Ann-Kristin Kupfer, Nora Pähler vor der Holte, Raoul V. Kübler, & Thorsten Hennig-Thurau

The Role of the Partner Brand's Social Media Power in Brand Alliances

Managers frequently seek strategies to profit systematically from social media to increase product sales. By forming a brand alliance, they can acquire an installed social media base from a partner brand in an attempt to boost the sales of their composite products. Drawing from power theory, this article develops a conceptual model of the influence of the social media power of partner brands on brand alliance success. The proposed framework details the partner brand's social media power potential (size and activity of the social media network), social media power exertion (different posting behaviors and comments), and their interaction. The authors test this framework with an extensive data set from the film industry, in which films function as composite products and actors represent partner brands. The data set features 442 movies, including 1,318 actor–movie combinations and weekly social media data (including 41,547 coded Facebook posts). The authors apply a linear mixed-effects model, in which they account for endogeneity concerns. The partner brand's social media power potential, power exertion, and their interaction can all lead to higher composite product sales. By coding different types of product-related posts, this article provides estimates of their varying monetary value.

Keywords: social media, content marketing, influencer marketing, movie stars, entertainment marketing

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The enormous growth of social media demands that managers and scholars understand how it influences the effectiveness of marketing strategies (e.g., Hennig-Thurau, Hofacker, and Bloching 2013). Managers dedicate vast resources to building their own brand presence on social media platforms (Pitney Bowes 2012), and scholarly insights suggest that a brand's social media–related activities can positively affect its performance (e.g., Saboo, Kumar, and Ramani 2016). However, it is unknown (1) whether brands can strategically harvest the social media networks of other brands, such as actors, athletes, and other types of influencers, and (2) which social media activities by those other brands would then be particularly promising for selling products. Obtaining richer insights into those strategy–performance links represents a key priority.

One constellation in which the strategic use of another brand's social media resources appears particularly well-suited is a brand alliance with a partner brand, wherein two or more brands combine to develop composite offerings. Such brand alliances are common in todays' brandscape; examples include McDonald's McFlurry ice cream featuring Oreos and *Terminator* movies emphasizing the participation of Arnold Schwarzenegger as a human brand. Traditionally, when forming a brand alliance, partner brands are selected for their expertise, such that they function as quality signals for consumers (Rao, Qu, and Ruekert 1999; Rao and Ruekert 1994). However, with the widespread use of social media platforms today, the potential to profit not only from partner brands' expertise but also from their social media presence might offer an additional reason to build brand alliances. However, the contributions of such social media effects—and thus, their valuation—are yet unclear. Whereas Disney's president of production rejoiced at the "unexpected byproduct" when Emma Watson's personal social media accounts triggered many trailer views of the *Beauty and the Beast* remake (Fleming 2017), the same social media power did not save her next movie, *The Circle*, from becoming a major flop (D'Alessandro 2017).

We investigate these contributions by offering a model based on power theory (e.g., Bacharach and Lawler 1980), which identifies various sources of social influence (French and

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Raven 1959). In addition to the power arising from expertise, it suggests the existence of a referent power base, among others. Here, power results from offering strong identification potential to others who seek a close association with that source. Social media might boost this form of power of partner brands over consumers by enabling them to interact with consumers in direct, personal, and reciprocal ways (Labrecque 2014). A brand's social media presence can grant customers the feeling of knowing the brand intimately, which may enhance their sense of identification with the brand. We thus argue that by strengthening the referent power base, social media gives partner brands a new opportunity to encourage consumers to buy the composite product, which differs from their function as quality signals.

The contribution of the strategic use of this social connection to composite product sales cannot, however, be determined by theoretical considerations alone, something that particularly applies to its relative role compared with the many other success drivers of composite products that have been identified (e.g., Simonin and Ruth 1998). Things get even more complicated when considering potential negative effects from the partner's social media power. Advertising-like communication in this social environment might trigger reactance and, consequently, hurt the composite product's performance. Moreover, what about those posts by the partner that do not pertain to the composite product? A related issue of importance for managers of brand alliances is the effectiveness of different social media strategies: What kinds of partner posts work best? Which do not work at all, or might even drive customers away from the composite product? Does it pay to be authentic or offer exclusive insights? Do persuasive appeals on social media by partner brands to purchase the composite product mobilize followers or repel them?

We address these intriguing research questions and inconclusive industry examples with this research and offer empirical insights. Our power theory–inspired model links the social media power of partner brands over consumers to brand alliance performance, distinguishing between a partner brand's social media power potential (i.e., the access of the partner brand to a large and active social media network) and its social media power exertion (i.e., different communication forms with which the partner brand actively addresses this network). We test our model in the movie industry, in which films represent composite products that combine movie brands as the host, and movie stars as the partner brands (Luo et al. 2010). Using weekly data about 442 movies featuring 1,318 actor–movie combinations, we link the actors' social media data with films' actual financial performance in theaters.[1] We analyze this longitudinal set of social media and sales data in a linear mixed-effects model, using instruments and extensive controls to account for the possible endogenous nature of social media activities and supply-side variables.

Our results make four contributions to research and practice. First, we contribute to the emerging literature on the value of social media by showing the incremental monetary value of the externally acquired social media presence of a partner brand. This social media power denotes a conceptually unique brand resource that exists beyond the brand's expert power and its traditional ways of promoting the composite product. Contrary to the often-expressed perception of social media's low effectiveness (*The CMO Survey* 2017), we can show its sizable economic value for selling composite products, both in absolute and relative terms.

Second, we analyze what determines social media's economic value by comparing the effectiveness of its facets. By applying established power theory to the emerging stream of social media research, we introduce the conceptual and empirical distinction between social media power potential, social media power exertion, and their interaction. We find all of them to be significantly linked to brand alliance success—namely, the sales of the composite product. The most powerful social media facet is the partner brand's product-related social media communication, especially if sent to a sizable and active social media fan base. Interestingly, non-product-related posts are associated with a significant *decrease* in composite product sales, suggesting a distraction effect.

Third, we contribute to social media research by being the first to link different social media posting strategies to actual sales data to determine which posting behaviors offer the highest monetary value. Persuasive product-related posts are associated with the greatest monetary value in our data, counter to the prevalent perception that such a communication style repels followers. We find that sending exclusive and authentic product-related posts are also promising approaches for increasing the composite product's financial performance.

Fourth, we study boundary conditions and derive actionable implications for implementing the social media power of partner brands. Concerning boundaries, we find the partner brands' social media power to be limited to the most central partner brand (i.e., the lead actor instead of the supporting cast) and the most visible communication form (i.e., posts instead of replies). Concerning actionable recommendations for social media managers, we offer specific guidelines for how to select and manage the social media power of partner brands for brand alliances.

Literature Review

Social Media Marketing

The emergence of social media has changed the ways consumers communicate and bond with one another and with brands (Hennig-Thurau et al. 2010). Their interactive, real-time nature enables consumer–brand relationships to evolve, marked by direct exchanges, intimate connections, and parasocial relationships (Labrecque 2014). Paralleling the rapid rise of social media, marketing research has investigated its strategy–performance link (e.g., Kumar et al. 2013). Srinivasan, Rutz, and Pauwels (2016) establish a significant link between a brand's Facebook likes and sales. Kumar et al. (2016) affirm that firm-generated social media content affects customer behavior. Mochon et al. (2017) find firm-solicited page likes to influence customer offline behavior, thereby highlighting the need to send those followers firm-initiated promotional communications. Saboo, Kumar, and Ramani (2016) show an

[1]By the term "actor" (or "star" or "human brand"), we refer to both male and female human beings.

increase in a musician's sales when more consumers follow him, comment on his page, or sample his products.

The economic value of firms' activities on social media largely results from consumers' sense of belonging to a community (Algesheimer, Dholakia, and Herrmann 2005). Manchanda, Packard, and Pattabhiramaiah (2015) attribute estimated sales increases to consumers who are more active and have more social ties in a community. Rishika et al. (2013) similarly find an economic effect from consumers who participate in firm-hosted social media sites, which increases with more social media activity. However, Algesheimer et al. (2010) show that firms' strategic efforts to increase consumers' participation can backfire, resulting in decreased consumer spending on the corresponding platform.

Thus, we must differentiate the various social media activities to determine their effectiveness. For example, De Vries, Gensler, and Leeflang (2012) find that vivid, interactive posts yield strong levels of consumer engagement; Stephen, Sciandra, and Inman (2015) also show that a post's content characteristics (e.g., relevance, message clarity, tone) influence engagement. Akpinar and Berger (2017) find that emotional appeals in social media advertising are more effective for fostering shares, but informational appeals are better at increasing brand evaluations and purchase intentions. Similarly, Lee, Hosanagar, and Nair (2017) find that brand personality–related posts increase engagement, but informational posts increase clicks on referenced external websites. Despite these insights, an important question remains unanswered: How do different posting behaviors relate to actual sales?

Brand Alliances

In brand alliance contexts, consumers confront two or more brands that jointly produce a composite product (Park, Jun, and Shocker 1996). Brand alliance studies often try to understand how integration of partner brands influences consumer perceptions (e.g., Desai and Keller 2002). A strong partner brand can signal quality and improve consumer evaluations of the composite product (Rao and Ruekert 1994). Simonin and Ruth (1998) note that consumers' preexisting attitudes toward individual brands and the level of fit between them drive their evaluations of a brand alliance. Thus, to increase their chances of success, host brand managers need to identify appropriate partner brands when building brand alliances (Venkatesh and Mahajan 1997). We propose that a partner brand's social media power is pertinent to such selections because of its likely influence on the success of the composite product.

Referent Power as the Base of Social Media Power

To address the role of social media power of partner brands in brand alliances, we draw from power theory, consistent with widespread applications of power concepts in marketing strategy and organizational theory (e.g., Gaski 1984; Homburg, Jensen, and Krohmer 2008; Mintzberg 1983), as well as political science, sociology, and social psychology (e.g., French and Raven 1959). Power is someone's ability to prompt another person to do what (s)he would not have done otherwise (Dahl 1957).

