# Essays on Brand-Related User-Generated Content in Online Social Networks

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| | |
|---|---|
| UGC | User-generated content |
| WOM | Word-of-mouth |
| eWOM | Eletronic word-of-mouth |
| SMI | Social media influencer |
| e.g. | Exempli gratia |
| Et al. | Et alii, et aliae, et alia |
| i.e. | Id est |
| SPT | Social penetration theory |
| CDT | Cognitive dissonance theory |

# ESSAYS ON BRAND-RELATED USER-GENERATED CONTENT IN ONLINE SOCIAL NETWORKS: SYNOPSIS

## 1. Introduction

In 2021, more than 50% of the world's total population uses social media, which accounts for more than 90% of all humans with access to the internet (Kemp 2020). Nearly all consumers access social media with their smartphone from any place at any time, resulting in more than two hours average daily usage, according to a study by Hootsuite (Kemp 2020). In contrast to traditional websites, social media is rooted in the idea that the users of the website create their own content and share it with others (user-generated content; UGC). From a marketer's perspective, consumers use social media to share their own consumption experiences and opinions on brands with other people they are connected to (Hennig-Thurau et al. 2004). Further, their purchase decisions and brand attitudes are driven by what other consumers share on social media (Rosario et al. 2016). While research on word-of-mouth (i.e., oral articulation of brand[1] related opinions; WOM) has a long tradition in marketing research, there are consequential differences between consumers that talk about brands with their friends and family and potentially unfamiliar consumers that create brand-related UGC on, for example, social media. The probably most important difference is the accessibility of UGC. Even before the diffusion of social media, Dellarocas (2003) formulated his expectation that "Through the Internet, […] for the first time in human history, individuals can make their personal thoughts, reactions, and opinions easily accessible to the global community of Internet users." (p. 1407). His expectations have since been proven and the accessibility of UGC has impacted the marketing world in a myriad of ways. In 2012, a special issue of the Marketing

[1] Unless explicitly mentioned, the term refers to product-, service-, human-, and corporate-brands equally.

Science journal titled “Introduction to the Special Issue on the Emergence and Impact of User-Generated Content” contemplated several questions related to UGC, such as “how and why people make UGC contributions, the impact of UGC contributions, and new methods for analyzing UGC data” (Fader & Winder 2012, p. 369). Building on that issue, the following three consequences of UGC’s accessibility are of major importance for marketers of brands (Kannan 2017) and constitute the three areas of research that are addressed within the essays of this dissertation:

*[A] Deriving Brand Perception from User-Generated Content*. Accessibility implies not only access by other consumers but also by brands themselves. Accordingly, brands can observe and extract potentially valuable information (e.g., brand perceptions and consumer preferences) regarding their own and competing brands by collecting and analyzing UGC (Decker & Trusov 2010; Schweidel & Moe 2014; Timoshenko & Hauser 2019). While marketing analysts traditionally[2] tried to infer such valuable information from consumer surveys and panels, collecting UGC on a large scale is less expensive and more up-to-date (Wedel & Kannan 2016).

*[B] Collaborating with Influential User-Generated Content Creators*. As brands can access the interaction between individual consumers, they are able to determine which consumers exert an extraordinary strong influence on the opinions and the behavior of other consumers via UGC on social media (i.e., social media influencers; SMIs; Mallipeddi et al. 2021). Collaborating with these SMIs has established as a very effective form of marketing throughout the last years (Hughes et al. 2019). While marketing traditionally collaborated with celebrities that were known to have great influence on their fans, these new SMIs might have closer parasocial relationship with their subscribers and might therefore be able to persuade consumers more effectively. Further, SMIs might be less expensive than celebrities are and

[2] In this dissertation the term „traditionally“ refers to the time before the large-scale proliferation of UGC which started roughly with the founding of Facebook in 2004 and Youtube in 2005.

therefore embody a cost-effective way of communicating key brand messages (Hughes et al. 2019).

*[C] Antecedents and Consequences of Negative User-Generated Content.* Brands are not able to control who shares an opinion via UGC, how favorable the opinion is, and how many other consumers will see it. Instead, consumers' interest in a single piece of UGC can rapidly spread it over the whole world. As consumers are able to access the opinions of other consumers through UGC in a large scale, at any place, and at any time, brands need to understand under which conditions connected consumers share positive and negative UGC about their brand. While consumers sharing their opinions via WOM is not new per se, UGC has amplified the magnitude of this phenomenon as the potential audience has changed from friends and family to, theoretically, all users of a social network (Rosario et al. 2016).

The aim of this dissertation is to advance the academic knowledge and derive practical implications within all three (i.e., A to C) of the aforementioned areas of research. The empirical analyses of this dissertation are primarily based on real (vs. experimental) observations of UGC to achieve a high degree of ecological validity, as the proposed effects are studied in a real-life setting. In addition, experiments are conducted to strengthen causal claims or to investigate psychological drivers of observed consumer behavior.

The structure of this dissertation is as follows: First, a conceptual framework that helps to understand how the three research areas are connected and how they affect important marketing outcomes (e.g., customer relationships and sales of a company) is presented. Afterwards, the three research areas (a detailed motivation is found in the individual essays) are briefly motivated, the current literature is presented and it is explained how the essays of this dissertation advance the academic knowledge in the respective fields. The next two chapters give an overview of how the research questions of the individual essays are related to the conceptual framework and list the essays of this dissertation including information on their current publication status. Afterwards the substantial findings of the conducted research are summarized and overarching (i.e., not discussed in the individual essays) theoretical and methodological contributions are discussed. Lastly, several opportunities for future research on UGC that stem from a joint consideration of the three research streams are derived.

# 2. Research Objectives

## 2.1 Conceptual Framework

To understand how connected consumers (i.e., consumers that use the internet to create and consume UGC) and brands use UGC and how they influence each other, this dissertation builds on and extends the conceptual framework by Hennig-Thurau et al. (2010), which emphasizes the opportunities and threats for brands that arrive from the existence of UGC in social media environments[3]. The framework is depicted in Figure 1. and explained in the following.

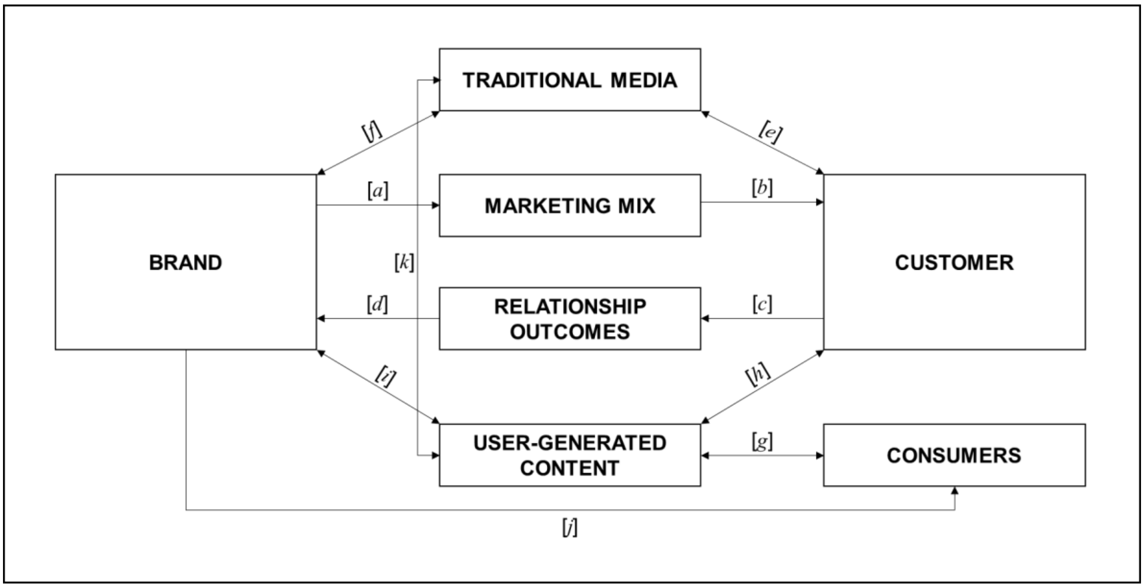


**Figure 1.** Conceptual framework of UGC on relationship outcomes.

[3] Conceptually, every website that facilitates users to generate their own content (UGC) and share it with other users can be considered as social media, although the term is most often used to describe popular social media platforms such as Instagram, Twitter, and Facebook.

Brands decide for a combination of marketing instruments referred to as the marketing mix (*a*). For example, a brand can decide to run an advertising campaign, release a new product, or give discounts to loyal customers. These instruments are sought to influence their current or potential customers (*b*) in a way that creates positive relationship outcomes between the customer and the brand (*c*). A positive relationship, in turn, translates into higher purchase intention and thus increases sales (*d*). Besides the marketing mix of a brand, traditional media such as newspaper articles can affect customers (*e*) and brands therefore try to avoid negative coverage (*f*). However, up to this point, customers are treated as passive receivers of information coming from the brand or traditional media channels.

With the introduction and wide spread of social media and the resulting proliferation of UGC, the marketing environment changes for brands. Similar to traditional media, UGC affects customers (*h*). In contrast, UGC is not controlled by a couple of institutions (e.g., media outlets) or selected persons (e.g., journalists), but created by the sum of all consumers who decide to contribute informational content (*g*). Accordingly, consumers can turn from passive receivers to active contributors and affect a brand's customers[4] in a way that can potentially be positive or negative regarding relationship outcomes with a brand. Additionally, brands can particularly impact UGC as they have their own voice through their accounts in social networks such as Instagram or Twitter (*i*). Further, brands can listen in to consumers' UGC and might even be able to get insights that were traditionally hard to observe with survey methods (*i*). Lastly, UGC and traditional mass media depend on each other (*k*) in a way that information disseminate through UGC is often addressed in traditional media and vice versa.

In addition to the original framework of Hennig-Thurau et al. (2010), this dissertation introduces an additional unidirectional arrow (*j*), which indicates a brand's approaches to

[4] Within the conceptual framework, the term „CUSTOMER" refers to a specific consumer that has a relationship with the brand, while „CONSUMERS" is used to describe the relationship between a specific customer and all other consumers.

collaborate with consumers regarding their UGC behavior. In the last year, brands increasingly collaborate with consumers whose UGC is surpassingly influential in the social media environment (i.e. social media influencers, SMIs; Geyser 2021). Following the framework, brands do not only directly reach their customers through the marketing mix (*a* and *b*), but also through collaborating with SMIs (*j*) that are compensated to articulate positive brand-related UGC (*g*), which is believed to positively affect customers (*h*), potentially in a way that might be more cost-effective that traditional instruments (Kumar et al. 2013; Kumar and Pansari 2016). In a study by Linqia (2018), more than 50% of the interviewed marketing managers (n = 181) state that SMI content outperforms brand-created content and only 6% find it to be less effective.

For both marketing researchers and practioners, this new social media environment yields several research questions that need to be answered in order to understand how brands can strategically handle opportunities and threats of this new environment. In the following, an overview of the research questions investigated in the essays of this dissertation is presented. Afterwards, three areas of research that have emerged as a result of the UGC phenomenon are described. For each area, a short literature review will be given followed by a description on how the essays in this dissertation help to advance the academic research in the respective field.

## 2.2. Overview of Research Questions

Figure 2 depicts a summary of all seven essays regarding their research questions and how they are positioned within the overarching conceptual framework presented in Figure 1. The letters (A to C) refer to the three areas of research and the numbers (1 to 3) to the number of the essay within the respective area of research. In summary, the research questions investigate how brands can collaborate with consumers that create UGC (*j*), which antecedence for the creation of UGC exist (*g*), how and under which conditions UGC affects customers (*h*), and how brands can utilize UGC (*i*).  The individual research questions are motivated in chapters 2.3, 2.4, and 2.5 according to the research area they belong to.

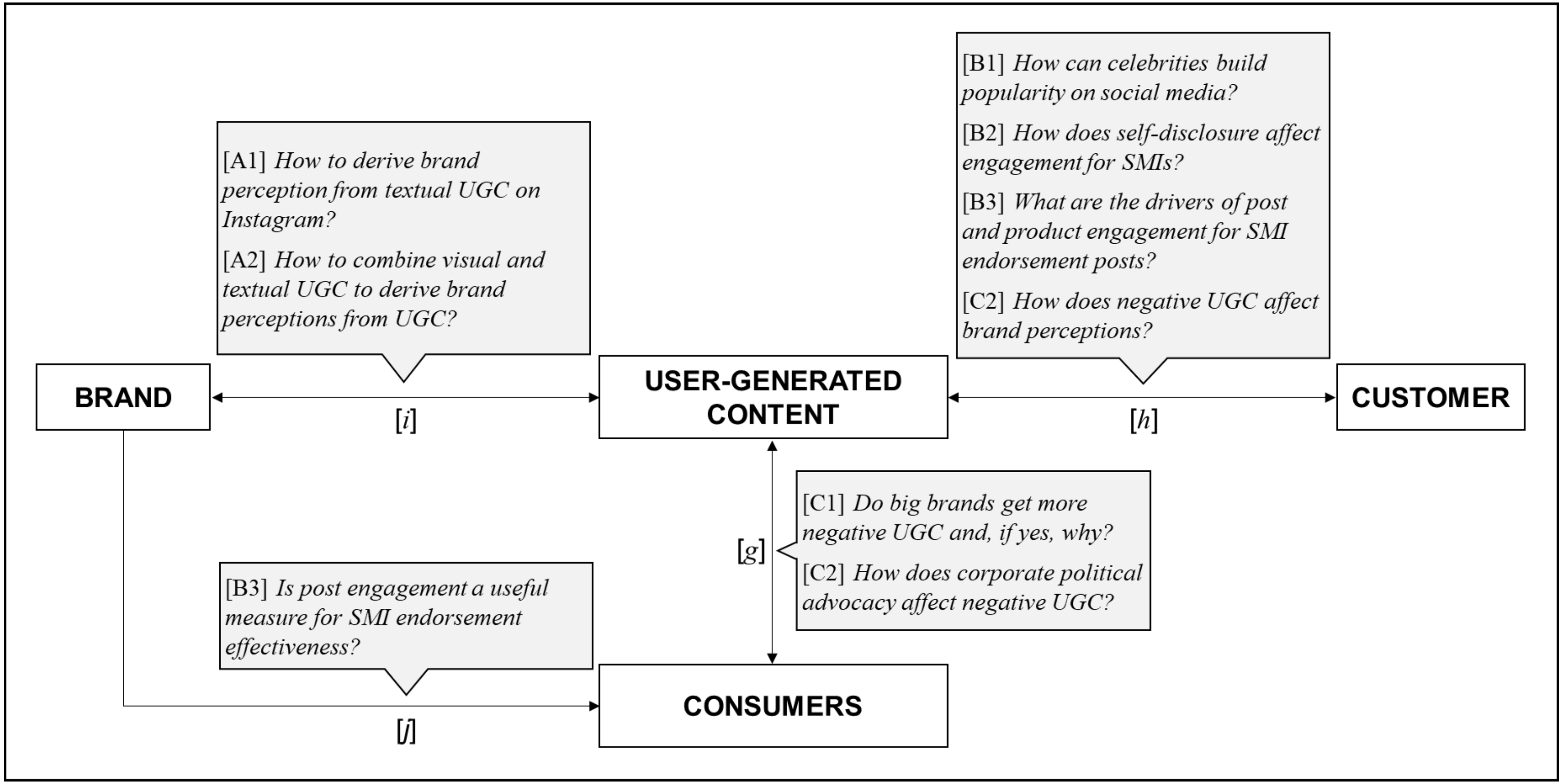


**Figure 2**. Summary of research questions within the conceptual framework.

## 2.3 Objective A: Deriving Brand Perception from User-Generated Content

*Motivation and Theory*. Understanding how consumers perceive brands is a basic requirement for any brand strategy and thus the core of brand management. Following Keller's (1993) framework of brand equity, brand perception consists of associations[5] that consumers connect with a brand in their mind. The psychological background of his framework is the theory of spreading activation (Collins and Loftus 1975) that conceptualizes human memory as a network of connected nodes. When sensing a stimulus related to a certain brand (e.g., seeing the brand logo of "BMW"), activation is spread to nodes with concepts that the consumer connects to the brand (e.g., the concept "sport"). Concepts connected to the brand can be defined as brand associations. Consumers associate several concepts with brands, like functional benefits, symbolic meaning, emotions, as well as their own experiences and attitudes with the brand. Brand managers strive to strongly connect their brand with favorable and unique associations in order to get a competitive advantage in the market. To reach this goal, it is necessary for managers to continuously measure consumers' perceptions regarding their own and competing brands in order to make objective data-driven decisions.

To elicit brand perceptions, marketing research traditionally relies on survey and focus groups data (Plumeyer et al. 2019). While basic techniques capture brand perception with a muli-item Likert or semantic differential scaling, more advanced methods try to capture the associations a consumer connects with a brand in the form of an associative network (John et al. 2006). While this method is able to produce an aggregate network of brand associations that can help to understand how the brand is perceived, it is costly to apply on a large scale (Meissner et al. 2015). However, in recent years, the proliferation of UGC has raised the questions whether it is possible to approximate results of traditional survey methods with publicly accessible UGC

[5] Within essays A1 and A2, "brand perception" can be understand as the aggregation of all associations consumers connect with the brand.

(Ruths and Pfeffer 2014). More precisely, is it possible to observe consumer's brand perception from the brand-related content they voluntarily share on social media on a large scale (i.e., for a big set of brands and/or for multiple points of time)? Following the conceptual framework presented in Figure 1, deriving brand perceptions from UGC is represented by arrow *i*.

*Literature review and contribution*. This dissertation presents two articles that contribute to the research area of methods that aim at eliciting brand perception from UGC, see Table 1.

**Table 1.** Essays for research objective A.

| ID. | Authors | Title | Research Question | Framework |
|---|---|---|---|---|
| [A1] | **Klostermann**, Plumeyer, and Decker | Deriving Brand Associative Networks from Instagram | *How to derive brand perception from textual UGC on Instagram?* | [*i*] |
| [A2] | **Klostermann**, Plumeyer, Böger, and Decker | Extracting Brand Information from Social Networks: Integrating Image, Text, and Social Tagging Data | *How to combine visual and textual UGC to derive brand perceptions from UGC?* | [*i*] |

First, the previous research in this domain will be reviewed and it will then be explained how this dissertation advances the state of the art. Table 2 summarizes recent academic articles that show how to elicit brand perceptions from UGC. As depicted in Table 2, several teams of authors relied on free text (i.e., text) generated by consumers through online opinion platforms (e.g., Epinions and Amazon). Following the theory of spreading activation and Keller's (1993) assertion of association strength, each of the methods in Table 1 is based on a metric that captures the strength of association between the brand and other concepts that, in turn, are defined as brand associations.

**Table 2.** Academic literature on brand perception elicitation from UGC.

| Authors | Platform | Type of data |
|---|---|---|
| Lee and Bradlow (2011) | Epinions | Text |
| Netzer et al. (2012) | Forum | Text |
| Tirunillai and Tellis (2014) | Amazon, Epinions, Yahoo! | Text |
| Culotta and Cutler (2016) | Twitter | Network structure |
| Nam, Joshi, and Kannan (2017) | Delicious | Hashtag |
| [A1 ] Klostermann, Plumeyer, and Decker (2018) | Instagram | Text and hashtag |
| [A2] Klostermann, Plumeyer, Böger, and Decker (2018) | Instagram | Image, text and hashtag |
| Liu, Dzyabura, and Mizik (2020) | Instagram | Images |

Most of the methods use a co-occurrence metric that follows the theory of spreading activation: Words that frequently appear together with a brand name also have a strong semantic relationship with the brand. For example, when consumers often use the word "green" and the brand name "Tesla" in the same sentence, one might interpret "green" as an important association consumers connect to the brand Tesla (Netzer et al. 2012). The same idea was transferred by Culotta and Cutler (2016) to the network of relationships on Twitter: When a high share of subscribers of the "Tesla" account also subscribe to accounts that represent the association "green" (e.g., Greenpeace), one might interpret this subscriber structure as evidence for a associative relationship between the Tesla account and the association "green". In 2017, Nam et al. used hashtags to compute the co-occurrence between brands and brand associations on Delicious (a nowadays less popular platform where users save websites and label them with tags). In contrast to words in open text, hashtags are used to summarize and label information. Therefore, Nam et al. (2017) argue that the distribution of social tags is more concentrated on several representative keywords and less biased by consumer-idiosyncratic word usage.

The first essay of this dissertation (A1) builds on the findings by Nam et al. (2017) and analyzes hashtags to elicit brand perceptions with two major distinctions: First, the authors[6] used UGC from Instagram. In contrast to Delicious, consumers use Instagram to spontaneously share everyday moments from their lives, which might help to infer spontaneous reactions to marketing stimuli. Additionally, Instagram is one of the most visited websites in world, yielding a potentially broader range of consumers who use it (Kemp 2020). Second, users on Instagram not only attach hashtags to their post, but also describe the situation as well as potential feeling in a short caption text. The authors measured the valence of the shared moment as conveyed through the sentiment of the caption text. In this way, they were not only able to compute a network of brand associations, but also to estimate the favorability of an association that was defined as the mean sentiment of all posts that use the respective hashtag (Keller, 1993). In the manuscript, the authors show how the proposed method can be used to infer the brand perception of a single and competing brands.

A third distinction between Instagram and Delicious is that Instagram posts always contain visual information, mostly images recorded with the camera of a smartphone. As depicted in Table 2 and to the best of the author's knowledge, essay A2 of this dissertation is the first to incorporate visual information from social media posts into the elicitation of brand perceptions from UGC. According to Dzyabura & Peres (2021), essay A2 "demonstrates the power of unsupervised analysis on visual data: while the UGC text contains associations related to brand functional and intangible attributes, unsupervised analysis of images generates a broad spectrum of associations for the brand, ranging from burger and McCafe to cartoon and urban." (p. 49). More precisely, in essay A2, the authors used images to distinguish between different situations in which consumers create UGC about a brand. The main underlying assumption is that consumers articulate brand associations depending on their situation. For example, a

[6] The term „the authors" refers to the authors of this dissertation and the co-authors of the respective essay.

consumer drinking a Cappucino inside a McDonalds cafe might connect other associations with the brand as one having dinner with his kids in a McDonalds restaurant. The authors therefore used the visual information from the Instagram post to cluster distinct moments that consumers connect with the brand and, subsequently, elicit their brand perception depending on the situation in a similar way as described in essay A1.

### 2.4 Objective B: Collaborating with Influential User-Generated Content Creators

*Motivation and Theory*. Brands regularly cooperate with celebrities (i.e., consumers who receive public recognition) to endorse their brand and products. This strategy can be very effective as celebrity endorsements can raise awareness, lead to positive attitudes, and increase sales of endorsed brands and products (Knoll & Matthes 2017). The effectiveness of the endorsement depends, among others, on the strength of the relationship a consumer shares with a celebrity (McCracken 1989, Knoll & Matthes 2017). Traditional celebrities nowadays are well represented on social media where they create UGC to connect to and build stronger relationships with their subscribers (Chung & Cho 2017). Additionally, several consumers become celebrities on social media as their UGC is interesting in a way that many consumers subscribe to their accounts. Brands have recognized that influential users on social media, referred to as social media influencers (SMIs), might exert strong influence on the behavior of their subscribers (Hughes et al. 2019). In contrast to traditional celebrities, SMIs are often experts in a specific category (e.g., fitness or food products) and are trusted based on parasocial relationships build by daily interaction with their subscribers (Chung & Cho 2017). Especially, following social penetration theory (SPT), interactions in which the SMIs self-disclose intimate moments from their personal life might reinforce the strength of the relationship (Altman & Taylor 1973).

Many brands thus started to collaborate with SMIs and pay them in exchange for brand endorsements, a practice now referred to as SMI marketing. According to the conceptual framework presented in Figure 1, collaborating with influential UGC creators is represented by arrows *h*, and *j*. While arrow *h* accounts for the effect that SMI generated UGC has on customers of a brand, arrow *j* represents the possibility for brands to collaborate with SMIs in the form of sponsored brand endorsements.

*Literature review and contribution.* This dissertation contains three research essays that are related to SMI marketing, see Table 3.

**Table 3**. Essays for research objective B.

| ID. | Authors | Title | Research Questions | Framework |
|---|---|---|---|---|
| [B1] | **Klostermann**, Meissner, Max, and Decker | Drivers of Celebrities' Social Media Capital | *How can celebrities build popularity on social media?* | [*h*] |
| [B2] | **Klostermann**, Meissner, and Decker | Disclosing Private, but Staying Focused – How Social Media Influencers Effectively Increase Post Engagement and Purchase Intention | *How does self-disclosure affect engagement for SMIs?* | [*h*] |
| [B3] | **Klostermann**, Meissner, Musalem, and Decker | How Can Social Media Influencers Create Valuable Engagement for Endorsed Products? | *What are the drivers on post and produt engagement for SMI endorsement posts?* | [*h*] |
| | | | *Is post engagement a useful measure for SMI endorsement effectiveness?* | [*j*] |

First, B1 seeks to answer the question how traditional celebrities can build popularity on social media. Popularity is defined as the number of subscribers (i.e., the number of other users that directly see UGC created by the SMI) as the number of subscribers indicates how many consumers are potentially aware of a brand endorsements shared by the SMI. Therefore, popularity of an SMI is represented by arrow *h* in the conceptual framework (see Figure 1), as it determines the impact of UGC on potential customers of the brand. The answer to this question is important for both celebrities, who use social media as a source of financial income, as well as brands collaborating with said celebrities, as higher social media popularity increases the marketing effectiveness for brand endorsements (Kupfer et al. 2018). While marketing research has investigated the drivers of celebrity popularity and favorability outside the context of social media (Luo et al. 2010; Mathys et al. 2016), engaging subscribers with their social media content is becoming very important for celebrities (Lane 2019). The authors analyzed both visual and textual data from a sample of 1,443 celebrities (professional soccer players) with more than 350,000 posts on Instagram. The results showed that celebrities' social media behavior is slightly more important than the popularity they have gained because of their professional career in driving social media popularity. In particular, it was found that celebrities focus too much on professional (vs. personal) content and, thus, squander potential social media popularity. Further, most celebrities increase the share of professional content over the course of their career, which has a negative effect on social media popularity.

In the second essay (B2) the authors went deeper into the question of how personal content affects the relationships between SMIs and their subscribers. In particular, the authors investigated how self-disclosing intimate moments from their personal lives helps SMIs to build parasocial relationships with their subscribers. Parasocial relationships can help to build trust between the SMI and subscribers that might, in turn, lead to more favorable reactions to brand endorsements (Chung and Cho 2017). Accordingly, the research objective of essay B2 is also represented by arrow *h* in the conceptual framework, as parasocial relationships change the way in which SMI generated UGC affects customers of a brand. While previous literature has already found a positive link between self-disclosure depth and parasocial relationship building (Chung and Cho 2017; Kim and Song 2016), research has not investigate how self-disclosure breadth (i.e., the number of major topical areas or categories that are disclosed by the SMI; Altman and Taylor 1973) affects the perception of an SMI. Further, this essay advances the current literature by showing the effects of self-disclosure in a real-world setting with observations from the social network Instagram. The empirical results of this research show that depth of self-disclosure drives parasocial relationship building, and more specifically trust building in SMIs, which, in turn, increases both engagement for social media content and purchase intention for endorsed products. The authors found that a SMI's decision to focus on fewer topics can increase engagement as they are perceived as having a higher level of expertise.

In the third essay (B3), the focus shifts from the perspective of the SMI to the collaborating brand by investigating how SMI product endorsements generate engagement that is directed at the endorsed product rather than the post itself. Therefore, essay B3 is best represented by arrows *h* and *j* in the conceptual framework. As marketers use SMIs to generate awareness and interest for their products, they are keen to understand which posts generate most engagement for the sponsored product. While several studies investigate the drivers of post engagement (Hughes et al. 2019; Tellis et al. 2019; Lie & Xie 2019), they often make the assumption that high post engagement (e.g., the number of comments) is favorable for the marketing effectiveness of endorsement posts. While one would intuitively agree that an advertisement that reaches more consumers is more effective, it was found that several important decisions (e.g., how to visually present the product) can affect post engagement positively, while they simultaneously reduce engagement for the endorsed product (i.e., the number of comments that explicitly mention the product). The authors therefore recommend researchers not only to focus on post engagement when studying SMI posts and managers to keep an eye on product engagement when measuring the effectiveness of their SMI campaigns.

## 2.5 Objective C: Antecedents and Consequences of Negative User-Generated Content

*Motivation and Theory.* As previously introduced, the rise of UGC is both a blessing and curse for brands. While the two previous topics deal with opportunities (i.e., [A] deriving brand perception from UGC and [B] collaborating with SMIs), the third topic [C] of this dissertation sheds light on threats that arise from negative UGC (i.e., UGC with information that affect the brand in a negative way). In contrast to the traditional marketing environment, UGC gives all individuals the opportunity to share their negative opinion about brands with, potentially, all other users through the internet (Hennig-Thurau et al. 2004). For example, in a recent consumer survey, 93% of participants said that online reviews affected their purchasing decisions (Fullerton 2017). In this way, negative UGC (in the form of negative online product reviews) is directly linked to the sales of a product. Additionally, in the last years, several online protests (i.e., a large amount of consumers simultaneously share negative UGC about a specific issue or brand) have shown the huge thread originated in negative UGC (Hansen et al. 2018). Consumers typically create negative UGC to vent their negative feelings that can originate in unsatisfied experiences or negative brand attitudes (Berger 2014). Following the conceptual framework, investigating antecedents of negative UGC is represented by arrow *g*, while the consequential effect of negative UGC on a customer is represented by arrow *h*.

*Literature review and contribution.* This dissertation contributes to the research stream of negative UGC with two essays which are very distinct depicted in Table 4.

Essay C1 investigates the hypothesis that big brands (brands that are more known and possess a high market share) receive more negative UGC compared to small brands. Accordingly, the research questions is represented by arrow *g* of the conceptual framework. While research on the process of UGC creation is vast (Rosario et al. 2019), nearly no prior research investigated how brand-level metrics (e.g., brand size) affect UGC creation. Only the paper by Paharia et al. (2014) shows that consumers with a positive experience are more

**Table 4.** Essays for research objective C.

| ID. | Authors | Title | Research Questions | Framework |
|---|---|---|---|---|
| [C1] | Flaswinkel, **Klostermann**, Max, and Decker | The Price of Popularity: Why Consumers Share More Negative Electronic Word of Mouth for Big Brands | *Do big brands get more negative UGC and, if yes, why?* | [*g*] |
| [C2] | **Klostermann**, Hydock, and Decker | The Effect of Corporate Political Advocacy on Brand Perception An Event Study Analysis | *How does corporate political advocacy affect negative UGC creation?* | [*g*] |
| | | | *How does negative UGC affect brand perceptions?* | [h] |

likely to create UGC (i.e., write a review) when a larger competitor is salient (i.e., when the existing competition is obviously recognizable to the consumer). In essay C1, the authors show that big (vs. small) brands receive more negative valence in brand-related UGC on social media and lower star ratings on online review platforms. Two mediators can explain this relationship. First, small brands evoke a stronger need to help those same brands, which leads to more positive UGC in social media articulations and online reviews. Second, consumers perceive creating UGC about small brands as more directly communicating with these brands, which leads to more positive UGC valence on online review platforms and social media.

The second essay (C2) investigates the phenomenon of brand's political advocacy. In recent years brands have increasingly engaged in corporate political advocacy (CPA; also termed brand activism or corporate sociopolitical activity) by taking positions on polarizing sociopolitical issues. While some articles in the marketing literature have found initial evidence that CPA has a negative effect on brand perception (Mukherjee and Althuizen 2020), no prior literature has shown this relationship with real-world observations. Even more importantly, in essay C2, the authors show how this relationship is mediated by negative UGC in the form of large-scale protests on Twitter. Accordingly, essay C2 is represented by arrows *g* and *h* of the conceptual framework, as it deals with the process of why consumers generated UGC (arrow *g*) and how UGC affects brand perceptions of potential customers of a brand (arrow *h*).

In this regard, the authors show that more negative UGC is created when the brand takes higher effort on their CPA (e.g., spending money for a political group vs. announcing support for the political group). It was also found that the volume of negative UGC is higher for events that are further back in time. Further, the authors found that the volume of negative UGC evoked by taking a political stance has a strong negative effect on brand perceptions, showing how the existence of negative UGC can cause threats for brands.

# 3. Synopsis of Dissertation Essays and Statement of Contribution

This dissertation comprises seven essays depicted in Table 5. As can be seen in the ID column, each essay is assigned to one of the three research objectives described in the previous chapter. All essays can be found in Appendix A of this dissertation.

**Table 5.** Overall overview of dissertation essays.

| ID. | Authors | Title | Journal | Status |
|---|---|---|---|---|
| [A1] | **Klostermann**, Plumeyer, and Decker | Deriving Brand Associative Networks from Instagram | *Proceedings of the 47th European Marketing Academy Conference (D)* | Published 2018 |
| [A2] | **Klostermann**, Plumeyer, Böger, and Decker | Extracting Brand Information from Social Networks: Integrating Image, Text, and Social Tagging Data | *International Journal of Research in Marketing (A[1])* | Published 2018[2] (63 citations[3]) |
| [B1] | **Klostermann**, Meissner, Max, and Decker | Drivers of Celebrities' Social Media Capital | *Journal of Business Research (B)* | Under Review |
| [B2] | **Klostermann**, Meissner, and Decker | Disclosing Private, but Staying Focused – How Social Media Influencers Effectively Increase Post Engagement and Purchase Intention | *International Journal of Research in Marketing (A)* | Major and Risky Revision |
| [B3] | **Klostermann**, Meissner, Musalem, and Decker | How Can Social Media Influencers Create Valuable Engagement for Endorsed Products? | *Information Systems Research (A+)* | Preparing for submission |
| [C1] | Flaswinkel, **Klostermann**, Max, and Decker | The Price of Popularity: Why Consumers Share More Negative Electronic Word of Mouth for Big Brands | *Journal of Marketing (A+)* | Reject and Resubmit |
| [C2] | **Klostermann**, Hydock, and Decker | The Effect of Corporate Political Advocacy on Brand Perception: An Event Study Analysis | *Journal of Product and Brand Management (C)* | Forthcoming |

Notes:
1) Ranking based on VHB-JOURQUAL 3 (2015).
2) The article was a finalist at the journal's annual best paper award.
3) According to Google Scholar 21.01.2022.

This thesis is based on a number of collaborative projects, which involve contributions from many authors. Table 6 explains how the co-authors and I contribute to the projects.

