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Christian Schulze, Lisa Schöler, & Bernd Skiera

# Not All Fun and Games: Viral Marketing for Utilitarian Products

The success of products such as FarmVille has prompted many firms to engage in viral marketing on Facebook and other social media websites. Yet is the viral marketing approach adopted for games suitable for other, more utilitarian products? This study aims to answer questions that link product characteristics and contexts to viral marketing success: Should primarily utilitarian products rely on the same sharing mechanisms for their viral marketing campaigns as less utilitarian products? If not, why is this the case, and how should viral marketing for primarily utilitarian products differ? This empirical study analyzes the Facebook viral marketing campaigns of 751 products and reveals that the same sharing mechanism that made FarmVille so successful is the worst possible mechanism for promoting primarily utilitarian products. These findings are in line with theory from social psychology: because consumers do not visit Facebook to learn about utilitarian products, they rely on simple cues and heuristics to process viral marketing messages about these products. This study thus contributes to literature on viral marketing in general and sharing mechanisms in particular; it also offers practical, hands-on recommendations to marketing managers in charge of designing viral marketing campaigns for both more and less utilitarian products.

*Keywords*: social media marketing, viral marketing, utilitarian, sharing mechanisms, Facebook, apps

Viral marketing is not a new phenomenon; as early as 1996, the free e-mail provider Hotmail launched one of the first viral marketing campaigns by attaching a promotional message to every e-mail sent through its service. Today, viral marketing has become a mainstream marketing instrument used by multinational firms in various industries, including Nike, Unilever, and Volkswagen. Firms appreciate viral marketing as a means to benefit from the additional trust and attention that messages from friends and other trusted sources receive (Bampo et al. 2008; Phelps et al. 2004) while remaining largely in control of the message content (Van der Lans et al. 2010). The recent trend toward viral marketing also has been fueled by the growing popularity of social network platforms such as Facebook, on which more than 1 billion connected consumers share marketing messages with a single click on their computers or mobile devices. The resulting potential for viral marketing campaigns on Facebook is evident from popular examples such as FarmVille and CityVille—games that reached as many as 100 million customers in just a few weeks (Schroeder 2011). Such success stories invariably attract the interest of marketing practitioners eager to learn the "recipe" for viral marketing success. If FarmVille and similar products represent best-practice examples, we might predict that the key ingredient is their sharing mechanism: unsolicited broadcast messages from friends that contain incentives to use the product. This view has found support in initial research highlighting the importance of sharing mechanisms for viral marketing success (Aral and Walker 2011).

However, for many firms aiming to follow FarmVille's lead to engage in viral marketing on Facebook, it is not at all clear whether the findings from existing research and best-practice examples actually translate to their own more utilitarian products, for which consumer value is the result of product usefulness, rather than fun. Consumers use Facebook and many other social network platforms primarily for fun and entertainment; does this hedonic orientation influence their perception of viral marketing messages for more utilitarian products?

Academic literature has remained largely silent about viral marketing for utilitarian products, and yet several indications have suggested important distinctions. Chiu et al. (2007) find that hedonic and utilitarian content in marketing messages (not the product itself) differentially affects the success of viral marketing campaigns. Pöyry, Parvinen, and Malmivaara (2013) find that consumers claiming a primarily utilitarian (rather than hedonic) motivation to visit a travel agency's Facebook presence are more likely to recommend that company to their friends. In related word-of-mouth research, Berger and Milkman (2012) show that high or low emotional involvement—often linked to hedonic and utili-

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tarian features—shapes consumers' sharing behaviors. Moreover, consumers' reactions to viral marketing seemingly should differ for more versus less utilitarian products,[1] according to theory from social psychology. Schema theory (Aronson, Wilson, and Akert 2012; Bartlett 1932) suggests that people unconsciously use situation-specific mental structures to organize and filter information. Thus, consumers will pay little attention to viral marketing messages for primarily utilitarian products in a fun- and entertainment-oriented environment such as Facebook. According to the elaboration likelihood model (ELM; Petty and Briñol 2012; Petty and Cacioppo 1986), information processing about these products will therefore be less deliberate and instead rely more on heuristics, such as social cues. As a result, sharing mechanism characteristics (e.g., unsolicited broadcast messages from friends that contain incentives to use the product) that work very well for products such as games might be ineffective or even harmful for marketing utilitarian products.

In this article, we investigate two main research questions: Should primarily utilitarian products rely on the same sharing mechanisms that less utilitarian products use for their viral marketing campaigns? If not, why is this the case, and how should viral marketing for primarily utilitarian products differ? To answer these questions, we use extensive information about viral marketing campaigns on Facebook for 751 products observed over the course of one year.

With this research, we contribute to literature on viral marketing in general and sharing mechanisms in particular. Viral marketing literature lacks insights into the impact of products' low- or high-utilitarian characteristics on viral marketing success. We show that failing to consider these product characteristics when designing viral marketing campaigns can be devastating to their success. We also present a substantive contribution to literature on sharing mechanisms in viral marketing by extending an existing single-case study by Aral and Walker (2011), in terms of size and dimensions covered. As a result, we can provide detailed practical recommendations to marketing managers, including which sharing mechanism characteristics (not) to choose when designing viral marketing campaigns for both low- and high-utilitarian products.

This article proceeds as follows: First, we link our research to existing literature in viral marketing and detail the motivation for this study. After we present the conceptual background, we derive the relevant characteristics of sharing mechanisms in viral marketing campaigns and then use information processing theory to develop hypotheses about their effects on success for low- versus high-utilitarian products. Next, we detail the setup and model for our empirical study and present the results. We conclude with a summary, a discussion of our research's implications for marketing theory and practice, and some limitations and opportunities for further research.

[1]We focus on products' utilitarian dimension (high vs. low). We leave it to the reader to regard the utilitarian and hedonic characteristics as either two opposite ends of the same scale (e.g., Drolet, Williams, and Lau-Gesk 2007) or two separate dimensions (e.g., Voss, Spangenberg, and Grohmann 2003).

# Previous Empirical Literature on Viral Marketing

Extant empirical research has primarily focused on two determinants of viral marketing success: the characteristics of the content (Chiu et al. 2007; Dobele et al. 2007; Teixeira, Wedel, and Pieters 2012; Tucker 2011) and the optimal seeding strategies given the social network structure (Bampo et al. 2008; De Bruyn and Lilien 2008; Hinz et al. 2011; Lee, Lee, and Lee 2009; Van der Lans et al. 2010). Whereas the "what" (content) and "who" (senders and receivers) of viral marketing have been researched extensively, the "how" (sharing mechanisms) has received little attention, despite relevant case evidence that suggests the mechanisms consumers use to share viral messages exert strong influences on viral marketing success (Aral and Walker 2011). Beyond the determinants of viral marketing success, studies have investigated the manageability of viral marketing campaigns (Kalyanam, McIntyre, and Masonis 2007; Leskovec, Adamic, and Huberman 2007; Van der Lans et al. 2010) and how their effectiveness compares with that of traditional media (Toubia, Stephen, and Freud 2009). Whereas in these studies, the firms create and largely remain in control of the viral marketing messages, Godes and Mayzlin (2009) analyze a unique form of communication among consumers, in which the firm initiates the process but does not prescribe the message content. Firms also might adopt consumer-generated messages for commercial purposes (Joshi and Trusov 2012), manipulate the word-of-mouth process (Dellarocas 2006), or use specific brand characteristics to influence word of mouth (Lovett, Peres, and Shachar 2013). We summarize prior empirical studies on viral marketing in Table 1.

Our research contributes to this empirical literature in two ways. In a narrow sense, we add to emergent research on the impact of sharing mechanisms by (1) addressing all four dimensions that distinguish and define them and (2) demonstrating their relevance for viral marketing success. We also evaluate their effect in viral marketing campaigns for a range of products, extending previous research focusing on in-depth analyses of one specific product. In a broader sense, we provide the first assessment of differences in viral marketing for low- versus high-utilitarian products. That is, previous research has relied on products with differing utilitarian value, but our study is the first to employ information processing theory (i.e., ELM) to specify how utilitarian value should influence the design of the corresponding viral marketing campaign (Table 1).

# Conceptual Background

## *Sharing Mechanism Characteristics in Viral Marketing Campaigns*

Previous research has characterized viral marketing communication along six dimensions:

1. Social position of the sender and the receiver (i.e., consumers' connectedness or bridging function across subnetworks; see Bampo et al. 2008; Hinz et al. 2011).