According to French and Raven's (1959) seminal work, such power is based on specific sources, called "power bases," such as the expert power base and the referent power base. An expert power base implies that someone is powerful because (s)he appears particularly knowledgeable or skillful in a given area. For instance, Intel's power is based on its ability to produce high-quality processors. In the movie industry, an actor's great acting skills or physical attractiveness constitute forms of expertise that may lead consumers to watch a movie featuring that actor. When forming a brand alliance, partner brands traditionally have been chosen for this expert power base—an observation consistent with general brand management literature, which shows how partner brands function mainly as quality signals (Rao and Ruekert 1994).

However, social media also implies the relevance of a different power base for selecting partner brands, called referent power base. A referent power base exists if someone or something offers strong identification potential to others that desire to be closely related or intimately connected with it (French and Raven 1959). Celebrities such as Kim Kardashian are influential less because of their expertise in a specific field and more because people strongly identify with and aim to be like them. Social media is a central tool for this referent power base, giving brands such as celebrities a new platform for building relationships with fans by offering a glimpse into their lives and addressing them directly. By fostering such personal bonds with consumers, social media increases the identification potential of brands, which adds to the power of the brand.

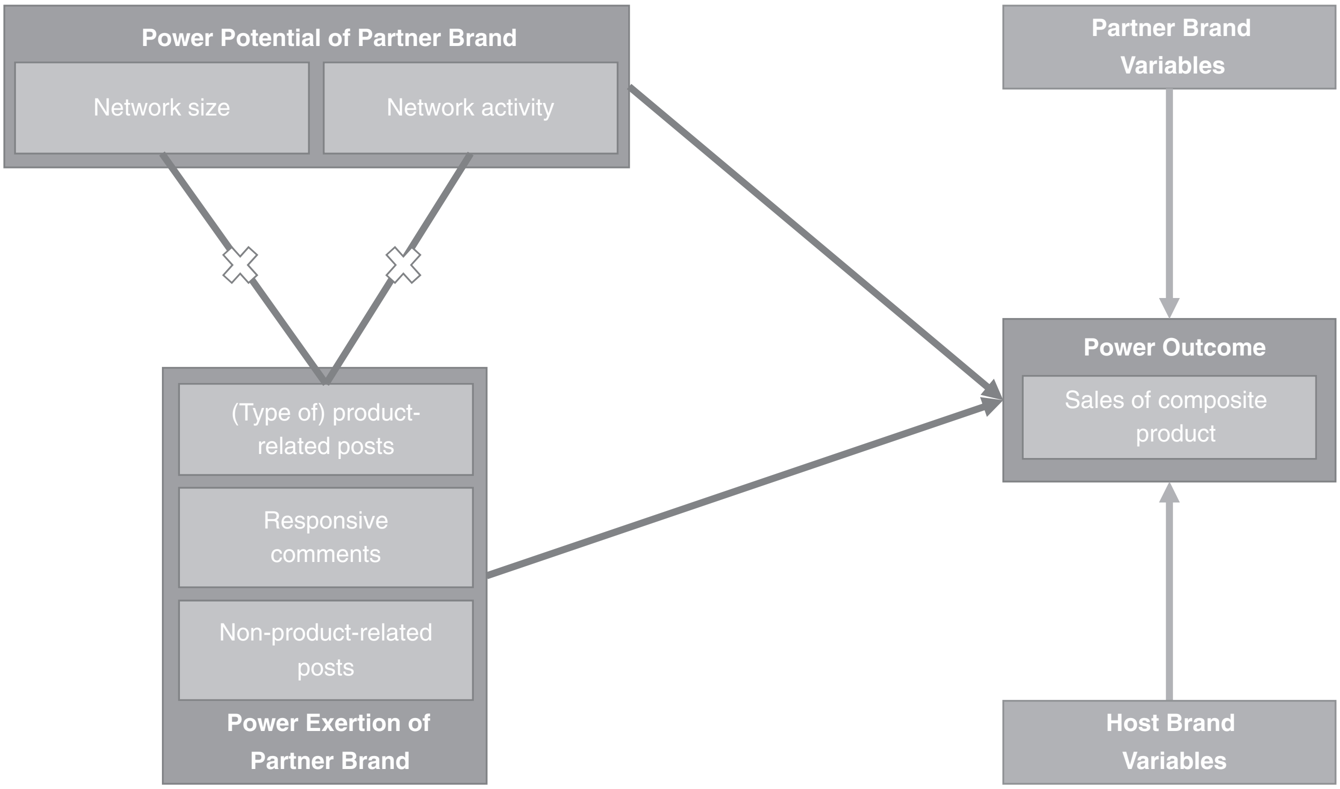
Marketing scholars have noted the general desire of consumers for identification and closeness with brands (for human brands, see Thomson 2006; for general concept of "consumer–brand relationship quality," see Fournier 1998). In the predigital era, consumer–brand relationships were one-sided or "parasocial" interactions that prohibited mutual exchange (Horton and Wohl 1956). Yet social media reduces the perceived distance between brands and consumers, such that relationships are (or appear to be) two-sided, intimate, and close (Labrecque 2014). This increased identification through social media strengthens a brand's referent power base, which should result in an influence over fans' consumption behavior, making it a relevant resource for marketers.

French and Raven (1959) stress that power is rarely limited to one source, and we assume that expert and referent power bases coexist in brand alliances. Partner brands can be recognized for their skills and talent (expert power base) but also for their social closeness, established through social media relationships (referent power base). Such social media power can thus act as a unique brand resource that partner brands might strategically leverage beyond their expert power, to the advantage of their (co)branded products.

Conceptual Model

Our conceptual model builds on power theory's three key concepts: (1) power potential and (2) power exertion, which then determine the (3) power outcome (Bacharach and Lawler 1980; Frazier 1983). Power potential reflects a structural position (Wrong 1968). For example, a central position in a network represents a power potential because it grants access

FIGURE 1
Conceptual Model



to and potential control over valuable resources (Brass and Burkhardt 1993). We apply the power potential concept to the context of social media, defining the social media power potential of a brand as the position that an entity (here, the partner brand) has achieved within a social media network. In turn, we distinguish two forms of social media power potential: the size and the activity level of the social media network of the partner brand. In our study context, having built a *large* social media network grants a partner brand access to a sizable pool of potential customers, and an *active* social media network grants the partner brand access to engaged promoters. For example, Vin Diesel has managed to accumulate more than 100 million prospective moviegoers who follow him on Facebook. His fan base is also highly active; his followers act as recommenders by sharing his posts, beyond his own network.

Power exertion generally refers to the actual use of power, which requires some expenditure of energy by the powerful person (Mintzberg 1983); for example, by requesting specific actions by subordinates (Brass and Burkhardt 1993). We define social media power exertion as the actual behavior by an entity (partner brand) of addressing its social media network. Forms of social media power exertion include posts on a social media wall or responsive comments to members of a social media network. In our study context, a partner brand might exert its social media power by informing the network about a new product or asking them to buy it, such as when Vin Diesel posted photos from the set of the *XXX* movie on his Facebook page, thereby actively sending product-related information to his social media followers.

In our conceptual brand alliance model in Figure 1, we link a partner brand's social media power (potential and exertion) with the success of a new composite product that features both host and partner brands. The partner brand's social media power potential and power exertion should generate power outcomes, manifested as the increased success of the brand alliance (i.e., additional sales of the composite product). Furthermore, we stress the relevance of their interaction, such that social media power potential and power exertion should amplify each other. To extend this general social media power model, we distinguish types of social media power potential and exertion. To specify the incremental impact of the partner brand's social media power, we also consider a set of brand alliance factors, encompassing host brand factors (e.g., host brand type, its social media network size) and partner brand factors (e.g., traditional partner brand strength, traditional partner brand promotions).

Impact of Social Media Power Potential and Exertion on Power Outcomes

Social media power potential. Greater social media power potential should be positively associated with power outcomes. Power can have an effect, even without being explicitly used (Wrong 1968). The presence of a professor, even if (s)he takes no specific action, can quiet a room of students. Students may sit down, which they anticipate will please the powerful professor, without requiring a direct request (e.g., Brass and Burkhardt 1993). This effect is well established for formal positions of power, but less certain for informal power (Mintzberg 1983).

In the context of social media, a bigger network of fans and followers enhances the focal brand's sales (Srinivasan, Rutz, and Pauwels 2016). Furthermore, more active consumers ("posters") within a social brand community particularly contribute to increasing the focal brand's sales (Manchanda, Packard, and Pattabhiramaiah 2015). We investigate whether this positive effect of social media power potential, derived from the referent power base, can be harnessed by another (host) brand that offers a composite product together with the powerful partner brand. The effect might stem from two key facets of social media power potential: the size of the social media network of the partner brand (i.e., number of fans) and the activity level of the social media network of the partner brand (i.e., fans' sharing activity). Consuming a new product (e.g., movie) that features the partner brand (e.g., star) can appease longing for the partner brand and comply with consumers' wish to "please" this partner brand. This effect should hold, to some extent, even if the partner brand does not explicitly refer to the product on social media. We thus offer hypotheses for both facets of social media power potential:

> H_1: The (a) size and (b) activity levels of the social media network of the partner brand relate positively to the sales of the composite product.

Social media power exertion. Power researchers emphasize the relevance of power exertion (Mintzberg 1983), in that certain behaviors, such as assertive communication, create perceptions of power (Brass and Burkhardt 1993). In a social media context, Kumar et al. (2016) uncover a significant link between the amount of firm-generated social media communication on a brand's official pages and the brand's sales.