**Table 6**. Statement of contribution.

| ID | Contribution |
|---|---|
| [A1] | ▪ I conceived the research idea, developed and programmed the proposed approach, collected the data to evaluate it, and wrote the manuscript.<br>▪ Plumeyer improved the manuscript. |
| [A2] | ▪ I conceived the research idea, developed and programmed the proposed approach, collected the data to evaluate it, and drafted the manuscript.<br>▪ Plumeyer and Böger improved the manuscript. |
| [B1] | ▪ Max and I conceived the research idea and collected the data.<br>▪ Meissner and I developed the theory.<br>▪ I analyzed the data and drafted the manuscript.<br>▪ Meissner, Max, and Decker improved the manuscript. |
| [B2] | ▪ Meissner and I conceived the research idea and developed the theory.<br>▪ I collected and preprocessed the data.<br>▪ Musalem and I analyzed the data.<br>▪ Meissner and I drafted the manuscript.<br>▪ Musalem and Decker improved the manuscript. |
| [B3] | ▪ Meissner and I conceived the research idea.<br>▪ Meissner developed the theory.<br>▪ I collected and preprocessed the data.<br>▪ Musalem and I analyzed the data.<br>▪ Meissner and I drafted the manuscript.<br>▪ Musalem and Decker improved the manuscript. |
| [C1] | ▪ Flaswinkel and I conceived the research idea and developed the theory.<br>▪ Max and I collected the data and preprocessed the data.<br>▪ I analyzed the data.<br>▪ Flaswinkel, Max, and I drafted the manuscript.<br>▪ Decker improved the manuscript. |
| [C2] | ▪ I conceived the research idea, developed the theory, collected and analyzed the data, and drafted the manuscript.<br>▪ Hydock and Decker improved the manuscript. |

### 3.1 Essay A1: Deriving Brand Associative Networks from Instagram

The increasing use of social media services has led to an enormous amount of content being shared every day. Brand-related user-generated content offers huge opportunities for learning what consumers currently think and feel about brands. Against this background, this paper presents an automatic approach for collecting, aggregating, and visualizing brand-related user-generated content. Using data from the social network Instagram, brand perceptions are visualized in the form of associative networks. To the best of the authors' knowledge, this is the first approach combining textual and tagging data, as well as network and sentiment analysis of user-generated content, from Instagram. The authors demonstrated the usefulness of the approach by deriving meaningful insights for brand managers from two brand networks. The approach enables easy and quickly accessible real-time monitoring of brands and, therefore, provides new possibilities for brand management and research. An appealing advantage of the approach arises from the versatility of social tags. Tags not only refer to single brands (e.g., #mcdonalds) but also to products (e.g., #bigmac), competitors (e.g., #burgerking), and even celebrity endorsers or detractors (e.g., #jamieoliver). Creating associative networks for additional objects of interest might yield further insights into perceptions of a specific brand and might help detect both positive and negative developments that require a reaction

### 3.2 Essay A2: Extracting Brand Information from Social Networks: Integrating Image, Text, and Social Tagging Data

Images are an essential feature of many social networking services, such as Facebook, Instagram, and Twitter. Through brand-related images, consumers communicate about brands with each other and link the brand with rich contextual and consumption experiences. However, previous articles in marketing research have concentrated on deriving brand information from textual user-generated content and have largely not considered brand-related images. The analysis of brand-related images yields at least two challenges. First, the content displayed in images is heterogeneous, and second, images rarely show what users think and feel in or about the situations displayed. To meet these challenges, this article presents a two-step approach that involves collecting, labeling, clustering, aggregating, mapping, and analyzing brand-related user-generated content. The collected data are brand-related images, caption texts, and social tags posted on Instagram. Clustering images labeled via Google Cloud Vision API enabled to identify heterogeneous contents (e.g., products) and contexts (e.g., situations) that consumers create content about. Aggregating and mapping the textual information for the resulting image clusters in the form of associative networks empowers marketers to derive meaningful insights by inferring what consumers think and feel about their brand regarding different contents and contexts. For example, brand managers can gain detailed insights of the situation about which users share brand-related images. One of the advantages of the proposed approach is the possibility to monitor effects that are not relevant for the majority of the consumers, but play an important role in specific situations.

### 3.3 Essay B1: Drivers of Celebrities' Social Media Capital

Alongside their professional careers, nowadays many celebrities also act as social media influencers. While current research shows that brands can profit from the social media popularity of celebrity endorsers, the question of how celebrities can become more popular on social media (i.e., accumulate high numbers of subscribers) has rarely been approached in the marketing literature. In this article, the authors investigate factors that increase celebrities' social media popularity, with a focus on their social media content, network, career success, and popularity gained outside the social media context. The authors analyze both visual and textual data from a sample of 1,443 celebrities (professional soccer players) with more than 350,000 posts in total on Instagram. The results show that celebrities' social media behavior is slightly more important than the popularity they have gained because of their professional career in driving social media popularity. In particular, it was found that celebrities focus too much on professional (vs. personal) content and, thus, squander potential social media popularity. Further, most celebrities increase the share of professional content over the course of their career, which has a negative effect on social media popularity. The results provide key insights into how celebrities can optimize their social media behavior, which can result in economic benefits for themselves and the brands with which they collaborate.

### 3.4 Essay B2: Disclosing Private, but Staying Focused – How Social Media Influencers Effectively Increase Post Engagement and Purchase Intention

Social media influencers (SMIs) are an integral part of today's digital brand communication strategies. Marketers take advantage of trustworthy parasocial relationships that SMIs build with their followers and, accordingly, pay them to endorse products and brands. To build trust, SMIs disclose themselves to their followers by sharing intimate moments (determining the depth of self-disclosure) on a range of topics (determining the breadth of self-disclosure). The empirical results of this research show that depth of self-disclosure drives parasocial relationship building, and more specifically trust building in SMIs, which, in turn, increases both engagement and purchase intention. Surprisingly, the authors found that a SMI's decision to focus on fewer topics can increase engagement as they are perceived as having a higher level of expertise. The empirical evidence for these findings comes from analyzing social media data of more than 2,500 SMIs on Instagram. Two additional online studies provide evidence that parasocial relationship building and trust building as well as expertise are key mechanisms that explain why "disclosing private, but staying focused" is a successful SMI strategy. Our results provide key insights into how SMIs can optimize their social media engagement, which can result in economic benefits for the brands with which they collaborate.

### 3.5 Essay B3: How Can Social Media Influencers Create Valuable Engagement for Endorsed Products?

Social-media-based influencer marketing has become a key component of digital marketing strategies. Influencers compete for social media users' attention by creating visually appealing content. Companies sponsor influencers in exchange for them advertising products in personal posts. To evaluate the effectiveness of influencer campaigns, marketers commonly track post engagement in the form of likes and comments that sponsored posts receive. Influencer payments are oftentimes based on post engagement (e.g., number of likes and comments), although this metric does not allow marketers to assess to what extent influencers were successful in directing attention to a product in a sponsored post. In this paper, the authors operationalize product engagement as the number of comments related to the product. Our analysis of more than 6,000 influencer product endorsement post on Instagram shows that some visual features that enhance post engagement decrease product engagement. Specifically, product depiction size, visual clutter of the image, and the presence of human faces have positive effects on post engagement but negative effects on product engagement. However, influencers can enhance product engagement (without diminishing post engagement substantially) by placing sponsored products more centrally and by making them more salient. Moreover, the results show that post features that direct attention toward the sponsored nature of the post positively affect both post and product engagement. The authors outline a theoretical framework based on vision research that helps understanding attentional processes in the influencer marketing context.

### 3.6 Essay C1: The Price of Popularity: Why Consumers Share More Negative Electronic Word of Mouth[7] for Big Brands

Increasing market share and awareness is among the cornerstones of each business strategy. In this article, however, it is shown that becoming popular may come at the price of receiving more negative electronic word of mouth (eWOM) ratings. In a field study on more than 100 chain restaurant brands, controlling for representative consumer brand ratings using panel data, the authors reveal more negative valence in brand-related social media posts and lower star ratings on online review platforms for big (vs. small) brands. Subsequent experiments reveal that consumers are more likely to share a positive experience with a small (vs. big) brand. Furthermore, small brand size leads to more positive eWOM valence. Two mediators can explain this relationship. First, small brands evoke a stronger need to help those same brands, which leads to more positive eWOM valence in social media articulations and online reviews. Second, consumers perceive sharing eWOM about small brands as more directly communicating with these brands, which leads to more positive eWOM valence on online review platforms and social media. The article concludes with a discussion of theoretical contributions and ends with managerial implications of how big brands can counteract the negative effects of popularity.

[7] According to Rosario et al. (2019, p. 425), electronic word-of-mouth can be defined as „consumer-generated, consumption-related communication that employs digital tools and is directed primarily to other consumers“. This concept is referred to as brand related UGC (p. 7) in this dissertation.

### 3.7 Essay C2: The Effect of Corporate Political Advocacy on Brand Perception: An Event Study Analysis

In recent years brands have increasingly engaged in corporate political advocacy (CPA; also termed brand activism or corporate sociopolitical activity) by taking positions on polarizing sociopolitical issues. Recent experimental research suggests that consumers respond to CPA based on its alignment with their own values, and that it typically induces an overall negative response. This research provides additional insights by exploring consumer brand perceptions following CPA. An event study of 106 CPA events and weekly consumer brand perception data was conducted. A regression model was used to investigate the moderating effects of CPA effort, concurrence, and the strength of the online protests evoked by the CPA. The results show that CPA has a negative effect on consumers' brand perceptions and that the effect is stronger for customers relative to non-customers. The negative effect was attenuated by CPA concurrence and amplified by effort. Additionally, online protests were driven by CPA effort and had a strong negative effect on brand perception. Online protests were stronger in the past, and in turn, the negative effects of CPA on brand perceptions have slightly weakened in recent years. This article contributes to the existing literature by highlighting the role of online protests following CPA and distinguishing consumer and customer responses. This study also provides converging evidence of the moderating effects of effort and concurrence identified in previous studies. The results help managers to reduce potential negative outcomes of CPA.

# 4. Conclusion and Future Research

In the following, the findings of the individual essay of this dissertation will be briefly summarized. Afterwards, theoretical and methodological contributions that stem from the joint consideration of the research essays and go beyond the contributions listed in the individual essays will be discussed. In the last part of this chapter, several limitations of the current research that translate into opportunities for future research are presented.

## 4.1 Summary of Findings and Managerial Implications

The aim of this dissertation was to advance the academic knowledge and derive practical implications within the three presented research areas. These implications are primarily important for managers of brands and SMIs that collaborate with brands. To achieve this goal, this dissertation comprises seven essays that deal with the phenomenon of brand-related UGC and are related to three distinct research areas taking different perspectives on how the proliferation of UGC affects the interplay between consumers and brands. The dissertation is based on and evolves the conceptual framework by Hennig-Thurau et al. (2010) that aims to explain how the passive role of the consumer as the receiver of marketing and traditional mass media communication has turned into an active role as a creator of UGC that influences the attitude and behavior of other consumers.

The first two essays of this dissertation show how brands can utilize UGC in order to learn what consumers associate with their brand. Essay A1 shows that using tag and open text data from Instagram enables marketers to extract relevant brand perceptions, their respective associations strength, as well as their valence, from UGC on Instagram. Essay A2 evolves the method by showing that visual UGC reveals information about the situation in which consumers share their experience via UGC. The findings suggest that consumers connect different associations with brands depending on the situation they experience. The presented method is able to capture the multitude of different situations consumers experience with a brand in an unsupervised way and, in a second step, extract relevant associations.

The next three essays of this dissertation belonging to research area B investigate how influential individuals affect the behavior of many others via UGC and how brands can effectively collaborate with said individuals. The first essay B1 investigates how celebrities can increase their influence on social media by accumulating more subscribers for the content they share. One of the key variables in the underlying statistical model is the share of personal content, i.e., how often should celebrities self-disclosure moments from their personal life vs. professional life. It was found that celebrities focus too much on professional (vs. personal) self-disclosure and, thus, squander potential social media popularity. Further, most celebrities increase the share of professional self-disclosure over the course of their career, which has a negative effect on social media popularity. Essay B2 goes deeper into the psychological mechanisms of self-disclosure by investigating how breadth and depth of self-disclosure can help to build stronger parasocial relationships with subscribers while maintaining the perception as an expert in a substantial field such as fitness or food products. The empirical results of this research indicate that depth of self-disclosure drives parasocial relationship building, and more specifically trust building in SMIs, which, in turn, increases both engagement and purchase intention. It was found that a SMI's decision to focus on fewer topics can increase engagement as they are perceived as having a higher level of expertise. While B1 and B2 focus on the perspective of the SMI, B3 incorporates the brand perspective by showing how the design of a product endorsement post on Instagram differently affects the goals of the SMI (i.e., creating high levels of engagement for their post) and brand (i.e., creating high levels of engagement for the endorsed product). Among others, the authors show that product depiction size, visual clutter of the image, and the presence of human faces are associated with greater post engagement but less frequent product engagement. However, influencers might be able to enhance product engagement without substantially diminishing post engagement by placing sponsored products more centrally and by making them more salient. Additionally, certain top-down processes triggered, for example, by visible cues of sponsorship disclosure, can simultaneously increase post and product engagement.

The last two essays of this dissertation, C1 and C2, investigate threats of negative UGC. First, essay C1 shows that consumers are more likely to share negative UGC about brands with a high vs. low market share. As increasing market share is a common goal of any profit-oriented business, the essay investigates the psychological mechanisms that explain why big brands get more negative UGC compare to small brands. Two mediators can explain this relationship. First, small brands evoke a stronger need to help them, which leads to more positive UGC valence in social media articulations and online reviews. Second, consumers perceive sharing UGC about small brands as more directly communicating with these brands, which leads to more positive UGC valence on online review platforms and social media. The second essay, C2, shows that consumers share high amounts of negative UGC when a brand takes a controversial political position, especially if the brand invests high effort, by, for example, spending money on a political cause. It is further shown that, as a consequence, the volume of negative UGC leads to a less positive brand perception. Finally, the authors found evidence that the volume of negative UGC was higher in the past.

## 4.2 Theoretical Contribution

The essays of this dissertation are built on and advance theories related to the creation (i.e., why do consumers create UGC) and consumption (i.e., how does the consumption of UGC affect consumer behavior) of UGC. In the following, two important theories underlying the research of this dissertation will be discussed and it will be explained how they are applied within the context of UGC and how the individual essays contribute to the theoretical understanding over and above the theoretical contributions already explained in the individual essays.

*Social Penetration Theory*. Social Penetration Theory (SPT, Altman & Taylor 1973) posits that self-disclosure (i.e., revealing beliefs concerning self-identity by sharing personally relevant feelings, thoughts, values, and believes) is a key element of building more intimate interpersonal relationships (Prisbell & Anderson, 1980). The theory is commonly used to explain why consumers form parasocial relationships among themselves and with SMIs in social networks (Chung & Cho 2017). In essay B1 the authors build on SPT to hypothesize that personal (vs. professional) self-disclosure is positively related to the popularity of celebrities on social media as those with higher personal self-disclosure build stronger relationships with their subscribers. Further, SPT posits that relationships strengthen over time with the proliferation of more intimate information. The authors accordingly hypothesis that celebrities should increase personal self-disclosure over time. Both hypotheses found support from the estimated model. In essay B2, two dimensions of self-disclosure, namely breadth (i.e., how many topics does a SMI cover in her conversation) and depth (i.e., how intimate the conversation is), and their effect on consumer engagement on social media was investigated. While the authors show that depth of self-disclosure increases engagement based on the theory that SMIs who share more intimate moments form stronger parasocial relationships, they find a negative effect of breadth on engagement. Subsequent surveys show that this effect might be caused by a lack of perceived expertise that stems from focusing on too many topics. Both essays contribute to SPT and its application in UGC research by showing that SPT can help to understand how individuals in social networks form relationships and how these relationships affect consumer engagement in turn. While SPT is traditionally used in the context of personal, non-parasocial, relationship building, this dissertation contributes to the theory by showing its application in the context of social media self-disclosure. Especially, the two essays find evidence for the theory-driven assumption that building relationships on social media has similarities with personal relationship building as captured by SPT. Therefore, this dissertation further develops SPT in the context of social media and SMI marketing, which are both important fields of future research.

*Cognitive Dissonance Theory*. Following the theory of cognitive dissonance (CDT, Festinger 1957), consumers share UGC in order to regulate their emotions by reducing dissonance (Berger 2014). For example, a consumer might share negative UGC on a review platform after an unsatisfying experience in a restaurant. Accordingly, dissonance can be considered a antecedent of creating UGC, and is therefore related to the two essays in research area C. In C1, the authors build on CDT to explain why consumers share less negative UGC for small brands. First, they show that consumers perceive smaller brands to be in higher need for help given that they face stronger competitors. Second, following equity theory (Adams 1963), dissonance is created in tension systems that arrive from cost-reward relationships that are perceived as not fair. As big brands are perceived as less in need for help, rewarding them with a positive review is not necessary to restore equity. The essay therefore contributes to the theory by showing that brand size might be an important factor in determining when consumers perceive exchanges as fair and, in contrast, when they vent negative feeling via negative brand-related UGC. In essay C2, the authors show that consumers create negative UGC after brands take a controversial political stand. Based on CDT, Heider (1958) proposed the balance theory, which assumes that dissonance is created when a set of attitudes is inconsistent. In the case of CPA, when a consumer perceives a brand as favorable but a certain politician as unfavorable, this consumer might experience cognitive dissonance when the brands starts supporting the politician or the political views he supports. In this case, consumers might change their attitude regarding the brand or the politician to reduce dissonance and, further, create negative UGC, which is observe in the data. The authors further find that effort amplifies the effect, which is in line with correspondent inference theory (Berkowitz 1965). The theory argues that consumers infer the internal disposition of a correspondent (i.e., the brand taking a stand) based on observable actions, and that more Effort signals one's commitment to a goal (Novacek and Lazarus 1990) and internal motivation (Dik and Aarts 2007). In this regard, the essay links correspondent inference and CDT in the context of UGC by showing how correspondent inference can increase consumers' motivation to reduce dissonance by sharing negative UGC. In summary, this dissertation contributes to CDT by applying it in the context of negative experiences with big (vs. small) brands and in the context of CPA, where dissonance might play a key role in consumers' motivation to change attitudes and participate in an online protest.

### 4.3 Methodological Contribution

Above the substantial contributions regarding the three areas of research listed above, the essays of this dissertation feature a broad range of methods used to process data from UGC. Apart from a few exceptions (e.g., product reviews with standardized one to five star ratings), UGC can be seen as qualitative data comparable to focus group data or depth interviews, as there is no predefined format that UGC creators need to follow (Netzer et al. 2012). As researchers often aim to test their hypothesis by measuring the underlying phenomena on a quantitative scale, it is inevitable to transform the vast amount of unstructured UGC into variables with structured data. This task can sometimes be demanding and Netzer et al. (2012) introduced their essay by saying that "Consumer generated content on the Web is both a blessing and a curse." (p. 521). In the following, different types of data will be briefly summarized and it will be outlined how they are used in the different essays.

*Textual UGC*. Most of the information consumers create on the internet is text based. For example, consumers write reviews about products, create a tweet about a brand they don't like, or comment the Instagram post of a SMI on Instagram. As shown in Table 6, textual UGC can be subdivided into hashtags (i.e., single words that often follow a given taxonomy) and free texts that are highly idiosyncratic (i.e., different users might use different words to describe the same thing). In essays A1 and A2, hashtags are used to capture concepts that consumers associate with a brand. Both articles are based on the idea that hashtags reduce heterogeneity in individual word usage to an abstract concept that helps to measure a more homogeneous set of brand associations with higher informational value compared to idiosyncratic text (Nam et al. 2017). In C1, hashtags are used to detect twitter posts that are related to an online protest against a brand's political standpoint. In fact, hashtags are often used in social movements as a tool for organization as it is easy to express support by using a common hashtags like #blacklivesmatter (Hansen et al. 2018). This example again shows the high semantic gist of this form of textual UGC.

**Table 7.** Application of textual UGC.

| ID | Type of data | Application |
|---|---|---|
| [A1] | Hashtag | Analyze co-occurrence of hashtags to elicit associative structure of brand perceptions |
| [A1] | Text | Sentiment detection for social media posts |
| [B2] | Text | Topic-model to measure heterogeneity in SMI posts |
| [B2] | Text | Analyze keywords to measure intimacy of SMI posts with LIWC |
| [B3] | Text | Sentiment detection for SMI posts |
| [B3] | Text | Analyze comments that mention the product category to operationalize product engagement |
| [B3] | Text | Analyze the text of the SMI posts to operationalize sponsorship disclosure and product mentions |
| [C1] | Text | Sentiment detection for brand related social media posts |
| [C2] | Hashtag | Analyze social media posts with #boycott to operationalize the volume of digital protests |

In contrast, open or free text (i.e., text that does not follow any rules regarding the usage of specific words) is more challenging to work with. The most convenient method is a dictionary based approach (Hartmann et al. 2019) for which the researchers sets a list of words that are assumed to capture a phenomenon (e.g., SMIs use the word "sponsored" when they endorse a brand) and then analyzes if the word is used in an observed text or not. This method is for example applied in B3, where the authors classify comments on SMIs' Instagram posts into those that engage for the product (e.g., "I like the watch.") and those that engage for the post or the SMI (e.g., "I like your posts." or "You look beautiful!"). To do so, the authors created a dictionary of words that represent the product and the product category. Dictionaries can also be used to measure the sentiment of the text (Gilbert & Hutto 2014) or the intimacy of communication (Melumad & Meyer 2020). The first is applied in A1, A2, B3, and C1 to capture the sentiment of UGC. The second is applied in B2 where the authors used the Linguistic Inquiry and Word Count (LIWC) dictionary that assigns words into categories that are linked to different dimensions of thoughts, feelings, personality, and motivations (Pennebaker, et al. 2015). A third method to analyze textual UGC, namely topic modeling, is applied in B2. A topic model is an unsupervised machine learning approach that identifies latent topics that are characterized by a vector that assigns a probability to each word in the corpus. These latent topics can then be interpreted by the researcher based on words that are very common within the respective topic. In B2, the authors used a Latent Dirichlet allocation (Blei 2003) model to distinguish between different topics that SMIs communicate about (e.g., food, fitness, and fashion). The authors were then able to measure if an SMIs focuses more on a specific topic or uses a broad range of different topics in her UGC. In summary, the essays of this dissertation show how researchers can use different types of textual data to compute meaningful variables that capture underlying phenomena of consumer behavior. Essays A1 and A2 are among the few academic essays that exemplify the informational value of social tags and especially, how this information can be enhanced by linking it with sentiment scores derived from user-generated texts. Further, to the best of my knowledge, B2 is the first essay that shows how to measure the heterogeneity of topics that users create content on. Future research can transfer the presented model and metrics to study topic heterogeneity in other domains, for example brand-generated content.

*Visual UGC.* In addition to textual UGC, an increase of visual UGC can be observed in the last decade. Popular social media websites like Instagram, Youtube, and TikTok are based on the idea that consumers share visual UGC that they record, primarily, with the camera of their smartphone. A major challenge in, for example, images is that there is no direct way to match them with keywords. In other words, while low effort is required to evaluate if the word "pizza" appears in a text, it is more elaborate to evaluate if a given image shows a pizza. In this dissertation, machine learning models from Google Vision (Google 2021) that are pre-trained on a large dataset of images are applied to extract annotations that are appropriate to describe the elements of an image. These annotations can in the next step be used as binary (i.e., is there a pizza in the image?) or continuous (i.e., how likely is it that there is a pizza in the image?) variables in traditional statistical models. For example, in A2, the authors use these keywords to conduct a cluster analysis on user-generated images on Instagram that are related to the brand McDonald's. The authors were thus able to distinguish between different situations consumers experience with a brand in order to infer which brand associations are important depending on the situation. The presented method can now be used by other researchers in other contexts, for example to not only study SMI topic heterogeneity with texts, but also with visual communication. In essay B1, the authors use images from football players on Instagram and train a decision tree based on the keywords associated with each image. The classifier was then able to accurately predict if a given images depicts a professional (i.e., football related) or private moment from the life of the person. The authors used this information to infer how strong the SMIs focus on professional vs. private content within the communication with their fans. The contributed method can be applied by other researchers to, for example, visual brand-generated content to study how consumers react to different kinds of advertising.  In B3, the authors detect products (e.g., watches and shoes) from images shared by SMIs. They were then able to measure the size, centrality, and saliency of the object to estimate how these metrics affect the consumer engagement for the product. The authors were also able to detect whether the SMI herself is present on the image. In summary, the essays of this dissertation show how to integrate visual UGC into an empirical analysis and how pre-trained models can be used to make the informational value of user-generated images accessible. The methodological contribution is that the presented methods can now be applied by other researchers to new contexts.

## 4.4 Limitations and Future Research

The essays in this dissertation yield several suggestions for future research as discussed in the future research sections in the individual essays. However, ideas for future research also stem from a joint consideration of each research area's essays as well as a joint consideration of the three research fields elaborated on in this dissertation. In the following, three areas for future research as well as their relationship with the limitations of the essays of this dissertation will be discussed.

*User-Generated Videos*. Deriving brand perception, or brand related information in general, from UGC has established as a popular research stream in the last years, with new top-tier publications advancing the methods used to listen to consumers brand-related conversations on the internet (e.g., Rust et al. 2021). As presented in essay A2, different types of UGC might yields different insights and a combination of multiple data formats is able to deliver more nuanced insights that are potentially hard to unveil even with traditional survey methods. In this regard, research has not yet investigated how consumer-generated videos can be utilized to extract brand-perceptions. As videos are a combination of visual and auditory information, extracting meaningful brand-related information is far from simple. However, marketing and other researchers have started to operationalize business-relevant metrics from video (Schwenzow et al. 2021) and audio (Hildebrand et al. 2020) data that, in a second step, could be used as a starting point to uncover the relationships between brand-related user-generated videos and brand perception.

Videos might not only be interesting for deriving brand perception, but nowadays also play a crucial role for SMIs, as video-sharing platforms like TikTok and Instagram are among the most popular choices for brands. While research has investigate the drivers of engagement and persuasive mechanisms for textual (Hughes et al. 2019) and visual UGC (see essay B3; Lie & Xie 2020; Hartmann et al. 2021), it is unclear how SMIs can effectively endorse brands with videos. A first step in this direction are the findings by Wang et al. (2021) showing how vocal tone affects persuasiveness. Yet the interplay between the visual and auditory presentation of products and brands within SMI generated content yields a multitude of questions to be answered by future research. For example, how do consumers infer trust and expertise from videos and what drives their attention to products and brands presented in a video?

*Self-selection and UGC*. A current issue of UGC research is the observation that consumers self-select to share UGC (Moe & Schweidel 2012). As a consequence, brands that infer consumer behavior (e.g., brand perceptions or consumer preferences) from UGC only observe the content of a non-random sample of consumers. Novel research tries to investigate why and in which ways consumers self-select to create UGC (Schoenmueller et al. 2020) and how platforms can motivate consumers to share UGC in order to overcome or at least reduce self-selection bias (Askalidis et al. 2017; Karaman 2020). Understanding self-selection is a keen interest for behavioral researchers that aim to understand consumer motivations in the context of UGC as well as platform operators that want to provide consumers an unbiased evaluation of, for example, product ratings. Further, brands need to understand the self-selection process in order to effectively use UGC as a source of consumer data. Brands also aim at receiving favorable UGC, and understanding the self-selection process might help to define a marketing strategy that leads to improved UGC. In this dissertation, essay C1 shows that self-selection can depend on the market-share of the brand and that big brands receive less positive UGC, even if their customers are equally satisfied with their products. In this regard, connecting research areas A and C is promising for future research to develop methods that are able to, among others, derive brand perception from UGC while controlling for processes of self-selection. It might be beneficial to mix UGC with survey data that represents the target group of the brand in order to learn how a random sample of relevant consumers differs from the self-selected sample of UGC.

*Selective Audiences of UGC.* Self-selection does not only appear in the creation process but also in the dissemination of UGC. First, consumers typically chose which content they want to see by subscribing only to a limited set of creators. While traditional media also allowed consumers to be selective (i.e., deciding for a certain TV channel or newspaper), the range of UGC creators is much bigger which makes it easy to find information from extremely like-minded people. Second, based on a set of UGC creators a consumer has decided to subscribe, most platforms like Instagram and Twitter suggest new content with algorithms based on the existing subscriptions. As a results, social media might reinforce echo chambers wherein consumers are exposed only to ideas by like-minded people (Appell et al. 2019). This phenomenon has several implications for marketing that are related to the essays in this dissertation. For example, selective audiences might be one of the reasons explaining the strong engagement for SMI posts as investigated in B3. In B2, the authors show that SMIs focusing their UGC on a small number of topics achieve higher engagement among their subscribers. In the essay the authors argue that communicating on a broad range of topics negatively affects perceived expertise regarding a focal topic but positively affects the parasocial relationship between the SMI and subscribers as the subscribers learns more about different facets of the influencers' life. However, on social media, consumers might be selective in a way that they subscribe to a specific SMI primarily based on a focal topic (e.g., shared interest in fitness) and sharing UGC on a broad range of topics does not fit consumers' expectations in the social media environment. Therefore, future research might investigate in how far social media echo chambers amplify consumers' selection process and their preference to receive UGC from like-minded persons. It would further be of importance to investigate how sampling observations from social media is biased by echo chambers and how researchers can potentially correct for this effect in econometric models (Ruths & Pfeffers 2014).

This research topic is also linked to a political context, as echo chambers might drive political polarization (Bakshy et al. 2015; Cinelli et al. 2021). In essay C2, the authors elucidate the critical role of online protests as a consequence to corporate political advocacy. Following the above argumentation on selective audiences, future research might investigate further how the audience selectivity of UGC explains the recent increase in online protests and to which extent brands should react to these forms. Further, by tanking a stand on controversial political issues as investigated in C2, brands themselves follow the logic of selective audiences as they expect consumers to shift to brands that are more like-minded (Schoenmueller et al. 2019). In this regard, future research needs to investigate how the political polarization of brands affects the polarization of the society and how marketing of brands has changed due to political polarization.

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# APPENDIX A: Dissertation Essays

# Essays on Brand-Related User-Generated Content in Online Social Networks

# About this Appendix

This appendix contains all seven essays referred to in the main document of this dissertation. In case the manuscripts were already published in an academic journal, the author accepted manuscripts are presented, which is in line with the respective Journals' copyright agreement. For the working papers, I present the manuscript at the stage of writing this dissertation.

# LIST OF ESSAYS

# Essay A1: Deriving Brand Associative Networks from Instagram

# Deriving Brand Associative Networks from Instagram

Abstract

The increasing use of social media services has led to an enormous amount of content being shared every day. Brand-related user-generated content offers huge opportunities for learning what consumers currently think and feel about brands. Against this background, this paper presents an automatic approach for collecting, aggregating, and visualizing brand-related user-generated content. Using data from the social network Instagram, brand perceptions are visualized in the form of associative networks. To the best of our knowledge, this is the first approach combining textual and tagging data, as well as network and sentiment analysis of user-generated content, from Instagram. We demonstrate the usefulness of our approach by deriving meaningful insights for brand managers from two brand networks. The approach enables easy and quickly accessible real-time monitoring of brands and, therefore, provides new possibilities for brand management and research.

**Keywords:** *Brand perception; Instagram; user-generated content*

***Track:*** Product and Brand Management

## 1. Introduction

The ongoing spread of user-generated content (UGC) marks one of the most significant developments in the field of marketing in recent years. Previously, to understand how consumers perceive brands, marketers usually had to employ costly and time-intensive market research methods. Today, consumers voluntarily engage on social networks and share content publicly, opening a new channel to hear the voice of the consumer (Moe, Netzer, & Schweidel, 2017). However, users not only share information in the form of UGC but also express themselves, their opinions, and their attitudes in this way (Manikonda, Meduri, & Kambhampati, 2016). In recent years, various studies have concentrated on extracting brand information from different types of UGC, such as consumer messages from forums (Netzer, Feldman, Goldenberg, & Fresko, 2012), product reviews (Gensler, Völckner, Egger, Fischbach, &

Schoder, 2015; Lee & Bradlow, 2011; Tirunillai & Tellis, 2012), social tags (Nam & Kannan, 2014; Nam, Joshi, & Kannan, 2017), social connections on Twitter (Culotta & Cutler, 2016), and tweets (Liu, Burns, & Hou, 2017).

This paper presents an approach for digital brand mapping that involves collecting, aggregating, and visualizing brand-related UGC. In line with Nam et al. (2017), social tags are collected to extract brand perceptions. In contrast with their research, this paper specifically focuses on data from Instagram, combines information extracted from captions and tags, and integrates sentiment and network analysis. Instagram is the world's most successful social network for brand–post interaction (Gottke, 2016), and it is number one for Generation Z in terms of coolness and awareness (Google, 2017a). Moreover, it is characterized by high dynamics revealing users' opinions and attitudes. Additionally, a remarkable proportion of UGC on Instagram is brand-related, with users, for example, creating over 63 million posts tagged with #nike. Visualizing brand perceptions in the form of associative networks based on this data enables marketers to gain comprehensive, up-to-date insights into what consumers actually think and feel about brands. The approach allows easy and quickly accessible real-time monitoring of brands because it runs automatically and therefore saves time and money.

In the following section, the theoretical background is provided, followed by a description of the approach. Then, two empirical applications are presented to demonstrate its usefulness. The article concludes with a discussion of the findings, their limitations, and directions for future research.

## 2. Theoretical and Practical Background

### 2.1 Literature overview

Researchers' interest in UGC has been increasing in line with the rapidly growing volume and impact of UGC, yielding various studies on extracting brand information from UGC. These studies vary in terms of their data sources, type of data, visualization of brand perceptions, use of predefined attributes, and applied sentiment analysis. Some studies have highlighted the value of UGC by using the content to predict brand performance measures (Nam & Kannan, 2014; Tirunillai & Tellis, 2012). Gensler et al. (2015) created brand maps based on product review data. Using natural language tokenization on review text and reviews' predefined pro and con categories allowed them to extract positive and negative brand associations. Nam et al. (2017) elicited brand associations from social tag co-occurrence and emphasized the information contained in social tags by extracting key representative topics, monitoring common dynamic trends, and understanding heterogeneous brand perceptions.

### 2.2 Instagram social network

Although the Instagram social network features an enormous amount of content on brands, academic research on the informational value of Instagram's content is scarce in the field of marketing. On Instagram, users share photos, give them a caption, and tag them with keywords, and other users can "like" and comment on these uploads. This content can be seen as a valuable source for brand management because Instagram users present their identities on the social network, refer to everyday moments, and express emotional attitudes with a relatively high level of intimacy (Sheldon & Bryant, 2016). Instagram, in contrast with Facebook, does not focus on social relationships but on personal identities (Marcus, 2015), and Instagram users are more likely to offer personal and intimate content than Twitter users (Manikonda et al., 2016).