**TABLE 1**
**Previous Empirical Studies of Viral Marketing**

| Publication | Research Focus | Sharing Mechanism(s) in Empirical Study | Dimensions on Which Sharing Mechanism(s) Differ | Analysis of Influence of Sharing Mechanism Characteristics | Differences Along Utilitarian Dimension for Studied Product(s) | Analysis of Influence of Utilitarian Product Context |
|---|---|---|---|---|---|---|
| Dobele et al. (2007) | Effect of emotions in viral messages on consumers' sharing behavior | — | — | No | Yes | No |
| Chiu et al. (2007) | Effect of message source, content, receiver characteristics, and Internet connection speed on e-mail forwarding | E-mail | 1 | No | No | No |
| Kalyanam, McIntyre, and Masonis (2007) | Influence of firm's viral marketing intensity and aggressiveness | E-mail over program interface | — | No | No | No |
| Leskovec, Adamic, and Huberman (2007) | Identification of communities, products, and pricing categories suitable for viral marketing | E-mail | — | No | Yes | No |
| Lee, Lee, and Lee (2007) | Influence of sender–receiver tie characteristics | E-mail over web interface | — | No | No | No |
| Bampo et al. (2008) | Influence of social structure on individual message transmission behavior | E-mail over web interface | — | No | No | No |
| De Bruyn and Lilien (2008) | Influence of viral messages on consumer awareness, interest, and decisions | E-mail | — | No | No | No |
| Toubia, Stephen, and Freud (2009) | Comparison of viral activity (as measured by coupon redemption) for product samples versus traditional offline media | Offline (paper-based coupons) | — | No | No | No |
| Van der Lans et al. (2010) | Prediction and management of viral marketing performance | E-mail over web interface | — | No | No | No |
| Hinz et al. (2011) | Effectiveness of seeding strategies | E-mail, e-mail over web interface; direct messages on social network site | 1 | No | Yes | No |
| Aral and Walker (2011) | Effectiveness of two sharing mechanisms | Direct and broadcast messages on Facebook | 1 | No | No | No |
| Tucker (2011) | Influence of viral video characteristics on reach versus persuasiveness | — | — | No | Yes | No |
| Teixeira, Wedel, and Pieters (2012) | Influence of viral video characteristics on user engagement | — | — | No | Yes | No |
| This article | Viral marketing for low- versus high-utilitarian products; differences in influence of sharing mechanism characteristics | Diverse sharing mechanisms on Facebook | 4 | Yes | Yes | Yes |

2. Sender–receiver relationship (i.e., are consumers close friends or complete strangers? For research on this dimension in the viral marketing context, see Chiu et al. 2007; De Bruyn and Lilien 2008; Lee, Lee, and Lee 2009; Leskovec, Adamic, and Huberman 2007; for a more general discussion, see Granovetter 1973).
3. Communication exclusivity (i.e., does communication rely on direct, one-to-one messages or on one-to-many broadcasts? See Aral and Walker 2011; Phelps et al. 2004).
4. Expressed interest (i.e., has the receiver requested or searched for the message, or is it unsolicited spam? See De Bruyn and Lilien 2008; Kalyanam, McIntyre, and Masonis 2007).
5. Message features (e.g., does the message come with an incentive to act? See Bampo et al. 2008; De Bruyn and Lilien 2008; Hinz et al. 2011; Lee, Lee, and Lee 2009; Leskovec, Adamic, and Huberman 2007; Van der Lans et al. 2010).
6. Message content (e.g., is the message inspirational, funny, or shocking? See Chiu et al. 2007; Dobele et al. 2007; Teixeira, Wedel, and Pieters 2012; Tucker 2011).

Viral marketing research has extensively covered two dimensions: social position (the "who") and message content (the "what"). In contrast, research on the other four dimensions has been rather selective, despite being recognized as determinants of viral marketing success. We therefore focus on these dimensions (i.e., 2–5), which collectively characterize the sharing mechanisms (the "how") by which viral messages spread across consumers and which have never been analyzed jointly (for details on these dimensions, see Table 2).

### *Influence of Environment on Processing Information About Utilitarian Products*

Success stories about viral marketing campaigns on Facebook and similar platforms almost exclusively involve products that fit well with the platforms' fun-oriented environments. However, not all products are fun oriented, and marketing literature abounds with examples illustrating that what works for one product does not necessarily work for all products. Thus, to shed more light on the role of product contexts in viral marketing campaigns, it seems paramount to investigate the differences between products that do and do not fit well with this environment. A popular approach captures these essential differences by classifying products into utilitarian and hedonic categories (e.g., Batra and Ahtola 1991; Chitturi, Raghunathan, and Mahajan 2008; Hirschman and Holbrook 1982; Spangenberg, Voss, and Crowley 1997). When purchasing primarily hedonic products, such as games, consumers seek items that are fun, exciting, delightful, thrilling, and enjoyable. Primarily utilitarian products instead should be effective, helpful, functional, necessary, and practical to appeal to consumers (Voss, Spangenberg, and Grohmann 2003).

When consumers choose to visit social network platforms such as Facebook, they also seek fun, enjoyment, excitement, and, ultimately, a feeling of connectedness through social interactions and content (Hoffman and Novak 2013). Consequently, when Facebook users receive viral marketing messages, they do not expect the messages to promote primarily utilitarian products, because such products do not fit well with their fun-focused expectations or schema.

According to schema theory, consumers build mental structures to organize their knowledge and channel the processing of new information (e.g., Aronson, Wilson, and Akert 2012; Bartlett 1932). Marketing research has used schemas to explain consumer biases in self-perceptions (Wheeler, Petty, and Bizer 2005) or media (Roskos-Ewoldsen, Roskos-Ewoldsen, and Dillman Carpentier 2009), for example. In our study, we employ this parsimonious theory to predict that consumers' fun-oriented Facebook schema primes them to focus on messages for hedonic products. In other words, the Facebook environment biases consumers such that they unconsciously devote fewer mental resources to processing messages related to primarily utilitarian products (Dijksterhuis et al. 2005).

### *ELM*

The ELM (for a general overview, see Petty and Briñol 2012; for a marketing-related perspective, see Rucker, Petty, and Priester 2007) describes how the scarcity of mental resources affects consumers' information processing. This dual-process theory from social psychology suggests that information processing, and thus attitude shifts, occurs through two routes. In the "central route," consumers diligently consider product-related information and invest thought and effort into the process. The "peripheral route," in contrast, is characterized by consumers' reliance on heuristics, social cues, and simple inferences in their attitude formation. Therefore, consumers expend little thought elaborating on a message; instead, they might reject or accept and act on that message on the basis of simple cues, such as whether the sender is a trusted expert.

Consumers unconsciously devote fewer mental resources to processing messages about products outside their situation-specific schema (Bitner and Obermiller 1985), so the ELM theorizes that consumers' information processing of such products follows the peripheral route. In other words, Facebook users seeking fun and entertainment should be fast and frugal in their information processing and rely primarily on heuristics, simple inferences, and social cues when evaluating (viral marketing) messages about primarily utilitarian products. In contrast, such heuristics and cues may be less relevant when consumers encounter messages about less utilitarian products that fit the schema and unconsciously devote more thought to the actual message.

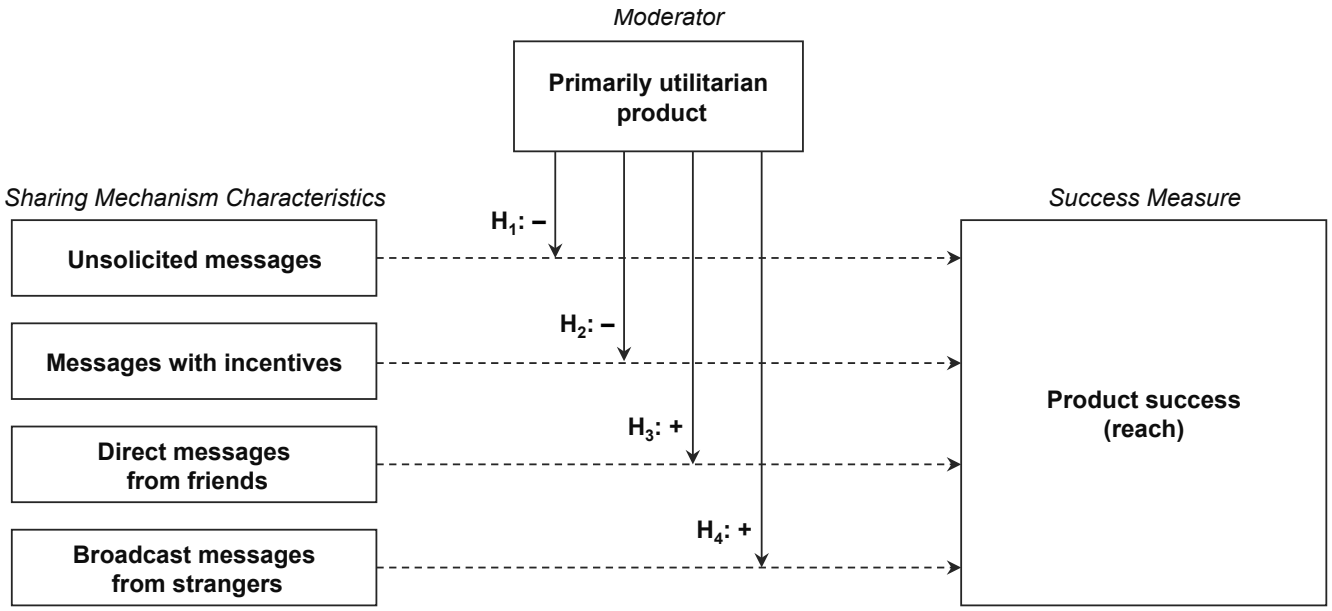
## Conceptual Model

Because consumers' approaches to processing viral marketing messages differ depending on the product context, the characteristics of sharing mechanisms for viral marketing messages should differ in their effectiveness as well. The empirical study tests the conceptual model depicted in Figure 1, which investigates the moderating effect of primarily utilitarian products on the effectiveness of sharing mechanism characteristics for viral marketing campaigns in a primarily fun- and entertainment-oriented setting. Drawing on the ELM, we derive four hypotheses about the effect of receivers' expressed interest, message features (particularly