We transfer this link to brand alliances, proposing that it holds for constellations of a partner brand's social media activities and a host brand's financial performance, even though such an effect would require substantial spillover from the partner brand to the composite product, which must exert an influence in addition to many other factors in a brand alliance. Based on our theoretical power model, we argue that every post shared by the partner brand should strengthen its referent power, by making fans feel closer and more intimately connected to it.

Direct communications with consumers and posting regular updates, such as pictures and general news about the partner brand, can all enhance intimate perceptions of closeness with the brand, which is positively associated with consumers' evaluations of connected products (Gong and Li 2017; Hung, Chan, and Tse 2011). When Vin Diesel posts behind-the-scenes footage from a film, replies to fans, or shares intimate photos of him with his daughter, it all likely fosters his identification potential for fans, increasing their desire for him and for products connected with him. This strengthening of his referent power base through posts that involve the partner brand should consequently encourage fans to buy composite products featuring the partner brand.

We expect this effect to result from various kinds of social media power exertion—namely, postings about the brand alliance (product-related posts), replies to fans' comments (responsive comments), and general postings about/by the partner brand that do not pertain to the composite product (non-product-related posts). Even if a partner brand's post is not linked to the composite product, it should positively affect the latter's success by strengthening consumers' perceptions of intimacy and connectedness with the partner brand that is part of the composite, but we concede that the effect might be weaker in this case. We thus predict that they are positively associated with brand alliance success as the ultimate power outcome:

> H_2: The number of (a) product-related posts, (b) responsive comments, and (c) non-product-related posts of the partner brand relate positively to the sales of the composite product.

Interaction effects. Power literature has suggested that the interplay of power potential and power exertion produces the strongest power outcomes (Mintzberg 1983). Consistent with this logic, Mochon et al. (2017) show that Facebook likes are most effective when addressed by firm-initiated promotional communication. Social media power potential and exertion thus may have an interaction effect on power outcomes, beyond their isolated effects, such that combinations of high values of both variables contribute to greater success. The effectiveness of social media power exertion efforts should be systematically higher if the social media power potential is also high, in terms of both network size and activity level. Accordingly, we offer a third hypothesis, which we limit for parsimony to product-related posts:

> H_3: (a) The larger the size of the social media network of the partner brand and (b) the higher the activity level of the social media network of the partner brand, the stronger the positive association of product-related posts with composite product sales.

Different Types of Product-Related Social Media Power Exertion

Findings by power scholars have suggested that power outcomes vary with the "skillfulness" of power exertion (Mintzberg 1983). Transferring this into the context of partner brands' social media power, we expect the respective effect sizes of different types of power exertion to differ. Consistent with this logic, social media research has found that different social media posting strategies result in varying levels of fan engagement (DeVries, Gensler, and Leeflang 2012; Lee, Hosanagar, and Nair 2017). Specifically, we investigate three types of a partner brand's social media power exertion: authentic, exclusive, and persuasive product-related posts.

Authentic social media power exertion. A brand is considered authentic if consumers perceive it to be faithful to itself and true to its fans (Morhart et al. 2015). This perception can be conveyed through a brand's communication style, by cues that express the brand's sincere motivation and care for consumers (Morhart et al. 2015). Authentic communication enhances relationships between human brands and consumers, increasing emotional brand attachment and brand choice likelihood (Morhart et al. 2015; Thomson 2006). We are not aware of any empirical research into the value of authentic social media communication, but several scholars have claimed that authenticity is a positive characteristic of social media exchanges (e.g., Hennig-Thurau, Hofacker, and Bloching 2013) and call for research on this topic (Morhart et al. 2015). Practitioners similarly stress the concept's importance, such as when the chief marketing officer of Paramount Pictures praised Emma Watson for her communication style: "When she speaks to her fans, it's authentic. She is incredibly tuned in to them with honest dialogue and conversation" (Busch 2014). Such authentic communication should enable consumers to infer that the brand, as a relational partner, is sincere and real (Giles 2002), offering increased identification potential. The referent power base thus might be exercised more effectively than is the case with other product-related posts.

H_4: The number of the partner brand's authentic product-related posts has a higher positive association with sales of the composite product than the number of other product-related posts.

Exclusive social media power exertion. A resource is exclusive if it is available only to a limited audience (Barone and Roy 2010); exclusiveness is an attribute that consumers generally value (Balachander and Stock 2009). Sharing information that is unknown to others can enhance relationships, particularly if the recipient attributes the disclosure of this exclusive information to the notion that (s)he is special (e.g., especially trustworthy; Collins and Miller 1994). Such exclusiveness should influence the effectiveness of social media posts; an example is when Vin Diesel released a *Fast Five* trailer exclusively to his social media followers ("before everyone else gets it") and cited this exclusiveness as evidence of "respecting the true fans." Being among a chosen group of people who see content "first" should create a feeling of being special and appreciated by the partner brand. In turn, the social relationship with the partner brand, and thus the influence drawn from its referent power base, should be stronger than it would be for other product-related social media posts.

H_5: The number of the partner brand's exclusive product-related posts has a higher positive association with sales of the composite product than the number of other product-related posts.

Persuasive social media power exertion. Direct requests and other types of assertive behavior are influential ways to exert power (Kipnis, Schmidt, and Wilkinson 1980). In a goal-directed form of power exertion, a partner brand can explicitly ask or persuade followers to act on its wishes. Some of these strategic appeals can be disillusioning for fans (Alperstein 1991), leading to negative forms of reaction such as reactance. However, they can also be activating and result in stronger mobilization of the social media network, evoking positive outcomes. Persuasive communication is also practiced by partner brands for brand alliances on social media, generally including explicit appeals to buy the composite product. For example, movie star Channing Tatum commanded his network to watch his movie, announcing, "There's a #MagicMikeXXL ticket with your name on it. Grab yours ... NOW!" We regard such persuasive product-related posts as the most goal-directed type of the partner's social media power exertion, directly aimed at influencing the network's behavior toward the composite product. Therefore, we expect such posts to result in above-average goal-directed activation of the brand's social media power potential, outweighing possible consumer reactance in terms of immediate performance outcome. Overall, we predict persuasiveness to increase the value of social media power for the financial performance of the composite product, more so than other product-related social media posts.

H_6: The number of the partner brand's persuasive product-related posts has a higher positive association with sales of the composite product than the number of other product-related posts.

Data and Measures

Industry Setting and Data Set

We test our hypotheses in the motion picture industry, in which each new movie constitutes a brand alliance (Luo et al. 2010). A movie is a composite product that combines the movie brand (host brand) and the actors as branded human ingredients (partner brands). Actors accumulate many fans; experts recommend them as role models for other brands for social media marketing (Seetharaman 2015).

Our data set covers all movies released in North American theaters between 2012 and 2014, with pre- and postrelease observations spanning from September 2011 to June 2015. After excluding specialty releases, productions from non-English-speaking countries, animated movies, and documentaries,[2] we use 442 movies in our analyses, combined with the actors credited first, second, and third on Box Office Mojo as partner brands, resulting in a total of 1,318 actor–movie combinations.[3]

For each of those actors in our data set who had a Facebook brand page or profile during (parts of) September 2011–June 2015, we collected extensive social media data about the number and content of posts, actor comments, and fan shares, using Facebook's official application programming interface. Facebook, as the largest social network with approximately 1.28 billion active daily users (Facebook 2017), supports open access historic data collection, which guarantees the completeness of our data set and rules out omitted variable bias due to unobserved social media behavior (Ruths and Pfeffer 2014). We aggregated the partner brand's social media power exertion to the weekly level to match movie-related variables, such as advertising spending and distribution intensity.

[2]We exclude specialty releases (with less than US$1 million domestic box office) because they follow a different business strategy. Excluding movies from non-English-speaking countries ensures a match between the language spoken by an actor and North American moviegoers. We exclude animated movies and documentaries because the role of actors in these genres differs from that of live-action scripted movies. We excluded 29 films because of missing data (i.e., number of Facebook followers and posts for the first three credited actors). The remaining 442 movies cover more than 75% of the revenues yielded in North American theaters by movies with at least US$1 million in domestic box office revenues.

[3]In some very rare cases, not all three actor ranks are taken.

TABLE 1
Variable Operationalizations

Variable	Description	Source
Social Media Power Potential Variables		
Network size	Number of Facebook followers of the actor (U.S. only, three months before product release)	Page Data, Facebook
Network activity	Number of Facebook shares by the partner brand's followers (U.S. only, in the fourth month before product release), residual after controlling for network size	Facebook
Social Media Power Exertion Variables		
Product-related posts	Weekly number of partner brand posts mentioning the focal composite product, detected using movie-specific dictionaries, stock variable (only Model A)	Facebook
Acknowledging responsive comments	Weekly number of partner brand comments that acknowledge the support of fans, detected using category-specific dictionaries, stock variable	Facebook
Promotional responsive comments	Weekly number of partner brand comments that promote composite products, detected using category-specific dictionaries, stock variable	Facebook
Non-product-related posts	Weekly number of partner brand posts not mentioning the focal composite product, detected using movie-specific dictionaries, stock variable	Facebook
Authentic product-related posts	Weekly number of authentic partner brand posts mentioning the focal composite product, detected using LIWC, stock variable, residual corrected for the occurrence of exclusive and persuasive posts (only Model B)	Facebook
Exclusive product-related posts	Weekly number of exclusive partner brand posts mentioning the focal composite product, detected using two human coders, stock variable, residual corrected for the occurrence of authentic and persuasive posts (only Model B)	Facebook
Persuasive product-related posts	Weekly number of persuasive partner brand posts mentioning the focal composite product, detected using two human coders, stock variable, residual corrected for the occurrence of authentic and exclusive posts (only Model B)	Facebook
Other product-related posts	Weekly number of partner brand posts mentioning the focal composite product, detected using movie-specific dictionaries, stock variable, residual corrected for the occurrence of authentic, exclusive, and persuasive posts (only Model B)	Facebook
Partner Brand Variables		
Traditional partner brand strength	Aggregation of (1) the combined revenues of the partner brand's previous three movies in which (s)he was listed among the first four actors, with a discount of 10% for each year, and (2) a ratio of the number of inclusions in Quigley's "Top 10 Money Making Stars" list, as polled by North American theater owners, over three years before movie release	Box Office Mojo, Quigley
Traditional partner brand promotions	Aggregation of (1) weekly appearances in TV shows (daytime and late night) and (2) weekly mentions in news outlets (magazines and newspapers), residual corrected for selection criteria of the media	IMDb
Host Brand Variables		
Host brand type	Binary variable equal to 1 if a previous host brand is extended, such as in the case of a sequel, remake, or bestseller adaptation	IMDb
Network size host	Number of Facebook followers of the host (U.S. only, three months before product release)	Page Data, Box Office
Fit	Binary variable equal to 1 if the partner brand is known for the product type that the composite product represents, measured as a match of the focal movie's genre with the genre of the actor's "most known for" movie	IMDb, Box Office Mojo