Like other social networks, Instagram involves the use of social tags. Social tags, also called hashtags, are usually space-free words and phrases that begin with a "#." They are used to categorize and describe any possible object (e.g., photos, comments, and bookmarks). Not only does this enable a user to find the object later, but it also allows every other user to find objects in which he or she is interested (Strohmaier, Körner, & Kern, 2010). Accordingly, users can label content about a brand (e.g., Adidas) by using the brand name as a tag (e.g., #adidas). Nam and Kannan (2014, p. 24) underlined that "social tags can be viewed as the categorization or description of content filtered through the lens of an individual user's knowledge structure." As social tags reflect a user's knowledge, they also indicate what users think and feel about brands.

## 3. Constructing Associative Networks

Instagram is dominated by emerging topics and trends, and content usually has a relative short life. Thus, instead of historical data, new posts receiving a brand tag are tracked using a Python-based automated Web crawler. The text, which contains tags and a caption, is extracted for every new post tagged with the brand of interest. To clean up Instagram's noisy captions, tags and emojis are identified and separated, whereupon the text is cleaned of any non-text characters. Emojis that represent sentiment (e.g., smileys) are translated into western-style emoticons and returned to the caption text, as they will be taken into consideration for a sentiment analysis. The language of posts is analyzed using Google Cloud Translation API (Google, 2017b). Posts that can clearly be identified as being in the English language will be stored in the final data file while posts without text will be removed. This cleaning process is required to ensure that no language-specific bias influences the sentiment detection. To analyze the sentiment of a caption, a rule-based sentiment detector by Hutto and Gilbert (2014) is applied as it provides two benefits: First, the algorithm is explicitly designed for short social media texts and involves characteristic abbreviations and emoticons. Second, the algorithm scores high on classification accuracy and does not depend on a training sample (Hutto & Gilbert, 2014). After conducting these steps, the final spreadsheet includes a row for each post with a caption text in English containing the caption's sentiment score and a list of the tags used.

To create a network, nodes are used to represent the tags that appear most frequently related to a brand, and edges represent the connection strength among tags. Accordingly, we refer to tags that appear in the associative network (i.e., the most frequently used tags) as brand associations. The connection strength of two tags is measured using the frequency of their co-occurrence (i.e., the number of Instagram posts tagged with both tags). As some tags are popular while others occur only rarely but still provide valuable information for the associative network, the frequency of co-occurrence is scaled considering the total frequency of a tag's appearance (Nam et al., 2017).

To limit the computational time and to focus on more impactful tags, the number of nodes is limited by a lower boundary of occurrence frequency or a user-specific upper boundary of nodes. For every tag in the network, the sentiment analysis provides a sentiment value between -1 and 1, calculated as the mean sentiment score of all posts that contain the tag. To compute node positions in a pleasing way, a force-directed graph algorithm is needed. Using the Fruchterman and Reingold (1991) algorithm, which is popular in research and included in several software applications, neatly arranged networks with a minimum of edge crossings, and equal edge length can be achieved. Here, the connection strength of two nodes is not represented as the Euclidean distance in the graph, but by the color of the edge. This procedure can represent all variance in the data and tends to place connected tags next to each other to prevent line crossings and overly long edges.

Edge color is adapted to represent association connection strength by indicating a strong (weak) co-occurrence with a dark (bright) edge. The node size depends on the mere occurrence of a tag and indicates how relevant an association is. The node color depends on the sentiment of the association, ranging from red (negative) to yellow (neutral) to green (positive). The sentiment range can be adjusted to include informational values represented by a full color range. The researcher can adjust parameters to obtain a distinctive representation of the variance in the data.

## 4. Empirical Application

Our empirical application is based on a dataset of 100,000 Instagram posts tagged with #mcdonalds, the common tag used to refer to the brand McDonald's. McDonald's is not only mentioned in more than five million Instagram posts but also yields some characteristics that make it a promising choice for elaborating brand perceptions: McDonald's involves high awareness and involvement and has a polarizing capacity that might lead to greater variance in certain metrics (Mafael, Gottschalk, & Kreis, 2016). Of the total posts, 37,537 were classified as written in English and therefore were retained for further analysis. The mean number of tags used was 9.7 (11.1 for the whole dataset). The data was tracked between January 22 and March 6, 2017 and reflects all data posted in this period.

To create a network from the given data, some parameters can be set by the researcher. These solely influence the way the network is depicted, and they can be freely chosen to match the researcher's needs. Figure 1 displays the top 40 tags for McDonald's. The network constructs a node for each of the 40 tags that occur more frequently in posts tagged with #mcdonalds. Here, edges are created for a minimum scaled co-occurrence of $c_{min} = 0.15$.

Figure 1 reveals interesting insights into how McDonald's is perceived. As expected, the map reflects McDonald's capacity to polarize: While most brand associations have a positive sentiment, a cluster of associations is characterized by negative sentiments. Competitors such as "kfc" and "burgerking," meat components such as "beef" and "bacon," and detractors such as "jamieoliver," a British celebrity chef suing the McDonald's company since 2012, can be found among this negatively perceived cluster of associations. The cluster could be interpreted as a proxy for the negative political chatter about McDonald's on the social network. Thus, marketers should carefully monitor the cluster to identify negative sentiments that could easily spread on Instagram and aim marketing efforts at negative associations. Considering McDonald's products, a marketer could observe product-range clusters that might contribute to adjusted marketing communications. Here, for instance, insights are yielded by the tag "shamrockshake," referring to a promotional shake for St. Patrick's Day. The tag not only reflects the awareness that the shake has generated but also reveals how impactful a transitory trend can be on Instagram. This again indicates Instagram's value as a source for detecting recent trends and buzzing topics.

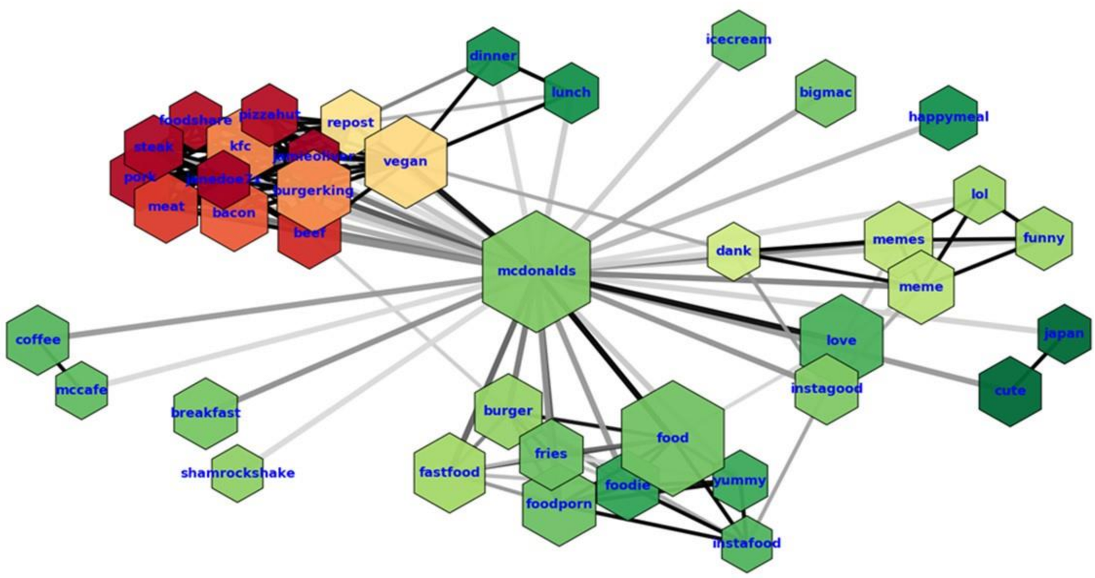


Figure 1. Associative network for McDonald's

Comparing brands' associative networks helps to identify a brand's strengths and weaknesses and unique associations and to investigate competitive market structures (Gensler et al., 2015; Netzer et al., 2012). Therefore, we focused on Adidas and Nike to analyze points of parity and points of difference, which are particularly revealing for such strong competitors. Figure 2 shows the associative network for both apparel brands. The network is based on a sample of 50,000 posts tagged with #adidas and 50,000 posts tagged with #nike.

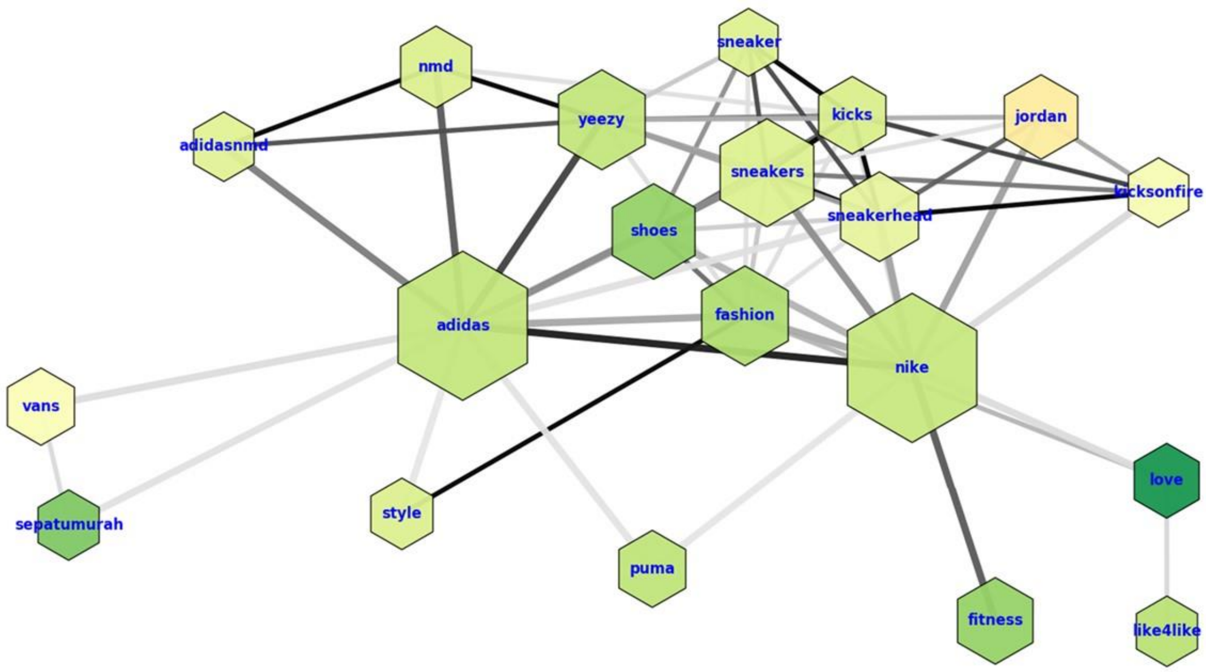


Figure 2. Competitive associative network for Adidas and Nike

Both brands receive many similar associations but still differ in some important aspects. In general, Nike predominates in terms of abstract, brand-related associations while Adidas has more concrete, product-related associations. "Fashion" is shared by both brands, while Nike receives the abstract associations "fitness" and "love," and Adidas is slightly connected to "style." The perception of Nike as a fitness brand is in line with the decades in which the company has presented famous athletes in its ads (e.g., Serena Williams). Adidas' unique perception is emphasized by the strong linkage to the sneaker models "yeezy" and "nmd," both of which are characterized by positive sentiments. In contrast, "jordan" (i.e., the sneaker model) is the only product-related association Nike receives, and it is characterized by a rather negative sentiment. For Nike's marketers, investigating the reasons for the negative sentiment toward this sneaker model may be recommended. Additional competitive landscape insights can be gained based on the appearance of two more brands. Adidas and Nike are both connected to their competitor Puma while Adidas also shares similarities with Vans. This analysis enables marketers to check whether the findings go hand in hand with current marketing strategies and with the intended positioning of the corresponding brand.

## 5. Discussion

This paper introduces an approach to measuring brand perceptions based on data collected from the social network Instagram. The approach is a first attempt at mining the rich informational value included in the vast amount of data shared by users all over the world on Instagram every day, and it features at least three advantages: First, the approach benefits from its ease of use. All information that is needed to create associative networks can be collected automatically in a very short timeframe and for free, unlike traditional surveys that are usually time and labor intensive. The second benefit is the resulting associative network that provides an up-to-date visualization of relevant brand associations and might reflect temporal developments over time. This temporal flexibility increases the scope of application, as the real-time monitoring of brands may assist marketers in making decisions and reacting to emerging topics, such as by improving awareness and evaluations of newly introduced brand extensions or ads. Consequently, the approach is also suitable for marketing control, especially, but not exclusively, in the context of monitoring social and viral marketing activities and their impact. In this way, the approach is the opposite of collecting historical data, which usually represent rigid snapshots in time. Third, an appealing advantage of the approach arises from the versatility of social tags. Tags not only refer to single brands (e.g., #mcdonalds) but also to products (e.g., #bigmac), competitors (e.g., #burgerking), and even celebrity endorsers or detractors (e.g., #jamieoliver). Creating associative networks for additional objects of interest might yield further insights into perceptions of a specific brand and might help detect both positive and negative developments that require a reaction.

As with every study, this one has a few limitations. First, measuring brand perceptions based on secondary data extracted from social networks cannot fully replace traditional techniques. For instance, experiments that focus on brand perceptions can hardly be conducted using UGC as the data source. A second limitation is the lack of information about specific Instagram users. In traditional surveys, various pieces of information can be collected about respondents (e.g., sociodemographics) that enrich brand-related data.

Finally, various promising directions can be identified for future research. As the use of social tags is not restricted to Instagram, such research could examine to what degree different sources of social tags reveal similar results.

We hope that this work can serve as a starting point for further investigating the potential of social networks like Instagram for brand management.

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# Essay A2: Extracting Brand Information from Social Networks: Integrating Image, Text, and Social Tagging Data

# Extracting Brand Information from Social Networks: Integrating Image, Text, and Social Tagging Data


**Abstract**

Images are an essential feature of many social networking services, such as Facebook, Instagram, and Twitter. Through brand-related images, consumers communicate about brands with each other and link the brand with rich contextual and consumption experiences. However, previous articles in marketing research have concentrated on deriving brand information from textual user-generated content and have largely not considered brand-related images. The analysis of brand-related images yields at least two challenges. First, the content displayed in images is heterogeneous, and second, images rarely show what users think and feel in or about the situations displayed. To meet these challenges, this article presents a two-step approach that involves collecting, labeling, clustering, aggregating, mapping, and analyzing brand-related user-generated content. The collected data are brand-related images, caption texts, and social tags posted on Instagram. Clustering images labeled via Google Cloud Vision API enabled to identify heterogeneous contents (e.g. products) and contexts (e.g. situations) that consumers create content about. Aggregating and mapping the textual information for the resulting image clusters in the form of associative networks empowers marketers to derive meaningful insights by inferring what consumers think and feel about their brand regarding different contents and contexts.



**Keywords:** Brand associative network; image classification; Instagram; sentiment analysis; social tag; user-generated content


## 1. Introduction

The ongoing spread of brand-related user-generated content (UGC) marks one of the most significant recent developments in the domain of marketing. Before this development, market researchers and brand managers had to employ costly and time-intensive surveys to understand how consumers experience, perceive, and interact with brands. Today, consumers voluntarily turn to online social networking services and publicly share this information for everyone to see. This public sharing of brand-related UGC has opened a window through which researchers and firms can hear the voice of the consumer (Moe, Netzer, & Schweidel, 2017).

In previous years, several articles have concentrated on deriving brand information from different types of UGC, including product reviews (Decker & Trusov, 2010; Gensler, Völckner, Egger, Fischbach, & Schoder, 2015; Lee & Bradlow, 2011; Moon & Kamakura, 2017; Tirunillai & Tellis, 2012, 2014), consumer messages from forums (Netzer, Feldman, Goldenberg, & Fresko, 2012), social tags (Nam & Kannan 2014; Nam, Joshi, & Kannan, 2017), social connections (Culotta & Cutler, 2016), and tweets (Liu, Burns, & Hou, 2017a).

Surprisingly, marketing research has paid little attention to the large amount of visual brand-related UGC (e.g., images).

However, images are an essential feature of many social networking services, such as Facebook, Instagram, and Twitter. In a first attempt to analyze brand-related images, Liu, Dzyabura, and Mizik (2017b) underlined that through brand-related images, consumers communicate about brands with each other and link the brand with rich contextual and consumption experiences. Consequently, incorporating an analysis of brand-related images is important to obtain a comprehensive understanding of brand-related UGC. Nevertheless, the analysis of brand-related images yields at least two challenges.

First, brand-related images, like any other images used in social online conversations, are enormously heterogeneous (Hu, Manikonda, & Kambhampati, 2014). Looking at images from Instagram marked with the social tag "#mcdonalds" (Fig. 1) illustrates this point. Among other aspects, brand-tagged images largely differ in their brand centrality (Smith, Fischer, & Yongjian, 2012), ranging from images that depict a concrete consumption of a brand's products to those that do not concretely depict the brand and appear to have little to do with it. Nevertheless, most related images show different situations in which consumers have direct contact with the brand or at least somehow connect with it.

=== Insert Fig. 1 here ===

Second, brand-related images rarely show what consumers think and feel in or about these situations. An image of only a McDonald's burger does not say whether the consumer who posted this image was delighted or disgusted. However, consumers may express this information in the post's caption text and its social tags. In such cases, these other data sources may provide insights into concrete product-related associations.

In summary, to analyze UGC from social networks, it seems natural to integrate image data and to pay special attention to its corresponding heterogeneity. By doing so, situations in which consumers have direct physical contact with a brand's product can be distinguished from those in which the brand plays a peripheral role. Such an approach should incorporate text and social tagging data in addition to image data to infer what consumers actually think and feel in these situations. Additionally this type of integrated analysis is likely to provide insights into how these different data types are linked.

Consequently, this article presents a two-step approach that involves collecting, labeling, clustering, aggregating, mapping, and analyzing brand-related UGC in the form of image, text, and social tagging data. Data were collected from Instagram, which, with 800 million monthly users (as of September 2017), ranks among the most popular social networking services (Everson, 2017). The service is especially favored among younger users (Think with Google, 2017), and its volume of brand interactions exceeds that of all other social networks (Gottke, 2016). Collected data included brand-related images, caption texts, and social tags posted on Instagram. Image data labeling was done via Google Cloud Vision API (application programming interface), which is a powerful deep learning approach for image classification. Clustering the labeled image data resulted in clusters that differed, among other aspects, in terms of their contents (i.e., actual entities displayed in the image) and contexts (i.e., situational circumstances in which content is created). Social tagging data and sentiments extracted from caption texts were aggregated to indicate how a brand was perceived in each cluster. By mapping the social tag and sentiment information in the form of associative networks for each cluster, marketers can gain a visual overview of what consumers in different contexts actually think and feel about brands. Analyzing social tag and sentiment information further offers a more detailed description of different clusters.

The article is organized as follows: First, the existing literature on extracting brand information from UGC, extracting information from images, and the social network Instagram is outlined. Then, the approach to extract brand information from social networks integrating image, text, and social tagging data is described in detail. Next, a multifaceted empirical application demonstrates the use of this data and highlights the resulting managerial and methodological insights. Finally, the article concludes with a discussion of the findings, implications, limitations, and directions for future research.

## 2. Research background

### *2.1 Capturing brand information from UGC*

Table 1 provides an overview of previous articles in the field of marketing analyzing brand information from UGC. As can be seen, these articles differ, among other aspects, in the type of data they have used, their application of a cluster analysis, their visualization of brand information, and the type of sentiment analysis applied.

Concerning the type of data used, texts from product reviews, forum messages, and tweets have been used to extract diverse kinds of brand information (Gensler et al., 2015; Lee & Bradlow, 2011; Liu et al., 2017a; Moon & Kamakura, 2017; Tirunillai & Tellis, 2012, 2014). In addition to text, social tags have been analyzed to extract brand perceptions (Nam & Kannan, 2014; Nam et al., 2017). Further, Culotta and Cutler (2016) have inferred attribute-specific brand perception ratings by mining a brand’s social connections on Twitter. In a recent article that analyzed brand-related images, Liu et al. (2017b) used deep convolutional neural networks to train an image classifier predicting four brand attributes (glamorous, rugged, healthy, and fun) from a training sample with corresponding images from Flickr. Afterwards, the classifiers were applied to brand-related images posted on Instagram to measure the above attributes for 56 brands.

=== Insert Table 1 here ===

As all these articles focused on one data type, this article is the first in the field of marketing to integrate brand-related images, texts, and social tags to meet the diversity of content provided on social networks, such as Facebook, Instagram, and Twitter and to capture a holistic picture of the brand. In contrast to Liu et al. (2017b), this article does not extract predefined attributes from images but clusters images according to the variety of contents and contexts displayed to detect the situations in which consumers have in some way made contact with a brand or at least connected with it. Building on social tagging analysis and sentiment analysis, this article additionally infers what consumers actually think and feel in these situations.

Surprisingly, clustering brand-related UGC has thus far been rarely applied. Lee and Bradlow (2011) have clustered phrases extracted from product reviews to elicit product attributes and Netzer et al. (2012) have clustered car models extracted from consumer messages on forums to gain insights into which car models are often mentioned together. However, these articles do not cluster brand-related UGC on a post or user level. Only Nam et al. (2017) have done this, in their case clustering users' social tags on a blog post into user segments. By clustering, marketers can understand and visualize heterogeneity in brand perceptions and gain insights for segmentation and targeting. This article builds on this argument and extends it by clustering images in Instagram posts to account for the heterogeneous contents and contexts displayed in brand-related images.

Brand information has mostly been visualized for many brands and a few attributes or dimensions or for a single brand and many attributes or dimensions. Articles focusing on many brands and few attributes or dimensions describe market structures and reflect brand positioning. Comparatively, articles visualizing brand information for a single brand based on many attributes provide a more detailed understanding of the brand (see Table 1). This article belongs to the second kind, as its aim is to extract comprehensive brand information for a single brand.

Regarding sentiment analysis, some articles relying on product reviews exploit the natural division of comments into pro and con. Additionally, the article by Moon and Kamakura (2017), which relied on product reviews, manually determined the valence of topics. Similarly, Nam and Kannan (2014) manually classified the sentiment of social tags as positive, negative, and neutral. They measured valence as the volume of positive and negative social tags scaled by the volume of bookmarks linked to a brand. Detection of the sentiment in social media text is commonly based on natural language processing. Accordingly, this article determines the caption texts' sentiments automatically using VADER (Hutto & Gilbert, 2014), a rule-based model for general sentiment analysis that is specifically attuned to sentiment in microblog-like contexts.

### *2.2 Extracting information from images*

As can be seen in Table 1, in the field of marketing, only the article by Liu et al. (2017b) and this article analyze images in order to extract brand information. Image (or video) analysis is rooted in the field of computer vision, which aims to extract information from collected and processed visual data (Mulfari, Celesti, Fazio, Villari, & Puliafito, 2016). Research in the field of computer vision encompasses various functions used to identify either abstract meanings (e.g., sentiments or emotions) or concrete contents (e.g., objects) displayed in images.

Detecting sentiments and emotions in visual content has attracted increasing attention in research and practical applications (Chen, Borth, Darrell, & Chang, 2014). State-of-the-art approaches usually apply deep learning algorithms to do so (e.g., You, Luo, Jin, & Yang, 2015). However, deriving abstract meanings from images remains a challenging task as visual features, such as color histograms, brightness, and attributes, typically lack this level of abstract meanings (Wang, Wang, Tang, Liu, & Li, 2015). Generally, classifying images according to abstract meanings, such as sentiments or emotions, is a difficult and often subjective task even for humans, as many images do not convey feelings or are perceived differently by different individuals. This difficulty has been underlined by Yang et al. (2014), who claimed that only 38% of images on Flickr were explicitly annotated with either positive or negative emotions. Consequently, some approaches use textual information to provide additional information about underlying images (e.g., Chen, Yang, Feng, & Gu, 2017; You, Luo, Jin, & Yang, 2016).

Likewise, much attention has been paid to recognition tasks to investigate which contents (i.e., objects) are displayed in images. This task is one of the most fundamental and challenging problems in computer vision (Girshick, Donahue, Darrell, & Malik, 2016). Object recognition broadly encompasses both image classification (determining which object classes are present in an image) and object detection (localizing objects present in an image; Russakovasky et al., 2015). Over the last few years, deep learning approaches, especially convolutional neural networks, have become state-of-the-art approaches for object recognition, including image classification (e.g., He, Zhang, Ren, & Sun, 2016) and object detection (e.g., Girshick et al., 2016; Sermanet et al., 2014). These achieve a predictive accuracy that outperforms humans in many tasks (Kwak & An, 2016). As convolutional neural networks typically require large sets of training data, pre-trained models are often used on large-scale datasets, such as ImageNet (e.g., Krizhevsky, Sutskever, & Hinton, 2012) and PASCAL VOC (e.g., Girshick, Donahue, Darrell, & Malik, 2014). At the same time, the proliferation of open-source libraries, such as TensorFlow (Abadi et al., 2016) and API-based object recognition services, has provided researchers feasible access to models pre-trained on large image data sets. Because of the difficulties of detecting abstract meanings in images and the immense recent progress in object recognition, this article analyzes images for the variety of contents (i.e., objects) and contexts (i.e., situational circumstances) they display.

### *2.3 Social network Instagram*

Instagram is a mobile social networking service for sharing images and videos. On Instagram, users share images, give them a caption, and tag them with keywords; other users can “like” and comment on these uploads. In contrast to other image-sharing networks (e.g., Flickr, Pinterest), the main idea behind Instagram is sharing “snapshots” of everyday moments (Colliander & Marder, 2018). Instagram users use the social network to document their lives in everyday moments, present their identities (Kim, Seely, & Jung, 2017), and express emotional attitudes on a relatively high level of intimacy (Pittman & Reich, 2016). Thus, when sharing content about specific brands, users provide deep insights into how they experience, perceive, and interact with these brands.

Fig. 2 shows an exemplary brand-related Instagram post with all its components. Images dominate Instagram because of their high visibility. Users who mention a brand on Instagram usually present brand products or situations that they connect with the brand in some way, even though the brand might not be the central element of the situation.

=== Insert Fig. 2 here ===

Social tags and a caption text complement such images. Social tags, also called "hashtags" or just "tags," are space-free words and phrases that begin with "#." Users can mark content about a brand (e.g., McDonald's) by using the brand name as a tag (e.g., "#mcdonalds"). Motivations for tagging can be described as a combination of the function (categorization vs. description) and the recipient (the user him or herself vs. other users; Ames & Naaman, 2007). In general, tags commonly follow network-specific traditions and trends regarding their structure, length, and content, but are still freely chosen by users and are therefore able to express their personal views (Robu, Halpin, & Shepherd, 2009). Nam et al. (2017) have underlined: "[T]ags reflect not only the content that is tagged but also a succinct representation of the user's knowledge structure—that is, his or her mental representation of related concepts. Thus, one can view tags as […] an individual-specific, thoughtful interpretation of content" (p. 91). Consequently, tags that co-occur with brand tags are well suited for indicating what concepts users associate with a brand.

In addition to tags, text captions can be added to posts, and users do so most of the time. Complementary to the keyword character of tags, the caption text is a statement that yields further contextual information. Within the text, users commonly reveal their emotional attitude towards the depicted content, which is facilitated by using emoticons to express feelings (Novak, Smailović, Sluban, & Mozetič, 2015).

To conclude, Table 2 provides an overview of how images, caption texts, and tags are used on Instagram. Using Fig. 2 as an example, it shows what pieces of information can be derived from the displayed image, caption text, and tags. Finally, it highlights the insights yielded from the approach. How these are integrated to draw a holistic picture will be described in Section 3, below.

=== Insert Table 2 here ===

## 3. Integrating image, text, and social tagging data

### *3.1 Data collection and preprocessing*

The first task of the approach used in this article is collecting and preprocessing brand-related posts from the social network Instagram. Social networks provide access to publicly shared content within an API that enables to receive the latest posts that are marked with a tag of interest. Posts include descriptive information, such as user name and upload date, and UGC, including image, caption text, and tags. To integrate these different types of UGC, several preprocessing steps are required.

*Preprocessing image data*. Before applying statistical methods to image data, quantitative features must be extracted to obtain a numerical representation of the images. This approach uses Google Cloud Vision API (Google, 2017a) for image classification. Google Cloud Vision API has been used in first attempts in marketing research (Mazloom, Rietveld, Rudinac, Worring, & van Dolen, 2016) and other domains that utilize image data. Besides being recommended by recent marketing literature (Wedel & Kannan, 2016), the use of Google Cloud Vision API increases methodological transparency, as no parameters have to be set and the results may be replicated by anyone. For every image in the data set, the service returns a list of labels that describe entities found within it. Each label is further described by a reliability score between 0.5 and 1. As a result, each image can be represented by a numerical vector that describes its label scores.

*Preprocessing text data*. Instagram caption text tends to be very noisy, containing a lot of special characters, letters from outside the Latin alphabet, and emojis, which are represented by their Unicode. Emojis are graphical symbols that represent emoticons or common objects such as animals, food, or national flags. To clean the text, tags (i.e., words starting with "#") and emojis are identified and separated, and then the text is cleaned of any non-textual characters. Emojis that represent sentiment (e.g., smileys) are translated into western-style emoticons and returned to the caption text, as they will be taken into consideration in a sentiment analysis.

The language of the posts is then identified using Google Cloud Translation API (Google, 2017b). Posts with non-English text are removed to ensure that no language-specific effects bias the sentiment detection. Posts with no text are also removed, as they are unable to reflect the user's sentiment. To analyze the sentiment of the caption text, several approaches with different applications can be found in the literature. The rule-based sentiment detector VADER, introduced by Hutto and Gilbert (2014), uses both qualitative and quantitative methods to meet the challenges of social media content. As a lexicon-based approach, the method relies on a list of lexical features provided with manually labeled sentiment scores specifically attuned to the sentiment in microblog-like contexts. The lexical features are combined with consideration of five general rules that include grammatical and syntactical conventions for expressing and emphasizing sentiment intensity (e.g., punctuation and words that intensify or invert polarity). In sum, VADER is applied because it features two main benefits: First, the algorithm is explicitly designed for social media text as it involves characteristic abbreviations and emoticons. Second, the algorithm scores higher on classification accuracy than comparable methods and even outperforms human raters. The output of the method is a continuous sentiment value between -1 and 1. The final spreadsheet has a row for each post having an English caption text that contains the sentiment score of the caption text and a list of the tags used.

### *3.2 Image clustering*

The first step of the analysis is exploring the heterogeneous contents and contexts displayed in Instagram images. For this purpose, a hierarchical agglomerative cluster analysis (Lance & Williams, 1967) based on the labels assigned to the image data is conducted. The similarity between images is measured as the Euclidean distance of the corresponding vectors, and the clusters are merged using Ward's minimum variance method. In addition to this method requiring a higher computational effort than do other clustering algorithms, the resulting hierarchical structure enables a better understanding of the information in brand-related images on Instagram by revealing how different contents and contexts are related to each other. To be more precise, images are labeled with more general terms and more specific terms. For example, an image of a hamburger receives the labels “food” and “hamburger,” and an image of fries is given the labels “food” and “fries.” Consequently, the semantic hierarchy is captured because of the higher frequencies of labels that are more general. The number of clusters can be increased to extract a more detailed view of the hierarchical image structure, from one (i.e., all images in one cluster) to the number of images in the data set (i.e., one cluster per image). A key characteristic of hierarchical clustering methods is that increasing the number of clusters does not reallocate objects between clusters but subdivides existing clusters into subordinate clusters. Therefore, this approach does not look for an optimal number of clusters according to quantitative criteria but rather investigates the whole hierarchical cluster structure to explore the semantic hierarchy of heterogeneous image contents.

### *3.3 Network visualization*

To investigate the information in brand-related text and tagging data, the second step of the analysis involves computing an associative network for each image cluster. Associative networks are based on the associative network memory model (Anderson & Bower, 1973; Collins & Loftus, 1975) and have found application in several methods that aim to analyze brand perceptions from survey data (e.g., Böger, Kottemann, Meißner, & Decker, 2017; John, Loken, Kim, & Monga, 2006) and from UGC (Gensler et al., 2015; Nam et al., 2017; Netzer et al., 2012). The basic purpose of associative networks is to compactly represent brand-related concepts (i.e., nodes of the network) and their connection strength (i.e., edges of the network) according to the structure of consumers’ mental models. This approach uses associative networks to represent the strength of brand-related tags (indicated by node size), their connection strength (indicated by edge color), and their sentiment (indicated by node color). In the following, formal definitions of these metrics and the network-creating process, including parameters that can be set by the researcher, are presented. Note that all approach parameters affect only the visual representation of the data, not the data itself. Consequently, the researcher can flexibly adjust the parameters to dive deeper into the data and extract meaningful insights.

*Tag strength*. The strength of tag $t$ is computed from the relative frequency of posts being marked with tag $t$. In the resulting network, the size of a node is computed according to the strength of the corresponding tag. Further, only tags that surpass a relative frequency of $p_{min}$ are presented in the network. Consequently, the number of nodes depends on the number of tags used in at least $p_{min}$ of posts used to compute the network.

*Connection strength*. The strength of the connection between two tags $t$ and $t'$ is measured using the scaled co-occurrence frequency of the two tags (i.e., the number of posts marked with both $t$ and $t'$). In line with Robu et al. (2009) and Nam et al. (2017), the scaled co-occurrence frequency $c(t, t')$ is defined as

$$c(t, t') = \frac{v(t, t')}{\sqrt{v(t)v(t')}} \quad (1)$$

where $v(t)$ denotes the volume of posts with tag $t$. Note that $c$ can range from 0, indicating no co-occurrence, to 1, indicating maximal co-occurrence. In the network, tags are connected if their connection strength is at least $c_{min}$. To represent connection strength, edges are colored on a scale from light grey ($c_{min}$), indicating low connection strength, to dark grey, indicating high connection strength ($c_{max}$).

*Tag sentiment*. The computation of a tag's sentiment is not based on the tag itself but on all posts marked with tag *t*. As each post receives a specific sentiment value based on the sentiment depicted in the caption text, the sentiment of tag *t* is defined as the mean sentiment value of all posts marked with *t*. To represent the metric, nodes are colored on a scale from dark red (strong negative sentiment) to bright yellow (neutral sentiment) to dark green (strong positive sentiment). While tag sentiment can range between -1 and 1, the color scale should be adapted to the actual data, as neutral posts tend to shift the mean sentiment value towards 0 and sentiment in social media is generally positively biased (Moe & Schweidel, 2012). Therefore, parameters $s_{min}$ and $s_{max}$ are defined to constrain the color scale.

*Network creation*. To compute node positions, a force-directed graph algorithm is used. The Fruchterman–Reingold (1991) algorithm, which is popular in research and included in several software packages, was chosen for node positioning. To visualize networks in Python, the freely available package NetworkX by Schult and Swart (2008) was used. Although the Euclidean distance between two nodes in the resulting network does not represent the connection strength of underlying tags, the Fruchterman–Reingold algorithm tends to place connected tags next to each other to prevent lines crossing and overly long edges. To summarize the different aspects described in Section 3, the main aspects of the two-step approach are depicted in Fig. 3.