**TABLE 2**
**Overview of Constructs**

| Construct | Description | Example in Study Context | Descriptive Details from Empirical Study | Notation |
|---|---|---|---|---|
| Number of sharing mechanisms | Sharing mechanisms should encourage consumers to recommend product to their peers. Each sharing mechanism has four dimensions. Viral marketing campaigns can use several sharing mechanisms simultaneously but must rely on at least one. | Sharing mechanisms on Facebook include a post on a friend's timeline or a direct message to friends with incentives. | Sixty-three products do not employ any sharing mechanism (i.e., do not use viral marketing), and 688 products do. The maximum number of unique sharing mechanisms per product is 8, with a mean of 2.79. | $M_i$ |
| Unsolicited messages | Messages are unsolicited if receiver has not expressed interest in receiving the message (e.g., De Bruyn and Lilien 2008). | A viral message from a friend in the inbox that promotes, for example, a new game. | Products employ between 0 and 5 sharing mechanisms (mean of 1.79) that use unsolicited messages. | $x_{unsolicited,i}$ |
| Solicited messages | Messages are solicited if the message receiver has expressed an interest in receiving the message or has searched for it (e.g., Diamond and Noble 2001). | A Facebook user visits a friend's "About" page to see which apps the friend is using. | Products employ between 0 and 5 sharing mechanisms (mean of 1.00) that use solicited messages. | (base case for $x_{unsolicited,i}$) |
| Messages with incentives | Incentives in viral marketing messages provide greater benefits for message receivers (compared with regular consumers) if they use the product. | A viral marketing message such as "Try Spotify now and get one month of premium membership for free!" offers an incentive to the receiver. | Products employ between 0 and 2 sharing mechanisms (mean of .29) that use viral marketing messages with incentives. | $x_{incentivized,i}$ |
| Messages without incentives | Without incentives, receivers of viral marketing messages have no benefit over regular consumers from using the product. | A viral marketing message such as "Try Spotify now and listen to music today!" does not offer a specific incentive to receiver. | Products employ between 0 and 8 sharing mechanisms (mean of 2.50) that use viral marketing messages without incentives. | (base case for $x_{incentivized,i}$) |
| Direct messages from friends | A direct message from a friend describes one-to-one communications (comparable to e-mail) between direct (first-degree) contacts. | Two befriended Facebook users can send each other messages to their Facebook inbox. Direct messages on Facebook require consumers to be direct, first-degree contacts. | Products employ between 0 and 3 sharing mechanisms (mean of 1.02) that rely on direct messages from friends. | $x_{directfriend,i}$ |
| Broadcast messages from strangers | Broadcast messages from strangers describe one-to-many communications between Facebook users who are not directly connected, such as second-degree contacts who share a common friend. | When a Facebook user posts a viral marketing message to a friend's timeline, that friend's contacts will see this message in their news feeds and view it as a broadcast message from a stranger. | Products employ between 0 and 1 sharing mechanisms (mean of .19) that rely on broadcast messages from strangers. | $x_{broadcaststranger,i}$ |
| Broadcast messages from friends | Broadcast messages from friends describe one-to-many communications between Facebook users who are direct (first-degree) contacts. | When a Facebook user posts a viral marketing message to her own timeline, her direct friends see this message in their news feeds as a broadcast message from a friend. | Products employ between 0 and 6 sharing mechanisms (mean of 1.58) that rely on broadcast messages from friends. | (base case for $x_{directfriend,i}$ and $x_{broadcaststranger,i}$) |
| Primarily utilitarian products | A product is primarily utilitarian if its main purpose is to be effective, helpful, functional, and practical (rather than fun, exciting, and enjoyable) (Voss, Spangenberg, and Grohmann 2003). | Facebook apps that, for example, enable consumers to track their stock investments or find a new house. In the context of our study, we classify apps as primarily utilitarian if they belong to the business, money, utility, alerts, or politics categories. | We characterize 233 of 751 apps (31%) as primarily utilitarian. | $x_{ut,i}$ |
| Product success (reach) | Success of a viral marketing campaign is typically measured by its reach, or the number of individual consumers that took action after receiving the viral marketing message (e.g., Hinz et al. 2011). | We operationalized reach by the maximum (estimated) number of installations. The estimated reach for the Facebook app "Cities I've Visited" is approximately 10 million unique consumers; the estimated reach for "City Trip" is only approximately 1,000 consumers. | In our study, the average app reaches 347,998 consumers (minimum reach of 12, maximum reach of 10,132,646). | Y |

**FIGURE 1**
**Conceptual Model**




incentives), communication exclusivity, and sender–receiver relationships in viral marketing campaigns for low- versus high-utilitarian products. Specifically, we hypothesize a negative effect for unsolicited messages (vs. solicited messages) and messages with incentives (vs. messages without incentives). We also expect a positive moderating effect for direct messages from friends (vs. broadcast messages from friends) and for broadcast messages from strangers (vs. broadcast messages from friends). For more detailed descriptions and examples of the focal constructs used in this study, see Table 2.

### *Hypotheses*

*Receivers' expressed interest*. When information processing for high-utilitarian products follows the peripheral route and consumers rely more on heuristics and simple inferences (Petty and Cacioppo 1986), the ELM predicts that they regard unsolicited push messages as a signal of the product's low quality and low personal relevance compared with information they (actively) seek out (the thought being, "If the product were truly useful and of high quality, the company would not have to market it so aggressively"). In contrast, if information processing follows a more central route, we expect a much smaller negative effect or even none at all from unsolicited messages. Consequently, we hypothesize a moderating effect of primarily utilitarian products:

$H_1$: The effectiveness of sharing mechanisms that rely on unsolicited viral marketing messages for which the receiver has not expressed a prior interest (rather than solicited messages) is lower for high-utilitarian products than for low-utilitarian products.

*Message features*. According to the ELM, when information processing follows the peripheral route, consumers do not actively evaluate the usefulness of an incentive included in a viral marketing message. Instead, they regard the incentive as a signal of inferior product quality ("If the product were good, the company would not have to offer me an incentive"), which reduces the effectiveness of the viral marketing message. At the same time, we expect a positive effect from incentives for less utilitarian products when consumers evaluate their usefulness more thoroughly.

$H_2$: The effectiveness of sharing mechanisms that rely on viral marketing messages containing an incentive for the receiver to use the product (rather than no incentive) is lower for high-utilitarian products than for low-utilitarian products.

*Communication exclusivity*. When information processing follows the peripheral route, consumers do not expend as much thought to elaborate on the merits of a broadcast message. Instead, they believe that the lack of a direct, individual message signals low personal relevance ("Had my Facebook friend thought this were truly relevant for me, she would have sent me a direct message"). In contrast, we do not anticipate a significant difference between direct and broadcast messages from Facebook friends when consumers spend more thought evaluating the actual message, as they should for low-utilitarian products.

$H_3$: The effectiveness of sharing mechanisms that rely on direct messages (rather than broadcast messages) from Facebook friends[2] is greater for high-utilitarian products than for low-utilitarian products.

[2]In $H_3$, we compare the effect of broadcast and direct messages from friends rather than strangers, because social networks such as Facebook typically do not allow direct messages from strangers. The same applies to $H_4$, in which we only compare the effect of messages from friends and strangers for broadcast (not direct) messages.

*Sender–receiver relationship*. The moderating effect of primarily utilitarian products on the effectiveness of messages from friends versus strangers should result from two simultaneous effects. First, consumers seeking fun and entertainment on Facebook rely on their friends for recommendations, because friends often have similar tastes and preferences. Thus, recommendations from friends are useful to consumers, regardless of whether they evaluate these recommendations on the basis of their objective, informational value (central route) or simply by following a heuristic (peripheral route) (Koroleva, Krasnova, and Günther 2011). We therefore expect viral marketing messages from friends that promote hedonic products to be more effective than messages from strangers.

Second, because consumers evaluate the quality of utilitarian products on the basis of their effectiveness, helpfulness, functionality, and usefulness (Voss, Spangenberg, and Grohmann 2003), if they follow the peripheral route. They should value information from a competent, neutral, external source at least as much as information from a friend with similar views and experiences. Godes and Mayzlin (2009, Table 3) support this notion, showing that word-of-mouth recommendations from actual customers are equally effective whether they involve friends or strangers. Thus, for utilitarian products, messages from strangers can be as effective as messages from friends, but messages from strangers should be significantly less effective for less utilitarian products.

$H_4$: The effectiveness of sharing mechanisms that rely on broadcast messages from strangers (rather than friends) is greater for high-utilitarian products than for low-utilitarian products.