TABLE 1
Continued

Variable	Description	Source
Product type (drama, comedy, action, horror, thriller)	Binary variable equal to 1 if the composite product belongs to the respective movie genre; one movie can belong to multiple genres (drama, comedy, action, horror, thriller)	IMDb
Advertising	Weekly advertising spending for the product, stock variable, predicted values after performing the first-stage regression	Kantar Media
Distribution	Weekly number of theaters in North America offering the product, predicted values after performing the first-stage regression	Box Office Mojo
Social media handles	Weekly number of posts mentioning the product by the Facebook pages of IMDb, Box Office Mojo, Yahoo Movies, Entertainment on Facebook, and Movie Pilot, stock variable	Facebook
Reviewer judgment	Average rating of the movie by professional movie critics	Metacritic
Reviewer dissent	Concentration of positive, mixed, and negative critical reviews, measured with Herfindahl index	Metacritic
Consumer evaluation	Average rating of the movie by consumers registered on IMDb	IMDb
Season	Binary variables indicating four seasons (January–March, April–June, July–September, October–December)	Box Office Mojo
Dependent Variable		
Sales	Weekly box office revenues of the composite product in North American theaters	Box Office Mojo

Notes: Social media power potential and exertion as well as partner brand strength and promotional activities are also measured for actors listed second and third in a movie. The sums across each of these variables form the variables for the supporting cast.

Measures

In Table 1, we detail the operationalization of the dependent and independent variables as well as their data sources. We report descriptive statistics of our metric variables in Table 2. The dependent variable captures the success of the new composite product (i.e., movie) as the power outcome. Specifically, we employ the weekly box office revenues (US$) generated by a movie over its lifetime in North American theaters. The independent variables correspond with our conceptual model; we include extensive industry controls to avoid an omitted variable bias.

Measuring social media power potential. The stars' number of Facebook followers and Facebook activity level provide our measures of the partner brands' social media power potential. Because the power potential concept describes an initial position, we use the pertinent values three months before a focal movie's release. Studios usually start their advertising campaigns at this point, so deliberately excluding these three months from both size and activity measures limits the potential for reverse causality (see Knapp, Hennig-Thurau, and Mathys 2014). Our measure of the partner brand's network size is the lead actor's number of Facebook fans (corrected by the U.S. percentage of fans) three months before movie release. We use the same approach for the supporting actors (credited second or third), then sum the values for model parsimony.

For the partners' network activity level, we use the cumulative number of shares of an actor's posts throughout the fourth month before the release. Shares signal a high level of engagement; by sharing, consumers recommend the content to their own Facebook friends. Because the number of shares also depends on the number of followers, we follow Chatterjee and Price (1977) and use the residuals of an auxiliary regression, in which the number of shares is the dependent variable and the number of fans is the independent variable.[4]

Measuring social media power exertion. We measure a partner brand's social media power exertion by the numbers of posts and responsive comments. Power exertion is a dynamic concept, spanning the weeks leading to the release of the composite product and the weeks that follow. We use weekly measures for these variables, starting 13 weeks before the release and ending when the film is no longer being shown in North American theaters (maximum weeks in theaters is 26).

In total, we collected 41,547 posts from actors. To separate product-related from non-product-related posts, we applied an automated text analysis. For each movie, we developed individual dictionaries that included the movie title (with abbreviations if necessary) and movie-related hashtags, identified by human coders from the movie's or starring actors' Facebook pages.[5] We applied these dictionaries to categorize each of the 41,547 actor posts as product related or not. Human coders

[4]We thus capture deviations from the mean activity level predicted by the network size, with positive (negative) values indicating greater than (less than) expected network activity (lnNetworkActivity = –.104 + .472 × lnNetworkSize; adj. R^2 = .713; p < .01 for all coefficients). We use the same approach for the supporting cast.

[5]For example, for the movie *X-Men: Days of Future Past*, posts were screened for the words "XMen," "X-Men," "X Men," "XMen: DOFP," "X2," "Days of Future Past," "DaysOfFuturePast," "MutantTruth," "Wolverine," "Professor Logan," "Quicksilver," "Mystique," "Professor Xavier," "ProfessorX," and "Iceman."

TABLE 2
Descriptive Statistics

	Min	Max	M	SD
Social Media Power Potential Variables of Partner Brand				
Network size	0	17,399,529	474,699	1,772,777
Network activity	0	535,026.830	4,765.133	31,736.891
Social Media Power Exertion Variables of Partner Brand				
Product-related posts	0	34.677	.370	1.638
Acknowledging responsive comments	0	18.099	.048	.573
Promotional responsive comments	0	4.126	.012	.131
Non-product-related posts	0	624.884	2.756	17.673
Product-related authentic posts	0	13.233	.154	.695
Product-related exclusive posts	0	3.004	.016	.117
Product-related persuasive posts	0	7.344	.053	.315
Social Media Power Variables of Supporting Cast				
Network size of supporting cast	0	10,459,089	325,261	1,151,602
Network activity of supporting cast	0	169,210.858	1,357.113	7,988.252
Product-related posts of supporting cast	0	421.322	.437	6.954
Acknowledging responsive comments of supporting cast	0	88.011	.172	2.152
Promotional responsive comments of supporting cast	0	11.577	.033	.321
Non-product-related posts of supporting cast	0	370.241	3.990	15.812
Partner Brand Variables				
Traditional partner brand strength	0	7.618	.609	.886
Traditional partner brand promotions	0	12.096	1.190	1.343
Traditional partner brand strength of supporting cast	0	6.708	.943	1.298
Traditional partner brand promotions of supporting cast	0	14.275	1.149	1.339
Host Brand Variables				
Network size of host brand	0	15,211,879	306,452	1,252,962
Advertising	0	17,572,343	1,099,345	2,151,441
Distribution	0	4,404	812	1,100
Social media handles	0	12.627	.213	.636
Reviewer judgment	0	10	5.7	1.8
Reviewer dissent	.337	1	.562	.169
Consumer evaluation	1.6	8.7	6.7	.9
Dependent Variable				
Sales	0	270,019,373	4,203,385	13,168,110

Notes: To avoid taking the logarithm of ≤0, we added a respective constant to each variable. Stock values are provided for the communication-related variables. Non-instrumented and non-residual-corrected values are provided. For time-varying variables, weekly values are provided.

ensured the reliability of this approach by manually checking for any erroneously coded product-related posts and removing them as needed. Overall, 4,857 posts were identified as product-related, and the remaining 36,690 were classified as non-product-related posts.

Our measure of responsive comments is the number of comments an actor made in reply to a prior fan comment on his or her own Facebook page. We identified 7,499 actor comments during the respective time frame. To address heterogeneity in the responsive comments variable, we coded these comments automatically into two major categories of replies: "Acknowledging partner brand comments" covers replies in reaction to fan engagement, thanking them for their support with words like "thank" and "appreciate." The "promotional partner brand comments" category includes responses that draw followers' attention to composite products, using words such as "check out" and "release." As for all social media power exertion measures, we aggregated the comments on a weekly basis and used the same approach for the supporting cast.

Measuring different types of product-related posts. We further classified each of the 4,857 product-related posts as authentic/not authentic, exclusive/not exclusive, and persuasive/not persuasive; these categories were not mutually exclusive. To code authenticity, we followed Humphreys and Wang (2017) by employing the computerized text analysis software Linguistic Inquiry and Word Count (LIWC). We used their well-established dictionary from linguistic research to rate authenticity, by identifying texts that are "honest, personal, and disclosing" (Pennebaker et al. 2015, p. 22), which corresponds to the conceptualization of perceived brand authenticity (Morhart et al. 2015). As a validation measure, two trained independent human coders rated each actor's overall communication style as authentic/not authentic on the basis of guidelines such as disclosures of personal information or the presence of the actor's "own" words. If both coders considered an actor's communication as authentic, the variable took a value of 1, and 0 otherwise. A correlation of .72 ($p < .01$) between these actor-movie-level assessments and the number of authentic posts identified by the LIWC software affirms the successful coding of authenticity at the post level.

Because LIWC does not provide established dictionaries for exclusiveness and persuasiveness, we trained two independent human coders to code these types of product-related posts. Neither was involved in the project, and they rated each of the 4,857 product-related posts using objective guidelines. For exclusiveness, the guidelines relied on keywords such as "my fans get to see first," "never-before-seen," and "for your eyes only." For persuasiveness, the guidelines required the use of imperatives (e.g., "go see the movie," "watch me in my new movie") or implicit activation callings (e.g., "there is a seat waiting for you," "who is going to see my new movie?"). The intercoder reliability was very high (99% agreement for both variables), providing confidence in these classifications. In both cases, the variable took a value of 1 only if both coders agreed a post was exclusive or persuasive, and 0 in all other cases.