=== Insert Fig. 3 here ===

## 4. Empirical application

The proposed approach is demonstrated on a data set generated from Instagram posts marked with the brand tag of McDonald's (i.e., #mcdonalds). As Instagram motivates people to create content about everyday moments, food is a focal topic of created content. McDonald's has not only been mentioned in over six-million Instagram posts (https://www.instagram.com/explore/tags/mcdonalds/?hl=en), but it also has some characteristics that make it a promising choice for elaborating brand information: McDonald's is associated with high awareness and involvement and has a polarizing capability, which may lead to a larger variance in the data (Mafael, Gottschalk, & Kreis, 2016).

### *4.1 Data collection*

As described in Subsection 3.1, the first task of the empirical application is to collect a sufficient amount of Instagram posts related to the brand. During the first two weeks of November 2017, 27,889 posts marked with the brand tag #mcdonalds were downloaded, and 10,375 posts having English caption texts were retained for further analysis. For each post, a list of labels describing entities in the image was retrieved using Google Cloud Vision API.

The Google Cloud Vision API detected 1,250 distinct labels for the images in our dataset. The number of labels describing an image ranged from 0 to 49. After removing 50 images receiving no label, the remaining data set contained 10,325 posts with an average of 10.06 labels describing each image.

*4.2 Validation of labels received from Google Cloud Vision API*

To validate the accuracy of image labels (Everingham, Van Gool, Williams, Winn, & Zisserman, 2010) received from Google Cloud Vision API, a lab study with six independent human raters $r$ was conducted. For a random sample of 100 images $i$, with a total of 1022 labels $l$, each label $l$ was classified by all raters as true ($e_{rl} = 1$) or false ($e_{rl} = 0$) according to the rater's evaluation of whether or not the label clearly identified an entity seen in the image. With a moderate inter-rater reliability of $\kappa = 0.41$ (Fleiss, 1971; Landis & Koch, 1977), the true positive rate for label $l$ is denoted as

$$\bar{e}_l = \frac{1}{6}\sum_{r=1}^{6}(e_{rl}) \tag{2}$$

and yields information about how well a specific label fits the corresponding image. Additionally, $L_i$ is defined as the set of all labels that are assigned to image $i$. Consequently, the true positive rate for image $i$ is given by

$$\bar{e}_i = \frac{1}{|L_i|}\sum_{l \in L_i}(\bar{e}_l) \tag{3}$$

and yields information about how well an image is described by its labels. Fig. 4 shows boxplots for the true positive rates for labels ($\bar{e}_l$) and images ($\bar{e}_i$). As can be observed, a majority of the labels achieved a true positive rate of one, indicating that all raters agreed that the described entity could be found in the corresponding image. Still, for some labels, the raters were discordant or agreed that the described entity was not present in the corresponding image. Regarding the images, no image was completely misclassified (i.e., images with only false labels) and most images were labeled with mostly true positive labels, validating the accuracy of the image labels. To account for the actual score that Google Cloud Vision API provided for each label, the correlation between $\bar{e}_l$ and $score_l$ was calculated using Pearson's correlation coefficient. A significant positive correlation of $r = 0.30$ ($p < 0.001$) indicates that the scores correspond to the human raters' agreement and, therefore, represent the certainty of a label. Overall, it can be concluded that the labels and the scores they received from Google Cloud Vision API validly reflect the images' contents.

=== Insert Fig. 4 here ===

*4.3 Analysis of image data*

To investigate the heterogeneous structure of brand-related images, the 20 cluster solution was chosen, which yielded the clusters *Burger*, *Diverse McDonald's fast food*, *Fries and nuggets*, *Lunch* (these four clusters belong to the superordinate cluster *Fast food*), *Car*, *Diverse food*, *Dog*, *Ice cream*, *McCafé*, *Monochrome photography*, *People*, *Sundries*, *Toys*, *Cartoon*, *Text* (these two clusters belong to the superordinate cluster *Illustrations*), *Buildings*, *Urban and nature* (these two clusters belong to the superordinate cluster *Outdoor*), *Selfies with glasses*, *Selfies I*, and *Selfies II* (these three clusters belong to the superordinate cluster *Selfies*). Table A1 provides an overview of the 20 clusters and the most frequent labels describing them. All cluster names have been manually annotated, summarizing the most frequent labels for that cluster and considering the actual image data. To obtain a visual impression of the images in the different clusters, Fig. 5 shows a sample of images from the clusters *Ice cream* (top left), *Burger* (top right), *Cartoon* (bottom left), and *Sundries* (bottom right).

=== Insert Fig. 5 here ===

First, it can be seen that clustering image data according to the labels extracted by Google Cloud Vision API works well and leads to widely homogeneous image clusters. Still, the image clusters differ in their observed homogeneity, ranging from very homogeneous (e.g., *Ice cream*, *Burger,* and *Cartoon*) to less homogeneous (e.g., *Sundries*). In general, brand-related image clusters can be described along the dimensions content and context.

The content of a cluster is the most intuitive dimension, reflecting the actual entities that can be seen in the images. It can be observed that a relevant part of the clusters depict some kind of food, the core product of the brand. While the superordinate cluster *Fast food* comprises different kinds of fast food clusters (e.g., *Burger* and *Fries and nuggets*), several other clusters reflect additional kinds of food and beverages (e.g., *Ice cream* and *McCafé*). Most remaining clusters fall into the categories of objects (e.g., the clusters *Dog*, *Toys*, *Cars*, and *Buildings*) and persons (e.g., the cluster *People* and the superordinate cluster *Selfies*). Few clusters reflect no distinct contents; nevertheless, they have other image cues, such as color (e.g., the *Monochrome photography* cluster) or style (e.g., the superordinate cluster *Illustrations*).

The context of a cluster reflects the situational circumstances in which content is created. Product-related clusters like *Burger*, *Fries and nuggets*, and *McCafé* consist of images that are usually photos taken at a brand touch point (i.e., a McDonald's restaurant), while clusters such as *Dog* and *Buildings*, as well as *Urban and Nature*, are likely to be photos taken from a different location. Apparently, the use of a brand-tag on Instagram does not disclose how central the brand is to the situation depicted in the image. However, based on the image clusters, it is possible to identify posts that imply a high degree of brand centrality by focalizing products, such as the *Fries and nuggets* cluster, or merchandising articles, such as the *Toys* cluster. On the other hand, (superordinate) clusters such as *Selfies*, *Dog*, and *Outdoor* tend not to focalize directly on brand-related entities and therefore suggest a lower degree of brand centrality, though the brand may still play a peripheral role. In contrast to these situational experiences captured in actual photography, 10% of the data reflect illustrations. The corresponding clusters consist of images depicting sketches, comics, and texts that are not created with a camera.

### *4.4 Analysis of text and tagging data*

As an analysis of the text and tagging data for all 20 clusters would go beyond the constraints of this article, four clusters were exemplarily chosen for further discussion. Although each cluster is worth consideration, the clusters *Ice cream*, *Burger*, *Cartoon*, and *Sundries* were selected. The *Ice cream* and *Burger* clusters are directly product-related and therefore might reveal interesting insights into consumers' associations with McDonald's product experiences. In contrast to these directly product-related clusters, the *Cartoon* cluster, consisting mostly of comics and Internet memes, might yield information about emerging brand-related Internet phenomena. Last, the *Sundries* cluster, being the largest and least homogeneous cluster, having no clear focus, might serve as an example for general Internet chatter connected to McDonald's.

### 4.4.1 Network visualization of text and tagging data

*By applying the procedure proposed in Subsection 3.3 to the corresponding text and tagging data, the associative networks for the image clusters* Ice cream, Burger, Cartoon, *and* Sundries *were constructed (Fig. 6). The number of network nodes depends on the volume of tags with a relative frequency of at least* $p_{min}$ *= 0.05. Edges are created for a minimum scaled co-occurrence of* $c_{min}$ *= 0.22 and colored depending on the co-occurrence, from* $c$ *= 0.22 in light grey to* $c$ *= 0.4 in dark grey. Nodes are colored depending on the mean sentiment of all posts that contain the tag, ranging from* $s_{min}$ *= -0.25 in dark red to* $s_{max}$ *= 0.55 in dark green. As the four McDonald's brand nodes in the networks are scaled to the same size, node sizes can be compared within and across networks. Fig. 6 offers numerous insights into specific brand topics about which Instagram users create brand-related content.*

*The* Ice cream *cluster includes tags that are categories (e.g.,* icecream, dessert*), products (e.g.,* mcflurry, sundae*), subjective product attributes (i.e.,* sweet, yummy*), objective product attributes (i.e.,* vanilla, chocolate*), and Instagram-specific terms (e.g.,* instafood*). Additionally, the tag* foodporn *refers to images of food across various social media platforms and describes spectacularly delicious-looking food. Thus,* foodporn *can be interpreted as a positive attribute expressing consumers' enthusiasm for food products. In general, indicated by the product attributes* sweet, yummy, *and* foodporn*, as well as the overall positive sentiment, McDonald's ice cream products, especially* mcflurry *and* sundae*, are generally evaluated well. Evaluating the tags* sundae *and* mcflurry *and their attributes further, it can be seen that only* sundae *is directly connected to* yummy*, indicating that it has a stronger relationship to that attribute. Interestingly, the flavor* chocolate *is an exception, as it is subject to the most negative sentiment in this network. This exception may serve as a guide for product managers to investigate further why the flavor chocolate seems to evoke a more negative sentiment than, for example, the flavor vanilla.*

*The* Burger *cluster, in line with the* Ice cream *cluster, includes tags that are categories (e.g.,* eat, food*), products (e.g.,* bigmac, cheeseburger*), product attributes (e.g.,* tasty, yummy*) and Instagram-specific terms (e.g.,* instafood, foodblogger*). Again, the tag* foodporn *plays an important role. Similar to the* Ice cream *cluster, indicated by the product attributes* delicious, tasty, yummy, *and* foodporn*, as well as the overall positive sentiment, McDonald's burgers* *are also evaluated very well. Interestingly, the most frequently used product tag and one of the most frequent tags overall in the* Burger *cluster, as indicated by the size of the nodes, is not the tag* bigmac*, McDonald's flagship burger, but the tag* mcrib*. Apparently, the McRib has a huge fan base, at least with Instagram users. Product, brand, and social media managers can use this insight to create marketing campaigns focusing on the McRib.*

=== Insert Fig. 6 here ===

*The* Cartoon *cluster shows a clearly divided positioning of tags. Generally, the tags divide in two groups, namely an* art *group (positioned on the left side) and a* memes *group (positioned on the right side). The* art *group has an overall positive sentiment, indicating that people express their positive attitude towards McDonald's in the form of illustrations, drawings, and sketches. A subgroup refers to specific anime series (i.e.,* narutoshippuden, dragonball*) with an extremely positive sentiment, indicating a positive consumer evaluation regarding corresponding promotions. The* memes *group deals particularly with tags that connect McDonald's to trending Internet topics and phenomena. It has a subgroup focusing on* dankmemes *having a very negative sentiment. Apparently, users express their discontent with the brand in the form of these* dankmemes*. Another subgroup revolves around the tag* rickandmorty*, a TV show where an old McDonald's product is part of a running joke. This product was re-released in 2017 in order to harvest the rich fanbase of the show, which backfired on social media due to excess demand (Alexander & Kuchera, 2017). As can be seen in the associative network, consumers are highly aware of this marketing disaster and articulate their dissatisfaction with the brand as indicated by tags' negative sentiments.*

*The visualization of the* Sundries *cluster shows that the number of frequently used tags is noticeably lower in comparison with the other clusters. Nevertheless, two topics are noticeable: vegan (i.e.,* vegan*) and meme (i.e.,* memes, dankmemes*). Whereas the* memes *topic also appears in the* Cartoon *cluster, the* vegan *topic only pops up in the* Sundries *cluster. Apparently, general Internet chatter connected to McDonald's is relatively often on* vegan *topics. Surprisingly, the* vegan *tag's sentiment is positive and seems not to be a big problem for McDonald's. Nevertheless, brand and social media managers should monitor how vegan topics effect perceptions of the brand, especially when introducing new products in this category (Petroff, 2017).*

In sum, the four associative networks reveal that clusters vary in the form of their tags, which can be allocated to categories, products, subjective and objective product attributes, Instagram-specific terms, artistic or trending topics, and Internet phenomena. Clusters further vary in terms of their sentiments (very negative to very positive). Moreover, the visualization discloses that the networks represent the contents of images, confirming that tags indeed describe the contents of images fairly well. As on first glance the networks reveal information (i.e., tags) that would have remained hidden by considering the images exclusively, the networks strongly complement the image clusters. Especially attributes such as delicious, tasty, or yummy, as well as the sentiments of the product-related tags, complement images of McDonald's products and express consumers' corresponding evaluations. By utilizing a network representation, insights can be derived not only for single tags but also for a group of tags that are strongly connected, as shown for the *Cartoon* cluster.

*4.4.2 Impact of text and tagging data*

To gain further understanding of the most impactful tags in each cluster, the impact *I* of a tag *t* is computed as

$$I_t = p_t \times s_t \tag{4}$$

where $p_t$ is the tag's relative frequency and $s_t$ is the mean sentiment of all posts' caption texts marked with $t$. The most impactful positive and negative tags are displayed in Table 3.

=== Insert Table 3 here ===

Table 3 reveals that the most impactful positive tags mostly include the most frequent tags (Fig. 6); therefore, they do not provide much further information beyond the visualized associative networks. A reason for this is that tags having a positive sentiment are generally more frequent and therefore dominate the visualized networks. Nevertheless, tags with a negative sentiment can point to bad states of affairs even if they are not that frequent and therefore do not appear in visualized networks. Consequently, the most impactful negative tags may contain valuable insights.

The tag *icecheckapp* has the highest negative impact in the *Ice cream* cluster. The ice check app allows users to search for nearby McDonald's restaurants with a working ice cream machine. The tag not only hints at a specific Internet phenomenon, a running joke that McDonald's ice cream machines are always broken, but also has serious implications for McDonald's. The negative impact indicates that users may have used the tag to express their frustration about a McDonald's restaurant unable to satisfy their demand for ice cream. Thus, the tag highlights a concrete technical problem for McDonald's restaurants. Product and social media managers should take these problems seriously and fix broken ice cream machines, as well as monitor related conversations online.

The tags *healthy* and *healthylifestyle* have the highest negative impact in the *Burger* cluster. Apparently, users use these tags ironically to show that they feel the opposite, namely that McDonald's burgers are not healthful. Of course, this information is not new for McDonald's, but it indicates that this topic remains relevant for some users and that McDonald's managers should maintain their efforts to position the brand as healthful.

Looking at the most impactful tags (positive and negative) for the *Sundries* cluster, it can be observed that this cluster indeed is dominated by vegan-related topics. Interestingly, this topic is posed positively and negatively, indicating controversy in the corresponding discussion. This finding supports the statement made above that brand and social media managers should monitor how vegan topics are discussed with respect to the brand and should prevent negative sentiments from gaining the upper hand.

*4.4.3 Contribution of image data to the analysis of text and tagging data*

To further highlight what image data bring to an analysis of text and tagging data and how they contribute to the research, Table 4 compares the most frequent tags of the investigated clusters with the most frequent tags of all data, which comprises the unclustered data without consideration of images. The table additionally contains the tags' relative frequencies in parentheses (with respect to the corresponding cluster or all data) and the tags' ranks with respect to all data. The tags are presented in increasing frequencies starting with the most frequently occurring tag. For example, the tag *icecream* is the most frequently occurring tag within the *Ice cream* cluster with a relative frequency of 0.439, and it is the 30th most frequent tag with respect to all data.

=== Insert Table 4 here ===

As can be seen in Table 4, clustering the data according to images enables to identify what consumers associate with the brand in different contexts. For example, for all data, the tag *love* is among the five most frequently used tags. However, inferring that the tag has overall importance for the brand would be only partially true. Clustering the image data reveals that the tag does not occur among the top 5 tags for any of the four considered clusters. Instead, the tag predominantly occurs in clusters in which McDonald's plays a rather peripheral role. Only in the clusters *People*, *Monochrome photography*, *Selfies with glasses*, and *Selfies II* does the tag occur among the top five tags. Additionally, while the most frequent tags for all data are more general, the most frequent tags within the clusters are much more specific and would possibly remain hidden to a researcher due to their low relative frequencies with respect to all data. In this sense, it can be observed that the tag *mcflurry* is only the 98th most frequent tag with respect to all data, seemingly indicating that it may not be that important. However, when looking at consumers that actually posted an image of McDonald's ice cream, the tag *mcflurry* becomes the 4th most frequent tag, signaling the importance of this specific product within the product category of McDonald's. The situation is similar with the tag *mcrib* within the *Burger* cluster. Further, while all data reveal that *memes* seem to play a major role in the depiction of the brand on Instagram, only an analysis of the images that specifically depict memes (and art) exposes the major meme topic *rickandmorty*, which is the 4th most frequent tag within the *Cartoon* cluster but only the 74th most frequent tag with respect to all data.

A closer look at the relative frequencies in Table 4 reveals that they are much higher within the clusters (except the *Sundries* cluster) than for all data. To gain a more general overview of the effects of image clustering on tag frequencies, the corresponding frequency distributions were investigated. To compute two parameters describing the tag frequency distribution, tags were plotted with descending relative frequencies and the power function

$$p_t = \alpha t^{-\beta} \quad (4)$$

was fitted to the data, with $p_t$ as the relative frequency of tag $t$. Parameter $\alpha$ determines the estimated relative frequency of the most frequent tag whereas parameter $\beta$ determines the kurtosis of the function and describes the decline in the tags' relative frequencies. Large values of $\alpha$ and $\beta$ indicate a distinct tag structure, meaning that a small number of tags occurs relatively frequently in comparison with other tags. Accordingly, low values of $\alpha$ and $\beta$ indicate an indistinct tag structure. A distinct tag structure helps to identify a reasonable set of tags that represent the most important information within the data.

Fig. 7 displays the power functions for the tags plotted with descending relative frequencies for the clusters *Ice cream*, *Burger*, *Cartoon*, and *Sundries* (blue graphs), all the other clusters (grey graphs), and the graph for all data (red graph). Table 5 shows the power functions' parameters and the resulting $R^2$ values for all data and the four selected clusters. First, it can be seen that all values for $R^2$ are nearly 1, indicating a very good fit of the power functions to the tag frequency distribution data. Additionally, the red graph representing all data is characterized by low values of the parameters $\alpha$ and $\beta$. This observation indicates an indistinct tag structure for all data. For the huge majority of clusters, their tag frequency distribution is more distinct than that of the whole data set. The *Sundries* cluster is an exception in this respect, having slightly lower values for $\alpha$ and $\beta$. This exception is not surprising as the *Sundries* cluster includes diverse images, which is apparently reflected by a less distinct distribution of tag frequencies. In contrast, the *Ice cream*, *Burger*, and *Cartoon* clusters are characterized by a clear distinction in their tag frequency distribution. This investigation confirms that clustering Instagram posts by images provides clusters with more distinct tag frequency distributions. Thus, a clearer representation of tags can be achieved.

To conclude, clustering the data according to images enables a more holistic and deeper analysis in terms of what users think and feel and, especially, what they associate with the brand in different contexts. Additionally, clustering the data according to images enables researchers to derive insights based on tags that are assigned to a more representative volume of posts.

=== Insert Fig. 7 here ===

=== Insert Table 5 here ===

### *4.5 Summary of results*

In sum, clustering posts based on their images and analyzing the corresponding caption texts and tags enable an integrated analysis of visual and textual content and, therefore, help to achieve differentiated insights into how consumers experience, perceive, and interact with brands. These insights are summarized in Table 6.

=== Insert Table 6 here ===

## 5. Discussion and conclusions

Prior articles in the field of marketing on extracting brand information from UGC have predominantly focused on textual content. As many social networks are characterized by a combination of visual and textual content, it is surprising that little research has investigated images to derive additional brand information. This article is first in the field of marketing to integrate image, text, and social tagging data from UGC. By integrating the complementary information from these types of data, a more comprehensive analysis of brand-related UGC on Instagram could be conducted. Clustering Instagram posts according to images yielded three benefits: First, an overview of what users share in their images was provided. Second, posts could be allocated to specific contexts; and third, a more differentiated view of a brand's perception could be obtained. To gain an understanding of users' perceptions, text and social tags were investigated in addition to images. The underlying text complements social tags and indicates the user's sentiment connected with the tags. Visualization in the form of associative networks enables the comparison of different clusters in terms of their tags, connections between tags, and underlying sentiment. An empirical application demonstrates the multifarious managerial and methodological implications of the proposed approach, which will be discussed in the following subsection.

### *5.1 Managerial implications*

The integrative analysis of image, text, and social tagging data presented in this article has meaningful implications for marketing practice. Recent articles in marketing literature (see Table 1) show multiple possible ways how UGC can be utilized in order to, for example, derive brand perceptions, consumer evaluations, and competitive market structure. However, consumers encounter brands and create content in heterogeneous contexts, which is reflected by the diverse situations depicted in the image data. Neglecting the heterogeneity in brand-related UGC would not only capture a less holistic picture, but even worse, it could lead marketers to draw inaccurate conclusions or miss important insights (as shown in detail in Subsection 4.4.3). In particular, brand perceptions can widely differ across different situations that consumers create content about, reflected by unique social tags in the presented associative networks. Consumer evaluations strongly depend on the specific products or situations, reflected by different tag strengths and sentiments. The competitive market structure in which a brand moves also relies on specific products the brand is offering. For instance, some brands may not be seen as competitors in general (e.g. McDonalds's and Starbucks), although they might compete regarding specific products (e.g. coffee products). Consequently, when converting UGC to market structures and competitive landscapes, managers might miss significant insights when only considering aggregate content. Analyzing and integrating image data, as the most distinctive aspect of this research, offers versatile opportunities for marketers. The tags most frequently used leave only an elusive impression of what consumers think and feel about the McDonald's brand. Consequently, the information obtained from the clustered images enables marketers to assess the contexts in which a tag is relevant for the brand. By doing so, marketers can draw more accurate conclusions from the tags for different fields of decision-making (Table 7).

Brand managers can gain detailed insights of the situation about which users share brand-related images. Among other aspects, these situations might focus on concrete products or services of a brand, documenting users' real consumption experiences. By considering the associative network for each cluster, users' thoughts and feelings can be allocated to these specific contexts. As consumers interact with brands through myriad touch points (Lemon &

Verhoef, 2016), brand managers are increasingly confronted with the challenging task of analyzing and understanding how different situations contribute to the customer experience. In this regard, the presented approach can be used to identify different touch points as reflected by the images.

An appealing advantage of the presented approach is that it enables product managers to gain a differentiated impression of perceptions of product-related clusters. Perceptions of different products can be compared in terms of, for instance, unique associations. Furthermore, promising or desirable associations (e.g., positively evaluated product attributes) within clusters can be identified. Similarly, product managers can identify neglected products to focus marketing efforts on. The sentiments displayed in associative networks further enable the identification of strengths and weaknesses of products or product attributes. The *Ice cream* cluster provides an example for identifying weaknesses. In the cluster's associative network, it can be seen that chocolate is the subject of the most negative sentiment. Thus, the flavor chocolate can be interpreted as a weakness of McDonald's ice cream. This insight could serve as a guide for product managers to investigate why the flavor chocolate evokes a more negative sentiment than, for example, the flavor vanilla.

Additionally, by looking at the cluster solution and the corresponding associative networks, marketers can learn more about Instagram users who like to connect to their brand, as images and tags also reflect users' interests beyond the brand, including pets, cars, traveling, or pop culture phenomena. These insights can be valuable for market segmentation, the positioning of new products, or creating new promotions. Additionally, the integrative analysis enables identification of trending topics and Internet phenomena that users like to connect to the brand as could be amplified with the *rickandmorty* topic within the *Cartoon* cluster. Marketing communications could address trending topics that users evaluate very positively in order to benefit from positive spillover effects. Especially promotions may pick up trending topics that have gained positive attention. At the same time, communication efforts could monitor and focus on topics that users evaluate negatively to mitigate these and prevent negative spillover effects.

The approach is also suitable for marketing control, as the real-time monitoring of brands and products might assist decision-making and reacting to emerging topics. Managers can infer which elements of their marketing mix create the most attention, how consumers evaluate product and brand experiences, and how these observations dynamically change over time. One of the advantages of the proposed approach is the possibility to monitor effects that are not relevant for the majority of the consumers, but play an important role in specific situations (see Table 4).

=== Insert Table 7 here ===

### *5.2 Methodological implications*

To account for image heterogeneity, this approach clustered Instagram posts according to their images. Image information as reflected by the cluster solution was extended through the complementary information of text and social tags. In this regard, this article contributes to the stream of brand-perception research by proposing the integration of image, text, and social tagging data to capture brand perceptions in a holistic way. It contributes to the upcoming stream of image mining in marketing by demonstrating the use of Google Cloud Vision API in labeling Instagram images. Finally, it advances knowledge about the Instagram social network by disclosing what users actually share publicly about brands.

From a methodological point of view, it was shown that clustering image data according to labels extracted by Google Cloud Vision API works well and leads to widely homogeneous image clusters. The resulting cluster solution (see Table A1 for an overview) indicates that brand-related images shared on Instagram can be divided into their content and context, and that they differ, among other aspects, in their brand centrality.

Further, analyzing the tags of each cluster revealed that they represent the image data. However, the results also indicated that users add additional information in tags that generally complements the image information. Together with the information extracted in caption texts, these pieces of additional information express what users think and feel in or about the situations displayed in an image. In addition, nearly all image clusters surpassed the unclustered data in terms of having a more distinct tag structure. This consequence enables researchers to derive insights based on tags that are assigned to a more representative volume of posts.

Utilizing an associative network structure to visualize the rich semantic content of textual data also provides methodological benefits. Going beyond a mere representation of tag frequencies, the underlying co-occurrence metric helps to identify groups of tags that are strongly connected and therefore represent underlying topics. While some tags represent attributes, it is important to investigate tags that are connected to an attribute rather than interpreting an attribute as relevant to all tags in a cluster.

Rather than categorizing tags as positive, neutral, and negative, this approach integrated the caption text of underlying posts marked with a specific tag to infer a tag’s sentiment. Accordingly, a tag that was mostly used on posts expressing a positive sentiment was assigned a positive sentiment, and vice versa, a tag that was mostly used on posts expressing a negative sentiment was assigned a negative sentiment. This procedure led to interesting insights, as exemplified by the tag *healthy*. The tag itself implies a positive sentiment, but it could be shown that the tag is mainly used in posts with a caption text having a negative sentiment. It was therefore concluded that the tag is used ironically to show that users feel the opposite, namely that McDonald’s burgers are not healthful.

### *5.3 Limitations and future research*

The present research features some limitations that directly suggest directions for future research. In the first place, it is worth mentioning that measuring brand perceptions based on secondary data extracted from social networks can only complement, but not replace traditional survey-based techniques for collecting primary data (Plumeyer, Kottemann, Böger, & Decker, 2017). For instance, experiments that focus on brand perceptions can hardly be substituted by

UGC as the source of data. Another limitation is the limited information that can be obtained about users. In traditional surveys, various pieces of information can be collected about respondents (e.g., sociodemographics) that enrich brand-related data. This lack of information limits the scope of further analyses that can be conducted based on UGC. Future research should therefore investigate how to infer additional information about content creators that can be used for further analysis.

Another limitation is a potential network-specific bias that refers to the comparison of different social networks (e.g., Facebook, Instagram, Twitter), as well as other manifestations of UGC (e.g., product reviews and forum messages). Each source differs in terms of who is creating the content, what the content is about, and why the content is created. These differences influence the data that can be collected from these sources and, in doing so, have an impact on the information and knowledge that can be extracted from the data. For example, an elaborated review of a McDonald's product might yield more associations about its utilitarian attributes while an Instagram post documenting the consumption of a product might help in analyzing the hedonic dimensions of the product experience. Therefore, including different aspects from different kinds of social media may improve the analysis of brand-related UGC. This assumption should be addressed in future research in order to understand the relationship among different digital data streams, how the respective information can be utilized, and how different motivations drive consumers to create content.

Furthermore, the presented approach yields some requirements of the brands to be investigated. Some brands receive only small numbers of user-generated Instagram posts, which limits the insights that can be extracted. While niche brands might have lower numbers of customers who are aware of the brand, some more popular brands sell products or services that are less suitable for Instagram content creation, in particular because of their intangibility (e.g., American Express, Verizon, Google). Future research should apply the presented approach to additional brands as well as to sets of brands to study similarities and dissimilarities and consequently derive additional general characteristics of the brand-related content on Instagram. In this context, a text mining approach that is based on the identification of latent topics could be used to reduce the complexity (i.e., dimensionality) of the user-generated texts (see Tirunillai & Tellis, 2014, for an application).

Including the Google Cloud Vision API to analyze image data at scale worked well within the presented approach and can be recommended for future approaches that integrate image content. From the perspective of a specific brand, the proposed approach might serve as a starting point that can be adjusted to brand characteristics and to the content created about the brand. In this regard, pre-trained convolutional neural networks could be fine-tuned with labeled image data to make more precise predictions about the content that are more useful in answering brand-related questions (e.g., detecting the occurrence of a special product or the brand's logo in the images). In addition to image classification, an approach incorporating object detection may give further quantifiable insights about the centrality of products and brands in the images (e.g., how focally are products and brands depicted in the images).

In order to analyze heterogeneity in brand-related images, an established clustering approach was used in this article (i.e., hierarchical agglomerative clustering). In doing so, a deeper understanding of the information in brand-related images on Instagram was obtained, because it revealed how different contents and contexts depicted in the images are related to one other. Future research could empirically and systematically compare different clustering approaches in order to determine the optimal approach to investigate the heterogeneity in brand-related images.

Last but not least, future research should focus on the dynamic aspect of the approach and the dynamics of UGC in general. As users constantly create new content, it should also be investigated how much and how far this content changes over time, if so. More precisely, the emergence of trending topics should be tracked and brand perceptions should be monitored over time to achieve a better understanding of users' interactions with brands. This kind of analysis can be based on a brand level to measure how aggregated brand perceptions change over time. In doing so, detecting general patterns in temporal dynamics might enable to predict the future volume and sentiment of specific brand associations. On a consumer level, insights about the customer journey can be derived by monitoring how individual consumers interact with different brand touch points over time. It is hoped that this work can serve as a starting point for further investigating the potential of image-based social networks like Instagram for brand management.

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## Appendix

| Cluster | Most frequent Google Cloud Vision API labels[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Burger (.06) | fast food (.81) | food (.75) | hamburger (.74) | junk food (.66) | sandwich (.64) | finger food (.54) | dish (.53) | breakfast sandwich (.50) |
| Diverse McDonald's fast food (.04) | fast food (.65) | junk food (.63) | food (.52) | flavor (.40) | cuisine (.40) | snack (.28) | product (.27) | dish (.13) |
| Fries and nuggets (.02) | fast food (.82) | junk food (.80) | food (.78) | dish (.72) | cuisine (.64) | french fries (.64) | side dish (.61) | fried food (.58) |
| Lunch (.06) | food (.78) | dish (.63) | cuisine (.61) | meal (.52) | breakfast (.33) | fast food (.30) | junk food (.29) | lunch (.29) |
| Car (.02) | car (.96) | vehicle (.86) | motor vehicle (.85) | automotive design (.62) | automotive exterior (.59) | family car (.42) | luxury vehicle (.40) | compact car (.35) |
| Diverse food (.07) | food (.34) | flavor (.29) | drink (.29) | product (.17) | dairy product (.15) | dessert (.13) | cuisine (.12) | cup (.11) |
| Dog (.01) | dog (.93) | dog like mammal (.88) | dog breed (.84) | snout (.71) | dog breed group (.49) | carnivoran (.41) | dog crossbreeds (.31) | puppy (.28) |
| Ice cream (.01) | ice cream (.82) | dessert (.77) | food (.75) | dairy product (.71) | frozen dessert (.65) | flavor (.55) | gelato (.46) | cream (.40) |
| McCafé (.03) | cup (.68) | coffee cup (.60) | tableware (.33) | drinkware (.32) | coffee (.31) | drink (.31) | product (.24) | font (.21) |
| Monochrome photography (.02) | black and white (.90) | monochrome photography (.79) | monochrome (.68) | photography (.59) | black (.43) | photograph (.43) | white (.35) | snapshot (.28) |
| People (.15) | product (.37) | fun (.30) | girl (.24) | child (.10) | shoulder (.10) | smile (.10) | costume (.09) | finger (.09) |
| Sundries (.21) | product (.23) | font (.15) | product design (.07) | advertising (.07) | photo caption (.06) | technology (.06) | red (.05) | square (.05) |
| Toys (.06) | toy (.52) | yellow (.40) | product (.30) | figurine (.16) | material (.15) | play (.14) | technology (.12) | stuffed toy (.11) |
| Cartoon (.03) | cartoon (.59) | art (.52) | illustration (.48) | fictional character (.46) | font (.40) | text (.37) | fiction (.35) | graphics (.30) |
| Text (.07) | text (.88) | font (.71) | product (.42) | line (.35) | brand (.31) | area (.26) | graphics (.13) | logo (.12) |
| Buildings (.01) | city (.82) | metropolitan area (.65) | downtown (.62) | building (.61) | urban area (.60) | metropolis (.59) | street (.58) | landmark (.49) |
| Urban and nature (.05) | sky (.33) | vehicle (.24) | car (.24) | light (.17) | darkness (.16) | night (.16) | phenomenon (.15) | tree (.14) |
| Selfies with glasses (.03) | glasses (.84) | eyewear (.82) | vision care (.81) | product (.50) | cool (.43) | sunglasses (.40) | fun (.34) | girl (.32) |
| Selfies I (.03) | girl (.43) | forehead (.41) | chin (.37) | selfie (.36) | eyebrow (.35) | face (.34) | smile (.32) | nose (.31) |
| Selfies II (.02) | nose (.89) | face (.86) | cheek (.83) | chin (.81) | forehead (.78) | eyebrow (.76) | head (.65) | lip (.62) |

[1] Note that the numbers in parentheses represent the labels' relative occurrence frequencies for each cluster.