# Empirical Study

## Setup

We test our proposed conceptual model with a large-scale empirical study based on 751 Facebook apps (for details, see Appendix A). Facebook apps are an ideal setting for this study because they spread primarily through viral marketing, which minimizes potential confounding effects. Facebook currently lacks a convenient "app store" for users to discover interesting new offerings, so producers must rely on consumers' recommendations. Typically, apps actively attempt to initiate the viral marketing process by asking users for permission to send a predefined marketing message on their behalf. For example, apps might request permission to post viral messages on users' Facebook timeline (Figure 2). Because all apps on Facebook are currently free, there should not be any confounding price effects. To use an app, a new consumer simply confirms the installation on his or her Facebook page; after this initial installation, the consumer can return to use the app at any time.

For our study, we collected information about the number and characteristics of the sharing mechanisms employed in each app. A team of coders, thoroughly trained by the authors, evaluated the app characteristics. The average time needed to rate an app was 30 minutes. Two coders independently coded approximately one-third of all apps. The interrater reliability achieved a correlation of .8; any differences were discussed until agreement was reached. In our sample, the average number of sharing mechanisms per app was 2.79, and 64% of all sharing mechanisms relied on unsolicited messages, whereas only 11% employed incentives. In addition, 57% of sharing mechanisms used broadcast messages from friends, 37% used direct messages from friends, and only approximately 7% used broadcast messages from strangers.

For the apps in our study, we observed the product categories (22 categories in total, including, e.g., games, entertainment, business, money; for a complete list, see Table A2 in Appendix A) as selected by the app producer. Our sample included the top 20 apps (in terms of number of installations) for each category as well as a random selection of remaining apps. For the dichotomous classification of each app as either more or less utilitarian, we relied on the category choice of the app developer. We considered an app more utilitarian if it belonged to the business, money, utility, alerts, or politics categories (n = 233) and less utilitarian otherwise (n = 518). To control for confounding effects, we tracked the types of network effects that each app used and included measures for app quality. We could not observe the content of sent messages, which were prescribed by the app and thus very similar across sharing mechanisms, to the benefit of our study. Nor could we capture differences in message characteristics between apps. Our data set thus contains aggregate information on the app level; we did not observe the behavior of individual consumers.

To analyze app success, we relied on daily information about the number of installations for each app (for details, see Table 2), which indicated product reach, a common success measure in practice that is widely used in viral marketing research (see, e.g., Bampo et al. 2008; De Bruyn and Lilien 2008; Hinz et al. 2011; Van der Lans et al. 2010). Although we observed the daily number of installations over the course of an entire year, we faced censored data about app success, because some apps existed before the first day of our observation period and others were launched near the end of the period such that they remained in their growth phase. To achieve performance comparability across products, we estimated a diffusion curve for each app using the technology substitution model (TSM; for applications in marketing, see Gupta, Lehmann, and Stuart 2004; Schulze, Skiera, and Wiesel 2012), which is conceptually similar but more robust than the recursive Bass model (Kim, Mahajan, and Srivastava 1995; for technical details, see Appendix A). We then used the estimated maximum number of installations for each app as the primary success measure in our analyses. We also replicated our results with alternative success measures, such as the number of daily active users and the growth rate.

## Statistical Model

We established our statistical model to test the notion that utilitarian apps moderate the effectiveness of sharing mechanism characteristics on app success. As Equation 1 shows, the model includes a parameter for the number of sharing mechanisms $M_i$ per app i ($\pi$), because apps can use more than one sharing mechanism. The four count variables

**FIGURE 2**
**Screenshot: App Request to Post on User's Timeline**




($x_{unsolicited,i}$, $x_{incentivized,i}$, $x_{directfriend,i}$, and $x_{broadcaststranger,i}$) capture how many of the $M_i$ sharing mechanisms that an app used exhibited a certain characteristic. We capture the main effect of each sharing mechanism characteristic (e.g., $\beta_{unsolicited}$) and the main effect of high-utilitarian apps ($\beta_{ut}$). To test $H_1$–$H_4$, we included the two-way interactions of sharing mechanism characteristics and primarily utilitarian apps (4 parameters, e.g., $\beta_{unsolicited_ut}$).

In addition, we integrated numerous control variables. To control for category-specific effects, beyond the distinction into less and more utilitarian apps, we included dummy variables for app categories (22 parameters, e.g., $\gamma_{category_business}$). We also used control variables for five types of positive network effects coded as dummy variables (5 parameters, e.g., $\gamma_{networkexternalities}$) and their respective interactions with high-utilitarian apps (5 parameters, e.g., $\gamma_{networkexternalities_ut}$). The control variables for network effects captured whether an app employed specific network effects that might influence its diffusion. In particular, these parameters captured the effect of apps without any base utility, when used in isolation ($\gamma_{noBaseUtility}$),[3] such that the app required connected peers to be of any value to the user (similar to telephone or e-mail). We also captured the effect for apps that encouraged interactions among users within

[3]Katz and Shapiro (1985, p. 426) describe base utility as the "basic willingness to pay" (r) for the product, excluding consideration of network effects (see their Equation 1).

a forum ($\gamma_{forum}$), allowed users to comment on others' contributions ($\gamma_{comment}$), or encouraged any other kind of interaction ($\gamma_{interaction}$). Finally, to capture other types of positive network externalities, we employed a fifth parameter ($\gamma_{networkexternalities}$) related to network externalities in apps with a base utility (comparable to smartphones, which offer functionality even without connected peers).

Finally, we included two measures to control for unobserved app quality: the number of fans and the number of reviews an app had received. We observed both metrics at the end of the observation period. To ensure they were comparable across apps of different ages (i.e., older apps have had more time to accumulate fans and reviews), we divided the recorded number of reviews and fans by the number of days the app had been available. Thus, we captured the main effects of fans per day and reviews per day ($\gamma_{reviews}$, $\gamma_{fans}$), their two-way interactions with high-utilitarian apps ($\gamma_{reviews_ut}$, $\gamma_{fans_ut}$) and with sharing mechanism characteristics (eight parameters; e.g., $\gamma_{reviews_unsolicited}$), and their three-way interactions with high-utilitarian apps and sharing mechanism characteristics (eight parameters; e.g., $\gamma_{reviews_ut_unsolicited}$). We did not include users' star ratings as a measure of app quality, because this measure was available for only a fraction of the observed apps. Correlations between variables were generally low and should not affect our analysis (Table A1 in Appendix A). As an overview, we summarize the conceptual definition, empirical operationalization, and descriptive results for our focal constructs in Table 2.

We used a standard multiplicative model with dummy variables to explain the success of Facebook apps (Y), because it is intuitive that sharing mechanism characteristics influence the relative success of Facebook apps rather than add a fixed number of additional users. Equation 1 is the transformed, log-linear version of the model, which we used to analyze our data:

$$
\begin{aligned}
(1)\ \ln\left(\hat{\mathbf{Y}}_i\right) = {} & \alpha' + \theta \times \mathrm{M}_i + \beta_{unsolicited} \times x_{unsolicited,\,i} \\
& + \beta_{incentivized} \times x_{incentivized,\,i} + \beta_{directfriend} \times x_{directfriend,\,i} \\
& + \beta_{broadcaststranger} \times x_{broadcaststranger,\,i} + \beta_{ut} \times x_{ut,\,i} \\
& + \beta_{unsolicited_ut} \times x_{unsolicited,\,i} \times x_{ut,\,i} \\
& + \beta_{incentivized_ut} \times x_{incentivized,\,i} \times x_{ut,\,i} \\
& + \beta_{directfriend_ut} \times x_{directfriend,\,i} \times x_{ut,\,i} \\
& + \beta_{broadcaststranger_ut} \times x_{broadcaststranger,\,i} \times x_{ut,\,i} \\
& + \gamma_{category_business} \times x_{category_business,\,i} + \cdots \\
& + \gamma_{category_video} \times x_{category_video,\,i} \\
& + \gamma_{networkexternalities} \times x_{networkexternalities,\,i} + \cdots \\
& + \gamma_{interaction} \times x_{interaction,\,i} \\
& + \gamma_{networkexternalities_ut} \times x_{networkexternalities,\,i} \times x_{ut,\,i} \\
& + \ldots + \gamma_{interaction_ut} \times x_{interaction,\,i} \times x_{ut,\,i} \\
& + \gamma_{reviews} \times x_{reviews,\,i} + \gamma_{fans} \times x_{fans,\,i} \\
& + \gamma_{reviews_ut} \times x_{reviews,\,i} \times x_{ut,\,i} \\
& + \gamma_{fans_ut} \times x_{fans,\,i} \times x_{ut,\,i} \\
& + \gamma_{reviews_unsolicited} \times x_{reviews,\,i} \times x_{unsolicited,\,i} + \cdots \\
& + \gamma_{reviews_broadcaststranger} \times x_{reviews,\,i} \times x_{broadcaststranger,\,i} \\
& + \gamma_{fans_unsolicited} \times x_{fans,\,i} \times x_{unsolicited,\,i} + \cdots \\
& + \gamma_{fans_broadcaststranger} \times x_{fans,\,i} \times x_{broadcaststranger,\,i} \\
& + \gamma_{reviews_ut_unsolicited} \times x_{reviews,\,i} \times x_{ut,\,i} \times x_{unsolicited,\,i} \\
& + \ldots + \gamma_{reviews_ut_broadcaststranger} \times x_{reviews,\,i} \times x_{ut,\,i} \\
& \times x_{broadcaststranger,\,i} + \gamma_{fans_ut_unsolicited} \times x_{fans,\,i} \\
& \times x_{ut,\,i} \times x_{unsolicited,\,i} + \cdots \\
& + \gamma_{fans_ut_broadcaststranger} \times x_{fans,\,i} \times x_{ut,\,i} \\
& \times x_{broadcaststranger,\,i}
\end{aligned}
$$

### *Endogeneity*

We addressed potential endogeneity in our model in two ways. First, we included control variables for app categories, network effects, and the number of reviews and fans per app as an indicator of unobserved app quality in the statistical model. The results for $H_1$–$H_4$ remained unchanged—indeed, the parameters even increased in significance—when we added these control variables, and the explained variance increased substantially as well.

