our hypotheses: product type, product involvement, and recent advertising exposure.

[INSERT FIGURE 3 ABOUT HERE]

Overall, the results indicate that low-fidelity mobile display advertisements can be effective when used in situations where consumers have both the ability and the motivation to process and elaborate on the information in a deliberate fashion. Equally importantly, in situations where these underlying conditions are not met (e.g., when consumers are more inclined to rely on “gut instinct” impressions in the case of hedonic products), mobile display advertisements appear to be ineffective (at least in lifting favorability and purchase intent).

Our main findings may also apply to other types of digital advertising where consumers are presented with relatively small amounts of information or the information presented to them is low quality and consequently hard to cognitively process in a fluent manner. Search advertising (e.g., Google Adwords) and newer forms of social media advertising such as Facebook ads (similar in form to Google Adwords) and Twitter ads (very short text, up to 140 characters) may fall into this category. The shortcomings of these types
of advertisements in terms of being predominantly text-based (and low-fidelity more generally) are likely to be exacerbated as companies such as Google, Facebook, and Twitter attempt to monetize their mobile applications with the addition of advertisements. Thus, while our focus was on mobile display advertisements, our findings are expected to generalize at least partially to other forms of low-fidelity digital advertising, including those that, like mobile display advertisements, are popular with advertising agencies and advertisers.

**Implications for Marketing Practice**

Our findings have clear implications for marketers intending to use mobile display advertisements either as standalone campaigns or as part of multi-channel campaigns. While mobile advertising offers many potential opportunities for marketers, it is not clear that all types of products are naturally suited to this advertising medium. As our results show, marketers can expect the best performance out of mobile display advertising campaigns when their brands are perceived by consumers as more utilitarian and higher involvement. Further, in the context of multi-channel campaigns, it may be advisable to use the mobile display channel earlier than other channels as prior recent exposure to products reduces the effectiveness of mobile advertisements.

While these findings perhaps suggest that mobile display advertisements are a worthwhile investment only for a very limited set of product classes, this need not be the case. Marketers of products that are more hedonic and/or lower involvement could attempt to position their products as more utilitarian and higher involvement when advertising in the mobile channel. This is similar to how advertisers frame their products differently to appeal to different customer segments or across different geographic markets.
Another approach marketers can take to make products more amenable to mobile display advertising is to vary the timing of delivery of these advertisements. Purchase decisions are more personally relevant and therefore of higher involvement to consumers the closer they are to the “moment of truth” when they need to make a choice. Mobile display advertisements may be more effective—even for products that are lower involvement—when they are served to consumers who are closer to making a purchase decision, such as when they are actively “on the market” as demonstrated by, for example, recent online search behavior that advertising networks are now able to track and feed into advertisement targeting programs.

A related aspect that could also improve the effectiveness of mobile display advertisements for products not inherently higher involvement and utilitarian is to take advantage of the physical context in which advertisements are served. Similar to the above point about timing, customers in a store environment are more likely to be in an active purchase decision-making mindset. This could potentially make them perceive the products they are physically examining in the store as higher involvement. Mobile location-based advertising, which targets mobile advertising messages based on where a consumer is (e.g., inside a particular store), could therefore be very effective in this regard.

A final approach that marketers could take is to customize mobile display advertisements to particular customer segments or even specific individuals based on available information such as demographics, past behaviors, and interests. We would expect consumers who receive customized and personalized messages aligned with, for instance, their idiosyncratic interests, to pay more direct attention to the advertisements. A consequence of this enhanced attention should be a greater likelihood of central-route processing, which in turn should increase the likelihood of the advertisement having a positive impact on that consumer’s purchase intentions, at least for the immediate future.
Limitations and Future Research Directions