Table A1. Most frequent labels per cluster

## Figures

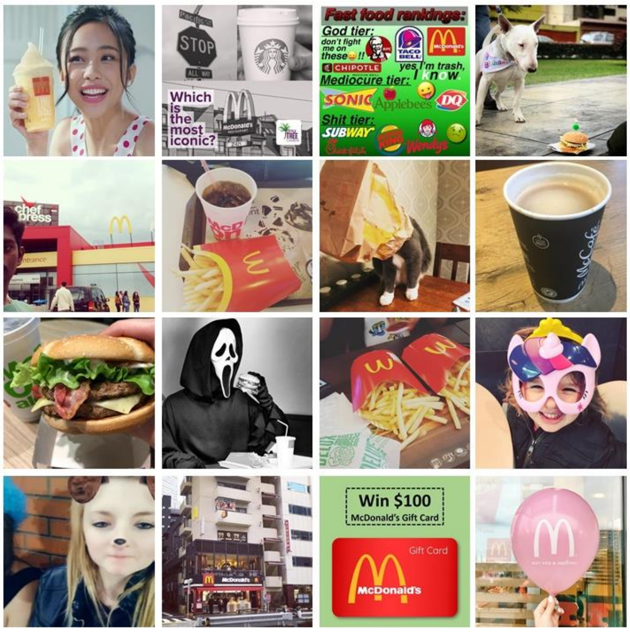


Fig. 1. Sample of Instagram images for #mcdonalds


Fig. 2. Exemplary brand-related Instagram post

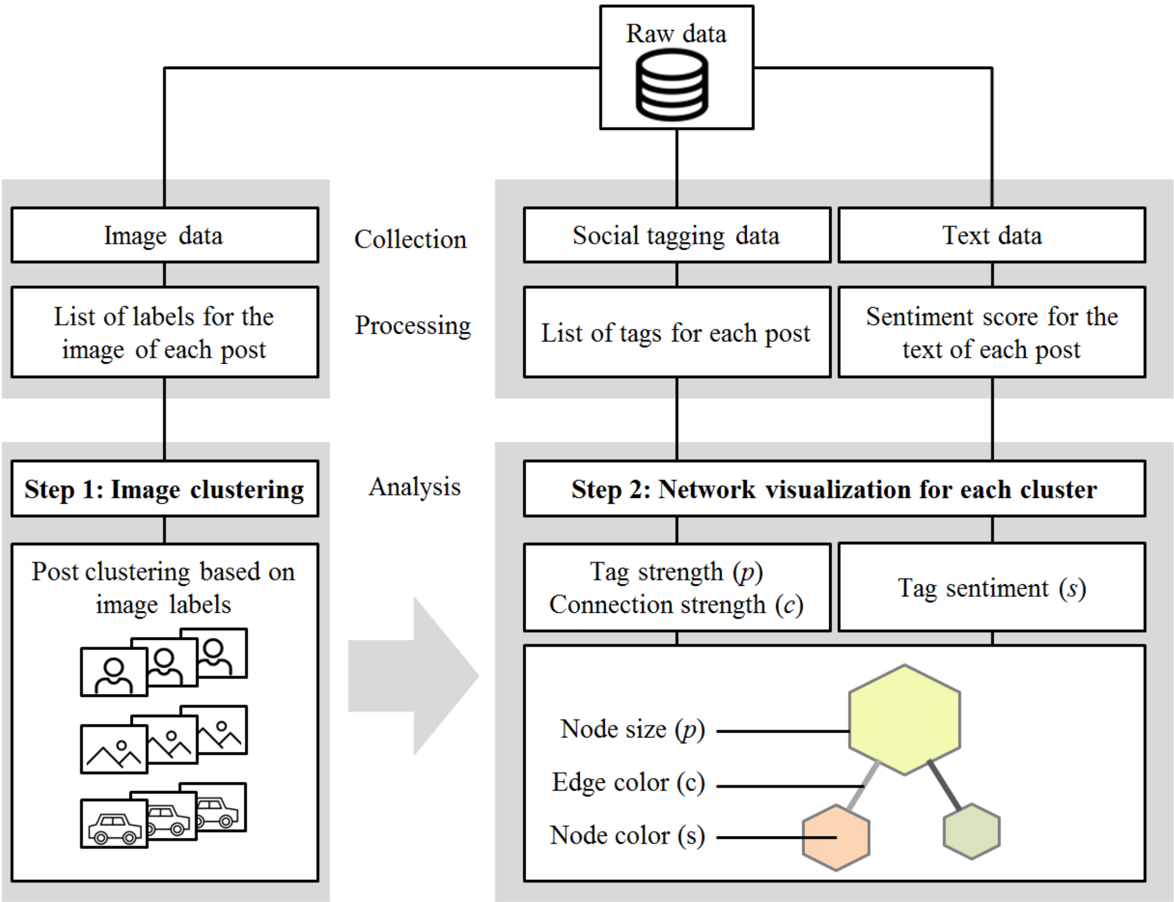


Fig. 3. Framework of the two-step approach

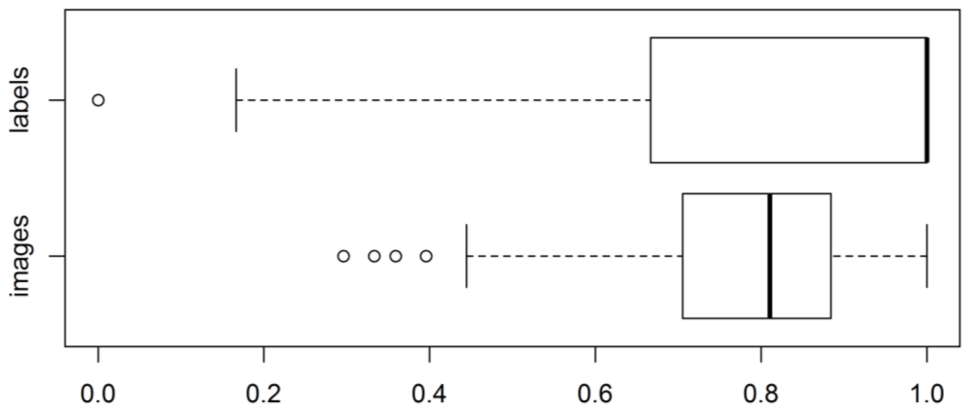


Fig. 4. True positive rates for labels and images

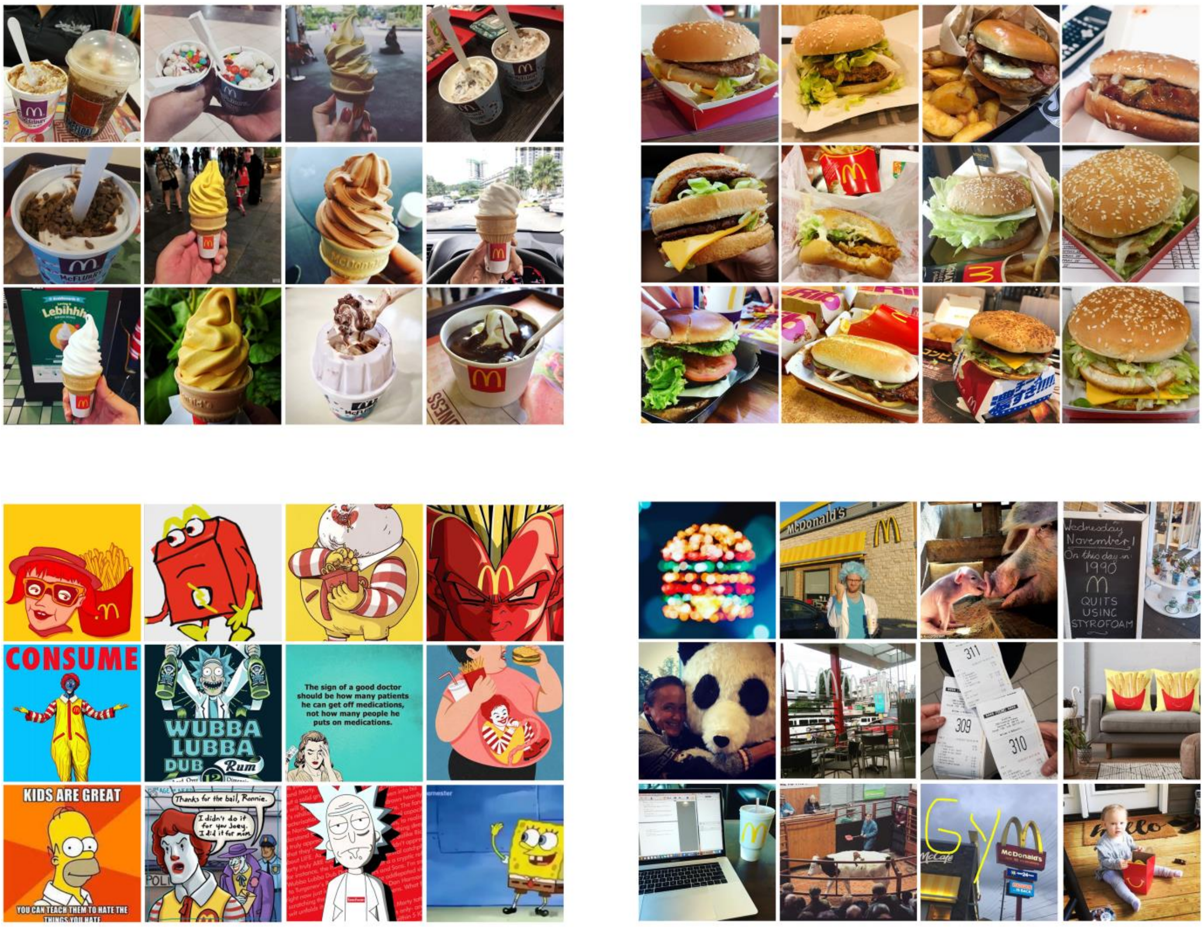


Fig. 5. Sample images for different clusters of McDonald's image data

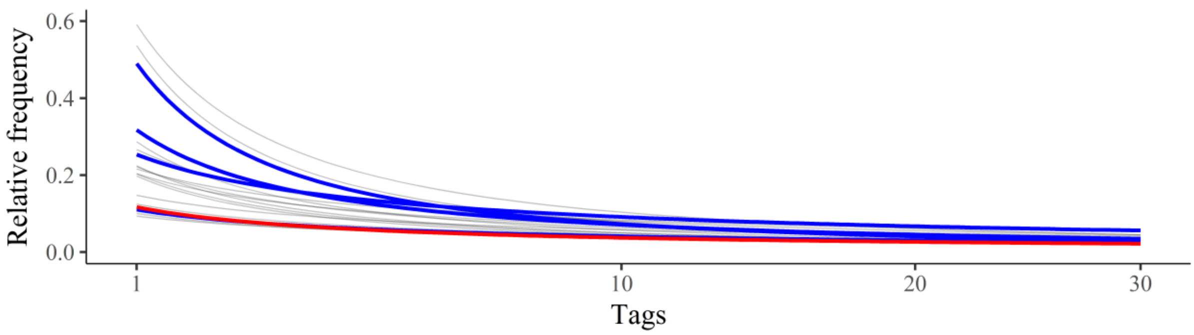


Fig. 7. Tag distribution in McDonald's image clusters

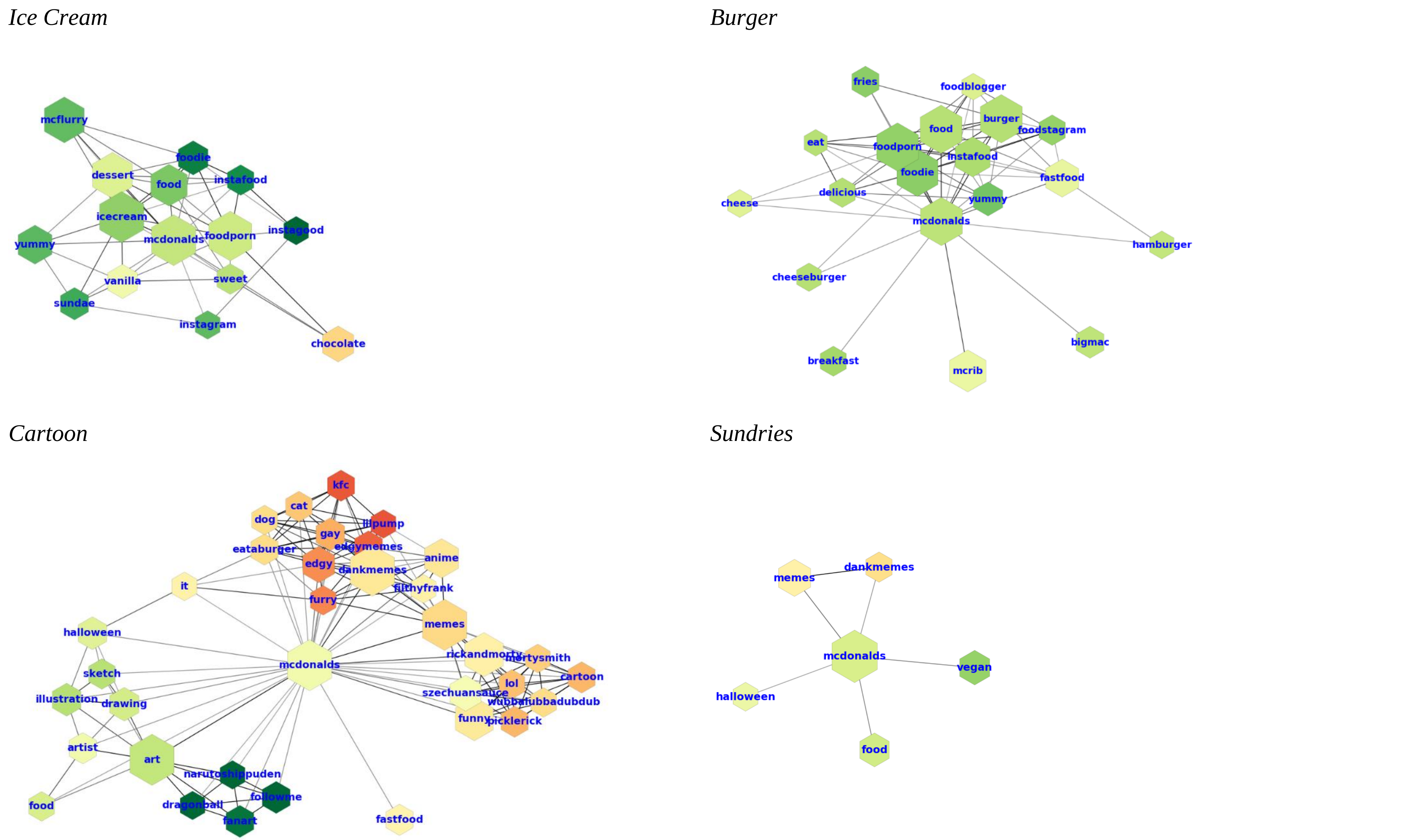


Fig. 6. Associative networks of the selected McDonald’s image clusters

## Tables

Table 1. Overview of previous articles in the field of marketing analyzing brand information from UGC

| Objective | Source | Data | Clustering | Visualization | Sentiment |
|---|---|---|---|---|---|
| Lee and Bradlow (2011) visualize market structure by automatically eliciting product attributes and brands' relative positions from product reviews | Epinions.com | Text | Clustering of phrases extracted from product reviews to elicit product attributes | Nine brands<br>Two dimensions | Natural division of comments (pro vs. con) in reviews |
| Netzer et al. (2012) visualize market structures and gain competitive landscape insights from consumer messages on forums | Edmunds.com | Text | Clustering of car models extracted from consumer messages | Three brands<br>Several attributes | No |
| Tirunillai and Tellis (2012) examine whether product reviews are related to stock market performance and which metric (volume and valence) has the strongest relationship | Amazon<br>Yahoo<br>Epinions.com | Text | No | No | Computer-based text analysis to derive the valence of a review |
| Nam and Kannan (2014) investigate how the information contained in social tags can act as a proxy measure for brand performance | Delicious | Social tags | No | Three brands / one brand<br>Several attributes | Manual classification of social tags into positive, negative, and neutral |
| Tirunillai and Tellis (2014) extract the key latent dimensions of consumer satisfaction from product reviews | Amazon<br>Yahoo<br>Epinions.com | Text | No | Two, three, and four brands<br>Two dimensions | Analysis of valence via extension of Latent Dirichlet Allocation |
| Gensler et al. (2015) extract consumers' brand associations and their interconnections, as well as depict and characterize the network of brand associations using product reviews | Unspecified product review platform | Text | No | One brand<br>Several attributes | Natural division of comments (pro vs. con) in reviews |
| Culotta and Cutler (2016) infer attribute-specific brand perception ratings by mining a brand's social connections | Twitter | Social connections | No | No | No |
| Liu et al. (2017a) derive latent brand topics automatically and classify brand sentiments | Twitter | Text | No | No | Sentiment analysis toolkit by the Stanford CoreNLP software package is applied to tweets |
| Liu et al. (2017b) classify brand-related images posted on social media networks to measure brand attributes (glamorous, rugged, healthy, fun) from images | Flickr<br>Instagram | Images | No | 56 brands<br>Four attributes | No |
| Moon and Kamakura (2017) translate product reviews into a product-positioning map that parses out perceptions and preferences for competing brands from reviewers' individual characteristics | Various wine review websites | Text | No | 249 (110) products<br>Three (two) dimensions | Manual classification of topics |
| Nam et al. (2017) demonstrate how the information in social tags can be used by extracting key representative topics, monitoring common dynamic trends, and investigating heterogeneous brand perceptions | Delicious | Social tags | Clustering of users' social tags on a blog post | One brand<br>Several attributes | No |
| This article combines image, text, and social tagging data to gain brand insights. Posts are clustered according to images; caption texts and social tags are used to visualize the brand perceptions of identified clusters | Instagram | Images<br>Text<br>Social tags | Clustering of posts' images characterized by labels extracted with the Google Cloud Vision API | One brand<br>Several attributes | Sentiment analysis by VADER (Hutto & Gilbert, 2014) is applied to caption texts |

| Data | Usage on Instagram | Example (see Fig. 2) | Insights |
|---|---|---|---|
| Image data | Users upload images to document their everyday moments. | The image displays someone having food in a restaurant, holding twister fries. | What (e.g., objects) do the images display? |
| Text data | Users add a caption text to give further contextual information to an image. In doing so, they commonly reveal their emotional attitude towards the depicted content, facilitated by using emoticons to express their feelings. | The text expresses a positive attitude towards the product. | How do users feel about the situations? |
| Tag data | Users add tags to categorize and/or describe what is displayed in the image and to provide further contextual information associated with the image. | The tags describe the product at the center of the image and another product in background of the image, relate the post to the brand, and categorize the image as *foodporn.* | What do users associate with the situations? |

Table 2. Information provided by the three data components

| Cluster | Most impactful negative tags | | | | Most impactful positive tags | | |
|---|---|---|---|---|---|---|---|
| Ice cream | theicecheckapp (-0.016) | regrann (-0.011) | justdelhiing (-0.006) | … | food (0.040) | mcflurry (0.053) | icecream (0.147) |
| Burger | healthy (-0.007) | healthylifestyle (-0.003) | steakhouse (-0.002) | … | food (0.064) | burger (0.065) | foodporn (0.075) |
| Cartoon | trump (-0.009) | kfc (-0.007) | edgymemes (-0.006) | … | fanart (0.034) | followme (0.038) | art (0.062) |
| Sundries | animalrights activism (-0.005) | deathrowdogs (-0.005) | vegetariansofig (-0.004) | … | govegan (0.024) | vegansofig (0.025) | lunch (0.025) |

Table 3. Most impactful tags in the selected McDonald’s image clusters

| Data | Most frequent tags | | | | |
|---|---|---|---|---|---|
| All | food (0.090) 1st | memes (0.069) 2nd | foodporn (0.059) 3rd | love (0.052) 4th | dankmemes (0.051) 5th |
| Ice cream cluster | icecream (0.439) 30th | dessert (0.159) 197th | foodporn (0.159) 3rd | mcflurry (0.136) 98th | food (0.114) 1st |
| Burger cluster | burger (0.228) 11th | food (0.228) 1st | foodporn (0.226) 3rd | foodie (0.161) 10th | mcrib (0.126) 42nd |
| Cartoon cluster | memes (0.248) 2nd | art (0.238) 18th | dankmemes (0.215) 5th | rickandmorty (0.125) 74th | funny (0.122) 12th |
| Sundries cluster | memes (0.084) 2nd | vegan (0.073) 16th | food (0.070) 1st | dankmemes (0.055) 5th | halloween (0.051) 6th |

Table 4. Most frequent tags in all data and in the selected McDonald's image clusters

| Data | $\alpha$ | $\beta$ | $R^2$ |
|---|---|---|---|
| All | 0.117 | 0.495 | 0.973 |
| Ice cream cluster | 0.318 | 0.649 | 0.963 |
| Burger cluster | 0.490 | 0.827 | 0.977 |
| Cartoon cluster | 0.254 | 0.443 | 0.963 |
| Sundries cluster | 0.110 | 0.428 | 0.961 |

Table 5. Power functions' parameters

| Cluster | Visual Contents | Textual Contents |
|---|---|---|
| Ice cream | Images reflect real product experience of McDonald's ice cream | Users share what they think and feel about McDonald's ice cream<br>McDonald's ice cream is evaluated very positively<br>McFlurry receives more attention than McSundae, which is, on the other hand, directly connected with the favorable product association *yummy*<br>The chocolate flavor receives negative attention<br>The ice check app can be identified as an association to focus on in marketing efforts: users are discontent with broken ice cream machines |
| Burger | Images reflect real product experience of McDonald's burgers | Users share what they think and feel about McDonald's burgers<br>The associations *delicious* and *yummy* occur frequently<br>The McRib is the most frequently occurring product association<br>The association *healthy* has a negative impact; users use this association to mock McDonald's and to show that they feel the opposite |
| Cartoon | Images represent cartoonish illustrations, art, | The cluster represents artistic and trending topics users connect to McDonald's |

| | | |
|---|---|---|
| | and memes posted to entertain other users | The associative network reveals a clearly grouped structure of associations (*memes* and *art*)<br>Users express a positive attitude towards McDonald's in the form of illustrations, drawings, and sketches<br>Marketing promotions about the anime series Naruto Shippuden and Dragonball receive positive evaluation<br>Consumers are highly aware of the Rick and Morty marketing disaster and articulate their dissatisfaction with the brand |
| Sundries | Images can be allocated to diverse contexts and do not reflect direct product experiences | The cluster represents political chatter around the brand<br>Users discuss vegan topics connected to McDonald's<br>The cluster serves as a refuge for different kinds of associations, which is reflected in the relative low occurrence frequencies |

Table 6. Results from image, text, and tagging data for McDonald's

| Field of decision making | Opportunities based on the integrative analysis |
|---|---|
| Brand management | Identify topics about which users share brand-related images<br>Allocate posts by context and the level of brand centrality<br>Discover what users in different contexts think and feel about the brand |
| Product management | Discover what users in specific product clusters think and feel about the corresponding product<br>Focus efforts on striking products (or product attributes) to maintain the strength of products (or product attributes)<br>Identify neglected products<br>Discover strengths and weaknesses of products (or product attributes) based on user sentiments |
| Marketing communications | Learn more about users (e.g., their interests) for market segmentation, the positioning of new products, or creating new promotions<br>Identify trending topics users like to connect to the brand in specific situations<br>Stress trending topics that gained positive attention to benefit from positive spillover effects |
| Marketing control | Monitor users' awareness and evaluation of newly introduced products, ads, or promotions |

Table 7. Overview of managerial implications

# Essay B1: Drivers of Celebrities' Social Media Capital

# Drivers of Celebrities' Social Media Capital


## Abstract

Alongside their professional careers, nowadays many celebrities also act as social media influencers. While current research shows that brands can profit from the social media popularity of celebrity endorsers, the question of how celebrities can become more popular on social media (i.e., accumulate high numbers of subscribers) has rarely been approached in the marketing literature. In this article, we investigate factors that increase celebrities' social media popularity, with a focus on their social media content, network, career success, and popularity gained outside the social media context. We analyze both visual and textual data from a sample of 1,443 celebrities (professional soccer players) with more than 350,000 posts on Instagram. The results show that celebrities' social media behavior is slightly more important than the popularity they have gained because of their professional career in driving social media popularity. In particular, we find that celebrities focus too much on professional (vs. personal) content and, thus, squander potential social media popularity. Further, most celebrities increase the share of professional content over the course of their career, which has a negative effect on social media popularity.

## Introduction

With 240 million subscribers, Christiano Ronaldo was by far the most popular celebrity on Instagram in 2020. Like other celebrities, he regularly shares content related to his professional career as a soccer player, discloses intimate moments with his family and friends, and endorses brands. Given his popularity on social media, he reportedly earns more income as an influencer on Instagram than as a professional soccer player (Lane, 2019). Celebrities like Christiano Ronaldo can thus turn their social media popularity into economic capital (Driessens 2013). Given that brands pay approximately $10 per thousand subscribers for an Instagram post that endorses a brand (Webfx.com 2021), growing the subscriber base substantially affects celebrities' incomes.

Brands alike benefit from celebrities' social media popularity. Studies by Jin and Phua (2014) and De Veirman (2017) have shown that celebrities with many subscribers are perceived as more trustworthy. As trustworthiness increases the probability that subscribers will buy a recommended product (Chung & Cho 2017), growing their social media popularity is a way for celebrities to increase the effectiveness of their brand endorsements on social media. Likewise, in the movie context, Kupfer et al. (2018) found that actors' social media popularity increased sales of movies they endorsed. In sum, the given example about Christiano Ronaldo, as well as prior research in the field, underlines the positive economic impact that social media popularity has on both celebrities (or their respective agencies) and brands. Therefore, our paper focuses on the factors that drive celebrities' social media popularity.

The following example illustrates that the determinants of social media popularity differ between celebrity and non-celebrity social media influencers. Like Christiano Ronaldo, most soccer players who become famous do so because of their excellent performance as athletes. Thus, it is reasonable to assume that players' performance affects their social media popularity, as people who admire their professional skills are more likely to follow them on social media. However, the way that athletes like Christiano Ronaldo use social media can also be assumed to affect their popularity. For example, sharing personal (i.e., not work related) information might make the content more interesting for some subscribers (i.e., those who are interested in their personal lives) but less interesting for others (i.e., those who are mainly interested in soccer). The goal of this article, therefore, is to address the following research question:

*To what extent do celebrities' professional careers and behavior on social media affect their social media popularity?*

Several streams of research are related to our research question. One stream investigates the drivers of celebrity popularity and favorability outside the context of social media (Luo et al. 2010; Mathys et al. 2016). Within social media, several field studies have examined what affects the popularity of a post (De Vries et al. 2012; Rooderkerk & Pauwels 2016; see Hughes et al. 2019 for a review). However, these articles treated social media popularity (usually operationalized as the number of subscribers) content creators as a control variable and did not explain how celebrities gain popularity. Additionally, most of these studies did not study traditional celebrities (i.e., people who became popular outside social media) but instead focused on brands and social media influencers (i.e., people who became popular on social media). Another stream of research relevant to celebrities and social media investigates how celebrities can build parasocial relationships with their subscribers on social media and how these relationships help improve celebrity credibility and subscriber loyalty (Yuan et al. 2016; Chung & Cho 2017; Kim & Song 2016; Ki & Kim 2019; Sokolova & Kefi 2020). Such research is mostly survey-based and thus does not empirically determine whether the drivers of parasocial relationships (such as sharing personal information with subscribers) also increase celebrities' popularity on social media. A third stream of research investigates how network activities (e.g., friend requests) can be used to increase the popularity of one's own account. For example, Ansari et al. (2018) investigated how artists built social networks by sending friend requests, comments, and uploading new songs. Lanz et al. (2019) found that individuals can increase their social media popularity by connecting to more influential users but that targeting very influential users is less efficient, given that they are very unlikely to respond positively to connection requests (due to large disparities in status). However, none of these prior studies investigated the extent to which celebrities' professional career popularity outside the social network affects their popularity within it.

In sum, prior research has been inconclusive with respect to our research question. This study advances research on celebrities' social media popularity in several ways. First, we built a comprehensive model that includes two sets of factors of social media popularity: celebrities' professional careers and social media behavior. We evaluated the degree to which social media popularity results from celebrities' social media behavior or their professional careers. Factors that represent celebrities' social media behavior include how actively they communicate with subscribers, what kind of content they share with subscribers, and with whom they are connected in the social network. Factors that characterize the professional career of soccer players include players' market value and age.

Second, we investigated real-world following behavior on Instagram instead of following intentions, which is common in survey-based research. We were thus able to quantify the actual magnitude of behavioral responses (e.g., when celebrities decide to post more personal rather than professional content) in terms of popularity and provide data-based managerial recommendations.

Third, we avoided instructing participants to think about their favorite celebrity, which is regularly done in survey-based research. According to Chung and Cho (2017), such a method tends to oversample people who have strong opinions and attitudes and thus may not be representative of the population of subscribers. Instead, we studied the aggregate behavior of all celebrity subscribers. Additionally, we sampled celebrities with all levels of popularity to avoid survivorship bias (i.e., we avoided oversampling top-of-mind celebrities) by analyzing all players under contract at a club in any of the three highest-revenue European soccer leagues.

To study the outlined factors that influence social media popularity, we built a novel sample of over 1,400 European soccer players with around 350,000 posts created on Instagram between 2012 and 2020. We analyzed both the visual and textual content of their posts to build a set of 10 predictors that describe the players' social media behavior (e.g., sharing of personal posts) and 6 predictors that describe their professional careers (e.g., market value of the player). To replicate the intriguing finding that the share of personal posts in a profile can be either too low or too high (i.e., it can have an inverse quadratic effect on subscription intentions), we conducted a second experimental study in which we manipulated the share of personal and professional posts. We investigated whether perceived intimacy and perceived appropriateness explain the inverse quadratic effect.

The remainder of this paper is structured as follows: First, we discuss empirical studies and theories on celebrities' use of social media and career influence factors to derive corresponding research hypotheses. We then describe our sample and the operationalization of the variables required to test these hypotheses. Next, we present the results of an estimated regression model. Subsequently, we outline the setup of the experimental study and corresponding results. We finally discuss the main findings and some managerial implications as well as the study's limitations and opportunities for future research.

## Theoretical Background

### How Do Celebrities Build Social Media Capital?

Competition for consumer attention across media outlets is intense, especially on social media platforms (Lee & Hosanagar 2018). Driessens (2013) defined celebrity capital as "accumulated media visibility that results from recurrent media representations" (p. 543). Similarly, we define celebrity social media capital as accumulated visibility on social media. Therefore, social media capital is a subset of celebrity capital restricted to social media instead of all media. In contrast to traditional media, the distribution of visibility on social media is not controlled by gatekeepers (such as publishers) but is instead determined by two key factors: a) users decide whether to subscribe to other users (and thus see more of their content), and b) social media platforms analyze users' personal usage (e.g., current subscriptions and recent interactions with similar users; Costine 2018) as well as other users' behavior (e.g., interactions of similar users) on the platform to recommend social media profiles that users might want to subscribe to (Hennig-Thurau et al. 2010). Consequently, subscriber counts represent users' accumulated potential visibility on social media and can thus be used to operationalize celebrity social media capital. Following the industry rule of thumb of $0.01 payment per subscriber per endorsement post, we can directly link celebrity social media capital to economic capital (Driessens 2013).

Building up a large community of subscribers on social media entails at least two challenges for celebrities. The first is generating sufficient interest in themselves such that potential subscribers search for their social media accounts. Following the uses and gratifications theory (Katz et al. 1974), people actively seek out specific media to gratify their personal needs. Studies by Clavio et al. (2010) and Frederick et al. (2012) found that subscribing to celebrity athletes on Twitter is driven by needs such as information seeking, self-status seeking, socializing, and entertainment. Mathys et al. (2016) showed that consumer interest (measured via the number of search queries on a movie community website) in an actor depends on their number of movie appearances, movie revenues, and actor–movie fit. The aforementioned factors directly affect subscriber interest and increase the likelihood that media outlets will report on a celebrity (e.g., extremely low revenues or actor–movie fit). A study by Luo et al. (2010) found that if consumers are not exposed to a celebrity on a regular basis, their favorability status can decay substantially. In line with these studies, we argue that interest in celebrities' social media accounts is mostly generated outside social media—i.e., through their careers and popularity in other mass media, such as television, newspaper articles, and website articles.

A second challenge celebrities face when building a large community of subscribers is not only to attract new subscribers but also to maintain current subscribers' interest in the long term. While we could not find research on the volatility of subscriber counts over time, we argue that, in contrast to weekly or monthly consumer interest (Mathys et al. 2016), subscriptions on social media are not highly dynamic. Figure 1 shows the development of subscribers for four exemplary celebrities (actors Dakota Johnson and Mark Wahlberg and athletes Lionel Messi and Samir Nasri). Compared to popularity as investigated in Mathys et al. (2016; see Figure 1), we see long periods with a rather monotonic increase and only rarely observe dynamic dilution and enhancement effects in the data[8] (Luo et al. 2010). Since we can only observe the aggregate number of subscribers, we cannot infer the fraction of new subscribers and lost subscribers over time. However, as exemplified in the case of Samir Nasri, the number of subscribers can also decrease over time. One reason for this might be that he went from a popular club (Manchester City) to a less-known club (Antalyaspor) in late 2017.

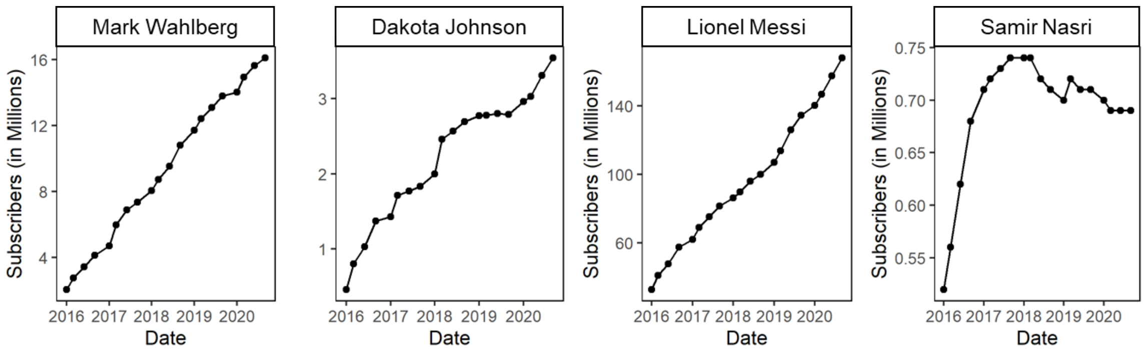


**Figure 1.** Number of subscribers over time.

### How Does Forming Parasocial Relationships Influence Celebrity Capital Building?

Accompanying the rise of traditional mass media, such as radio, television, and movies, Horton and Wohl (1956) coined the term "parasocial relationship" to describe the seeming relationships between performers/actors and spectators. Social media researchers now broadly use this term to describe relationships formed on social media between celebrities (and other social media influencers) and their subscribers. Repeated exposure to content created by a celebrity creates a sense of intimacy, perceived friendship, and identification with them (Chung & Cho 2017). Accordingly, celebrities' posts represent parasocial interactions between them and their subscribers. This interaction is "one-sided, nondialectical, controlled by the performer, and not susceptible of mutual development" (Horton & Wohl, 1956, p. 215), yet it makes subscribers believe that they build personal relationships with popular social media figures (Chung & Cho 2017).