Second, we investigated potential endogeneity concerns through in-depth interviews with 23 industry professionals (marketing managers directly responsible for firms' Facebook activities, app programmers, and agency representatives), which helped us better understand the data-generating process. Among other things, we discussed three potential endogeneity concerns in our data set (for details on these questions and respondents' answers, see Appendix B, Table B1).

First, if programmers and designers knew a priori which sharing mechanism characteristics were superior and used them more frequently, this would create endogeneity. However, average agreement with the item "I am fully aware of which sharing mechanisms work and which do not" was only 4.4 on a ten-point scale (1 = "do not agree," and 10 = "fully agree"). The respondents also disagreed widely about their specific expectations. Therefore, we do not expect systematic prior expectations about the superiority of certain characteristics to have an influence on our data; we find support for this assumption in the relative frequency of the various characteristics (i.e., some of the most effective characteristics were rarely used).

Second, endogeneity might result if app developers used certain characteristics only as a "last resort" for apps with otherwise very low chances of success. We cannot entirely rule out this possibility, but the wide disagreement with this notion among industry professionals (average

agreement of 2.7 on a ten-point scale) suggests that such behavior is not common.

Third, endogeneity could arise if app developers tailored their sharing mechanisms to certain types of apps (e.g., utilitarian). In our survey, industry professionals concurred with the assertion that sharing mechanisms in less utilitarian leisure apps should function differently than those in primarily utilitarian business-related apps (7.7 on a ten-point scale). However, when asked about their specific expectations, most professionals answered that they had "no idea." Those who formulated specific expected differences varied greatly in their predictions. It is thus very unlikely that endogeneity poses a problem for our analysis.

# Results

### *Hypotheses Testing*

In Table 3, we present the results for the full model (Equation 1) in the last column. The results confirm a moderating influence of primarily utilitarian products on the effectiveness of sharing mechanism characteristics. We find a significant negative effect of unsolicited messages in viral marketing (−1.37, $p < .01$) for utilitarian products, which confirms $H_1$. Similarly, incentives for the receiver in viral marketing messages that promote utilitarian products are significantly less effective (−2.05, $p < .05$), which confirms $H_2$. Sharing mechanisms that use direct messages from friends are significantly more effective for utilitarian products (1.84, $p < .01$), in support of $H_3$. Finally, we find that broadcast messages from strangers are significantly more effective for utilitarian products (3.83, $p < .01$), in line with $H_4$. These effects are not only statistically significant but also substantial. For example, unsolicited messages are 75% less effective (1 – exp(–1.37)) for primarily utilitarian products. The results are consistent across the six regressions in Table 3, which differ in the number of focal and control variables they use (for details on the control variables' parameters, see Appendix A).

**TABLE 3**
**Effects of Sharing Mechanism Characteristics on Product Reach**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Number of sharing mechanisms | .69*** | .75*** | .77*** | .82*** | .73*** | .63*** |
| | (11.23) | (6.61) | (6.92) | (7.17) | (6.27) | (5.53) |
| **Sharing Mechanism Characteristics** | | | | | | |
| Unsolicited message | | −.51 | −.28 | −.09 | −.02 | .02 |
| | | (−1.45) | (−.71) | (−.23) | (−.05) | (.07) |
| Message with incentive | | 1.14*** | 1.49*** | 1.09*** | 1.38*** | 1.36*** |
| | | (3.49) | (4.18) | (2.77) | (3.66) | (3.58) |
| Direct message from friend | | .59 | .31 | −.03 | −.39 | −.36 |
| | | (1.58) | (.68) | (−.07) | (−.94) | (−.85) |
| Broadcast message from stranger | | −.54 | −1.18* | −1.46** | −1.34** | −1.44** |
| | | (−.98) | (−1.89) | (−2.39) | (−2.23) | (−2.36) |
| **Moderator for Sharing Mechanism Characteristics in Primarily Utilitarian Apps** | | | | | | |
| Unsolicited message × utilitarian | | | −.90* | −1.21** | −1.00* | −1.37*** |
| | | | (−1.68) | (−2.35) | (−1.88) | (−2.58) |
| Message with incentive × utilitarian | | | −2.37*** | −1.84* | −2.00** | −2.05** |
| | | | (−2.68) | (−1.95) | (−2.31) | (−2.27) |
| Direct message from friend × utilitarian | | | 1.28 | 1.33* | 1.23* | 1.84*** |
| | | | (1.60) | (1.78) | (1.75) | (2.62) |
| Broadcast message from stranger × utilitarian | | | 3.30*** | 3.55*** | 3.12*** | 3.83*** |
| | | | (2.84) | (3.03) | (2.75) | (3.11) |
| **Control for App Type** | | | | | | |
| Utilitarian | | | .16 | 1.03 | .95 | .37 |
| | | | (.34) | (1.19) | (1.10) | (.48) |
| **Controls for App Categories** | | | | Yes | Yes | Yes |
| **Controls for Network Effects** | | | | | Yes | Yes |
| **Controls for App Quality (Reviews and Fans)** | | | | | | Yes |
| **Constant** | | | | | | |
| Constant | 6.64*** | 6.58*** | 6.43*** | 7.10*** | 6.97*** | 7.70*** |
| | (34.47) | (28.20) | (21.62) | (4.79) | (4.71) | (5.80) |
| N | 751 | 751 | 751 | 751 | 751 | 751 |
| R-square | .129 | .160 | .175 | .272 | .318 | .406 |
| Adjusted R-square | .128 | .155 | .164 | .240 | .279 | .353 |

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: t-values are in parentheses. We use robust standard errors in all regressions.

### *Investigation of Moderating Effects*

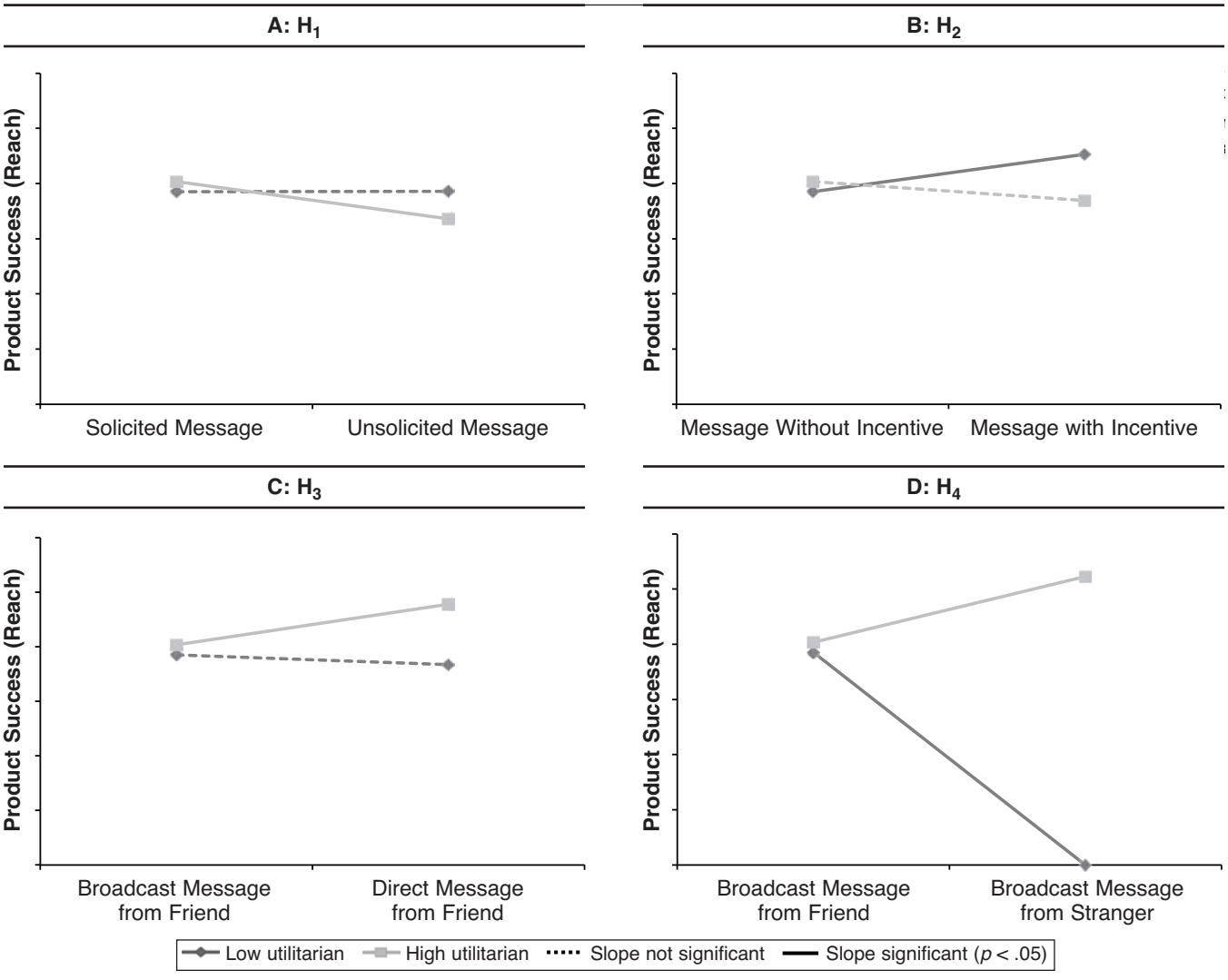
To better understand what drives the observed moderating effects from utilitarian apps, we further investigate the interaction effects. Figure 3 shows that the confirmation of $H_1$ stems from a significant negative effect of unsolicited messages for high-utilitarian products. For low-utilitarian products, we do not observe a significant difference for solicited versus unsolicited viral marketing messages (as the dotted line indicates). Both findings are in line with our hypothesis. Regarding $H_3$, we find a similar pattern, in that the significant positive slope for high-utilitarian products drives the observed effect. Primarily utilitarian apps benefit from the increased personal relevance signaled by direct viral marketing messages from friends. We do not observe a significant slope for low-utilitarian products, which indicates that broadcast and direct messages for these products work equally well.