The current research is not without limitations. First, our data covered low-fidelity mobile display advertising campaigns and not other types of mobile advertising. A very promising avenue for future research on mobile advertising would entail a comparison between the effectiveness of campaigns employing exclusively low-fidelity advertising units (such as those examined here), exclusively high-fidelity advertising units, and combinations of these types. However, despite the potential appeal of high-fidelity mobile advertising to both advertisers and consumers (see Table 1 for examples), deployment of these units requires consumers to be using smartphones and other sophisticated mobile devices that support rich-media content (and high-speed data connections). Although access to smartphones and mobile broadband Internet is increasing, the penetration of these technologies remains low, especially in emerging markets (The Economist 2011). Hence, low-fidelity mobile advertising units, at least for the immediate future, are more attractive to advertisers seeking to reach broader consumer populations.

A second limitation is the focus on purchase intent as our primary indicator of advertising effectiveness. Advertisers are often concerned with achieving other objectives, and mobile advertising campaigns may not always be designed to directly impact purchase intent and, accordingly, sales. For instance, a campaign objective may be to generate word-of-mouth (e.g., viral marketing). Notwithstanding, increasing purchase intent (and, by expected positive correlation, actual purchase behavior) is the most important campaign objective and is also related to consumers being more likely to include a given brand or product in a consideration set. Moreover, although our focus was on purchase intent we also examined favorability as an attitudinal measure of advertising effectiveness. A future
research direction would be to examine other objectives and, where possible, to link mobile advertising directly to purchase behavior.

Digital advertising in both mobile and non-mobile channels is currently experiencing explosive growth. As advertisers shift larger proportions of their budgets into digital advertising channels, a more detailed understanding of the conditions under which different types of digital advertising will be effective is increasingly important. Despite a considerable amount of literature on various forms of non-mobile digital advertising, mobile advertising research has received much less attention. The current research with its foundations in consumer psychology and field test data from a diverse set of campaigns is an important step towards a better understanding of the determinants of mobile advertising effectiveness. We hope this research encourages future work on this exciting advertising channel.
References


Figure 1
Examples of Mobile Display Advertisements

A. Nike advertisement in mobile WAP browser

B. Match.com advertisement in The Weather Channel app for iPhone
Figure 2
Exposed Versus Control Conditions and Survey Invitation for Field Tests

Exposed Condition

Control Condition
Figure 3
Distributions of Average Treatment Effects Across Campaigns

A. Histogram of Average Treatment Effect for Favorability

B. Histogram of Average Treatment Effect for Purchase Intent
<table>
<thead>
<tr>
<th></th>
<th>Low-Fidelity</th>
<th>High-Fidelity</th>
</tr>
</thead>
</table>
| **Defining Attributes** | • Can convey relatively small amounts of information to consumers  
• Low image resolution  
• Static  
• Limited interactivity  
• Small size or size-constrained  
• Simple  
• Lower production cost  
|                | • Can convey relatively large amounts of information to consumers  
• Visually appealing, including higher image resolution and/or video content  
• Dynamic  
• Interactive  
• Large size and size-adjustable, including ability to dynamically expand/contract with user input  
• Higher production cost  
| **Examples: Non-mobile** | Display banners, Facebook Ads, Google Adwords, Sponsored Tweets, YouTube overlay  
|                | Interactive Flash/HTML5, full- or part-screen interstitial image or video, Pre-roll video, YouTube video  
| **Mobile**     | Display banners, MMS, SMS  
|                | Apple iAd, click-to-call/locate, standalone apps, video Apple iAd, click-to-call/locate, games, standalone apps, video  