[8] The authors have no access to weekly numbers of subscriber data for the celebrities used in the final sample. The data for the time-series in Figure 1 has been copied from www.hypeauditor.com, a professional social media analysis company that tracks historic data for a set of celebrities.

Several studies have investigated how parasocial relationship building affects subscribers' behavior within and outside the celebrity context. Chung and Cho (2017), for example, found a positive relationship between parasocial relationships with Korean singers and perceived source trustworthiness, which in turn led to increased brand credibility and purchase intentions for endorsed products. Further studies confirmed the link between parasocial relationships and various attitudinal and behavioral constructs, especially source credibility (Munnukka et al. 2019), attitude toward the celebrity (Tran et al. 2019), attachment and loyalty to the celebrity (Labrecque 2014; Aw & Labreque 2020; Ki et al. 2020), electronic word-of-mouth intention (Hwang & Zhang 2018), and self-brand connection (Escalas & Bettman 2017). In the context of celebrity athletes, Yuan et al. (2016) surveyed 350 social media subscribers of basketball star LeBron James and found that forming a parasocial relationship was related to the brand equity of his main sponsor, Nike, and hence increased its customer lifetime value. In summary, building parasocial relationships is relevant for celebrities because it influences trust building, loyalty, and attachment toward the celebrity. For sponsoring brands, selecting celebrities who build strong relationships with their subscribers is important, as research has shown that endorsements will be more effective (in terms of increasing purchase intentions and enhancing brand perceptions) when subscribers build strong relationships with celebrities. Consequently, increasing celebrity social media capital is likely to be affected by celebrities' ability to build parasocial relationships with subscribers, as forming a bond with a celebrity makes it harder for subscribers to decide to unfollow that celebrity. As shown in Figure 1 for Samir Nasri, some players may lose followers if they fail to build sufficiently strong parasocial relationships with their subscribers. But how can celebrities foster parasocial relationships on social media?

Social penetration theory (SPT; Altman & Taylor 1973) is frequently used to identify factors that influence relationship building. In line with this theory, relationship building is based on revealing intimate, personal, and private information to others, which is called self-disclosure (Cozby, 1973; Wheeless & Grotz, 1977). Self-disclosing to others makes the discloser vulnerable (see also Cozby 1973; Omarzu 2000), as disclosure implies giving up some amount of privacy and control by sharing personal information with others (Derlega et al. 1993). At the same time, self-disclosing allows subscribers to form a personal bond with social media influencers, as shown by several studies (Chung & Cho 2017; Kim & Kim 2020; Kim & Song 2016). Several factors that favor parasocial relationship building are discussed and investigated in this paper.

## Conceptual Model and Development of Research Hypotheses

We propose a conceptual model that comprises two sets of factors expected to affect celebrities' social media capital: factors related to celebrities' social media behavior and factors related to their professional careers (Figure 2). Social media behavior comprises content posted by celebrities and network factors that reflect how well connected they are on social media. Celebrities' professional careers can be further subdivided into factors that describe the status of their careers and factors that reflect their external popularity (i.e., popularity outside of social media). In what follows, we develop research hypotheses for all four groups of factors: content, network, career,[9] and external popularity, as shown in Figure 2.

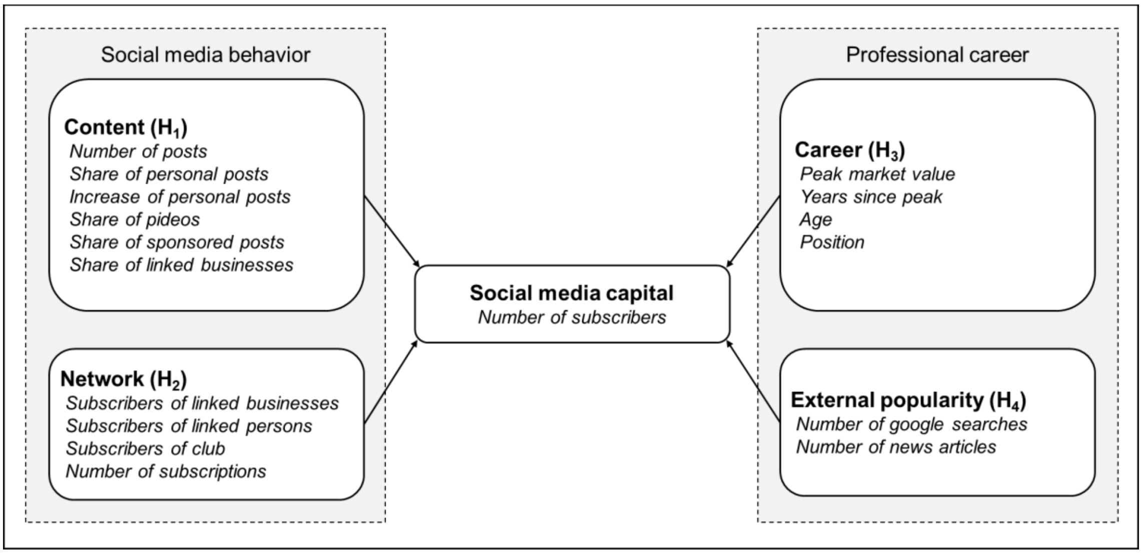


**Figure 2.** Conceptual framework. Measured variables are in italics.

## Content Factors

**Number of Posts**. Posts contain images, videos, and text and are the main form of communication between celebrities and their subscribers. The number of posts is likely to contribute to forming parasocial relationships with celebrities, as each post constitutes a parasocial interaction between a celebrity and their subscribers (Horton & Wohl 1956). As in conversations with friends, subscribers form stronger parasocial relationships with celebrities they frequently encounter (Chung & Cho 2017). Platform algorithms will also show new posts to potential subscribers more frequently (Costine 2018) when celebrities post more often; thus, an increase in the number of posts is expected to increase the number of subscribers. Therefore, we expect the following:

**$H_{1a}$:** A larger number of posts has a positive effect on the number of subscribers.

**Personal and Professional Posts**. Celebrities use social media to share details regarding their professional and personal lives. For example, a soccer player might post images showing how his team exercises, gets to games by bus, and celebrates wins (Hambrick et al., 2010). They might also post moments with family and friends during holidays or at birthday parties. In addition, celebrities use social media to endorse brands and promote products in their posts, which can take place in either a professional or personal context (Yuan et al. 2016).

Some studies have investigated how subscribers perceive professional vs. personal posts. Kim and Song (2016) found that both professional and personal posts positively affect parasocial relationship building. They also emphasized that a professional context was more suitable for building a strong connection between celebrities and subscribers. Eng and Jarvis (2020)

[9] Please note that all career factors were context specific and had to be adapted for different types of celebrities, such as actors or singers.

conducted an experiment in which participants rated their attachment to a fictious celebrity who was either presented in a "personal narrative" (focusing on his role as a father and husband) or a "professional narrative" (focusing on his role as an actor and his success). They found that personal narratives led to more celebrity attachment. However, a study by Orben and Dunbar (2017) also showed that the high vs. medium intimacy of social media posts reduced the perceived appropriateness of a post, which in turn had a direct negative effect on the perceived social attractiveness of the content creator (i.e., motivation to develop a parasocial relationship with them) and a mediated negative effect on social attractiveness via perceived homophily (i.e., how similar the target feels to the content creator). Lin and Utz (2017) partially confirmed the link between intimacy and appropriateness and concluded that "intimate public self-disclosure is thus a double-edged sword: it may increase the feeling of closeness, but it may also decrease social attraction when it is perceived as inappropriate" (Lin & Utz 2017, p. 431).

Given the proposed link between attachment and social media capital, we expect that celebrities who share personal content are more successful in creating attachment and growing their number of subscribers. At the same time, and in line with the aforementioned studies, we also expect a negative quadratic effect, as posting too many personal posts could be perceived as inappropriate. We therefore generated the following hypotheses:

**$H_{1b}$:** A larger share[10] of personal posts has a positive effect on the number of subscribers.

**$H_{1c}$:** A larger share of personal posts has a negative quadratic (inverted U-shape) effect on the number of subscribers.

Furthermore, the perceived appropriateness of intimacy is dynamic, and thus, as parasocial relationships develop, higher post intimacy might be perceived as more appropriate (Altman & Taylor 1973). Thus, an advisable strategy for celebrities might be to increase the share of personal posts over time. In line with SPT, they would first reveal more superficial information before disclosing more fundamental, core characteristics of their personality. Therefore, we assume the following:

**$H_{1d}$:** Increasing the share of personal posts over time has a positive effect on the number of subscribers.

**Share of Videos**. In contrast to images, videos appeal to both the visual and acoustic senses and therefore tend to be more engaging than other forms of content (Choi & Johnson 2005). Appealing to both senses with videos might make social media profiles look more authentic and realistic. Studies from the field of information systems (Kirk et al. 2010; Neustaedter & Greenberg 2012) found that videos make people feel closer to the content creator, mainly because videos resemble face-to-face conversations with other people. Therefore, we expect the following:

**$H_{1e}$:** A larger share of video (vs. image) posts has a positive effect on the number of subscribers.

**Share of Sponsored Posts**. Celebrities' credibility can be negatively affected by an increasing number of product endorsements (Tripp et al. 1994). Sponsored content is the purposeful

[10] By "share" we mean the number of posts with a certain attribute (e.g., depicting a personal moment) divided the total number of a celebrity's posts.

integration of brands or branded persuasive messages in social media content in exchange for compensation by a sponsor (Eisend et al. 2020). Soccer players promote the sponsoring brand of their club, their individual equipment sponsors, and a variety of other brands. For example, Christiano Ronaldo has sponsorship contracts with Nike, Tag Heuer, DAZN, Electronic Arts, and Herbalife, which regularly appear in his social media posts. Celebrities and other users are required by Federal Trade Commission (FTC) (2015) regulations to disclose the sponsored nature of a post. Experimental studies have shown that adding a sponsorship disclosure statement to a post can activate persuasion knowledge (i.e., make receivers aware of a persuasion attempt), which can increase resistance to sponsored content (Eisend et al. 2020). Persuasion knowledge is likely to increase negative reactions, such as skepticism and cognitive/affective resistance and feelings of deception, which are expected to decrease the attractiveness of a celebrity's social media profile. We therefore generated the following hypothesis:

**$H_{1f}$:** A larger share of posts with a sponsorship disclosure has a negative effect on the number of subscribers.

**Share of Posts Linked to a Business**. Celebrities can link a business (i.e., the Instagram account of the business) in their post by including @[business name] in the caption text. In line with the argumentation for sponsored posts, the nature of a post that is linked to a business changes, as it could be perceived by subscribers as a "mild" persuasion attempt. Viewers of a post that includes links to a business will suspect that the business paid to get the celebrity to include the link in the post. We therefore predict the following:

**$H_{1g}$:** A larger share of posts linked to a business has a negative effect on the number of subscribers.

**Network Factors**

**Number of Subscribers of Linked Businesses, Linked Persons, and the Club**. As described above, Instagram posts can be professional, personal, and can additionally be sponsored. Celebrities link other users in their posts to indicate that the linked person is involved in a situation (e.g., exercising together with another player or visiting a restaurant with friends) or to connect with a branded product. In the latter case, the linked user is the business account of the brand. The included links indicate that the celebrity has some sort of relationship with the linked user, either as part of an interpersonal relationship (e.g., a friend, colleague, or player from another team) or as part of a commercial relationship (e.g., the player's club or a brand sponsoring product endorsements). While we do not observe the behavior of the linked users, collaborating and connecting with other users who have many subscribers has been identified as a successful strategy to build a subscriber base (Kupfer et al. 2018). The main reason is that subscribers of a linked person or brand are more likely to explore a profile that is linked to the profile they are currently following. For example, subscribers of Nike might subscribe to Ronaldo after being linked in Nike's product posts. Additionally, subscribers of Ronaldo might subscribe to Real Madrid's defensive player Sergio Ramos after Ramos links him multiple times in his posts, showing them having dinner together. Analogously, when soccer players start playing for a new club, it is likely that their subscribers will partially start subscribing to the club, and subscribers of the club will partially start subscribing to the player. Consequently, celebrities' social media capital not only depends on their behavior but also on the social media capital of the users with whom they connect. We argue that linking another user (a business or a person) in a post signals closeness between the two users. As relations with users with high social media capital might also positively affect the social media capital of a celebrity, we propose that the number of subscribers of all linked businesses and linked persons, as well as the number of subscribers of the club, is positively associated with the number of subscribers a celebrity has. However, it should be noted that these effects are most likely observed with reverse-causality. Following our argumentation, the number of subscribers of all linked businesses, linked persons, and the club are also affected by the number of subscribers a celebrity has. Furthermore, popular brands might be more likely to collaborate with celebrities who have many subscribers. Therefore, we consider the estimated effects to be purely correlational and do not claim causality.

**$H_{2a/b/c}$:** The number of subscribers of linked businesses and persons, as well as the number of subscribers of the club, is positively associated with the number of subscribers.

**Subscriptions**. Research examining the role of the number of subscriptions of a celebrity on social media is scarce. However, in a recent study, Valsesia et al. (2020) showed that the number of subscriptions can serve as an indicator with which subscribers can evaluate the autonomy of influential social media users. They found that more subscriptions might lead to fewer interactions (e.g., "liking" or "sharing" the post) mediated by lower levels of perceived influence. In line with Valsesia et al. (2020), we expect the following:

**$H_{2d}$:** The number of subscriptions of a celebrity is negatively associated with the number of subscribers.

### Career Factors

Several studies provide evidence that individual performance and media presence positively affect the success of a celebrity, quantified as the celebrity's salary, economic value, and/or human-brand image (Rosen 1981; Adler 1985; Lehmann & Schulze 2008; Franck & Nüesch 2012; Hofmann et al. 2021). Hofmann et al. (2021) showed that media presence is strongly dependent on performance and correlates with the number of subscribers on social media as well as the number of Google search hits for a celebrity's name. Therefore, we assume that these factors might also affect soccer players' social media capital.

***Career***. Quantifying the success of a celebrity's career requires taking into account the celebrity type. For example, an actor's success could be quantified by counting the number of movies in which they starred (Mathys et al. 2016). For athletes, particularly soccer players, we follow the existing economics literature and use a player's market value as a representation of success achieved through their career (Franck & Nüesch 2012). Notably, market value is not only related to performance but also to the player's popularity (Hofmann et al. 2021). Accordingly, we propose the following:

**$H_{3a}$:** A celebrity's market value is positively associated with the number of subscribers.

Carrillat and Ilicic (2019) provide a "celebrity capital life cycle" framework that conceptualizes the ups and downs of celebrities' career journeys according to their celebrity capital. According to the authors, celebrities build capital during the acquisition and consolidation stage. After reaching the "height of fame" (p. 5), celebrities might face a slow decline or abrupt downfall in their celebrity capital.

When a celebrity reaches the peak of the life cycle (i.e., the height of fame) depends on the celebrity category. For example, athletes are usually beyond their peak at the age that politicians start becoming more popular. To account for effects related to the life cycle framework, we propose that a celebrity's age and number of years since the peak of their career influence social media capital. First, as celebrities get older, their number of subscribers will grow (during the acquisition and consolidation stage). Second, the farther a player's peak lies in the past, the more subscribers will lose interest in them (during the decline/downfall stage). We therefore hypothesize the following:

**$H_{3b}$:** The age of a celebrity is positively associated with the number of subscribers.

**$H_{3c}$:** The number of years since the peak of a celebrity's career is negatively associated with the number of subscribers.

Depending on the context of the career, a celebrity might have a different position that affects their popularity. For example, the lead actor in a movie will likely receive more attention than the supporting roles. In professional soccer, strikers generally acquire more fans than their teammates, as scoring goals is the decisive moment of a soccer match. Additionally, game summaries often only include goals and closely missed chances by the strikers. Therefore, we predict the following:

**$H_{3d}$:** Playing in the "striker" position is positively associated with the number of subscribers.

### External Popularity Factors

External popularity refers to the capital of a celebrity outside social media. While popularity can be affected by career success, the interest of consumers and the mass media can also stem from injuries, negative publicity, and celebrity characteristics, such as eccentric appearance and attractiveness (Hock & Raithel 2020; Hofmann et al. 2021). In turn, popularity might be a key driver of social media capital, as subscribers' interest outside social media is likely to be the main reason they start following celebrities on social media. Therefore, we propose the following:

**$H_{4a/b}$:** The number of Google searches/the number of news articles (as indicators of popularity outside of social media) is positively associated with the number of subscribers.

## Field Study on Drivers of Social Media Capital

### Sample

To study the proposed mechanisms, we collected a novel sample that included data from 1,437 European male soccer players. We chose to focus on one type of celebrity because variables that indicate career and external popularity are celebrity type specific. Soccer players share a common career life cycle with respect to the age at which they start and end their careers (Carrillat & Ilicic 2019). Furthermore, market values can be used to quantify the success of a career on a unified scale. Lastly, consumers who subscribe to celebrity athletes' social media might be different from those who subscribe to actors' and musicians' social media in terms of sociodemographic and attitudinal dimensions, inducing further heterogeneity that is too complex to control for. Athletes, especially soccer players, yield several advantages in operationalizing the aforementioned constructs. First, it is straightforward to train a statistical model that accurately predicts whether a given image is personal (i.e., depicts elements or a situation from the personal life of a celebrity) or professional (i.e., depicts elements or a situation directly related to the professional career of a celebrity). Second, soccer players' market values are publicly available and provide information on their career success (Hofmann et al. 2021).

To build the sample, we first identified all players who are under contract at a club in any of the three highest-revenue European soccer leagues, namely the British Premier League, the Spanish Primera Division, and the German Bundesliga. We then manually collected the Instagram account name for each player and downloaded all posts made by each player with at least ten posts. The final dataset comprised 363,533 Instagram posts by 1,437 players from 58 clubs. For each player, we downloaded all profile information (number of subscribers, number of subscriptions, and number of posts). We further downloaded the profile information of all users linked[11] in the players' posts (30,377 unique accounts were mentioned).

**Variables**

To analyze the content of a post, we used the visual information of the posted image. In the case of a video, we used the first frame as an image (Schwenzow et al. 2021). We first annotated each image using Microsoft's Azure Computer Vision application programming interface (API). In the last year, marketing researchers have frequently utilized API-accessible computer vision models, as they are easy to use and provide high accuracy in annotating images (Klostermann et al. 2018; Li & Xie 2020). For each image sent to the API, the server responds with a list of tags and scores. Tags can be objects (e.g., "stadium"), scenery ("outside"), or actions ("running") that jointly reflect how humans describe the content of an image. Each tag has an accuracy score between 0 and 1 to assess the model confidence. In the following, every celebrity is represented by a vector of images $\mathbf{c_i} = \{\mathbf{i}_{\mathrm{ij}}\}$ and every image is represented as vector of tag confidence scores $\mathbf{i}_{\mathrm{ij}} = \{\mathrm{t}_{\mathrm{ijk}}\}$ with index *i* denoting celebrities, *j* denoting posts, and *k* denoting different tags.

**Share of Personal Posts**. After representing all images with tags, we manually labeled random images as "professional" ($\mathrm{label}_{\mathrm{ij}} = 0\ \forall i,j$ ) and "personal" ($\mathrm{label}_{\mathrm{ij}} = 1\ \forall i,j$), following the definition above. We then trained a random-forest classification model with 1,000 images, with half of the images previously labeled as personal and the other half labeled as professional. We used $\mathbf{i}_{\mathrm{ij}}$ as the input vector and $\mathrm{label}_{\mathrm{ij}}$ as the output variable. We cross-validated the model with 100 repeated random validation subsamples of 250 images each (25% of the labeled images). The average number of misclassified validation sample images per iteration was M = 2.36 (SD = 1.37, MIN = 0, MAX = 7), which equals a classification accuracy of 99.06%. The high

[11] On Instagram, an "@" character can be used to link another account, for example when endorsing a brand or another person. We only considered accounts linked in the text of the post.

accuracy was achieved because the Azure tags reliably described the content of the images, and distinguishing soccer players' professional and personal moments is unambiguous.

**Increase of Personal Posts**. To compute the *increase in the personal posts* variable, we took the number of personal posts divided by all posts for each player. To assess whether the celebrity increased or decreased the share of personal posts over time, we estimated a logistic regression model $P\left(\mathrm{label_{ij}} = 1\right) = \frac{1}{1+\exp(-(\beta_{i0}+\beta_{i1}x_{ij}))}\ \forall i, j$, where $x_{ij}$ is the index[12] of post j for celebrity $i$. Accordingly, if $\beta_{i1} > 0$, then the probability of posting a personal post increased with time (*increase of personal posts* = 1), whereas $\beta_{i1} \leq 0$ meant that it decreased (*increase of personal posts* = 0).

To operationalize the characteristics of celebrities' network (i.e., to determine to which users they are connected and how popular these users are), we generated a list of all linked users and extracted the respective number of subscribers for all linked accounts. We then classified users into business accounts and people (i.e., non-business accounts). Instagram accounts are characterized by the two boolean variables "is business" and "business type" in the website's source code. We treat accounts with "is business" = FALSE as persons. For the rest of the accounts, we first inspected the "business type" variable. We classified businesses with the types "Creators & Celebrities" and "Publishers" as persons, as we observed that these accounts primarily represent other celebrities instead of companies. We also created a list of the accounts of all clubs in our sample and removed these accounts from the lists of business accounts and persons. We then calculated the *share of linked businesses* as the number of posts in which at least one business account was linked divided by the total number of posts. Additionally, we aggregated the number of subscribers of all linked businesses across all posts to calculate the *subscribers of linked businesses* variable and did the same for all linked non-business accounts to measure *subscribers of linked persons*. We measured the popularity of the club by including the current number of subscribers in the variable *club subscriber*. We later report a model in which we replaced this variable with a club fixed effect to validate whether the model estimates would be affected by unobserved club-specific heterogeneity (e.g., social media strategy) that correlates with our other explanatory variables and the dependent variable. For example, if more popular clubs are more likely to hire a social media agency that advises the players to increase their share of personal posts, the observed share of personal posts is endogenous and the estimated effect on celebrity capital is biased if one omits the club's decision to hire an agency.

To measure the *share of sponsored posts*, we created a list of phrases that celebrities frequently include in post captions to adequately disclose the sponsored nature of a post. The list contained 12 terms, such as "#ad," "sponsored," and "/advert," and was matched with the caption text. If at least one phrase was found, the post contained a sponsorship disclosure.

For the career variables, we used KPMG's Soccer Benchmark Player Valuation to obtain information about the highest market value a player ever achieved and the date when that occurred. To control for yearly market value inflation, we divided a celebrity's market value by the total market value of all European soccer players in that year. We also recorded the position of the soccer player (striker vs. non-striker), because strikers often receive additional attention

[12] The index indicates the chronological order in which the celebrity created the posts with an integer value.

in the media because they score more goals than non-strikers. To account for the life cycles of the celebrities' careers (Carrillat & Ilicic 2019), we included their current age and the number of years since their peak market value.

The measurement of external popularity (i.e., popularity outside social media) was based on the number of Google search queries for the player's name to assess consumer interest in the celebrity, as well as the number of news articles on the website www.eurosport.com to take into account media interest in the celebrity. We excluded news articles related to the social media activity of the player by excluding the word "Instagram" in search queries to reduce the potential effect of social media capital on the number of news articles. For each player, we recorded their first and last names and ignored their middle names. No names appeared twice in our data. When we found a common nickname for the player in the respective Wikipedia article, we used the nickname instead, as both the media and fans might refer to the celebrity by their nickname. We ran a log-linear auxiliary regression for both variables, in which we controlled for the length of the name and the age of the player (see Kupfer et al. 2018 for a similar approach). Players with longer names might be referred to only with their second name by fans and news article authors, thus reducing the number of search queries and news articles for the full name. We also controlled for age in both auxiliary regression models, as Google search queries and the number of news articles are count variables that accumulate over time. In both models, the two predictors (length of the name and age) had a significant effect ($p < .001$), and we used the residuals of both models as our measures for the *number of Google searches* and the *number of news articles*.

All the variables are summarized in Table 1, and descriptive statistics are presented in Table 2. Table 3 shows all the variable correlations.

**Table 1.** Variable descriptions.

| Variable | Description | Source |
|---|---|---|
| **Content** | | |
| *Number of posts* | Total number of posts created by the celebrity | Instagram |
| *Share of personal posts* | Percentage of posts that is classified as showing a personal (vs. professional) situation depicted in the post's image | Instagram |
| *Increase of personal posts* | Binary variable equal to 1 if the probability of observing a personal post increases with time | Instagram |
| *Share of videos* | Percentage of posts that are videos (vs. images) | Instagram |
| *Share of sponsored posts* | Percentage of posts that include a textual sponsorship disclosure (e.g., "#sponsored", "#ad") | Instagram |
| *Share of linked businesses* | Percentage of posts in which a business account is linked | Instagram |
| **Network** | | |
| *Subscribers of linked businesses* | Aggregate number of subscribers for all linked business accounts | Instagram |
| *Subscribers of linked persons* | Aggregate number of subscribers for all linked non-business accounts | Instagram |
| *Subscribers of club* | Number of subscribers of the club with which the celebrity is currently under contract | Instagram |
| *Number of subscriptions* | Number of accounts the celebrity has subscribed to | Instagram |
| **Career** | | |
| *Peak market value* | Highest market value ever achieved by the celebrity, corrected for market value inflation | KPMG |
| *Position* | Binary variable equal to 1 if player is a striker | KPMG |
| *Years since peak* | Years between data collection and year of peak market value | KPMG |
| *Age* | Age of the celebrity in years | KPMG |
| **External popularity** | | |
| *Number of Google searches* | Number of Google search queries for the player's name, residual after controlling for age and name length | Google |
| *Number of news articles* | Number of articles on www.eurosport.com with the player's name, residual after controlling for age and name length. | Google |

**Table 2.** Descriptive statistics.

| Variable | Mean | Median | Min | Max | SD |
|---|---|---|---|---|---|
| Dependent variable: | | | | | |
| **Social media capital** | | | | | |
| *Number of subscribers*[a] | 1,123k | 56k | 883 | 166,255k | 5,884k |
| **Content** | | | | | |
| *Number of posts*[a] | 253 | 153 | 10 | 2303 | 289 |
| *Share of personal posts*[c] | 0.37 | 0.37 | 0.03 | 0.87 | 0.15 |
| *Increase of personal posts*[d] | 0.35 | 0.00 | 0.00 | 1.00 | 0.48 |
| *Share of videos*[c] | 0.05 | 0.04 | 0.00 | 0.50 | 0.05 |
| *Share of sponsored posts*[c] | 0.00 | 0.00 | 0.00 | 0.08 | 0.01 |
| *Share of linked businesses*[c] | 0.04 | 0.02 | 0.00 | 0.84 | 0.06 |
| **Network** | | | | | |
| *Subscribers of linked businesses*[a] | 155,035k | 30,981k | 0 | 10,043m | 525,307k |
| *Subscribers of linked persons*[a] | 508,701k | 82,156k | 0 | 19,500m | 1359,458k |
| *Subscribers of club*[a] | 8,728k | 588k | 54k | 91,864k | 20,235k |
| *Number of subscriptions*[a] | 443 | 374 | 2 | 3870 | 314 |
| **Career** | | | | | |
| *Peak market value*[b] | 17,083k | 10,000k | 25k | 180,000k | 22,792k |
| *Position*[d] | 0.30 | 0.00 | 0.00 | 1.00 | 0.46 |
| *Years since peak* | 4.35 | 3.97 | 0.21 | 16.64 | 2.51 |
| *Age* | 28.48 | 28.21 | 18.05 | 43.40 | 4.63 |
| **External popularity** | | | | | |
| *Number of Google searches*[a] | 78 | 75 | 0 | 594 | 54 |
| *Number of news articles*[a] | 922 | 188 | 0 | 50,200 | 3,231 |

Notes: All values are reported in the original scale; k indicates thousands, m indicates millions; a) count variable, log-transformed in the model; b) original rather than yearly market size corrected values are reported; c) variable is a percentage and takes values between 0 and 1; d) binary variable.

**Table 3.** Variable correlations.

| No. | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | *Number of subscribers* | | | | | | | | | | | | | | | | |
| 2 | *Number of posts* | .34 | | | | | | | | | | | | | | | |
| 3 | *Share of personal posts* | .09 | .27 | | | | | | | | | | | | | | |
| 4 | *Increase of personal posts* | -.05 | -.26 | -.23 | | | | | | | | | | | | | |
| 5 | *Share of videos* | .18 | .17 | .09 | .04 | | | | | | | | | | | | |
| 6 | *Share of sponsored posts* | .05 | .07 | .02 | -.01 | .13 | | | | | | | | | | | |
| 7 | *Share of linked businesses* | .09 | .06 | .02 | .02 | .19 | .12 | | | | | | | | | | |
| 8 | *Subscribers of linked businesses* | .17 | .34 | .06 | -.07 | .11 | .04 | .43 | | | | | | | | | |
| 9 | *Subscribers of linked persons* | .43 | .63 | .09 | -.11 | .18 | .07 | .16 | .36 | | | | | | | | |
| 10 | *Subscribers of club* | .42 | .26 | -.05 | -.01 | .08 | .00 | .05 | .12 | .39 | | | | | | | |
| 11 | *Number of subscriptions* | -.01 | .24 | .11 | -.12 | -.01 | -.07 | .03 | .13 | .07 | -.03 | | | | | | |
| 12 | *Peak market value* | .54 | .43 | .07 | -.06 | .21 | .06 | .13 | .20 | .44 | .42 | -.07 | | | | | |
| 13 | *Position* | .07 | .02 | .06 | .07 | .15 | -.03 | -.01 | -.01 | -.03 | -.01 | -.04 | .10 | | | | |
| 14 | *Years since peak* | .05 | .20 | .24 | -.16 | .13 | -.02 | .07 | .02 | .11 | -.02 | .16 | -.01 | -.01 | | | |
| 15 | *Age* | .14 | .36 | .31 | -.24 | .16 | .05 | .11 | .08 | .23 | -.04 | .07 | .13 | -.03 | .67 | | |
| 16 | *Number of Google searches* | .15 | .19 | .01 | .02 | .13 | .01 | .06 | .10 | .17 | .20 | -.08 | .34 | .08 | -.02 | .00 | |
| 17 | *Number of news articles* | .25 | .34 | -.02 | -.03 | .17 | -.02 | .07 | .18 | .29 | .34 | .02 | .58 | .14 | -.04 | .00 | .48 |

## Model

To estimate the effect of the proposed variables on the number of subscriptions, we used a generalized linear model. As the number of subscribers is a positive integer variable, a count-distribution like the Poisson distribution or the negative binomial distribution for the error term is more appropriate than the normal distribution commonly used in econometric models applied by social media researchers (Hughes et al. 2019). A likelihood ratio test indicated overdispersion in the data for the number of subscribers ($X^2$ = 534,883,978, p < .001). Thus, we used a negative binomial model instead of a Poisson model. Note that our model uses the logarithm of the expected count as a function of the predictor variables. We could therefore interpret the coefficients (b) as the difference in the logs of the expected counts of the response variable given a one-unit change in the predictor. We used a log-transformation for all social count variables (indicated by superscript "a" in Table 2) to account for the large spread. We added one if the concerning variable had zero-valued observations (see Table 3). The estimated coefficients for the log-transformed variables can be interpreted as elasticities (percent change in the response variable when the predictor variable increases by one percent). The other variables were z-standardized if they were not binary (*increase of personal posts* and *position*). To test the hypothesis of the U-shaped effect of *share of personal posts,* we added a quadratic term to the model.

## Results

Table 4 reports the results of the generalized linear model, with the *number of subscribers* as the dependent variable (n = 1,437). A likelihood ratio test indicated that the model was significant ($X^2$ = 2923.7, p < .001) and had a high goodness-of-fit with Nagelkerke pseudo-$R^2$ of.869. The model had a log-likelihood of -18,407, an Akaike information criterion (AIC) value of 36,888, and a Bayesian information criterion (BIC) value of 36,988. We used the glm.nb function from the MASS R package, and the shape parameter of the negative binomial distribution was $\theta$ = 1.108. There was no multicollinearity concern, as the variance inflation index of all linear predictors was below 3.1.

**Table 4.** Regression results.

| Variable | Coefficient (b) | Standard Error | p-Value | VIF | Hyp. |
|---|---|---|---|---|---|
| *(Intercept)* | **4.986** | .344 | .000 | | |
| **Content** | | | | | |
| *Number of posts* | **.359** | .040 | .000 | 3.1 | **$H_{1a}$: +** |
| *Share of personal posts* | **.147** | .028 | .000 | 1.2 | **$H_{1b}$: +** |
| *Share of personal posts$^2$* | **-.048** | .020 | .018 | | **$H_{1c}$: -** |
| *Increase of personal posts* | **.251** | .057 | .000 | 1.2 | **$H_{1d}$: +** |
| *Share of videos* | **.231** | .027 | .000 | 1.2 | **$H_{1e}$: +** |
| *Share of sponsored posts* | **-.043** | .026 | .097 | 1.0 | **$H_{1f}$: -** |
| *Share of linked businesses* | -.007 | .029 | .801 | 1.4 | $H_{1g}$: - |
| **Network** | | | | | |
| *Subscribers of linked businesses[a]* | **.019** | .005 | .000 | 2.2 | **$H_{2a}$: +** |
| *Subscribers of linked persons[a]* | **.015** | .007 | .047 | 2.0 | **$H_{2b}$: +** |
| *Subscribers of club[a]* | **.296** | .016 | .000 | 1.7 | **$H_{2c}$: +** |
| *Subscriptions[a]* | -.056 | .038 | .137 | 1.2 | $H_{2d}$: - |
| **Career** | | | | | |
| *Peak market value* | **.651** | .036 | .000 | 2.0 | **$H_{3a}$: +** |
| *Position* | **.151** | .058 | .009 | 1.1 | **$H_{3b}$: +** |
| *Years since peak* | .014 | .035 | .689 | 1.9 | $H_{3c}$: - |
| *Age* | **.202** | .040 | .000 | 2.4 | **$H_{3d}$: +** |
| **External popularity** | | | | | |
| *Number of Google searches* | **.137** | .023 | .000 | 1.3 | **$H_{4a}$: +** |
| *Number of news articles* | **.201** | .020 | .000 | 2.0 | **$H_{4b}$: +** |
| **Fit** | | | | | |
| AIC | 36888 | | | | |
| BIC | 36988 | | | | |
| Nagelkerke $R^2$ | .869 | | | | |

Note: Coefficients with a p-value below .10 are bold. Hypotheses are bold if they are confirmed.

*Content*. In line with $H_{1a}$, the number of posts positively affected the number of subscribers ($b = .359$, $p < .001$), with a 1% change in posts being associated with a 0.4% change in the number of subscribers. The *share of personal posts* had a positive linear ($b = .147$, $p < .001$) and a negative quadratic effect ($b = -.048$, $p < .05$), supporting both $H_{1b}$ and $H_{1c}$. The optimum of the quadratic function implies that slightly more than half (60%) of posts should be personal to maximize the number of subscribers.