Both findings—the superiority of direct messages for high-utilitarian products and the insignificant difference between broadcast and direct messages for low-utilitarian products—challenge the generalizability of previous findings (Aral and Walker 2011). Although we can only speculate that these differences might stem from the greater product variety we include in this study, our findings are fully in line with the hypothesized effects.

Regarding $H_4$, Figure 3 shows the expected significant negative slope for low-utilitarian products. For high-utilitarian products, however, broadcast messages from strangers are not just equally but even more effective than broadcast messages from friends. As we have noted, the significant positive slope might reflect consumers' desire for unbiased outside information that complements their own perspective regarding the functionality and usefulness of high-utilitarian products, which seems to be more influential than recommendations from friends with often similar views.

Finally, we find the expected significant positive effect from incentives in viral marketing messages for low-utilitarian products ($H_2$), but we do not observe a significant negative effect from incentives for high-utilitarian products. In other words, incentives are not detrimental to viral marketing success for these products, just ineffective. A potential reason for this finding is that the value of the actual benefit of

**FIGURE 3**
**Moderating Effects of Primarily Utilitarian Products**



the incentive (e.g., one free month of premium membership) is comparable to the negative quality signal such that we observe an insignificant overall effect.

### *Robustness Checks*

To increase confidence in our results, we used the full model (Equation 1) with a different sample as well as with other dependent variables. We present the results for several alternative success measures in Table 4. In the first column, we present the full original model again for reference.

*Estimated reach without the top 20 apps*. In our original analysis, we selected the top 20 apps and a random selection of remaining apps in each category. This selection process might lead to biased results if sharing mechanism characteristics in top 20 apps work differently than those for other apps. We therefore excluded the top 20 apps from the regression in the second column. Although the parameter and significance levels changed slightly, the results remain the same with this smaller sample.

*Reach as observed in the data*. To account for censored data, we used the TSM to estimate the maximum number of installations for each app in our original analysis. This estimation might lead to improper dependent variables if the functional form of the TSM were unsuitable. For this regression, we did not estimate the reach of each app; instead, we used the highest observed number of installations in the observation period as an alternative dependent variable. As we show in the third column of Table 4, the results from this analysis were almost identical to those from our original approach.

*Usage as observed in the data*. Reach is a popular, commonly used measure of viral marketing success, but other potentially relevant success measures exist. Our interviews with industry professionals indicated that the number of active users and the growth rate are relevant, so we used the

**TABLE 4**
**Robustness Checks: Effects of Sharing Mechanism Characteristics on Alternative Success Measures**

| | Reach (Estimated) | Reach Without Top 20 (Estimated) | Reach (Observed) | Usage (Observed) | Early Growth (Estimated) |
|---|---|---|---|---|---|
| Number of sharing mechanisms | .63*** | .41*** | .61*** | .57*** | .50*** |
| | (5.53) | (4.08) | (5.14) | (5.48) | (4.76) |
| **Sharing Mechanism Characteristics** | | | | | |
| Unsolicited message | .02 | .20 | .09 | –.01 | .37 |
| | (.07) | (.61) | (.23) | (–.03) | (1.05) |
| Message with incentive | 1.36*** | .76** | 1.24*** | 1.36*** | 1.34*** |
| | (3.58) | (2.10) | (3.24) | (4.06) | (3.97) |
| Direct message from friend | –.36 | –.62* | –.34 | –.34 | –.64* |
| | (–.85) | (–1.69) | (–.81) | (–.89) | (–1.69) |
| Broadcast message from stranger | –1.44** | –.86 | –1.51** | –1.25** | –1.59*** |
| | (–2.36) | (–1.56) | (–2.43) | (–2.26) | (–2.85) |
| **Moderator for Sharing Mechanism Characteristics in Primarily Utilitarian Apps** | | | | | |
| Unsolicited message × utilitarian | –1.37*** | –.87* | –1.34** | –1.35*** | –1.49*** |
| | (–2.58) | (–1.93) | (–2.51) | (–2.91) | (–3.16) |
| Message with incentive × utilitarian | –2.05** | –3.08*** | –1.90** | –1.54* | –1.38* |
| | (–2.27) | (–3.91) | (–2.06) | (–1.91) | (–1.74) |
| Direct message from friend × utilitarian | 1.84*** | 1.47** | 1.83** | 1.92*** | 1.96*** |
| | (2.62) | (2.49) | (2.58) | (3.06) | (3.20) |
| Broadcast message from stranger × utilitarian | 3.83*** | 4.18*** | 3.63*** | 3.21*** | 3.66*** |
| | (3.11) | (3.62) | (2.89) | (2.93) | (3.50) |
| **Control for App Type** | | | | | |
| Utilitarian | .37 | .06 | .33 | –.02 | –.02 |
| | (.48) | (.10) | (.43) | (–.02) | (–.02) |
| **Controls for App Categories** | Yes | Yes | Yes | Yes | Yes |
| **Controls for Network Effects** | Yes | Yes | Yes | Yes | Yes |
| **Controls for App Quality (Reviews and Fans)** | Yes | Yes | Yes | Yes | Yes |
| **Constant** | | | | | |
| Constant | 7.70*** | 5.75*** | 7.76*** | 5.51*** | 3.37*** |
| | (5.80) | (5.36) | (5.90) | (4.91) | (2.89) |
| N | 751 | 597 | 751 | 751 | 751 |
| R-square | .406 | .438 | .401 | .431 | .408 |
| Adjusted R-square | .353 | .374 | .348 | .380 | .356 |

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: t-values are in parentheses. We use robust standard errors in all regressions.

observed maximum number of daily active users as a third alternative dependent variable. Again, the results confirmed our initial findings and were very similar to our original analysis (see the fourth column of Table 4)—which is not surprising, considering the high correlation between the number of daily active users and the number of installations.

*Estimated growth*. For some practical applications, not only potential reach but also the time frame in which a product realizes its potential can be important. We therefore constructed a measure for speed of growth that enables us to compare apps that differ in their estimated reach. We calculated the number of days the app needed to reach 90% of its potential installations (the asymptote $\alpha$ in the TSM) and then divided this number by the app's total estimated reach such that the measure was comparable across apps with different reach. Other growth measures exist, but this one seemed least arbitrary for our purposes. The results in the last column of Table 4 again resemble the results from our original model.

# Summary and Implications

## Summary of Results

The viral marketing success of products such as FarmVille has attracted many firms to Facebook—not only game producers but also makers of primarily utilitarian products, whose value for consumers results more from their products' usefulness and less from the fun they offer. Marketing managers from all industries wonder whether they can replicate the success of FarmVille and similar products by simply imitating their approach—that is, encouraging consumers to broadcast unsolicited viral marketing messages to their Facebook friends and offering small incentives to convince the receiver to try and use the product. Thus far, the marketing literature has not answered this question.

In our study, we investigate two important questions regarding viral marketing on primarily fun- and entertainment-oriented platforms such as Facebook: Should primarily utilitarian products rely on the same sharing mechanisms for their viral marketing campaign as products that are not utilitarian? If not, why is this the case, and how should viral marketing for utilitarian products differ? From our study of 751 products, we present new answers.

In particular, we note that primarily utilitarian products should not rely on the same sharing mechanisms as FarmVille and other fun-oriented products. The very mechanism that made FarmVille so successful is a recipe for failure when used in a different product context. Unsolicited and incentivized broadcast messages from friends are the least effective sharing mechanisms for primarily utilitarian products (Table 3).