Again, we aggregated each type of product-related post on a weekly basis and applied the same approach to the supporting cast. Post types are not mutually exclusive (e.g., they can be authentic and exclusive at the same time), so we residual corrected each of them for the existence of the other two types to remove overlap, then used only the respective residuals in the analyses. The specific auxiliary regressions necessary for this correction can be found in Web Appendix A. In Web Appendix B, next to the variable descriptions in Table 1, we detail our operationalization of partner brand and host brand variables that we include as controls.

Modeling Approach

Modeling Challenges

To rigorously test our hypotheses, we need to address four main methodological challenges: (1) carryover effects, (2) endogeneity of social media activities, (3) endogeneity of advertising and screens, and (4) the nested data structure. These four challenges guide our data preparation and model selection, which leads us to a two-stage model approach with stock variables, in which we account for endogeneity using a probit estimation to create inverse Mills ratios and instrumental variables. Then we include these variables into a hierarchically structured linear mixed-effects model that accounts for the nested structure of our data.

Carryover effects. Posts, comments, advertising spending, and promotional activities in the prerelease phase likely have lagged effects on future sales. To account for such anticipation-based forms of communication prior to product launch, we use a stock specification for weekly measures of social media power exertion, host brand variables involving any mentions of a film by social media handles and advertising, and the partner brand variable of an actor's traditional promotional activities (see Burmester et al. 2016). To build the stocks for each lagged variable, we use the Koyck (1954) model, with the respective stock variables determined as follows:

$$\text{Stock}_{it} = \lambda \text{Stock}_{it-1} + X_{it}, \tag{1}$$

where X denotes a particular variable (product-related posts, responsive comments, non-product-related posts, authentic product-related posts, exclusive product-related posts, persuasive product-related posts, promotional activities, mentions by social media handles, or advertising) for movie i in week t, for all i (= 1, ..., I) and t (= –13, ..., T). We set the carryover coefficient λ to .5, in line with meta-analytical findings for mass media advertising (Köhler et al. 2017). When we reestimate our model with a λ value of .25, the results remain robust; however, higher Bayesian and Akaike information criteria (BIC and AIC) values confirm the eligibility of $\lambda = .5$.

Endogeneity of social media activities. We further account for the endogeneity of whether an actor engages in activities on social media or not, as such decisions are likely correlated with unobservables. Systematic differences might exist between actors who decide to engage in such activities and those who do not. Failure to account for such differences can bias parameter estimates. For example, if studio executives take an actor's proclivity to post into consideration when casting a role, an actor's social media activity may be related to unobservables (also considered by a studio executive) that affect movie sales. To control for this proclivity to post online, we build on the procedure proposed by Heckman (1979) and extensions (Wooldridge 2010). We estimate a probit model, which predicts the probability that an actor engages in social media power exertion, to calculate the inverse Mills ratios needed to implement a control function approach. These inverse Mills ratios control for unobservables in the movie performance equation that may be related to actors' proclivity to post on social media. Including them in the main model accounts for the endogenous nature of partner brands' social media activities.

For this first-stage probit model, we classify actors as those who are more or less likely to post. The resulting binary dependent variable separates a group with high social media activities (second/third terciles) in the fourth month before release from a control group with no or limited social media activities (no activities/first tercile). We leverage the dichotomous nature of this variable to generate more efficient estimates by modeling it as a probit and obtaining relevant inverse Mills ratios. Because this potentially endogenous variable is highly correlated with several measures of the actor's social media activity that are included in the main model, the constructed inverse Mills ratios enable us to control for any average bias that might affect the coefficients of these more detailed social media activity measures over the run of the movie. As independent variables, we exclusively include variables in our probit model that have strong impacts on the decision to engage in social media activities, but little or no impact on movie revenues. This step minimizes concerns about the collinearity of the Heckman correction factor with other variables in the equation of interest (Wooldridge 2010). Three pertinent variables appear likely to fulfill this requirement:

- Age of the partner brand: Unlike older actors, younger actors have grown up with social media. Consistent with survey data (Pew Research Center 2018), we expect them to be more prone to post on Facebook. Yet it is unlikely that consumers base their movie decision on unobservables related to actor age that are not captured by the movie-specific observables we control for in the main equation (e.g., fit).
- Gender of the partner brand: Survey data suggest that women tend to post more content on social media than men (Pew Research Center 2018). Specifically, women overtook men in terms of social media activities by the end of 2008. Although we therefore expect female actors to be more likely to engage in social media activities, we do not expect consumers to decide in favor of or against a movie on the basis of unobservables related to the actor's gender that are not captured by the movie-specific observables in the main equation.
- Social media account age: Actors who have been active on social media for longer (measured as days since account creation) have gained more familiarity with the platform and are thus expected to be less inhibited about posting content. At the same time, consumers are unlikely to make ticket purchases dependent on this information (or even be aware of it).

Following Wooldridge (2010), we use these three variables, along with all other independent variables from our main model, to estimate the probability that a partner brand engages in social media activities or not using a probit model:

$$\text{SocialMediaEngagement}_{ij} = \Phi\left(\beta_0 + \beta_1 \text{PBA}_{ij} + \beta_2 \text{PBG}_j + \beta_3 \text{SMA}_{ij} + \sum_k \beta_k \text{IV}_k\right), \tag{2}$$

where Social Media Engagement is a binary variable indicating whether the lead actor j belonged to a group with medium/high (taking the value of 1) or no/limited social media activities (taking the value of 0) in the fourth month before the release of movie i. PBA (partner brand age), PBG (partner brand gender), and SMA (social media account age) denote the three exclusion restriction variables, pertaining to lead actor j before the release of movie i.[6] Finally, $\sum_k \beta_k \text{IV}_k$ depicts the k independent variables from the final second-stage model that explain composite product success.

To derive the correction terms for our final composite product success model, we subsequently determine two inverse Mills ratios (Wooldridge 2010) for actor j being active on social media before the release of movie i or not. We first determine the inverse Mills ratio for an actor's decision to be active by $\text{IMR}^{ij}_{\text{Active in}} = [\phi(z)]/[\Phi(z)]$ and $\text{IMR}^{ij}_{\text{Active out}} = 0$. Here, z represents the z-score associated with the predicted probability of being active on social media, $\phi(z)$ is the standard normal propensity distribution function (evaluated at z), and $\Phi(z)$ is the standard normal cumulative distribution function (also evaluated at z). Similarly, we determine the inverse Mills ratio for actor j not being active on social media before the release of movie i by $\text{IMR}^{ij}_{\text{Active in}} = 0$ and $\text{IMR}^{ij}_{\text{Active out}} = [\phi(z)]/[\Phi(z) - 1]$. Both inverse Mills ratios enter the main model that explains composite product success (see Equations 3 and 4 in the model specification section).[7]

Endogeneity of advertising and screens. Previous movie research has suggested that the allocation of weekly screens and advertising can be endogenous with movies' revenues (e.g., Elberse and Eliashberg 2003; Gopinath, Chintagunta, and Venkataraman 2013). To control for this effect, we apply an instrumental variable approach. We model the endogenous variables, advertising and screens, as functions of the exogenous variables and three instrumental variables, which we select on the basis of their strong associations with decisions by theater owners and studios to be relevant and lack of association with the unobserved heterogeneity component of consumers' demand for the movie to be exogenous (Luan and Sudhir 2010). The combined budget of competing movies per week provides our first instrument (Karniouchina 2011). It likely encourages managers to assign fewer scarce resources to the focal movie (due to the strong alternatives), independent of the unobserved heterogeneity component pertaining to the focal movie. Our second and third instruments leverage the patterns of theater owners' repeated decisions to allocate screens to movie categories. Specifically, we form movie categories according to the movies' production budget and to their genre and age restriction affiliations. We then construct typical screen allocation patterns for the resulting movie categories over time (Lee 2013; Papies and Van Heerde 2017). These instruments can capture patterns in allocation decisions, but, by construction, are unrelated to the movie's unobserved characteristics (Lee 2013). We rely on these three instrumental variables when applying our two-stage least squares approach to account for the endogeneity of advertising and screens. We explain the endogenous variables with the instruments and all other time-variant variables from our main model in a first-stage regression, then use the resulting predicted values in our second-stage model of composite product sales. We report a more detailed description of the instruments used, the model specifications, and the results of the first-stage regressions in Web Appendix C.

To test the instruments, we mimic a linear mixed-effects model in two-stage least squares as closely as possible (see Papies and Van Heerde 2017). The multivariate Sanderson–Windmeijer F-test confirms the sufficient strength of our instruments ($\text{F-value}_{\text{advertising}} = 969.91$, d.f. = 3, $p < .01$; $\text{F-value}_{\text{screens}} = 1{,}183.01$, d.f. = 3, $p < .01$). A nonsignificant Sargan test confirms that the exclusion restriction is satisfied

[6]Research has shown that actor age and gender have no meaningful effect on movie performance (Hennig-Thurau et al. 2013). In addition, we estimated the probit model without those two variables and found results to be robust.

[7]In addition to implementing inverse Mills ratios, we conduct additional checks for endogeneity concerns that result from actors' posting behavior. A fixed-effects model with actor-specific fixed-effects and all the time-varying variables yields robust results. Regressions using success expectations and abnormal returns to explain the amount of product-related posts indicate insignificant results. Theoretically, this can be explained by the fact that actors are aware that their value depends on the performance of each of their movies (Luo et al. 2010). With only one or two movies to promote each year, actors sense great pressure for each of them to perform well. Thus, active posters on Facebook likely support each movie, independent of success expectations or the movie's current popularity.

($\chi^2 = .138$; d.f. = 1, $p = .21$). The Hausman–Wu test also shows systematic differences between the models with and without endogeneity controls ($\chi^2 = 53.91$, d.f. = 2, $p < .01$).