Celebrities who increased the share of personal posts over time saw a significant increase in the number of subscribers, by around 29% ($b = .251$, $p < .001$), supporting $H_{1d}$. As predicted, a higher share of videos was associated with an increase in the number of subscribers ($b = .231$, $p < .001$), supporting hypothesis $H_{1e}$. We found a slightly significant negative effect for the share of sponsored posts ($b = -.043$, $p < .10$) and, contrary to our expectations, no significant effect for the share of posts linked to a business account (b = -.007, p = .801). Thus, we confirmed $H_{1f}$ and disconfirmed $H_{1g}$.

**Network**. The number of subscribers of the linked business accounts (b =.019, p < .001), linked persons (b = .015, p < .05), and the club (b = .296, p = .001) were all significantly positively associated with the number of subscribers to soccer players' social media, thus providing evidence for $H_{2a}$, $H_{2b}$, and $H_{2c}$. The largest effect size was found for the number of subscribers of the club, as a 1% increase in club subscribers was associated with an approximately 0.3% increase in subscribers. Although these relationships cannot be interpreted as purely causal, the results suggest that soccer players can substantially increase their subscriber base by playing for a club with many subscribers/fans. Additionally, we found that the number of subscriptions had a non-significant negative effect on the number of subscribers (b = -.056, p = .137), disconfirming $H_{2d}$.

**Career**. The market value of a player had a significant positive effect on the number of subscribers (b = .651, p < .001), supporting $H_{3a}$. The effect size was the strongest among the standardized predictors, and a standard deviation increase in market value was associated with a 90% increase in the number of subscribers. In line with $H_{3b}$, playing as a striker positively affected the number of subscribers (b = .151, p < .010). A player's age was significantly associated with a higher number of subscribers (b = .202, p < .001) supporting $H_{3d}$; however, players did not lose subscribers over time after the peak of their careers (b = .014, p = .689), which is evidence against $H_{3c}$.

**External popularity**. In line with $H_{4a}$ and $H_{4b}$, both factors measuring celebrity capital outside of social media were positively related to the number of subscribers. More precisely, a 1% increase in the number of Google search queries was associated with a .14% increase in the number of subscribers (b =.137, p < .001), while a 1% increase in the number of news articles about the player was associated with a .22% increase (b =.201, p < .001).

**Robustness and Replication**

In addition, we estimated two alternate models to investigate whether the findings would be robust when we included club fixed effects to test whether the non-linear effect of the share of personal posts holds in an unrestricted model (i.e., not restricted to a second-order polynomial). We conducted a short experiment to validate the non-linear effect of the share of personal posts on social media capital.

**Club Fixed Effects**. We estimated the same model but replaced *subscribers of club* with a fixed effect for each club to test whether club-specific non-observable effects (e.g., effects related to the social media strategy of the club) would change the results of our estimates. In doing so, we found similar results and reported the estimates in Web Appendix Table WA1.

**Quadratic Effect of Share of Personal Posts**. One restriction of our model is that we estimated only a linear and quadratic effect, while the true relationship between the share of personal posts and the number of subscribers could be asymmetric. We therefore followed Tellis et al. (2019) and replaced the quadratic polynomial of the share of personal posts with a penalized spline term (Eilers & Marx 1996), while the rest of the model remained unchanged. Figure 3 confirms the inverted U-shaped relationship, with a peak at around 59% of personal posts.

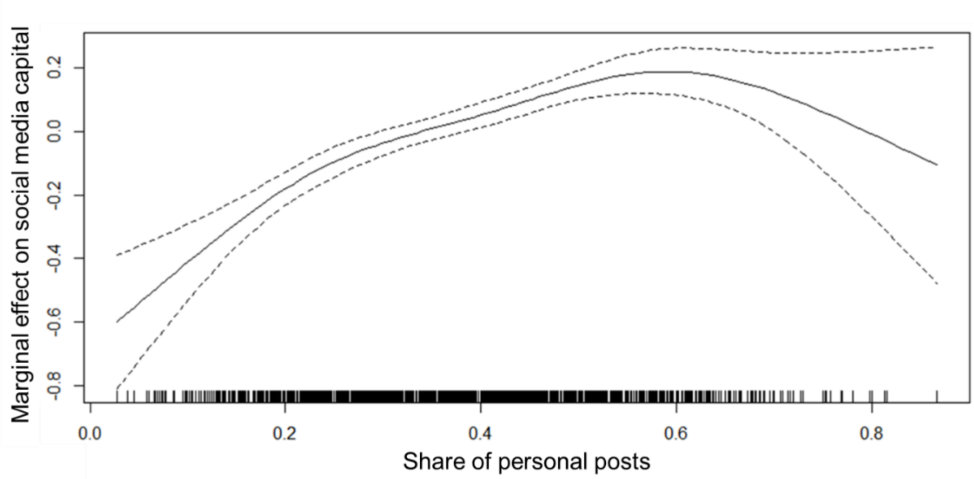


**Figure 3**. Marginal effect of the share of personal posts on social media capital in a general additive model.

**Experimental Replication of the Quadratic Effect of the Share of Personal Posts**. To manipulate the share of personal posts in an experimental setting, we created a fictious Instagram profile of Robert Lewandowski (profile page with information about the account and nine images), a popular soccer player from FC Bayern Munich. We only considered participants that were aware of the player but were not aware of the actual content of his Instagram profile, which we manipulated in the experiment. This was to prevent a potential selection bias that would occur if we included participants who were already subscribed to a given celebrity. While we used the original images posted on his feed, we showed participants a profile page showing only *professional posts*, only *personal posts*, and one profile with a balanced mix[13] of both (*balanced posts*). The participants comprised 105 consumers (61 male and 44 female) from the United Kingdom who are interested in soccer, use Instagram frequently, and know of Robert Lewandowski but who have never been subscribed to his Instagram page. We asked the participants to indicate their intention to subscribe to Lewandowski's page. We controlled for participants' involvement in soccer, social media use, and prior attitudes toward Lewandowski, as these factors might be potential predictors of the intention to subscribe. The results as depicted in Table 5 show that, compared to a balanced profile, only showing personal posts ($b = -.711$, $p < .05$) or only showing professional posts ($b = -.841$, $p < .05$) significantly decreased the intention to subscribe. The findings are in line with $H_{1c}$ and explain that the quadratic effect of the share of personal posts on social media capital might partially stem from a reduced intention to subscribe after observing that a celebrity focuses too much on either personal or professional content.

[13] Each profile had nine images. In the "balanced posts" profile, we showed 4 professional and 5 personal posts.

**Table 5.** Experiment results for intention to subscribe (n = 105).

| Variable | Coefficient (b) | Standard Error | p-Value |
|---|---|---|---|
| (Intercept) | 0.400 | 0.737 | 0.589 |
| *Personal posts*[a] | **-0.711*** | 0.341 | 0.040 |
| *Professional posts*[a] | **-0.841*** | 0.356 | 0.020 |
| *Category involvement* | **0.145***** | 0.126 | 0.252 |
| *Social media usage* | 0.379 | 0.087 | 0.000 |
| *Celebrity attitude* | **0.222**† | 0.124 | 0.076 |

Note: a) Reference category "Balanced posts"; †p < .01; *p < .05; **p < .01; $R^2$ = .234.

**Simulation**

To compare[14] the effect sizes of the four factors (i.e., content, network, career, and external popularity) on the number of subscribers, we used a fitted model to predict the number of subscribers for fictious celebrities who represented different quantiles of the distribution of the variables for the four factors. We combined content and network, as both represent a celebrity's actions inside a social network, and career and external popularity, as both factors are affected by a celebrity's actions outside social media. We compared all combinations of 0.1-quantile steps for social media behavior variables ($q_1$) and the professional career variables ($q_2$). We reversed the quantile for variables with a negative sign. For example, the 0.8-quantile of the content and network factors combines the 0.8-quantile value for the variable share of personal posts and the (1–0.8)-quantile (i.e., the 0.2-quantile) value for the share of sponsored posts, as the latter has a negative effect on subscribers. Accordingly, higher quantile values were related to a growing number of subscribers according to the estimates of our model. We present the estimated number of 1,000 subscribers in Table 6. The values in brackets are provided to compare the respective estimate with the median celebrity (i.e., the celebrity with both dimensions set to the 0.5-quantile).

[14] Note that in the model some predictors are log-transformed and their coefficient cannot be directly compared to predictors that are not log-transformed.

**Table 6.** Model estimates for simulated celebrities.

| Social Media Behavior ($q_1$) (Quantiles for content and network variables) | Professional Career ($q_2$) (Quantiles for career and external popularity variables) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| 0.1 | 3.7 (-96%) | 5.8 (-94%) | 7.8 (-92%) | 10 (-90%) | 13 (-87%) | 16.9 (-83%) | 23.6 (-76%) | 43.8 (-55%) | 96.4 (-1%) |
| 0.2 | 6.4 (-93%) | 10 (-90%) | 13.4 (-86%) | 17.3 (-82%) | 22.4 (-77%) | 29.3 (-70%) | 40.7 (-58%) | 75.6 (-22%) | 166.4 (72%) |
| 0.3 | 12.5 (-87%) | 19.6 (-80%) | 26.4 (-73%) | 34 (-65%) | 44.1 (-54%) | 57.6 (-41%) | 80.2 (-17%) | 148.9 (54%) | 327.6 (238%) |
| 0.4 | 18.3 (-81%) | 28.8 (-70%) | 38.6 (-60%) | 49.8 (-49%) | 64.6 (-33%) | 84.4 (-13%) | 117.4 (21%) | 218.1 (125%) | 479.7 (395%) |
| 0.5 | 27.5 (-72%) | 43.1 (-55%) | 57.9 (-40%) | 74.6 (-23%) | 96.9 (0%) | 126.5 (31%) | 176 (82%) | 327 (238%) | 719.1 (642%) |
| 0.6 | 39.6 (-59%) | 62.1 (-36%) | 83.3 (-14%) | 107.5 (11%) | 139.5 (44%) | 182.2 (88%) | 253.5 (162%) | 470.9 (386%) | 1035.6 (969%) |
| 0.7 | 69.1 (-29%) | 108.4 (12%) | 145.5 (50%) | 187.7 (94%) | 243.6 (152%) | 318.1 (228%) | 442.7 (357%) | 822.4 (749%) | 1808.5 (1767%) |
| 0.8 | 166.1 (71%) | 260.6 (169%) | 349.8 (261%) | 451.3 (366%) | 585.6 (505%) | 764.6 (689%) | 1064.1 (999%) | 1976.6 (1940%) | 4346.8 (4387%) |
| 0.9 | 304.2 (214%) | 477.3 (393%) | 640.6 (561%) | 826.4 (753%) | 1072.4 (1007%) | 1400.2 (1345%) | 1948.8 (1912%) | 3619.8 (3637%) | 7960.5 (8118%) |

Notes: Values represent the number of subscribers in thousands. Values in brackets are percentage change of estimated subscribers compared to the median celebrity.

As can be deduced from the estimates in Table 6, both social media behavior (content and network) and professional career (career and external popularity) impact social media capital. The estimates further show that social media behavior is slightly more important regarding the variables captured in our model. For example, compared to the median celebrity ($q_1 = q_2 = .5$), we observed a 44% increase ($CI_{95\%}$[15] = [30%, 60%]) of subscribers when social media behavior was slightly improved ($q_1 = .6$ and $q_2 = .5$), while an improvement in professional career ($q_1 = .5$ and $q_2 = .6$) only increased the number of subscribers by 31% ($CI_{95\%}$ = [18%, 46%]). Additionally, a celebrity with excellent social media performance ($q_1 = .9$, $q_2 = .5$) had an estimated subscriber growth of 1007% ($CI_{95\%}$ = [789%, 1278%]), while a strong career ($q_1 = .5$

[15] The range indicates the 95%-confidence interval for the predicted variable. Note that the interval is not symmetric given the log-transformation of the dependent variable (i.e., number of subscribers).

and $q_2$ = .9) was only associated with a 642% ($CI_{95\%}$ = [509%, 771%]) subscriber growth compared to the median. In the latter example, the 95% confidence intervals of the two estimates did not overlap, indicating a significant difference in social media capital for the two compared celebrities.

## General Discussion

This research sheds light on the key drivers of social media capital and offers a novel contribution by being the first to identify and empirically test the relevant predictors of social media capital. While professional career factors affect social media capital, we found that celebrities' behavior on social media is the strongest driver of social media capital. We advanced prior research on celebrity social media capital by a) building a comprehensive framework that includes both sets of factors, b) investigating real-world subscribing behavior on Instagram, and c) investigating the reasons for the observed share of personal post effect in an additional experiment.

### Theoretical Contributions

Our key contributions involve understanding the impact of both sets of factors—professional career factors and social media behavior factors. Social media behavior factors have primarily been investigated using survey-based research and have focused on investigating their effects on engagement and purchase intention (see, e.g., Chung & Cho 2017). This stream of research, however, leaves open the extent to which real-world social media capital is influenced by social media behavior factors (such as sharing personal content with subscribers). The importance of network factors has been investigated (see, e.g., Lanz et al. 2019), but their impact has not been compared to other influence factors, such as celebrities' popularity outside social networks. Our study is the first to use a comprehensive approach to test all factors' effects on social media capital, and it allows us to compare the effects of changes in these factors (see Table 6. The analysis of real Instagram data revealed the intriguing result that celebrities' social media behavior impacted their social media capital more than their professional careers.

Our findings contribute to the literature on self-disclosure effects in social media by making evident the importance of creating a good mix of professional and personal posts, in line with SPT, which predicts that building relationships (with subscribers) requires posting an appropriate amount of personal information. We also provide a nuanced explanation of why self-disclosure is effective in social media. The results of an experimental replication study showed that a profile that consists of only professional posts is perceived as less intimate, which decreases subscription intention. Moreover, the results also showed that a profile that consists of only personal posts is perceived as less appropriate, which also decreases subscription intention. Thus, the additional experimental results replicate the results we obtained using the Instagram data and show that changes in perceived intimacy and appropriateness explain the decrease in following intention.

Our findings also show the relevance of network effects and external popularity in increasing social media capital. These findings advance the literature by showing that content and network effects both enhance social media capital building and ideally should be used in combination, such as when posting a photo showing a celebrity with another celebrity in a personal context.

## Managerial Implications

Building social media capital is a key objective for many celebrities, as brand endorsements have become a major source of their income. Our results provide key insights into how celebrities can optimize their social media behavior, which can result in economic benefits for themselves and the brands with which they collaborate. Based on our results, celebrities should continuously create new posts ($H_{1a}$). These posts should be a mix of moments from their professional careers and personal lives ($H_{1b}$ and $H_{1c}$). We found an optimum when around 60% of the posts showed a personal moments. In our sample, we observed a mean share of personal posts of 37%, which indicates that celebrities tend to share too much content related to their careers. Additionally, celebrities should increase the share of personal posts over time ($H_{1d}$) and, in addition to images, post videos ($H_{1e}$). While celebrities can generate income by endorsing brands, these posts hurt their social media capital ($H_{1f}$) and therefore should be made sparingly. Besides their own content, celebrities can build social media capital by collaborating with businesses and persons who already have high social media capital ($H_{2a}$ and $H_{2b}$). For soccer players, the social media capital of the club they are signed with has additional potential to increase their social media capital ($H_{2c}$). Interestingly, we found that social media capital does not fade substantially after a soccer player passes the peak of their career ($H_{3c}$). Therefore, social media capital might be a very sustainable source of income for celebrities, even when their careers decline (Carrillat & Ilicic 2019).

## Limitations and Future Research

Our paper has several limitations that open up opportunities for future research. First, our two empirical studies only focused on one type of celebrity: male soccer players. A recent meta-study by Knoll & Matthes (2017) showed that the effectiveness of celebrity endorsement strongly depends on celebrity type. Actors granted the strongest positive effect, potentially, as the authors suggested, because fans form strong relationships with actors outside social media over a long period. The celebrity type might therefore change the impact of social media and career factors on subscription intention. Thus, replicating the results for other types of celebrities is an important next research endeavor. This paper focused on one type of celebrity, because career factors can hardly be compared between different types of celebrities. For example, while age and position are substantial career factors in the soccer context, one would have to find comparable factors for celebrity actors, such as whether they primarily star in Hollywood or independent movies. Moreover, accurately and automatically classifying personal or professional contexts using a set of images was technically feasible for athletes. For celebrity actors, however, it will be more difficult to determine whether an image shows a personal or professional context using automatic image classification. Thus, the analysis would require manual coding of images to replicate the analysis for celebrity actors. We leave the application of our model to different celebrity contexts (and the replication) to future research. Additionally, we focused our analysis on male celebrities. While the meta-study by Knoll & Matthes (2017) found that male celebrities achieve higher advertising effectiveness than female celebrities do with their endorsements, the effectiveness of female endorsers could well change in the course of current political discussions on the subject of gender equality. For example, persuasiveness depends on power and status (Kenton 1989), which are two goals of feminist movement. The mechanisms found might also differ for female athletes. For example, it is possible that female celebrities have more female fans who are more or less likely to share or comment on posts. Accordingly, future research could compare male and female athletes with respect to the strategies they use to build social media capital, for example, by quantifying the extent to which they share personal information with subscribers.

Second, our research neglected the interaction frequencies between celebrities and subscribers as well as among subscribers. In line with Kim and Kim (2020), we argue that celebrities who interact with subscribers more frequently will be able to more effectively grow their subscriber base, as potential subscribers get the impression that they can form virtual relationships with celebrities. For popular celebrities, it might be very difficult to respond to a large number of questions and comments on social media. However, these celebrities might use new instruments, such as live streams, to document sincere interest in building relationships with fans. The effectiveness of using such new instruments needs to be studied further. Survey-based findings of Kim and Kim (2020) also suggest that self-disclosure (measured as the share of personal posts in our study) influences celebrity loyalty. Thus, our research could be further extended by examining whether sharing personal posts reduces the probability that celebrities lose subscribers over time (Luo et al. 2010) as a consequence of a professional career decline (Carrillat & Ilicic 2019) or after events that lead to negative publicity (Hock & Raithel 2019).

Third, our research could be extended by investigating image characteristic effects, as proposed by Li and Xie (2020), who showed that the colorfulness, source, and quality of social media influencers' profile images significantly enhanced engagement. As the aforementioned factors can significantly change the appeal of posted images, and thus the visual impression that potential subscribers get when first seeing a celebrity's social media profile, these factors should also increase the probability of increasing the number of followers a celebrity has on social media. Moreover, image characteristics might moderate the effect of the share of personal posts. For example, a large share of personal posts might increase the number of subscribers more effectively if the images are of superior quality. However, images with a very professional appearance might also make personal posts appear less authentic and thus reduce the number of subscribers (Colliander & Mader 2018). Such research would provide celebrities with further insights into how they should design personal image posts to grow their subscriber base more effectively.

Fourth, we did not examine the dynamics of social media capital building. The examples in Figure 1 suggest that subscriptions on social media are not highly dynamic and, thus, investigating the volatility of the number of subscribers over time, as done by Mathys et al. (2016), seems less promising when investigating how celebrities grow their follower base on social media. However, the volatility of the number of subscribers might also be context specific and therefore make it appropriate to build such a model for other types of celebrities, such as singers or actors.

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# Essay B2: Disclosing Private, but Staying Focused – How Social Media Influencers Effectively Increase Post Engagement and Purchase Intention

# Disclosing Private, But Staying Focused – How Social Media Influencers Effectively Increase Post Engagement and Purchase Intention

*Keywords*: Social media influencer, post engagement, self-disclosure, expertise, parasocial relationship

## Abstract

Social media influencers (SMIs) are an integral part of today's digital brand communication strategies. Marketers take advantage of trustworthy parasocial relationships that SMIs build with their followers and, accordingly, pay them to endorse products and brands. To build trust, SMIs disclose themselves to their followers by sharing intimate moments (determining the depth of self-disclosure) on a range of topics (determining the breadth of self-disclosure). The empirical results of this research show that depth of self-disclosure drives parasocial relationship building, and more specifically trust building in SMIs, which, in turn, increases both engagement and purchase intention. To our surprise, we find that a SMI's decision to focus on fewer topics can increase engagement as they are perceived as having a higher level of expertise. The empirical evidence for these findings comes from analyzing social media data of more than 2,500 SMIs on Instagram. Two additional online studies provide evidence that parasocial relationship building and trust building as well as expertise are key mechanisms that explain why "disclosing private, but staying focused" is a successful SMI strategy.

## Introduction

Social media based influencer marketing has evolved into a key component of digital marketing strategies (Gerrath and Usrey, 2020; Hughes et al., 2019) and is one of the most pressing research topics as it challenges current marketing practices (Appel et al., 2019; Moorman et al., 2019). Marketers use social media influencers (SMIs) to communicate key product messages and build up brand images in sponsored posts (Stubb & Colliander, 2019) with the goal of strengthening online brand engagement (Hughes et al., 2019). The role of SMIs as powerful opinion leaders (Hwang & Zhang, 2018) is based on followers forming parasocial relationships with SMIs. Survey-based research by Chung and Cho (2017) and Kim and Song (2016) showed that self-disclosure (that is the "voluntary communication of feelings, thoughts, or other information deemed to be private" (Melumad and Meyer 2020, p. 29)) is essential for creating strong relationships between SMIs and their followers. In this article, we explore two fundamental questions that underlie relationship building: To what extent does self-disclosure help SMIs to create social media engagement on Instagram as well as purchase intention for sponsored products? Which mechanisms explain these effects of self-disclosure?

While two groups of authors, Chung and Cho (2017) and Kim and Song (2016) investigated the effect of self-disclosure in a social media context using surveys, we could not find research that investigated the effect of two main dimensions of self-disclosure, namely the breadth and the depth of self-disclosure, using field data. Given that engagement reflects the acceptance of a social media campaigns (De Vries et al. 2012), has the potential to influence consumer attitudes and behavior (Oh et al. 2017; Mochon et al. 2017) as well as positively influences profitability (Kumar, Petersen, and Leone 2010), our paper first focuses on investigating social media engagement (as it is an established proxy for social media influencer effectiveness (Hughes et al., 2019)) using field data. Second, to demonstrate that self-disclosure similarly affects consumers' behavioral intentions, we study purchase intention in two additional online studies.

The analysis of field data (study 1) shows that SMIs posting more intimate information (referred to as depth of self-disclosure) are more successful in creating engagement. We also find that SMIs posting content that is related to a larger variety of topics (referred to as breadth of self-disclosure) usually create less engagement. The effect is robust among three alternate measures of breadth of self-disclosure. Moreover, additional online studies provide further insights regarding the mechanisms that lead to behavioral change. We find that depth of self-disclosure increases respondents' feelings of having a parasocial relationship with a SMI (Study 2) and of trusting a SMI (Study 3) which positively affects purchase intention for sponsored products recommended by a SMI. Breadth of self-disclosure, however, has a negative effect on parasocial relationship building and purchase intention. More importantly, we also find that the breadth of self-disclosure decreases the perceived expertise of SMIs, which, consequently, also decreases the purchase intention of the followers.

This paper advances prior research by examining how depth and breadth of self-disclosure affect engagement using field data and purchase intention using survey data. Prior studies (Chung and Cho 2017; Kim and Song 2016) asked participants to evaluate SMIs they follow and recall. This design approach, however, produces a potential recall- and selection-bias, that can be avoided by analyzing field data. Second, prior studies did not distinguish between depth and breadth of self-disclosure. Our research is first to suggest that the breadth of self-disclosure has a negative effect on engagement and purchase intention as posting about a wide range of topics signals a lack of expertise. This finding has severe implications for practitioners who lack insights whether to select SMIs with rather broad or with rather narrow interests. Our results suggest that practitioners should select those SMIs who share private information but focus on posting in their key areas of expertise. Thus, our research contributes to the practical goal of identifying and selecting suitable SMIs to partner with (Djafarova and Rushworth 2017; Kannan 2017).

This research is the first to use real-world social media posts from Instagram to investigate the impact of depth and breadth of self-disclosure on the engagement with social media posts. Consequently, we are not only able to investigate if – but also to what extent – self-disclosure affects engagement. Engagement, for its part, has been shown to positively affect consumer attention and behavior (Oh et al. 2017; Mochon et al. 2017). We supplemented the findings for engagement by collecting data in two further studies that investigated its potential positive effect on purchase intention. Besides testing the effect of self-disclosure on purchase intention, this survey-based, complementary research allows us to additionally closely examine corresponding mechanisms of the effect. In Study 2, we tested parasocial relationship building and expertise. To further understand whether the mechanism of parasocial relationship building equates trust building, and to replicate the results of Study 2, we replaced parasocial relationship with trustworthiness in Study 3.

The remainder of the paper is structured as follows. First, we introduce the concept of self-disclosure and review the relevant literature that investigated the effect both outside as well as within the influencer marketing context. In the following section, we explain how we collected field data on Instagram and how we operationalized key constructs. We then outline the setup of our surveys and present empirical findings from two mediation analyses. The final section of the paper summarizes key findings and discusses limitations and opportunities for future research.

## Theoretical Background

### *Parasocial Relationships Building and Self-disclosure*

Researchers have used the term "parasocial relationship" to describe the relationship that SMIs have with their followers (see, e.g., Lee & Watkins, 2016). Parasocial relationships are most often purely virtual and unilateral for most SMIs with many followers. The experiences in these relationships have been characterized as illusionary (Munnukka et al., 2019; Luo and Kim 2019) because the relationships are not reciprocal in most cases. Followers, in return, can observe how SMIs interact with their followers (Collinander & Erlandson, 2015), which increases the familiarity with and the accumulated knowledge about the values and motives of a SMI. Social media interactions, even if only observed, can therefore create feelings of connectedness, perceived friendship, and even a sense of intimacy (Chung & Cho, 2017).

Social Penetration Theory (SPT, Altman & Taylor 1973) posits that revealing beliefs concerning self-identity by sharing personally relevant feelings, thoughts, values, and believes is a key element of building more intimate interpersonal relationships (Prisbel & Anderson, 1980). Outside the social media context, empirical research has already shown that this form of self-disclosure is critical to the development of interpersonal relationships and revealing intimate information to another person increases the probability of being liked by a person (Collins & Miller, 1994). Breadth and depth have been identified as two key dimensions of self-disclosure (Derlega et al. 1993; Omarzu 2000). Depth of self-disclosure refers to how deeply an individual discloses him/herself by revealing private and intimate information. Breadth of self-disclosure, in contrast, refers to the number of topics covered in the communication between individuals. Self-disclosing satisfies fundamental human needs, as it helps to build social connections ("relationships") with others, increases feelings of belonging and is intrinsically rewarding (Tamir & Mitchell, 2012). Self-disclosing to others, however, also makes the discloser vulnerable (see also Cozby 1973; Omarzu 2000) as the disclosure implies giving up some part of privacy and control by sharing personal information with others (Derlega et al. 1993). A person disclosing information thus usually tries to minimize personal risks of vulnerability and at the same time tries to maximize the potential benefits resulting from forming a closer bond with the receivers of a disclosure message (Petronio 2002). SPT postulates a layered structure (using an "onion" analogy) that includes superficial information on the outer layers and more fundamental, core characteristics of personality on the inner layers.

SPT also posits that self-disclosure takes place gradually by first revealing less intimate information from the outer layers, before revealing more intimate information from inner layers. Depth of self-disclosure is related to the inner layers that contain fears, self-concepts, and basic values. Moreover, enhanced emotionality is considered as an important marker of depth of self-disclosure (Houghton and Joinson 2012). In line with this definition, several authors proposed that depth of self-disclosure can be measured by the extent that messages contain emotional (and not factual) information, are self-referencing (e.g., by using first-person pronouns) and include information about intimate relations to friends and family (Kim and Song 2016; Melumad and Meyer 2020). Breadth of self-disclosure, in contrast, is based on the number of major topical areas or categories that are disclosed (Altman and Taylor 1973).

Public self-disclosure on social media does not fully conform with this classic understanding of self-disclosure for several reasons. First, while self-disclosure messages via traditional communication channels can be shared with only a fraction of followers using private messages, social media posts are almost always shared with an entire network of followers (Liu and Brown 2014). Thus, the audience occasionally comprises large and diverse groups of followers, ranging from strangers to close friends and family members (Gilbert and Karahalios 2009). Second, many SMIs even share very intimate (e.g., sexual preferences or depressive syndromes) next to peripheral information. Therefore, the idea that self-disclosing takes place gradually is less appropriate in the social media context. Third, empirical results published by Ruppel et al. (2017) suggest that people reveal more intimate information when using a computer compared to when being in a face-to-face situation. More recently, Melumad and Meyer (2020) found that consumers are more self-disclosing when generating content on their smartphones compared to when generating it on their computers, as they feel more comfort when using their smartphones and more narrowly focus attention on the disclosure task at hand. As many influencers will use smartphones (or computers) to publish content for practical reasons (constant accessibility, frequent use as well as high psychological comfort), these devices will generally support users to be more self-disclosing when using social media. However, research currently lacks an understanding of how strongly both components of self-disclosure affect engagement as well as purchase intention in the influencer marketing context.

***Parasocial relationship building and trust mediate the effects of depth and breadth of self-disclosure on engagement and purchase intention***

Several studies provide initial evidence that building relationships with SMIs based on establishing trust is a key mechanism that can have positively affect behavioral outcomes. Colliander and Dahlén (2011) argued that bloggers may generate stronger relationships by writing about their personal lives. A study by Liu and Brown (2014) investigating a Chinese social network provided evidence that students' level of self-disclosure positively affects the social influence they have on others (the authors therefore used the term "bonding capital"). The authors measured the level of intimacy (which, as already outlined, is supposed to be an important component of depth of self-disclosure) by asking respondents whether they shared photos of just themselves, photos of themselves and friends or photos of themselves and romantic partners or family members. However, their study tested the effect of intimacy outside the influencer marketing context. Lin and Utz (2017) tested fictitious Instagram profiles and found that a higher amount of intimacy led to increased feelings of closeness, which is an essential component of building parasocial relationships with SMIs. However, as stressed by the authors, the generalizability of these findings is questionable, as perceived closeness was rather low in the empirical study, because participants did not actually follow the SMIs, but were unknown to them. This limitation highlights the need to analyze data from actual social media interactions.

In the context of consumer online reviews, a recent study by Melumad and Meyer (2020) showed that greater depth of self-disclosure (measured by using more first-person pronouns, by references to family/friends and by words that convey emotionality) increased the persuasiveness of reviews and also increased the interest in visiting restaurants the reviews were about. These empirical results suggest that increased depth of self-disclosure may have positive effects on intended behavior. Ki et al. (2020) emphasize that the emotional attachment to SMIs is an important factor that affects behavioral intentions. The authors found that the sense of intimacy (i.e., relatedness) has a positive effect on the level of emotional attachment to a SMI. The authors outlined that this attachment mechanism is a key instrument for SMIs to build relationships with their followers.

In line with SPT as well as the above-mentioned studies, we expect that depth of self-disclosure contributes to establishing trust and building parasocial relationships. Empirical research on the effects of breadth of self-disclosure on parasocial relationship building is currently lacking. We expect that both potential mediators (i.e., parasocial relationship and trust) will increase engagement when investigating social media field data and purchase intention for promoted products when testing the effect in a survey conducted specifically for this purpose.

***Expertise mediates the effects of depth and breadth of self-disclosure on engagement and purchase intention***

Expertise can be described as the source's level of knowledge regarding a certain topic (Wiedmann and von Mettenheim 2021). The source credibility model posits that knowledgeable sources are more credible and, thus, more likely to persuade message receivers. Research has mostly focused on three credibility components, expertise, trustworthiness, and attractiveness (Yuan et al. 2016; Joseph, 1982; Kahle & Homer, 1985; Maddux & Rogers, 1980).

In the context of sponsored posts on social media, expertise can be described as the amount of knowledge a SMI has about a product category that s/he promotes in her/his posts. As emphasized by several authors, focused interest in a single domain might indicate a high level of SMI expertise (Tafesse and Wood 2021; Ladhari et al., 2020). Tafesse and Wood (2021) argue that SMIs who have many followers and post content about a variety of different topics might create feelings of detachment. They outline that a post might be perceived as an "incoherent information about influencers' domains of interest" (p. 4). In contrast, SMIs who focus on a few topics might be better able to create human brand identities in followers' minds, analogous to the idea that strong brands evoke few, but strong associations in consumers' minds (Keller 1993). Thus, it might be advisable for SMIs to focus on a specific topic to signal expertise (Tafesse and Wood 2021). In line with this argumentation, we expect that SMIs who focus on fewer topics, that is who have a lower level of breadth of self-disclosure, will be perceived as having a higher level of expertise. To the best of our knowledge, a potential effect of depth of self-disclosure on perceived expertise has neither been discussed nor investigated.

Two theories predict that an endorser's level of perceived expertise will affect the behavioral outcome (e.g., purchase intention) of followers. First, the so-called match-up hypothesis predicts that the effectiveness of endorsed advertisements depends on the extent to which the expertise of the endorser fits the advertised product or brand (e.g., Kamins & Gupta, 1994). In line with this hypothesis, a study by Schouten et al. (2019) confirmed that brand-influencer fit may have a significant positive effect on perceived expertise for SMIs. Second, the heuristic-systematic model (Chaiken 1980; Ratneshwar and Chaiken 1991) assumes that expertise cues (such as a diploma) are often used as a cognitive heuristic. People who have formed the cognitive heuristic that "experts can be trusted" can use cues of expertise when evaluating a sponsored SMI post. Both theories have in common that they predict a positive influence of expertise on behavioral outcome variables, such as purchase intention.

This assessment is backed by several empirical studies: Jin and Sung (2010) showed that experts (in the form of avatars) generate more positive attitudes towards a brand and increased satisfaction (with recommendations) than non-experts. An experiment conducted by Uribe et al. (2016) showed that high-expertise communicators are perceived as more credible leading to greater behavioral intentions (the authors investigated the intention to obtain more information about a product, the intention to make a positive recommendation as well as the intention to buy a specific product). Empirical results provided by Martensen et al. (2018) support the idea that expertise makes fashion brand influencers more persuasive. Another survey-based study in the influencer marketing context by Torres et al. (2019) showed that increased brand-influencer fit leads to more favorable attitudes toward the endorsement and the brand, and also increases the intention to purchase the endorsed brand. On the contrary, a study by Balabanis and Chatzopoulou (2019) did not find a significant effect of perceived expertise on the intention to purchase a beauty product recommended by a SMI. The study, however, found a significant effect when followers are strongly dependent on the expertise of a SMI. Finally, a study by Hughes et al. (2019) analyzed real in-market customer response data and showed that expertise drives engagement for blogger's awareness campaigns but has less impact in the case of trial campaigns.