The reason for this somewhat surprising finding can be found in dual-process theory from social psychology: the ELM (Petty and Cacioppo 1986). Consumers use Facebook with the intention of having fun and being entertained rather than doing something useful. Thus, viral marketing messages for utilitarian products on Facebook do not correspond with their situational expectations or schema (Bartlett 1932). Consequently, consumers unconsciously devote fewer mental resources to evaluating the actual message content and instead rely more on heuristics, simple inferences, and social cues. Put simply, consumers generally do not visit Facebook to learn about utilitarian products, so they process viral marketing messages about such products differently than, say, messages about games.

## Implications for Marketing Theory

The current research contributes to literature on viral marketing in general and work on sharing mechanisms in particular. This study is the first to examine differences in viral marketing strategies for low- versus high-utilitarian products. We find stark differences in the effectiveness of sharing mechanism characteristics for different types of products, which should motivate further research along similar lines for other known determinants of viral marketing success, such as seeding strategies and message content. Moreover, the theory we applied specifically focuses on viral marketing for utilitarian products in fun-oriented settings such as Facebook. Our findings should translate to other social networks with similar settings, such as YouTube; further research should investigate whether a reversal of our results might occur in more utilitarian social networks (e.g., LinkedIn), as schema theory and the ELM would predict.

We also contribute to the sparse literature stream on the effectiveness of sharing mechanism characteristics for viral marketing. Aral and Walker (2011) focus on the in-depth (customer-level) analysis of one particular product and analyze two sharing mechanisms that differ on one dimension (communication exclusivity). In contrast, we compare 751 products representing 22 categories that include highly successful blockbusters with millions of customers as well as average and entirely unsuccessful products. With this variety, we can test the generalizability of previous results and—through our comparison of low- versus high-utilitarian products—extend and refine previous findings (Figure 3). We also analyze all four dimensions (sender–receiver relationship, communication exclusivity, expressed interest, and message features) of viral marketing sharing mechanisms. To our knowledge, ours is the first study to combine all four dimensions, which collectively characterize the sharing mechanisms through which viral messages spread between consumers.

## Implications for Marketing Practice

Marketing managers in charge of viral marketing activities face difficult decisions when designing campaigns for their products. In line with previous research (Aral and Walker 2011), we offer strong empirical evidence that the success of such campaigns hinges on choosing the right sharing mechanism. A suitable sharing mechanism should encourage consumers to recommend a product to their peers; indeed, the results of our study show that a well-chosen sharing mechanism can increase app success (as measured by the number of installations) by a factor of 19. Conversely, a viral marketing campaign that uses an inappropriate sharing mechanism can severely limit a product's success.

The results of our analysis of viral marketing campaigns on Facebook for 751 products shows that for low-utilitarian products (e.g., games, music services), the ideal sharing mechanism uses incentives and suggests that customers recommend products to their friends rather than to strangers. We also find that sharing mechanisms that rely on unsolicited viral marketing messages are as effective as sharing mechanisms that use solicited messages (Figure 3). In other words, viral marketing campaigns for low-utilitarian products on Facebook are well-advised to follow the best-practice strategy of products such as FarmVille and encourage unsolicited and incentivized broadcast messages from friends for spreading viral marketing messages (Figure 2).

Recommendations for viral marketing campaigns for high-utilitarian products on Facebook, such as job search or stock market applications, differ radically. Sharing mechanisms for such useful offerings should avoid using unsolicited messages or broadcast messages from friends. In addition, although incentives associated with these products are not harmful, they are ineffective in Facebook's fun- and entertainment-oriented setting (Figure 3). Incentives (e.g., one free month of premium membership) often come at a cost to the firm, so marketing managers should probably avoid them. Instead, viral marketing campaigns for primarily utilitarian products should rely on solicited viral marketing messages that customers can either direct at individual friends or broadcast to strangers. On Facebook, for example, promoting a useful product in the "Likes" section on consumers' "About" pages[4] will be far more effective than simply copying FarmVille's approach. In fact, not using any viral marketing sharing mechanism is four times better for these products than FarmVille-type, unsolicited, incentivized broadcast messages from friends (Table 3).

In summary, marketing managers must adapt their Facebook viral marketing strategy to their product. The same sharing mechanism characteristics that helped products such as FarmVille reach more than 100 million consumers in less than 40 days can severely harm the chances of success of primarily useful products.

### *Limitations and Further Research*

In our empirical study, we analyzed the viral marketing campaigns of 751 products. To achieve this breadth, we had to accept some limitations in our empirical setup. First, our data did not come from a controlled experiment. We went to great lengths to control for product differences along relevant dimensions, such as the category, quality, and network effects; still, a small risk of unobserved heterogeneity persists for our study. Second, our observed app data did not allow us to distinguish individual users and their interactions with the sharing mechanisms. Such data would be desirable and helpful for understanding individual (rather than typical) consumers' reactions.

In addition to addressing these data limitations, our findings point to at least five worthwhile directions for further research. First, we focused on viral marketing on Facebook, a fun- and entertainment-oriented social media platform. Additional research could attempt to replicate our findings on other fun-oriented platforms, such as YouTube, as well as test our findings in more utilitarian social networks, such as LinkedIn. In the latter environment, schema theory suggests that consumers will process viral marketing messages about utilitarian products via the central route rather than the peripheral route, which should reverse the effects for $H_1$–$H_3$ but not for $H_4$.

Second, we investigated the moderating effect of a primarily utilitarian product context on sharing mechanism characteristics only. Understanding whether the effects of other known determinants of viral marketing success, such as content characteristics and seeding strategies, also differ between low- and high-utilitarian settings could inform both theoretical and managerial perspectives.

Third, in the Facebook environment, the basic versions of all products are available free of charge to the consumer. As a result, we could not investigate price effects (Fandrich, Kübler, and Pauwels 2013; Lambrecht, Seim, and Skiera 2007), which might be an important area for future studies.

Fourth, it would be worthwhile to investigate whether the findings from this study replicate in a word-of-mouth context. The main difference between viral marketing and word of mouth pertains to the origin of the marketing message. If consumers rather than firms create the content of a marketing message, consumers' reactions should be strongly affected when they process information through the peripheral route, which implies that they rely strongly on social cues ("I can trust another customer more than I can trust the firm") (Hinz, Schulze, and Takac 2014; Phelps et al. 2004). Messages about primarily utilitarian products therefore should benefit most from word-of-mouth messages on Facebook. Yet we expect that the effectiveness of the remaining sharing mechanism characteristics (solicited vs. unsolicited messages, no incentives vs. incentives, and direct messages from friends vs. broadcast messages from friends or broadcast messages from strangers) is similar to that within the viral marketing context.

Fifth, encouraging consumers to make recommendations to their contacts through sharing mechanisms might raise ethical concerns. Viral marketing messages are not always undesirable; for example, consumers tolerate unsolicited (or spam) messages if the promoted product fits well with their expectations about the environment. However, we cannot rule out the possibility that message receivers might have difficulties distinguishing firm-generated viral marketing activities and original content from peers, at least in some cases. Further research should continue to discuss the ethical implications and limitations of (not clearly identifiable) viral marketing in more detail.

[4]Users can limit the visibility of the "About" section to strangers through more restrictive privacy settings.

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# Appendix A: Details on the Empirical Study of 751 Facebook Apps

### *Estimating Product Reach*

In our empirical study, we analyzed the effect of sharing mechanism characteristics on 751 Facebook apps. Although we observed the daily number of installations over the course of an entire year, we faced censored data about app success, because some apps existed before the first day of our observation period and others were launched near the end of the period such that they remained in their growth phase. To achieve performance comparability across products, we estimated a diffusion curve for each app using the TSM (Gupta, Lehmann, and Stuart 2004; Kim, Mahajan, and Srivastava 1995; Schulze, Skiera, and Wiesel 2012), as Equation A1 shows. We then used the estimated maximum reach for each app (denoted by $\alpha$ in Equation A1) as the primary success measure in our analyses.

$$\text{(A1)} \qquad \text{Reach}_i = \frac{\alpha}{1 + \exp(-\beta - \gamma \times t)}.$$

For our empirical study, we collected information on 863 apps in total. However, information on the daily number of installations was insufficient for 112 apps. For these apps, the nonlinear least squares estimation of the TSM did not converge, a common occurrence when S-shaped diffusion curves have not yet reached the inflection point. Consequently, we focus our analysis on the 751 apps with sufficient information (87% of the original sample).

### *Estimation Details*

Table A1 provides correlations between all variables. Overall, the correlations are low; only unsolicited message and direct message from a friend show few correlations with other variables greater than .5, but never greater than .75. Thus, we do not expect correlations to affect our results. Space constraints precluded us from presenting coefficients for all control variables in Table 3. For full estimation results, see Table A2.