Table 2
Campaign Summary Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of campaigns</td>
<td>54</td>
</tr>
<tr>
<td>Mean number of respondents per campaign (st. dev)</td>
<td>513.94 (554.87)</td>
</tr>
<tr>
<td>Mean campaign length in days (st. dev)</td>
<td>54.80 (32.79)</td>
</tr>
<tr>
<td>Percent of campaigns for business-to-consumer brands (versus business-to-business brands)</td>
<td>96.30%</td>
</tr>
<tr>
<td>Percent of campaigns for new products (versus existing products or extensions)</td>
<td>7.41%</td>
</tr>
<tr>
<td>Percent of campaigns for products (versus services)</td>
<td>85.19%</td>
</tr>
<tr>
<td>Percent of campaigns by industry:</td>
<td></td>
</tr>
<tr>
<td>Alcohol</td>
<td>3.70%</td>
</tr>
<tr>
<td>Automotive</td>
<td>12.96%</td>
</tr>
<tr>
<td>Consumer Packaged Goods</td>
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<tr>
<td>Entertainment</td>
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<tr>
<td>Finance</td>
<td>16.67%</td>
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<tr>
<td>Government &amp; Non-Profit</td>
<td>3.70%</td>
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<tr>
<td>Health &amp; Pharmaceutical</td>
<td>5.56%</td>
</tr>
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<td>Restaurant</td>
<td>3.70%</td>
</tr>
<tr>
<td>Retail</td>
<td>1.85%</td>
</tr>
<tr>
<td>Technology &amp; Communications</td>
<td>9.26%</td>
</tr>
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</table>
Table 3
Numbers of Participants and Campaigns by Campaign Product Type and Involvement

<table>
<thead>
<tr>
<th>Type</th>
<th>Involvement</th>
<th>Campaigns</th>
<th>Participants</th>
<th>Represented Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedonic</td>
<td>High</td>
<td>8</td>
<td>2,244</td>
<td>Automotive, Technology &amp; Communications</td>
</tr>
<tr>
<td>Hedonic</td>
<td>Low</td>
<td>19</td>
<td>7,371</td>
<td>Alcohol, Consumer Packaged Goods, Entertainment, Restaurants</td>
</tr>
<tr>
<td>Utilitarian</td>
<td>High</td>
<td>17</td>
<td>9,895</td>
<td>Automotive, Finance, Government &amp; Non-Profit, Health &amp; Pharmaceuticals, Technology &amp; Communications</td>
</tr>
<tr>
<td>Utilitarian</td>
<td>Low</td>
<td>10</td>
<td>8,243</td>
<td>Consumer Packaged Goods, Government &amp; Non-Profit, Retail</td>
</tr>
<tr>
<td>Totals</td>
<td></td>
<td>54</td>
<td>27,753</td>
<td></td>
</tr>
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Table 4
Numbers of Exposed Versus Control Participants by Campaign Product Type and Involvement

<table>
<thead>
<tr>
<th>Type</th>
<th>Involvement</th>
<th>Exposed</th>
<th>Control</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedonic</td>
<td>High</td>
<td>1,177</td>
<td>1,067</td>
<td>2,244</td>
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<tr>
<td>Hedonic</td>
<td>Low</td>
<td>3,811</td>
<td>3,560</td>
<td>7,371</td>
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<tr>
<td>Utilitarian</td>
<td>High</td>
<td>5,891</td>
<td>4,004</td>
<td>9,895</td>
</tr>
<tr>
<td>Utilitarian</td>
<td>Low</td>
<td>3,578</td>
<td>4,665</td>
<td>8,243</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>14,457</td>
<td>13,296</td>
<td>27,753</td>
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# Table 5

Random Effects Linear Model for Purchase Intent (1-5 Scale)