Data structure. A final modeling challenge arises from the different nature and nested structure of our data. Actors as partner brands appear in specific movies as composite products. In this setting, several actor-specific variables, such as their social media power potential and most of the brand alliance variables (e.g., movie genre) do not vary over the time that the particular movie is shown. However, variables such as social media power exertion and marketing efforts vary for each movie over time. Furthermore, our conceptual model requires interactions across both sorts of variables. Such nested structures with interactions across time-varying and non-time-varying variables are common in management and marketing practice (see, e.g., Hofmann 1997 or Allenby and Rossi 1998). To account for the nested structure of our data, we follow previous work in the field (e.g., Allenby and Rossi 1998) and apply a linear mixed-effects model (often also referred to as a hierarchical linear model). It allows us to model effects on different levels and apply cross-level interactions. Interaction effects in linear mixed-effects models require centered variables (Kreft, De Leeuw, and Aiken 1995); we use a residual centering approach, which also addresses potential multicollinearity concerns (Lance 1988).

Model Specifications

Consistent with previous movie and social media research, we adopt a log-log formulation. This formulation not only accounts for nonlinear effects but also generates elasticities (e.g., Burmester et al. 2016). We add constants where necessary to avoid taking a log of 0. We adopt Pauwels, Erguncu, and Yildirim's (2013) notation for a two-level linear mixed-effects model, with time-invariant observations on level 1 and time-varying observations in week t, captured throughout the theatrical run of movie i, on level 2. To facilitate readability, we formulate our model in general terms, with the random component at the movie level i (see also Pauwels, Erguncu, and Yildirim 2013):

$$(3)\qquad \begin{aligned} \text{Sales}_{it} = {} & \alpha + \beta_1 \text{PE}^{(2)}_{ijt} + \beta_2 \text{PE}^{(2)}_{ist} + \beta_3 \text{PPOT}^{(1)}_{ij} \\ & + \beta_4 \text{PPOT}^{(1)}_{is} + \beta_5 \text{PE}^{(2)}_{ijt} \times \text{PPOT}^{(1)}_{ij} \\ & + \beta_6 \text{PE}^{(2)}_{jt} + \beta_7 \text{PE}^{(2)}_{st} + \beta_8 \text{PBPROM}^{(2)}_{jt} \\ & + \beta_9 \text{PBPROM}^{(2)}_{st} + \beta_{10} \text{HBPROM}^{(2)}_{it} \\ & + \beta_{11} \text{PBST}^{(1)}_{ij} + \beta_{12} \text{PBST}^{(1)}_{is} \\ & + \beta_{13} \text{HBST}^{(1)}_{i} + \beta_{14} \text{IMR}^{(2)}_{ijt} + u_i + e_{it}, \end{aligned}$$

where Sales_{it} represents the logged sales of movie i in week t, and α is the main constant of the hierarchical model. The vector $\text{PE}^{(2)}_{ijt}$ represents the effects of social media power exertion from actor j for movie i in week t, which equal the logged number of product-related posts from actor j about movie i in week t. Similarly, $\text{PE}^{(2)}_{ist}$ depicts the logged number of product-related posts from supporting actors s related to movie i in week t. Vector $\text{PPOT}^{(1)}_{ij}$ incorporates all social media power potential variables of actor j, which reflect the logged size of j's network three months prior to the release of movie i and the residual-corrected logged average network activity of j in the fourth month before release. Similarly, $\text{PPOT}^{(1)}_{is}$ contains the logged network size and logged, residual-corrected network activity for the supporting actors s.

$\text{PE}^{(2)}_{ijt} \times \text{PPOT}^{(1)}_{ij}$ presents the cross-level interactions between actor j's social media power exertion for movie i and the two social media power potential variables of actor j before the release of movie i. Vector $\text{PE}^{(2)}_{jt}$ depicts general social media power exertion by actor j that is not specifically related to movie i, consisting of the logged number of non-product-related posts from actor j in week t, as well as the logged numbers of responsive comments sent by actor j in week t. $\text{PE}^{(2)}_{st}$ contains similar variables for the supporting actors.

Next, $\text{PBPROM}^{(2)}_{jt}$ and $\text{PBPROM}^{(2)}_{st}$ represent traditional promotional activities by actor j and supporting actors s in week t, operationalized as the stocked, residual-corrected, and logged number of media appearances in week t. Similarly, vector $\text{HBPROM}^{(2)}_{it}$ spans the promotion and distribution values for movie i in week t, containing the stocked and logged number of instrumented advertising, and the logged number of instrumented screens for movie i in week t, as well as the stocked and logged number of mentions of movie i by other social media handles in week t. With $\text{PBST}^{(1)}_{ij}$ and $\text{PBST}^{(1)}_{is}$, we represent the variables that measure the traditional brand strength of actor j and the supporting actors s in relation to movie i. Then $\text{HBST}^{(1)}_{i}$ accounts for traditional host brand–related values of movie i, including the logged number of social media fans of movie i three months before release; movie i's host brand type; a vector indicating the genre of movie i; a vector indicating the season in which movie i is released; the logged scores for reviewer judgment, reviewer dissent, and consumer evaluations for movie i; and a fit indicator for movie i. The vector $\text{IMR}^{(2)}_{ijt}$ contains the two inverse Mills ratios from the probit estimation, generated by Equation 2. Finally, u_i depicts the random intercept for each movie i, the beta values incorporate movie-specific slopes, and e_{it} accounts for the model's error term. We estimate the models with the LME4 package in R (Bates et al. 2015). The variance inflation factors stay below 3, indicating that multicollinearity is not an issue.

Equation 4 similarly offers the linear mixed-effects model that incorporates the different types of social media power exertion by the lead partner brand:

$$(4)\qquad \begin{aligned} \text{Sales}_{it} = {} & \alpha + \beta_1 \text{PET}^{(2)}_{ijt} + \beta_2 \text{PE}^{(2)}_{ist} + \beta_3 \text{PPOT}^{(1)}_{ij} \\ & + \beta_4 \text{PPOT}^{(1)}_{is} + \beta_5 \text{PE}^{(2)}_{jt} + \beta_6 \text{PE}^{(2)}_{st} \\ & + \beta_7 \text{PBPROM}^{(2)}_{jt} + \beta_8 \text{PBPROM}^{(2)}_{st} \\ & + \beta_9 \text{HBPROM}^{(2)}_{it} + \beta_{10} \text{PBST}^{(1)}_{ij} \\ & + \beta_{11} \text{PBST}^{(1)}_{is} + \beta_{12} \text{HBST}^{(1)}_{i} \\ & + \beta_{13} \text{IMR}^{(2)}_{ijt} + u_i + e_{it}. \end{aligned}$$

The main difference between Equations 3 and 4 is that $\text{PE}^{(2)}_{ijt}$, covering general product-related social media power exertion by the lead actor, is replaced by the vector $\text{PET}^{(2)}_{ijt}$, which spans the different types of product-related posts, as proposed in H_4–H_6. Specifically, $\text{PET}^{(2)}_{ijt}$ consists of the residual-corrected,

TABLE 3
Results from Linear Mixed-Effects Model of Social Media Power

	Model A			Model B		
	b	*p*-Value	VIF	b	*p*-Value	VIF
Intercept	9.117	.000		9.346	.000	
Social Media Power Potential Variables of Partner Brand						
Network size	.031	.003	1.849	.039	.000	1.885
Network activity	.049	.070	1.139	.056	.041	1.141
Social Media Power Exertion Variables of Partner Brand						
Product-related posts	.255	.000	1.826	—	—	—
Acknowledging responsive comments	–.041	.775	1.380	–.066	.650	1.378
Promotional responsive comments	–.140	.587	1.343	–.322	.234	1.469
Non-product-related posts	–.188	.000	2.130	–.169	.000	1.935
Interaction Effects Power Potential and Exertion						
Product-related posts × network size	.018	.089	1.144	—	—	—
Product-related posts × network activity	.032	.036	1.097	—	—	—
Types of Product-Related Posts by Partner Brand						
Authentic product-related posts	—	—	—	.601	.000	2.977
Exclusive product-related posts	—	—	—	.605	.021	1.602
Persuasive product-related posts	—	—	—	1.014	.000	2.541
Other product-related posts	—	—	—	.082	.444	1.096
Social Media Power Variables of Supporting Cast						
Network size of supporting cast	.006	.550	1.498	.005	.580	1.495
Network activity of supporting cast	.056	.040	1.138	.054	.050	1.137
Product-related posts of supporting cast	.016	.749	1.402	.023	.655	1.396
Acknowledging responsive comments of supporting cast	.094	.400	1.465	.115	.308	1.467
Promotional responsive comments of supporting cast	.186	.252	1.430	.188	.247	1.430
Non-product-related posts of supporting cast	.008	.810	1.512	.009	.787	1.507
Partner Brand Variables						
Traditional partner brand strength	.395	.003	1.318	.367	.006	1.317
Traditional partner brand promotions	.221	.000	2.048	.220	.000	2.054
Traditional partner brand strength of supporting cast	.492	.000	1.347	.483	.000	1.346
Traditional partner brand promotions of supporting cast	.067	.214	2.019	.067	.213	2.022
Host Brand Variables						
Host brand type	.310	.006	1.216	.304	.007	1.216
Network size of host brand	.047	.000	1.285	.047	.000	1.284
Fit	.287	.012	1.124	.299	.009	1.122
Action	.252	.052	1.523	.266	.041	1.522
Comedy	–.112	.354	1.598	–.117	.335	1.597
Horror	.547	.004	1.362	.555	.003	1.364
Drama	–.379	.002	1.758	–.389	.002	1.757
Thriller	.145	.263	1.381	.140	.281	1.379
Advertising	.536	.000	1.898	.519	.000	1.910
Distribution	.458	.000	1.952	.491	.000	1.970
Social media handles	.561	.000	1.555	.566	.000	1.557
Reviewer judgment	–.096	.706	2.869	–.081	.751	2.864
Reviewer dissent	–.259	.634	1.318	–.186	.733	1.319
Consumer evaluation	1.447	.005	2.614	1.348	.010	2.605
Season 1	.275	.040	1.571	.270	.045	1.572
Season 2	.116	.385	1.499	.115	.393	1.499
Season 4	.258	.048	1.577	.254	.053	1.578
Inverse Mills Ratios						
Inverse Mills ratio active in	–.243	.147	1.253	–.247	.146	1.238
Inverse Mills ratio active out	–.062	.661	1.216	–.031	.827	1.220

Notes: Dependent variable = weekly box office revenues. N = 5,722. VIF = variance inflation factor.

stocked, and logged numbers of authentic, exclusive, and persuasive product-related posts from actor j about movie i in week t. It also includes a measure of "other" product-related posts, which serves as the comparison standard for testing these hypotheses. It is operationalized with product-related posts that are classified as not authentic, exclusive, or persuasive (e.g., Channing Tatum's post, "Chan is at Comic-Con in San Diego promoting 'Haywire' today").[8] To avoid multicollinearity issues, this model does not incorporate additional cross-level interaction effects.