# Appendix B: Details on In-Depth Interviews with Industry Professionals

For our study, we conducted in-depth interviews with 23 industry professionals about the effect of sharing mechanism characteristics on Facebook apps. Among our interview partners were marketing managers directly responsible for firms' Facebook activities, app programmers, and agency representatives whose main expertise was designing and programming Facebook apps. We conducted 17 interviews individually and in person during two major gatherings of industry professionals and 6 interviews over Skype or telephone. None of the respondents were aware of our study before the interview. We informed respondents that their answers would be used to "improve an ongoing research study about Facebook apps," guaranteed them anonymity, and offered them a management summary of the empirical findings as compensation for their efforts. We report their answers as related to this research in Table B1. In Question 5, instead of differentiating more and less utilitarian apps, we used the terms "business-related apps" and "leisure-related apps," which are conceptually similar.

**TABLE A1**
**Correlation Table: Data on 751 Facebook Apps**

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Ln(Reach) | 1.00 | | | | | | | | | | | | | |
| 2. Number of sharing mechanisms | .36 | 1.00 | | | | | | | | | | | | |
| 3. Unsolicited message | .26 | .74 | 1.00 | | | | | | | | | | | |
| 4. Message with incentive | .22 | .34 | .60 | 1.00 | | | | | | | | | | |
| 5. Direct message from friend | .27 | .51 | .66 | .51 | 1.00 | | | | | | | | | |
| 6. Broadcast message from stranger | .04 | .31 | .64 | .45 | .08 | 1.00 | | | | | | | | |
| 7. Utilitarian | −.08 | −.15 | −.21 | −.18 | −.13 | −.16 | 1.00 | | | | | | | |
| 8. Network externalities | .18 | .20 | .12 | −.08 | .18 | −.08 | −.04 | 1.00 | | | | | | |
| 9. Network externalities without base effect | .10 | −.06 | −.08 | −.09 | .02 | −.04 | .00 | .07 | 1.00 | | | | | |
| 10. Forum | .13 | .31 | .17 | −.05 | .16 | .03 | −.07 | .44 | .00 | 1.00 | | | | |
| 11. Comments | .16 | .32 | .18 | −.07 | .20 | −.10 | .00 | .47 | −.01 | .50 | 1.00 | | | |
| 12. Interaction | .26 | .28 | .18 | .00 | .25 | .02 | −.16 | .49 | .11 | .45 | .46 | 1.00 | | |
| 13. Reviews | .25 | .03 | .04 | .07 | .08 | −.06 | −.06 | .03 | .00 | −.03 | .08 | .12 | 1.00 | |
| 14. Fans | .15 | .03 | .01 | .03 | .03 | −.01 | −.01 | .00 | .09 | .00 | −.03 | .05 | .14 | 1.00 |

Notes: All values greater than $|.07|$ are significant at $p < .05$.

**TABLE A2**
**Full Results: Effects of Sharing Mechanism Characteristics on Product Reach**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Number of sharing mechanisms | .69*** | .75*** | .77*** | .82*** | .73*** | .63*** |
| **Sharing Mechanism Characteristics** | | | | | | |
| Unsolicited message | | –.51 | –.28 | –.09 | –.02 | .02 |
| Message with incentive | | 1.14*** | 1.49*** | 1.09*** | 1.38*** | 1.36*** |
| Direct message from friend | | .59 | .31 | –.03 | –.39 | –.36 |
| Broadcast message from stranger | | –.54 | –1.18* | –1.46** | –1.34** | –1.44** |
| **Moderator for Sharing Mechanism Characteristics in Primarily Utilitarian Apps** | | | | | | |
| Unsolicited message × utilitarian | | | –.90* | –1.21** | –1.00* | –1.37*** |
| Message with incentive × utilitarian | | | –2.37*** | –1.84* | –2.00** | –2.05** |
| Direct message from friend × utilitarian | | | 1.28 | 1.33* | 1.23* | 1.84*** |
| Broadcast message from stranger × utilitarian | | | 3.30*** | 3.55*** | 3.12*** | 3.83*** |
| **Control for App Type** | | | | | | |
| Utilitarian | | | .16 | 1.03 | .95 | .37 |
| **Controls for App Categories** | | | | | | |
| Business | | | | –1.22** | –1.28** | –1.17** |
| Chat | | | | .89 | .40 | –.01 |
| Classified | | | | –1.97** | –1.92** | –2.01*** |
| Dating | | | | –.26 | –.12 | –.48 |
| Education | | | | –.29 | –.12 | –.38 |
| Events | | | | –1.45* | –1.30 | –1.57** |
| Fashion | | | | .27 | .35 | .19 |
| File sharing | | | | –1.09 | –1.24 | –1.42* |
| Food and drink | | | | –.62 | –.55 | –.78 |
| Gaming | | | | .92 | .62 | –.50 |
| Just for fun | | | | .28 | .38 | –.09 |
| Messaging | | | | .11 | –.07 | –.42 |
| Mobile | | | | –1.70** | –1.55* | –1.85** |
| Money | | | | –1.31* | –1.36** | –2.21*** |
| Music | | | | –.92 | –.65 | –.95 |
| Photo | | | | –.55 | –.56 | –.76 |
| Politics | | | | –1.20** | –1.30** | –1.65*** |
| Sports | | | | –1.33 | –2.10** | –1.92** |
| Travel | | | | –.33 | –.30 | –.68 |
| Utility | | | | –.36 | –.54 | –.52 |
| Video | | | | –2.17*** | –2.28*** | –2.25*** |
| **Controls for Network Effects** | | | | | | |
| Network externalities | | | | | .25 | .29 |
| Network externalities without base effect | | | | | 2.52*** | 2.50** |
| Forum | | | | | .30 | .29 |
| Comments | | | | | .66 | .50 |
| Interaction | | | | | .74 | .57 |
| Network externalities × utilitarian | | | | | .62 | .43 |
| Network externalities without base effect × utilitarian | | | | | –1.69 | –.69 |
| Forum × utilitarian | | | | | .20 | –.32 |
| Comments × utilitarian | | | | | –1.00 | –.98* |
| Interaction × utilitarian | | | | | 1.14 | .35 |
| **Controls for App Quality** | | | | | | |
| Reviews | | | | | | .32*** |
| Fans | | | | | | .00 |
| Reviews × utilitarian | | | | | | 3.02** |
| Fans × utilitarian | | | | | | .04 |
| Reviews × unsolicited message | | | | | | .04 |
| Reviews × message with incentive | | | | | | –.22** |
| Reviews × direct message from friend | | | | | | –.07 |
| Reviews × broadcast message from stranger | | | | | | 2.53** |
| Fans × unsolicited message | | | | | | .00 |
| Fans × message with incentive | | | | | | .00 |
| Fans × direct message from friend | | | | | | .01 |
| Fans × broadcast message from stranger | | | | | | .00 |
| Reviews × utilitarian × unsolicited message | | | | | | –1.13* |
| Reviews × utilitarian × message with incentive | | | | | | 3.05* |

**TABLE A2**
**Continued**

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **Controls for App Quality (Continued)** | | | | | | |
| Reviews × utilitarian × direct message from friend | | | | | | –.26 |
| Reviews × utilitarian × broadcast message from stranger | | | | | | 11.70 |
| Fans × utilitarian × unsolicited message | | | | | | .19*** |
| Fans × utilitarian × message with incentive | | | | | | –.12 |
| Fans × utilitarian × direct message from friend | | | | | | –.24*** |
| Fans × utilitarian × broadcast message from stranger | | | | | | –.24*** |
| **Constant** | | | | | | |
| Constant | 6.64*** | 6.58*** | 6.43*** | 7.10*** | 6.97*** | 7.70*** |
| N | 751 | 751 | 751 | 751 | 751 | 751 |
| R-square | .129 | .160 | .175 | .272 | .318 | .406 |
| Adjusted R-square | .128 | .155 | .164 | .240 | .279 | .353 |

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: We use robust standard errors in all regressions.

**TABLE B1**
**Survey Results: 23 Industry Professionals on Sharing Mechanisms in Facebook Apps**

| Survey Questions | Average Score | SD | Respondent Comments |
|---|---|---|---|
| **How much do you agree with the following statements**? | | | |
| 1. Sharing mechanisms in Facebook apps (e.g., wall posts, direct messages) are a major driver of app performance. | 8.2 | 1.3 | |
| 2. I would expect the effect of different sharing mechanisms on app success to vary strongly. | 8.2 | 1.5 | |
| 3. I am fully aware of which sharing mechanisms work and which do not. | 4.4 | 2.5 | |
| 3a. In particular, I expect... | | | •Nothing specific.<br>•Posts on my own wall will be more effective than direct invitations.<br>•Direct invitations will be more effective than posts on my own wall.<br>•Wall posts from strangers are better than wall posts from friends.<br>•Incentives do not work. |
| 4. There are certain sharing mechanisms I would only use for apps that have a very small chance of success. | 2.7 | 2.4 | |
| 4a. In particular, that means... | | | The use of (expensive) incentives is a "last resort." |
| 5. I would expect sharing mechanisms for business-related apps to work very differently from leisure-related apps. | 7.7 | 2.8 | |
| 5a. In particular, I expect... | | | •Nothing specific.<br>•Wall posts are better for leisure, whereas direct messages are better for business.<br>•Wall posts are better for business, whereas direct messages are better for leisure. |

Notes: All items measured on a ten-point scale (1 = "do not agree," and 10 = "fully agree").



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