<table>
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<tr>
<th>Effects Corresponding to Hypotheses:</th>
<th>Full Model</th>
<th>Model Without Controls</th>
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<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-value</td>
</tr>
<tr>
<td>Utilitarian × Exposed (H1)</td>
<td>.03**</td>
<td>2.87</td>
</tr>
<tr>
<td>Involvement × Exposed (H2)</td>
<td>.03**</td>
<td>3.13</td>
</tr>
<tr>
<td>Utilitarian × Involvement × Exposed (H3)</td>
<td>.03**</td>
<td>2.88</td>
</tr>
<tr>
<td>Recent exposure × Exposed (H4)</td>
<td>-.04***</td>
<td>-4.15</td>
</tr>
<tr>
<td>Other Effects:</td>
<td></td>
<td></td>
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<tr>
<td>Intercept</td>
<td>2.68***</td>
<td>4.53</td>
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<tr>
<td>Utilitarian</td>
<td>.26**</td>
<td>3.27</td>
</tr>
<tr>
<td>Involvement</td>
<td>-.24</td>
<td>-.86</td>
</tr>
<tr>
<td>Recent exposure</td>
<td>.29***</td>
<td>27.33</td>
</tr>
<tr>
<td>Exposed</td>
<td>.02</td>
<td>1.19</td>
</tr>
<tr>
<td>Utilitarian × Involvement</td>
<td>.07</td>
<td>.91</td>
</tr>
<tr>
<td>Utilitarian × Recent exposure</td>
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<td>-.80</td>
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<td>Involvement × Recent exposure</td>
<td>-.01</td>
<td>-.36</td>
</tr>
<tr>
<td>Utilitarian × Involvement × Recent exposure</td>
<td>.02</td>
<td>1.53</td>
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<tr>
<td>Utilitarian × Recent exposure × Exposed</td>
<td>.00</td>
<td>.02</td>
</tr>
<tr>
<td>Involvement × Recent exposure × Exposed</td>
<td>.01</td>
<td>.27</td>
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<tr>
<td>Utilitarian × Involvement × Recent exposure × Exposed</td>
<td>-.01</td>
<td>-.38</td>
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<tr>
<td>Industry fixed effects</td>
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<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>New product vs. existing product fixed effects</td>
<td>Yes**</td>
<td>No</td>
</tr>
<tr>
<td>Product vs. service fixed effect</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>B2C fixed effect</td>
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<td>No</td>
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<tr>
<td>Campaign length</td>
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<td>No</td>
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<tr>
<td>Campaign random effect</td>
<td>.10***</td>
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<tr>
<td>-2 log likelihood</td>
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<td>AIC</td>
<td>91,768.04</td>
<td>91,757.30</td>
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<td>BIC</td>
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<td>91,757.30</td>
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<tr>
<td>R²</td>
<td>.45</td>
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Notes: * p < .05, ** p < .01, *** p < .001
Table 6
Estimated Means and Treatment Effects for Purchase Intent (1-5 scale)

<table>
<thead>
<tr>
<th></th>
<th>Utilitarian</th>
<th></th>
<th>Hedonic</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exposed</td>
<td>Control</td>
<td>Δ</td>
<td>%</td>
</tr>
<tr>
<td><strong>High Involvement</strong></td>
<td>2.98</td>
<td>2.76</td>
<td>0.12***</td>
<td>7.97</td>
</tr>
<tr>
<td><strong>Low Involvement</strong></td>
<td>3.19</td>
<td>3.23</td>
<td>-0.04</td>
<td>-1.24</td>
</tr>
</tbody>
</table>

Notes: Δ = Average Treatment Effect = Exposed – Control. % = 100*(Exposed – Control)/Control. *p < .05, **p < .01, ***p < .001 based on an F-test of Δ = 0
Table 7
Robustness Checks: Random Effects Binary Logit and Ordered Logit Models for Purchase Intent