Results

Before reporting the results of our modeling efforts, we calculated bivariate correlations between our focal power concepts (i.e., the different kinds of social media power potential and exertion) with power outcome to provide some model-free evidence. We find significant positive associations between all social media variables and power outcome; correlations differ from greater than .20 (for product-related posts and power potential variables) to less than .10 (for responsive comments and non-product-related posts) (see Web Appendix D). Whereas these results provide some initial support for the proposed role of the partner brand's social media resources and activities, they do not address the several econometric challenges noted previously.

Probit Estimation

We first evaluate the probit estimation (Heckman 1979; Wooldridge 2010). Here, we test whether our proposed characteristics significantly explain the probability that partner brands engage in social media activities. The age of the lead actor relates significantly to the probability of engaging in social media activities (b = –.84, $p < .01$). Consistent with our prediction, younger actors post more than older actors. The gender of the lead actor is significantly linked to the probability of posting (b = .68, $p < .01$); as anticipated, women post more messages than men. The age of the partner brand's social media account is significantly associated with the partner brand's probability of posting on social media (b = .46, $p < .01$). As we predicted, actors who are more familiar with the social media platform are more likely to post. Because we find strong and significant estimates for all our exclusion restriction variables, we conclude that we successfully corrected for unobservables in the main model that may be related to actors' proclivity to engage in social media activities. We report the full table of the probit estimation in Web Appendix E.

Hypothesis Tests

Partner brand's social media power. We next evaluate the results of our linear mixed-effects model on the social media power of actors as partner brands, as displayed in Table 3, Model A. The model explains the success of the movie as a composite product well (conditional $R^2 = .87$).[9] Changes in the R^2, AIC, and BIC values point to a substantial impact of partner brands' social media power ($\Delta_{AIC} = -155.9$, $\Delta_{BIC} = -22.8$, $\Delta_{R2} = .06$). The inverse Mills ratios are nonsignificant in the model of interest, meaning that our coefficients are not biased.[10]

In the test for H_1, we find that the partner brand's social media power potential is positively related to success. The size of the actor's social media network has significant associations with composite product sales (b = .03, $p < .01$), as does the activity level on a marginal level (b = .05, $p < .10$). We treat this finding as empirical support for H_1.

The results also support H_{2a}, showing a strong association between product-related posts sent by the actor on his or her own Facebook page and composite product sales (b = .26, $p < .01$). However, we cannot confirm H_{2b}, because we find no significant relationship between the number of responsive comments and sales, whether in the form of acknowledging comments (b = –.04, $p > .10$) or promotional comments (b = –.14, $p > .10$). The nonsignificant effect also persists when we rerun the model with all responsive comments. For H_{2c}, we find a significant but *negative* association with sales for non-product-related posts (b = –.19, $p < .01$), which contrasts with our expectations. Interestingly, instead of profiting from a strengthened bond, the community seems distracted from the composite product when an actor issues non-product-related posts.

In the test of H_{3a}, we find that the interaction of product-related posts with the partner brand's social media network size has a marginally significant association with composite product sales in the proposed direction (b = .02, $p < .10$). The interaction between product-related posts and network activity reaches significance (b = .03, $p < .05$), in support of H_{3b}. An actor's social media power thus is most strongly linked to fostering composite product sales when goal-directed social media power exertion is amplified by a high level of social media power potential.

Different product-related post types. We next consider the results for the different types of product-related posts, as specified in Table 3, Model B. The model explains the success of the new composite product well (conditional $R^2 = .87$).[11] In

[8]We determined the "other" product-related posts variable by conducting a regression in which the total number of weekly product-related posts is the dependent variable and the number of authentic, exclusive, and persuasive posts are independent variables, then we used the residuals in our main analysis (see Web Appendix A).

[9]Our model uses fixed and random effects, so we use the random slope extension of Johnson (2014), implemented in R's piecewise structural equation modeling package, to calculate the conditional R^2 that accounts for the variance of the fixed effects as well as the sum of the random variance components for each level of the random factor.

[10]We further tested an alternative coding mechanism for the dependent variable in the probit model by differentiating between actors being active on social media or not (instead of using terciles). We find the results again to be robust. For comparison purposes, we provide models without endogeneity correction (one without inverse Mills ratios and one without inverse Mills ratios and instruments) in Web Appendix F.

[11]Model parameters, such as the intercept, remain largely the same as in Model A. The slight change results from different specifications across the two models. Whereas Model A includes a "product-related posts" variable (which captures all product-related posts) and accompanying interactions, Model B drops the interactions and exchanges the product-related posts variable for its constituting parts—namely, authentic, exclusive, and persuasive product-related posts compared to "other" product-related posts.

support of H_4, H_5, and H_6, we find strong, positive associations of authentic, exclusive, and persuasive product-related posts with composite product success (authentic: b = .60, $p < .01$; exclusive: b = .61, $p < .05$; persuasive: b = 1.01, $p < .01$). All three parameters are clearly larger than the small and insignificant parameter for "other" product-related posts (b = .08, $p > .10$), which captures the remaining product-related posts after controlling for authenticity, exclusiveness, and persuasiveness. A likelihood ratio test (LRT) further confirms that these effects are also significantly different from the base category of other product-related posts ($LRT_{authentic} = 15.85$, $p < .01$; $LRT_{exclusive} = 5.36$, $p < .05$; $LRT_{persuasive} = 23.20$, $p < .01$). Thus, it matters *how* social media power is exerted.

Findings for other partner brands and controls. For movies as composite products, several partner brands generally participate in the brand alliance. Our results (Table 3) show that social media power exertion by the supporting cast has no significant impact on the composite product.[12] If the supporting cast has a very active fan base, it might result in a minor advantage at the box office, but the impact remains small, indicating that social media power mainly stems from the leading partner brand in our context—the one featured most prominently in the alliance.

The results for the partner and host brand variables are as expected. The traditional brand strength of the partner and its promotional activities in traditional channels are significant, despite the simultaneous inclusion of its social media activities; the promotional effect is comparable in size with the one reported by Burmester et al. (2016) for prelaunch publicity of video games. The host brand type, the host's network size, and fit are also associated with higher composite product sales. Different product types show varying effects; for example, horror movies outperform dramas. We find positive associations of advertising, distribution, and weekly product mentions by social media handles. Controlling for movie quality, we find significant effects of consumer evaluations (but not critic evaluations or dissent); seasonal effects also exist.

Additional analyses for industry specifics. We ran additional analyses to check for potential industry-specific effects, as displayed in Web Appendix G. A notable characteristic of our setting is the human character of the partner brand in the movie industry, such that demographic traits of this human brand might affect the results. However, adding the lead actor's gender as an independent variable produced an insignificant interaction with product-related posts. We checked for time-varying effects of social media power exertion by testing interactions of product-related posts with the week count and the opening week; both remain insignificant.

Awards as external quality signals are important for movies as experience products. We thus tested whether social media power exertion might interact with Oscar nominations. A positive, significant interaction suggests that product-related posts amplify the positive effect of award nominations (b = .48, $p < .05$). By sending this quality signal to their social media networks, partner brands can enhance the effect of award nominations on composite product success.

Finally, we tested whether social media mentions by other stars (those not involved in the movie but who act as influencers) affect movie performance. We find a significant effect (b = .29, $p < .01$), with the previously reported findings remaining unchanged. That is, partner brands' social media power is not limited to their own composite products but is also significantly associated with other endorsed products to which they are unrelated.

Illustration of the Monetary Value of a Partner Brand's Social Media Posts

To illustrate the relevance of our findings and enhance managerial insights, we ran a simulation in which we compared box office predictions for movies featuring a lead actor who engages in product-related social media power exertion versus the same movies featuring the same actor who does not engage in it on Facebook.[13] The difference in the predicted weekly box office revenues offers a descriptive estimate of the monetary value product-related partner brand posts had for the observations in the analyzed data set, from 2012 until 2014. We exclude the top and bottom 5% to avoid deriving implications based on outliers and arrive at more reliable estimates (e.g., Hawawini, Subramanian, and Verdin 2003). Table 4 displays the descriptive statistics of our estimates, generated for the average effect determined with Model A und differentiating between types of product-related posts in Model B.

For Model A, we find that product-related posts have an estimated mean value of US$107,839 and a median of US$86,099. This value is similar to the value we estimate for traditional promotional activities by the partner brand (mean = US$103,466; median = US$85,398)[14]; we consider this result as support of social media posts' relevance as a marketing tool relative to more established forms of partner brand promotions (i.e., mentions in television shows or news outlets).