<table>
<thead>
<tr>
<th>Effects Corresponding to Hypotheses:</th>
<th>Binary Logit 1&lt;sup&gt;a&lt;/sup&gt;</th>
<th></th>
<th>Binary Logit 2&lt;sup&gt;b&lt;/sup&gt;</th>
<th></th>
<th>Ordered Logit&lt;sup&gt;c&lt;/sup&gt;</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-value</td>
<td>Estimate</td>
<td>t-value</td>
<td>Estimate</td>
<td>t-value</td>
</tr>
<tr>
<td>Utilitarian × Exposed (H1)</td>
<td>0.03</td>
<td>1.35</td>
<td>0.04&lt;sup&gt;*&lt;/sup&gt;</td>
<td>2.24</td>
<td>0.04&lt;sup&gt;*&lt;/sup&gt;</td>
<td>-2.53</td>
</tr>
<tr>
<td>Involvement × Exposed (H2)</td>
<td>0.06***</td>
<td>2.96</td>
<td>0.04&lt;sup&gt;***&lt;/sup&gt;</td>
<td>2.54</td>
<td>0.04&lt;sup&gt;***&lt;/sup&gt;</td>
<td>-2.79</td>
</tr>
<tr>
<td>Utilitarian × Involvement × Exposed (H3)</td>
<td>0.04&lt;sup&gt;**&lt;/sup&gt;</td>
<td>1.94</td>
<td>0.02</td>
<td>1.27</td>
<td>0.04&lt;sup&gt;**&lt;/sup&gt;</td>
<td>-2.35</td>
</tr>
<tr>
<td>Recent exposure × Exposed (H4)</td>
<td>-0.05&lt;sup&gt;**&lt;/sup&gt;</td>
<td>-2.48</td>
<td>-0.03&lt;sup&gt;***&lt;/sup&gt;</td>
<td>-2.01</td>
<td>-0.05&lt;sup&gt;***&lt;/sup&gt;</td>
<td>3.51</td>
</tr>
</tbody>
</table>

| Other Effects:                      |  |  |  |  |  |  |
|-------------------------------------|  |  |  |  |  |  |
| Intercept                           | -2.22<sup>**</sup> | -2.24 | -75 | -0.87 |
| Intercept 1                         |  |  |  |  |  |  |
| Intercept 2                         |  |  |  |  |  |  |
| Intercept 3                         |  |  |  |  |  |  |
| Intercept 4                         |  |  |  |  |  |  |
| Utilitarian                        |  |  |  |  |  |  |
| Involvement                        | -0.23    | -50     | -58 | -1.44 | -0.26** | 3.22 |
| Recent exposure                     |  |  |  |  |  |  |
| Exposed                            |  |  |  |  |  |  |
| Utilitarian × Involvement           |  |  |  |  |  |  |
| Utilitarian × Recent exposure       |  |  |  |  |  |  |
| Involvement × Recent exposure       |  |  |  |  |  |  |
| Utilitarian × Involvement × Recent exposure |  |  |  |  |  |  |
| Utilitarian × Recent exposure × Exposed |  |  |  |  |  |  |
| Involvement × Recent exposure × Exposed |  |  |  |  |  |  |
| Utilitarian × Involvement × Recent exposure × Exposed |  |  |  |  |  |  |

| Industry fixed effects              | Yes | No | Yes | No |
| Year fixed effects                  | Yes | No | Yes | No |
| New product vs. existing product fixed effects | Yes | No | Yes | No |
| Product vs. service fixed effect    | Yes<sup>**</sup> | Yes | Yes | Yes<sup>**</sup> |
| B2C fixed effect                   | Yes | No | Yes | No |
| Campaign length                    | Yes | No | Yes | No |
| Campaign random effect             | 0.28*** | 4.92 | 0.21*** | 4.95 | 0.23*** | 5.02 |
| -2 log likelihood                  | 121,584.00 | 117,016.30 | 302,489.40 |
| AIC                                 | 121,666.00 | 117,098.30 | 302,555.40 |
| BIC                                 | 122,003.48 | 117,435.78 | 302,827.03 |

Notes: * Binary logit 1 uses a response variable where 1 = (purchase intent = 5) and 0 = (1 ≤ purchase intent < 5). ** Binary logit 2 uses a response variable where 1 = (purchase intent ≥ 4) and 0 = (1 ≤ purchase intent < 4). Ordered logit uses purchase intent (1-5) as the response variable. * p < .05, ** p < .01, *** p < .001.
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