Drawing on Model B, we estimated the monetary values of different types of product-related posts, focusing on particularly promising communication styles with above-average expected performances. Persuasive posts are most valuable in our data (mean = US$638,824; median = US$513,662), followed by exclusive posts (mean = US$326,251; median = US$262,330) and authentic posts (mean = US$323,705; median = US$260,283). All three subsets return substantially higher values than the remaining set of other product-related posts (mean = US$36,778; median = US$29,572).

[12]When testing the different posting types for the supporting cast, we again found no significant effects. For parsimony, we included only the lead partner brand in the reported estimations.

[13]Specifically, we use the LME4 package's predict function to predict sales for each movie i in week t that features a lead actor with at least one Facebook follower three months before release. Equations 3 and 4 serve as the basis. Setting each movie to its mean, we predict sales for the first scenario with zero posts and for the second scenario with one post for an average week. We repeat this approach for each type of product-related social media power exertion.

[14]We applied the same procedure, this time setting posts to their mean and varying promotional activities. To ensure comparability of estimates, we used the same cases (i.e., movies with lead actors on social media).

TABLE 4
Overview of Estimations for Monetary Value of Different Types of Product-Related Social Media Posts

	Model A	Model B			
Type of Product-Related Post	**Average**	**Other**	**Authentic**	**Exclusive**	**Persuasive**
Mean	107,839	36,778	323,705	326,251	638,824
Median	86,099	29,572	260,283	262,330	513,662
Minimum	30,212	9,997	87,991	88,683	173,648
Maximum	379,568	126,342	1.112,011	1.120,758	2.194,528

Notes: All values are estimated values in U.S. dollars. The top and bottom 5% cases were dropped to eliminate outliers.

We interpret these values as descriptive indicators of the economic relevance of social media power exertion for a composite product; they are also in the range of managerial estimates in domains similar to ours.[15] The observed variations suggest that the value of a product-related post is not a fixed amount but depends on contextual factors, such as the type of post (e.g., persuasive), the type of social media power potential (e.g., large and active network), and the type of brand alliance (e.g., fit), as well as other variables in our model.

Discussion and Implications

Findings

This research provides evidence of a positive link between the partner brand's social media power and the economic success of the brand alliance. We test our theory-inspired social media power framework empirically, and the results reveal how the social media power potential of partner brands, together and in interaction with its exertion, are linked with composite product sales; a simulation exercise demonstrates the substantial size of these effects.

To achieve the greatest value, a host brand should team up with a partner brand with strong product-related social media power exertion that can be amplified by its large and active social media network. Substantial differences arise in the monetary implications, depending on the different ways a partner posts about the composite product, among other factors. Persuasive product-related posts, the most goal-directed type of social media power exertion in our study, are associated with the strongest power outcomes and highest monetary estimates. An activating, imperative communication style does not appear to repel fans, as oftentimes expected, but rather seems to help mobilize them to buy. Other effective tactics to exert social media power include the release of exclusive movie content and authentic references to the product.

Interestingly, we find a negative association between partner brand posts that do *not* refer to the alliance and composite product success, cautioning that some social media activities might backfire. Instead of fostering beneficial bonds with potential consumers, they seem to cause a distraction, diverting consumers' thoughts away from the composite product (Petty and Cacioppo 1986). Although non-product-related posts might have beneficial effects for strengthening the partner brand, they seem to hinder the success of composite products.

The findings also point to boundary conditions. First, the visibility of the communication might explain why partner brand comments, contrary to posts, do not significantly relate to composite product sales. Whereas posts are prominently featured on social media, comments instead appear in smaller font underneath a post, receiving less exposure. Although offering responsive replies to a fan might have a strong influence on the commenter's relationship with the partner brand, it does not translate into immediate, aggregate-level sales at the box office. If the goal is to increase immediate composite product sales, the expenditure of energy should be rather directed to generating posts as the more visible communication form.

Second, the centrality of the partner brand appears to serve as an additional boundary condition, explaining why we find no significant effects of social media activities of the supporting cast. Because the leading partner brand is perceived as central and important to the composite product, information coming from and being spread about this partner brand should be processed through a central route, resulting in stronger elaboration and persuasion (Petty and Cacioppo 1986). Messages from the supporting cast are likely processed at lower levels and are thus less influential in persuading consumers to buy tickets at the box office.

Managerial Implications

Our findings offer rich insights into the strategy–performance link in the context of social media. They provide recommendations for implementing the social media power of partner brands in brand alliances, pertaining to both the selection and management of partner brands.

Partner brand selection. Practitioners have been debating whether hiring partner brands on the basis of their social media fan numbers is a good idea (Hod 2015). Our results offer an answer: Host brand managers can profit from the external social media power of a partner brand (beyond its expert-based power), as indicated by a significant increase in composite product sales. The social media power of a brand can thus act as a valid criterion for selecting a brand alliance partner, especially because "piggybacking on a star's established social media presence can be easier than building a new online platform from scratch" (Zerbib and Verhoeven 2015).

[15]We found business press estimates that ranged from US$6,250 to US$1 million (see, e.g., *The Economist* 2016; Heine 2016; Robehmed 2016).

However, managers must realize that the number of followers reflects only a *potential*, with limited impact on its own. Instead, the brand alliance–specific *exertion* of this potential power is the key for sizable social media power outcomes. Yet most managers seemingly look at only follower numbers, rather than actual posting behaviors (*The Telegraph* 2017). A host brand manager is recommended to use both the size and activity of a prospective partner brand's social media network as selection criteria but is advised to put special emphasis on product-related social media power exertion. The interaction effects stress that both potential and exertion are needed to maximize the value of a partner's social media power.

Partner brand management. Different drivers of social media power effectiveness also inform the strategic management of social media in ongoing alliances. To leverage their social media power potential and its link to composite product sales, partner brands are recommended to actively refer to the composite product in their posts. Posts mentioning other activities detract from the alliance, so unrelated posts should be limited during the launch phase of the product.

Not only should managers encourage partner brands to address their network actively during the ongoing brand alliance, but they can also offer concrete guidance for *how* to do so. In leaked emails, producers allegedly debated what type of tweet they wish Kevin Hart would post, debating the effectiveness of persuasive "calls to action" (Spargo 2014). Our findings would have helped these practitioners, as we show that persuasive appeals are linked with a mobilizing effect, sharing exclusive content is linked to further increases in sales, and adopting an authentic tone is advisable. Neutral product referrals, without exclusive content or authentic product references, have no significant impact, and posts that distract fans from the product should be avoided. These insights suggest *what* to post and *how*—assuming the goal is to increase composite product sales.

Theoretical Implications, Limitations, and Further Research

We contribute to social media theory by introducing our conceptual framework. The application of well-established power theory to the modern context of social media enables us to offer a theory-inspired categorization for the unstructured occurrence of social media variables. The conceptual and empirical distinction between social media power potential and exertion, including its identified facets, provides linkages that scholars could use to systematically extend theoretical knowledge and to resolve and integrate some seemingly inconsistent observations.

Furthermore, our novel brand alliance setting offers scholars a new way to provide a clear assessment of social media effectiveness. Our use of an externally acquired social media power helps us isolate its relationship to the sales of a composite product while controlling for confounding variables. We find the partner brand's social media power to be of high economic value—both while accounting for and compared with traditional brand- and publicity-related variables.

Concerning the generalizability of our findings, we emphasize the particularities of our empirical setting. We analyze the combination of hedonic host brands (movies) with human partner brands (talented professional actors) who represent an integral part of the composite product. What contexts offer similar structures that may facilitate (or hinder) the applicability of our general findings? Regarding the host brand, several products exist that are not purely hedonic but offer at least a certain amount of hedonic benefits and are paired with human brands (e.g., the Tiger Woods Golf collection sold by Nike). We expect the pattern of our results to be transferable to such similar contexts. Our findings may also apply to some services offering hedonic benefits that are paired with human brands, as is the case with founders such as Virgin's Richard Branson, but also with sports clubs (paired with athletes) and political parties and their candidates. We study professional actors as *human* partner brands; a multitude of comparable settings also include human brands—for example, athletes and musicians as well as other types of influencers on social media. Some similarities might exist with nonhuman partner brands for hedonic brand alliances that offer anthropomorphic characteristics, but we refrain from probing other contexts, such as search goods with mainly nonemotional utilitarian attributes.

Our empirical analysis reflects the social media environment at the time represented by our data set. During this period, stars were engaged in social media activities rather unsystematically, which is beneficial for our investigation. However, the continuing changes in social media usage by partner brands might influence their general effectiveness. For example, our sample includes a limited amount of persuasive posts; increased usage might lower their effectiveness as a result of satiation effects. This caution is pertinent, especially when interpreting the value estimations derived from our simulations, which we consider descriptive rather than prescriptive.

Several exciting avenues for further research emerge from our study. Our results show that using a referent power base with social media is strongly associated with composite product sales, as are mentions by actors not involved in the movie. Future research could use these insights to further address the phenomenon of influencer marketing. For example, how can aspiring influencers build a referent power base from scratch? What are valid fit criteria for brand managers to identify good brand–influencer matches?

Another avenue would be to link our findings on the monetary value of product-related posts to those from engagement studies. Akpinar and Berger (2017) and Lee, Hosanagar, and Nair (2017) have noted differences in the effects of post types for engagement, clicks, and purchase intentions. For example, whereas persuasive appeals by partner brands are associated with a sales lift for the composite product, we might find a reversed pattern for engagement scores of the partner brand (see Stephen, Sciandra, and Inman 2015). Both outcomes are important metrics, connected to different goals (immediate product sales or strengthening long-term consumer relationships). Further research could examine their interplay and consider both short- and long-term effects.

A final avenue might be to analyze patterns of posting behaviors to develop a more holistic understanding of content marketing. How important is consistency and integration in a brand's communication within and across social media platforms? Insights on integrated marketing communications offer a starting point for scholars to address these urgent industry questions.

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