As outlined earlier, indicating expertise is seen as a means to build a link to an endorsed product in the literature (Till and Busler, 1998). Thus, a mismatch between a SMI and an advertised product or brand might be noticed by followers as unsuitable, resulting in more thoughts about the persuasion attempt or the commercial intent of a SMI. In line with most previous empirical studies, we therefore expect that the level of perceived expertise has a significant effect on the intention to purchase a product that is recommended by a SMI. Based on the predicted negative effect that breadth of self-disclosure has on the SMIs' perceived expertise, we expect breadth of self-disclosure to have a negative indirect effect on the intention to purchase a recommended product via perceived expertise.

## Empirical Studies

To investigate the above-mentioned relationships between self-disclosure and behavioral outcomes, we collected field data from Instagram (2,799 SMIs on Instagram with a total of nearly 5 million posts (Study 1)), a survey with 327 participants (Study 2) and another survey with 277 participants (Study 3). The use of these three data sets to investigate the relationships in question is illustrated by means of Figure 1.

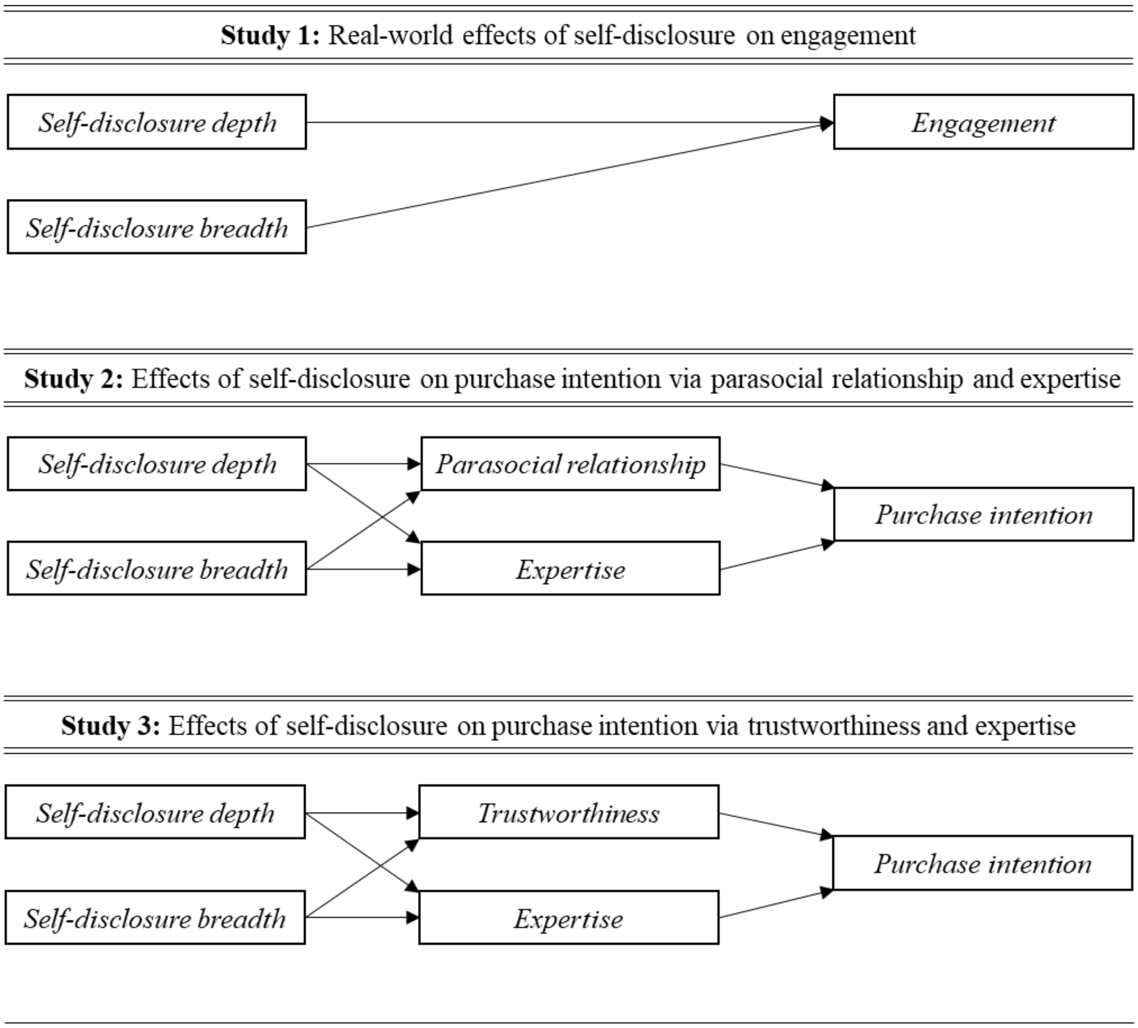


**Figure 1.** Study designs and modeling framework

While the goal of Study 1 is to test the effects of depth and breadth self-disclosure on the engagement for social media posts, we conduct Studies 2 and 3 to learn about mediators of behavioral intentions which are not directly observable from social media data. We included parasocial relationship in Study 2 to test whether a relationship-building mechanism explains the effects of self-disclosure on purchase intention. To more closely understand whether trust building is the mechanism that equates relationship building, we replaced parasocial relationship with trustworthiness in Study 3.

**Study 1**

The aim of the first study is to test how the two dimensions of self-disclosure affect post engagement on a popular social media platform, Instagram. We first created a data set of 3,041 SMI profiles by combining lists of recommended influencers from blog posts (blog-sample) and influencer names from a digital network that helps influencers to find brands for collaboration (network-sample). While the blog sample allows for a potential survivorship bias (e.g., SMIs will only get mentioned in a blog post if they met certain criteria chosen by the author), it is not likely that SMIs can self-select to be included in a blog post. In contrast, SMIs in the network-sample self-select to create a profile in the network (e.g., based on their need to connect to more brands for endorsement contracts), but no survivorship bias is likely to affect the outcome. By mixing the samples, we avoid that the whole sample is underlying the same systematic bias (See Web Appendix A for a detailed description of how we built the sample). We downloaded profile information (total number of posts, number of followers, number of followees[16], verification badge[17]) as well as all posts created during the last year based on the time of the last post. As we operationalize both breadth and depth of self-disclosure based on the caption texts of the respective posts, we first created a document for each SMI which contains the caption texts of all posts. Profiles with less than 30 posts were removed as the volume of textual information is not enough to measure the required constructs. After removing textual links to other account (account names with @ sign), we detected the language of each document using Google translate. We finally kept a sample of 2,799 documents (i.e., 2,799 SMI profiles) with English as the primary language and removed the rest from the data. Table 1 summarizes the SMI profile information for the given sample.

**Table 1.** Key social media sample characteristics

| n = 2,799 | Mean | Median | Min. | Max. |
|---|---|---|---|---|
| *Number of posts (total)* | 1,742.3 | 1,216 | 102 | 40,005 |
| *Number of posts (last year)* | 224.6 | 178 | 30 | 4,520 |
| *Number of followers* | 1,180,479 | 81,231 | 165 | 131,699,474 |
| *Number of followees* | 1,828 | 881 | 0 | 1,169,458 |
| *Verification*[a] | 27.20% | | | |

*Note: a) Share of profiles with a verification badge.*

While Instagram is known for posting images, SMIs caption these images with supplementing textual information, for example to describe how they feel in a specific situation. Further, SMIs use hashtags like #love or #funny to express their mood (Klostermann et al. 2018). In our sample, the average (rounded) number of words per post is M = 43 (SD = 34, MIN = 1, MAX = 270). In comparison, in the study by Melumad and Meyer (2020) the average word count per

[16] The number of profiles a user follows herself.

[17] A verified profile on Instagram has a blue mark next to the profile name which helps users to differentiate between the official profile of a public person and profiles created by others (e.g., fanclub).

tweet used to measure self-disclosure was less than 14. We therefore assume that the textual proliferation on Instagram is sufficient to measure self-disclosure.

***Variables***

*Dependent variable.* As the dependent variable, we investigate engagement rate measured by the average number of likes and comments a post receives divided by number of followers. Engagement rate is a key social media metric frequently used in other studies (Hughes et al. 2019). While the number of followers indicates how many people can potentially see the post in their personal feed[18], engagement reflects how many people are interested in the content and therefore has high managerial relevance.

*Self-disclosure depth.* To measure the depth of self-disclosure in a social media setting, we analyze the textual caption of the social media posts in order to identify linguistic markers that indicate a higher depth of self-disclosure. Melumad and Meyer (2020) proposed that social media texts are more self-disclosing when first-person pronouns (e.g., "I" and "me"), negative emotions [19](e.g., sadness and anxiety) and social references (e.g., friends and family) are mentioned and when the text is written in a more authentic and less analytical style of writing. We use Lingustic Inquiry and Word Count (LIWC) dictionaries to measure each of the five dimensions (First-person pronouns, Negative emotions, Family and friends, Authentic writing style, Analytic writing style) along the textual information of the influencer posts (Pennebaker et al., 2015)[20]. More precisely, for each of the dimensions, LIWC provides a list of words (for example, there are 744 words covering negative emotions) that are indicators for that dimension as rated and validated by a group of judges in multiple steps (Pennebaker et al., 2015). An authentic style of writing is concerned with credibility and trustworthiness and reflects whether people express themselves in a trustworthy and honest way. An analytic style of writing is reflected by logical reasoning and more formal texts. However, since the dimensions of both styles of writing were derived from the creators of LIWC in a non-transparent way (i.e., it is not accessible how they are calculated), we build on Melumad and Meyer (2020) showing that tweets written in a more authentic and less analytical writing style were rated as more self-disclosing by human judges. We calculate each dimension for each document and include the variable self-disclosure depth in the model (M1) as the mean of all five dimensions after standardizing. Further, we estimate a model (M3) with five dimensions as independent predictors to test which dimensions affect post engagement most strongly.

*Self-disclosure breadth.* To measure the breadth of self-disclosure, we first need to measure how important a certain topic is for a SMI (in terms of how strongly her posts are focused on that topic) which then allows us to measure how many different topics are addressed in a SMI's posts. We therefore first fit a latent Dirichlet allocation (LDA) topic model to the documents[21]. LDA is a generative probabilistic model for collections of discrete data such as text corpora.

[18] Most social media platforms like Instagram, Facebook and Twitter feature a feed view in which new content by all accounts a user is following is displayed in a platform specific order.

[19] We also estimate a model where we add positive emotions as a control variable and get similar results.

[20] The authors do not provide details on how they measure authentic writing style and analytic writing style

[21] The texts in the documents were vectorized by counting the occurrence of each word. Words were stemmed to the root ("like" for "likable," "liked," and "liking"). English stop-words (e.g., "and" and "the") and outlier words (i.e., words occurring in less than 1% of the documents) were removed.

The model statistically explains the occurrence of words in a document by underlying topics, which are defined by loadings assigned to each word in the corpus (i.e., the collection of all words in all documents as in Blei et al. 2003; see Tirunillai & Tellis 2014 for a similar approach). As LDA is an unsupervised machine learning approach, the number of topics (K) must be set by the researcher. We first ran the model for an increasing K (with K = number of topics in the model) and observed that the model fit increases degressively with K. In the following, we present the model with K = 25 topics and later test whether changing K affects the regression results presented in Figure 3. The topics reflect a wide variety of different areas of interest such as fitness, cooking, traveling, family, fashion, and shopping. Table 2 depicts exemplary topics with words that have the strongest loading (from left to right) and also shows a manually given label for each topic based on the words with the highest loadings (See Web Appendix Table WA1 for a more detailed elaboration on all 25 topics).

**Table 2.** Words with highest loading for exemplary topics

| Label | Words | | | | |
|---|---|---|---|---|---|
| | *#1* | *#2* | *#3* | *#4* | *#5* |
| "cooking" | *cup* | *oil* | *salt* | *recipe* | *pepper* |
| "family" | *baby* | *day* | *family* | *time* | *love* |
| "fashion" | *outfit* | *look* | *wear* | *shop* | *dress* |
| "traveling" | *travel* | *time* | *day* | *place* | *photo* |
| "food" | *food* | *friend* | *eat* | *restaurant* | *chicken* |
| "fitness" | *workout* | *leg* | *exercise* | *set* | *rep* |

For each SMI's document d, the model predicts a weight for each topic $\mathrm{p}_\mathrm{d}^\mathrm{k}$, depending on how much variance in the document's words is explained by the respective topic k. If, for example, a SMI only uses words given by the exemplary topic "fitness", the weight would be close to 1 ($\mathrm{p}_\mathrm{d}^\mathrm{fitness} \approx 1$) for document d while the remaining topics (i.e., k ≠ "fitness") would be assigned a weight close to 0. In this case, we would argue that the influencer has a low breadth of self-disclosure, as she is concerned with only one topic. Likewise, a SMI using words from all the topics would have equal weights ($\mathrm{p}_\mathrm{d}^\mathrm{k} \approx \frac{1}{K}, \forall k$) for each topic. In this case, the SMI has a high breadth of self-disclosure as she is concerned with all topics. To measure self-disclosure breadth following this intuition, we calculate the Shannon entropy of the vector of weights for each document (Shannon, 1948). Formally, the entropy E of a document d is defined as $\mathrm{E(d)} = -\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{p}_\mathrm{d}^\mathrm{k} \log \mathrm{p}_\mathrm{d}^\mathrm{k}$. The entropy will have the lowest value in the first case (low breadth) and the highest value in the latter case (high breadth).

To validate this measure, we conduct an online survey with 60 participants who use Instagram at least once a month. We randomly choose 10 SMI accounts with an entropy value in the first quartile (low entropy) and 10 from the fourth quartile (high entropy). The participants were instructed to use the Instagram app on their smartphone to view each SMI's profile for at least 30 seconds. Afterwards, the participants had to indicate the perceived breadth of self-disclosure on a 7-point Likert scale with four items ($\alpha = .88$) used in Hollenbaugh and Ferris (2014). Note that we use the same scale in Studies 2 and 3. All participants rated 10 randomly chosen profiles (five from the low and five from the high entropy set). In total, we collect n = 30 observations for each of the 20 SMI profiles. As can be seen in Figure 1, mean rated self-disclosure breadth differs significantly between SMI's with low and high entropy values. The significant difference was also confirmed by a linear model where we included a constant for each participant to control for between-subject variance ($b_{entropy\ low} = -1.525$, $p < .001$).

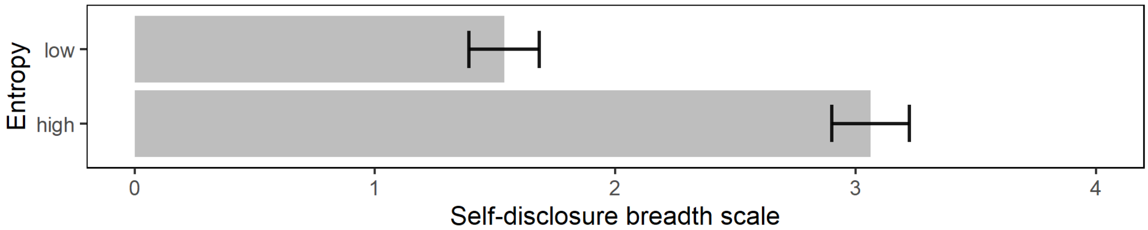


**Figure 2.** Self-disclosure breadth scale for SMIs with low and high entropy (95% confidence interval)

*Control variables*. There are several influencer-specific profile information cues that influence the popularity and status of SMIs and, thus, can have an effect on post engagement (Valsesia et al. 2020). Further, these variables might correlate with depth and breadth of self-disclosure and not including them in the model might cause endogeneity. For example, an influencer that creates only a few posts per month might create more engagement for a single post and have a low breadth of self-disclosure as s/he focuses on a single topic. In this case, not controlling for the number of posts could lead to a biased estimate of self-disclosure breadth on engagement. We therefore add log-transformed count variables to control for the number of total posts, the number of posts in the last year (i.e., the span from which we calculate the average engagement), the number of followers, and the number of followees. We further add verification as a dummy variable (1 if the profile has a verification badge). Variable correlations are summarized in Table 3.

**Table 3.** Correlations and descriptive statistics

| No. | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| 1 | *Number of posts (total)* | | | | | | | |
| 2 | *Number of posts (last year)* | .683 | | | | | | |
| 3 | *Number of followers* | .129 | .087 | | | | | |
| 4 | *Number of followees* | -.010 | -.006 | -.009 | | | | |
| 5 | *Verification*[a] | .177 | .116 | .267 | -.024 | | | |
| 6 | *Self-disclosure depth* | -.109 | -.145 | .054 | .005 | .054 | | |
| 7 | *Self-disclosure breadth* | -.013 | -.097 | .016 | .020 | .008 | .181[22] | |

Notes: a) Point-biserial correlation coefficient; all |r| > .037 significant at .05% level; all |r| > .049 significant at .01% level.

[22] Please note that the correlation between depth and breadth of self-disclosure is weak, but significant. This result shows that SMIs who talk about a larger number of topics also tend to disclose more deeply. However, as can be seen from the below results, both dimensions of self-disclosure affect engagement differently.

### *Model*

We use traditional linear regression as our dependent variable is a continuous variable (engagement rate). While comparable studies often use engagement as a count variable (i.e., count of likes and comments), we find modelling the rate more intuitive as it allows to compare SMIs with different numbers of followers. As a robustness check, we also ran a negative-binomial regression model with the sum of likes and comments as the dependent (count) variable and found similar results.

We first fit the model M1 with only control variables (see Table 1). We then add the two dimensions (depth and breadth) of self-disclosure in model M2 and finally break down depth of self-disclosure into its five dimensions in model M3. While we use the measure proposed and validated by Melumad and Meyer (2020), we note that their study is based on Twitter posts which might differ regarding their content. Therefore, M3 allows us to better understand how the dimensions of depth of self-disclosure affect engagement in the context of an image-focused social media platform like Instagram (compared to a microblog site like Twitter as investigated by Melumad and Meyer 2020).

### *Results*

Table 4 depicts the results for engagement rate as the dependent variable. All regression coefficients are standardized and the dependent variable ranges from 0 to 100, indicating the percentage of followers who, on average, engage with a post. We conducted likelihood-ratio tests and all models have a significant fit compared to the null-model without explanatory variables ($\chi^2 > 508$, $p < .001$). Both M2 and M3 have a higher model fit compared to M1 ($\chi^2 > 27$, $p < .001$), indicating that the inclusion of self-disclosure helps to predict engagement. Multicollinearity is no concern as all variance inflation indices (VIF) are below 2.3.

**Table 4.** Regression results

| | M1 (Control variables) | | M2 (Main model) | | M3 (Dimensions of depth of self-disclosure) | |
|---|---|---|---|---|---|---|
| | Est. | SE | Est. | SE | Est. | SE |
| (Intercept) | **3.143*** ** | .056 | **3.145*** ** | .056 | **3.149*** ** | .056 |
| Control variables | | | | | | |
| *Number of posts (total)* | **-.880*** ** | .055 | **-.837*** ** | .055 | **-.841*** ** | .055 |
| *Number of posts (last year)* | **-.188*** ** | .054 | **-.181*** ** | .054 | **-.174*** ** | .054 |
| *Number of followers* | **-.205*** ** | .061 | **-.227*** ** | .061 | **-.224*** ** | .062 |
| *Number of followees* | **-.168*** ** | .049 | **-.165*** ** | .050 | **-.168*** ** | .050 |
| *Verification* | **.630*** ** | .127 | **.620*** ** | .127 | **.605*** ** | .127 |
| Main variables | | | | | | |
| *Self-disclosure depth* | | | **.200*** ** | .045 | | |
| *Self-disclosure breadth* | | | **-.159*** ** | .045 | **-.192*** ** | .047 |
| Dimensions of depth of self-disclosure | | | | | | |
| *First-person pronouns* | | | | | **.158** ** | .066 |
| *Negative emotions* | | | | | .002 | .044 |
| *Family and friends* | | | | | .049 | .054 |
| *Authentic writing style* | | | | | **.145*** ** | .053 |
| *Analytic writing style* | | | | | .033 | .065 |
| Fit | | | | | | |
| Adj. $R^2$ | 0.164 | | 0.172 | | 0.175 | |
| LLH | -6,319 | | -6,306 | | -6,299 | |
| VIF (max) | 1.964 | | 1.975 | | 2.296 | |
| $\chi^2$ (vs. null-model) | **508*** ** | | **536*** ** | | **548*** ** | |
| $\chi^2$ (vs. M1) | | | **27*** ** | | **39*** ** | |
| AIC | 12,652 | | 12,629 | | 12,625 | |
| BIC | 12,694 | | 12,683 | | 12,703 | |

Notes: Significant results are in bold. LLH = Log-Likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; VIF = Variance inflation index. * p < .10; ** p < .05; *** p < .01.

The results shown in Table 4 provide evidence that depth of self-disclosure has a significant positive effect on the engagement rate (b = .200, p < .001) while breadth of self-disclosure has a significant negative effect (b = -.159, p < .001). Regarding the dimensions of the depth of self-disclosure, we see that the usage of first-person pronouns (b = .158, p = .016) and an authentic writing style (b = .145, p < .006) have significant positive effects on engagement, while negative emotions do not seem to affect engagement (b = .002, p = .991). While disclosing negative emotions are assumed to increase self-disclosure (Melumad & Meyer, 2020), it is reasonable that the effect largely depends on the social media platform. SMIs using Instagram might be more inclined to share positive emotions and experiences with their followers compared to other platforms, such as Twitter.

### *Robustness and alternate measures*

*Number of topics underlying the breadth of self-disclosure.* To validate the robustness of the findings regarding the effect of the breadth of self-disclosure, we estimate model M2 with different choices for the number of topics K. As K affects the calculated entropy and thus our measure for breadth of self-disclosure, it might also affect the p-value associated with the regression coefficient for that variable. We estimated three LDA models (i.e., with different random states for the starting configuration) for each K and observe an exponential log-likelihood increase for low number of topics, with linear increase in log-likelihood for high numbers of topics (see Figure 3, panel A). For the coefficient of the self-disclosure breadth variable, we observe p-values < .01 for all LDA models with K > 10 topics. As these models also have a more favorable likelihood, we consider the effect of the breadth of self-disclosure on engagement reliable.

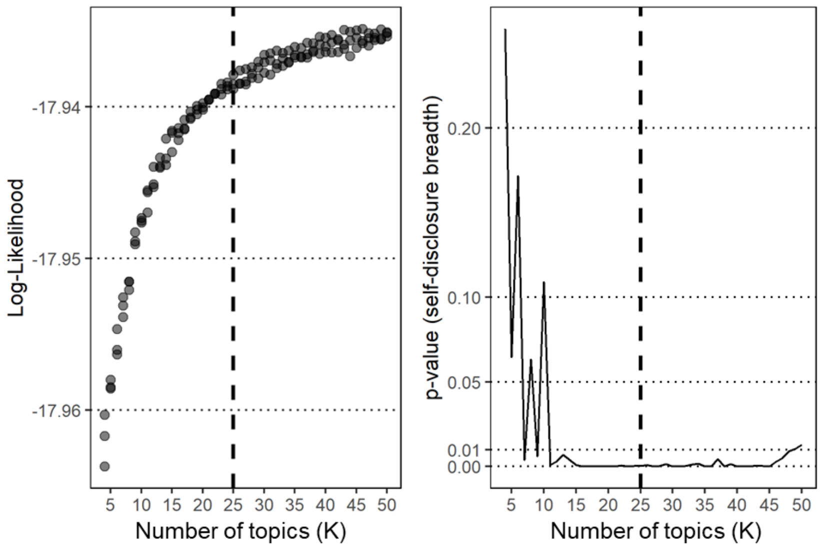


**Figure 3.** LDA model fit and regression results for different number of topics (K)

*Alternate measures of breadth of self-disclosure.* While breadth of self-disclosure has often been conceptualized by observing if participants “discuss a wide variety of topics”, Altman and Tylor (1973) do not conclusively delineate the term “topic.” Jourard and Lasakow (1958) developed a questionnaire where subjects rated six topics (attitudes and opinions, tastes and interests, work, money, personality, and body) according to how much they currently disclosed information and feelings to their partners. These measures can then be summed to evaluate the variety in topics as a measure of breadth of self-disclosure (Tolstedt & Stokes 1984). In contrast, researchers define breadth as “the quantity of the information” (Moon 2000, S. 328) and operationalize it with word or time counts for questionnaire or interview responses (Collins & Miller 1994; Moon 2000; Houghton & Joinson 2012). Summarizing the different views on breadth of self-disclosure, operationalizations obviously differ with regard to the definition of relevant topics, ranging from a) an a priori defined set of topics (Jourard & Lasakow 1958) to b) the number of different topics (Hollenbaugh & Ferris 2014) to c) the mere length of self-disclosing statements (Houghton & Joinson 2012). The self-disclosure breadth measure in our main study (no. 1) presents case b, as it depicts the variety in topics that are not pre-defined but learned from the textual data in an unsupervised manner. We validated the measure using human judgements from 60 participants of an online survey. However, one might question to what extent our results depend on the measure of breadth of self-disclosure chosen. Therefore, we additionally tested two other operationalizations that follow the idea of a and c. First, we create a set of predefined topics by using the LIWC categories that match the questionnaire ideas suggested by Jourard and Lasakow (1958). More precisely, we standardize scores of the LIWC dimensions “body”, “health”, “sexual”, “ingest”, “work”, “leisure”, “home”, “money”, “religion”, “death”, “family”, and “friend". We then use binary measures for each category according to the sign of the standardized value, which then represents whether an SMI is concerned with each of the 12 topics more (= 1) or less (= 0) than the mean of all SMIs. We then follow the idea by Tolstedt and Stokes (1984) and sum up these binary variables for each topic to measure how many of the 12 predefined topics a given SMI is concerned with. When running model M2 with this alternate measure, we again found a significant negative effect of the breadth of self-disclosure on engagement ($b = -.096$, $p < .05$), while the effects for the remaining variables remain qualitatively unchanged. Following Houghton and Joinson (2012), we additionally operationalize self-disclosure by counting the average number of words per post. Again, we found a negative effect ($b = -.145$, $p < .01$).

*Including topics as control variables.* While we include several control variables in the model to alleviate endogeneity concerns, one could argue that the choice of topics affects both dimensions of self-disclosure. For example, an influencer interested in cooking might be more likely to talk about friends and family than an influencer concerned with traveling. In this case, a positive effect of self-disclosure breadth on engagement might be caused by the underlying topics rather than the breadth of topics itself. We estimated model M2 but included the respective topic weights $\mathrm{p}_\mathrm{d}^1, \dots, \mathrm{p}_\mathrm{d}^{K-1}$ as control variables for all except one (as a reference category) topic. We still found that breadth of self-disclosure has a significant positive effect on the engagement rate ($b = -.116$, $p < .05$).

## Study 2

### *Sample*

The main goal of Study 2 is to investigate the mediating process by which depth and breadth of self-disclosure affect behavioral intentions. 327 respondents (149 men, 176 women, and 2 diverse; average age 25.5 years) who use Instagram at least once a month were recruited from the Prolific[23] panel. In the beginning, participants were asked to name a SMI they follow on Instagram. We recorded the profile names and matched them with the real Instagram profiles to compare the SMI selection between the two studies (i.e. Study 1 and Study 2). On average, SMIs in Study 2 have 1,800 posts (versus 1,742 posts in Study 1), 1.21 million followers (versus 1.18 million followers in Study 1), 2,000 followees (versus 1,828 followees in Study 1) and are

[23] Several studies showed that Prolific is a platform that allows collecting high quality data. Peer et al. (2017), for example, show that Prolific has several advantages and no major disadvantages compared to heavy-used alternatives like Amazon’s Mechanical Turk.

verified users in 23,5 % of the cases (versus 27,2% in Study 1). These results suggest that the two samples are quite similar with respect to key SMI characteristics.

***Measures***

We used 5-point Likert scales and measured *self-disclosure depth* (Cronbach's α = .754) including three items following Hollenbaugh and Ferris (2014) and Wheeless (1978) and *self-disclosure breadth* (α = .867) using four items from Hollenbaugh and Ferris (2014). *Parasocial relationship* (α = .689) was measured with three items following Hwang and Zhang (2018) and *expertise* (α = .850) with four items as proposed in Munnukka et al. (2016). To access behavioral intentions, we measured *purchase intention* (α = .906) based on the four-item scale used by van Reijmersdal et al. (2016). For a detailed item description and the factor loadings see Web Appendix Table WA2. In line with Study 1, we also measured engagement intention (two-item scale used by Su et al. 2016; See Web Appendix Table WA3).

***Results***

Most of the latent variables show good convergent validity (average variance extracted (AVE) > 0.50, Cronbach's α > 0.70), while parasocial relationship has acceptable values (AVE = .39, α > 0.60). As Table 5 shows, all factors have sufficient discriminant validity with AVE values larger than the correlation with other latent variables (Fornell & Larcker, 1981).

**Table 5.** Factor Reliability, Validity, and Correlations

| No. | | α | AVE | $\sqrt{AVE}$ | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Self-disclosure depth | .754 | .507 | .712 | - | | | | |
| 2 | Self-disclosure breadth | .867 | .636 | .797 | .303 | - | | | |
| 3 | Parasocial relationship | .689 | .391 | .625 | .283 | .078 | - | | |
| 4 | Expertise | .850 | .595 | .771 | .136 | -.046 | .388 | - | |
| 5 | Purchase intention | .906 | .711 | .843 | .159 | .001 | .331 | .434 | - |

Notes: |r| > .108 significant at .05% level; |r| > .142 significant at .01% level.

We used maximum likelihood estimation to estimate the path coefficients of the model. The chi-square statistic was significant ($\chi^2 = 315.64$, $p < .001$) and the comparative fit index (CFI = .934), the standardized root mean square residual (SRMR = .089), as well as the root mean squared error of approximation (RMSEA = .067) were acceptable (Hu and Bentler 1995).

**Table 6.** Study 2 – Structural model evaluation

| Structural path | | | Est. | SE | p-value |
|---|---|---|---|---|---|
| Self-disclosure depth | → | Parasocial relationship | **.515***** | .103 | .000 |
| Self-disclosure breadth | → | Parasocial relationship | -.050 | .063 | .434 |
| Self-disclosure depth | → | Expertise | **.275***** | .077 | .000 |
| Self-disclosure breadth | → | Expertise | **-.100*** | .052 | .057 |
| Parasocial relationship | → | Purchase intention | **.264***** | .075 | .000 |
| Expertise | → | Purchase intention | **.531***** | .079 | .000 |

Notes: *p < .10; ** p < .05; *** p < .01.

As depicted in Table 6, the model shows that depth of self-disclosure, in line with the literature (Chung & Cho 2017), has a significant positive effect on parasocial relationship (b = .515, p < .001) and expertise (b = .275, p < .001). While breadth of self-disclosure has no effect on parasocial relationship (b = -.050, p = .434) but a marginally significant negative effect on expertise (b = -.100, p = .057). Both mediators have significant positive impact on purchase intentions. The results remained qualitatively unchanged if we allowed the independent variables to affect each other. The correlation between depth and breadth of self-disclosure is positive and significant (r = .303, p < .010). This result matches the result for the field data in Study 1, for which we also found a positive significant correlation between both constructs.

We further estimated the same model but replace purchase intention with engagement intention (two items by Su et al. 2016 measuring the word of mouth intention). We find very similar results. The full model is depicted in Web Appendix Table WA3.

**Study 3**

277 respondents (219 women and 58 men; average age 24.8 years) were recruited directly from a social network to participate in an online questionnaire. The design of this study was the same as the one in Study 2, with the only exception that we replaced parasocial relationship with trustworthiness as a mediator. Trustworthiness was measured with five items (α = .88) following Ohanian (1990). Model fit statistics were comparable to Study 2 ($\chi^2$ = 568.07, p < .001; CFI = .910; SRMR = .114; RMSEA = .075).

**Table 7.** Study 3 – Structural model evaluation

| Structural path | | | Est. | SE | p-value |
|---|---|---|---|---|---|
| Self-disclosure depth | → | Trustworthiness | **.246*** ** | .077 | .001 |
| Self-disclosure breadth | → | Trustworthiness | **-.191** ** | .090 | .034 |
| Self-disclosure depth | → | Expertise | .083 | .101 | .410 |
| Self-disclosure breadth | → | Expertise | **-.550*** ** | .141 | .000 |
| Trustworthiness | → | Purchase intention | **.470*** ** | .119 | .000 |
| Expertise | → | Purchase intention | **.228*** ** | .084 | .007 |

Notes: *p < .10; ** p < .05; *** p < .01.

As shown in Table 7, the effect of the depth of self-disclosure on trustworthiness is highly significant (b = .246, p < .01), while we did not find an effect on expertise (b = .083, p < .410). In line with Study 2, breadth of self-disclosure has a negative effect on expertise (b = -.550, p < .001) and also a significant negative effect on trustworthiness (b = -.191, p = .034). Both trustworthiness and expertise are strong (positive) predictors of purchase intention.

Comparing the results of Study 2 and Study 3, we found a positive effect of the depth of self-disclosure on both parasocial relationships and trustworthiness, while the breadth of self-disclosure has a negative effect on expertise in both studies, confirming our expectation that disclosing too broadly might have negative outcomes as followers attribute less expertise to the influencer regarding a specific topic. We did not find consistent results on the relationships between depth of self-disclosure and expertise, though both studies show a positive relationship. Additionally, the effect of breadth on parasocial relationship and expertise is negative in both studies, yet not significant in Study 2.

## General Discussion

SMIs increasingly reveal their personal lives and thoughts to followers and make use of social media platforms to promote parasocial relationships with their followers. This trend is in line with Chung and Cho's (2017) observation that celebrity-follower interactions on social media become "more intimate, open, reciprocal, and frequent" (p.482). Against this background, our research aims at better understanding the impact of influencers' self-disclosure on post engagement using field data and purchase intention using survey data.

The results of a quantitative analysis of real-world social media data from Instagram showed that depth of self-disclosure (in the form of more intimate posts) increases post engagement (measured as the number of likes and comments a post received). A more detailed analysis revealed that using first-person pronouns as well as using an authentic writing style were the main drivers of the positive effect of depth of self-disclosure on engagement. To our surprise, and contrary to social penetration theory, the results also show that breadth of self-disclosure (measured as the number of topics touched by an influencer) has a negative effect on follower' engagement. To better understand this effect, we ran two additional studies that asked participants about the relationships they had with their favorite SMI. The empirical studies replicated a positive effect of depth of self-disclosure and a negative effect of breadth of self-disclosure on purchase intention for sponsored posts. The studies further provided evidence that two mechanisms explain the effect of self-disclosure. First, depth of self-disclosure has a positive and breadth of self-disclosure has a negative (although not significant) effect on parasocial relationships. Thus, participants seemingly feel closer to SMIs if they post intimate content and if most of the content focuses on fewer topics. A second study replicated the effect using trustworthiness (instead of parasocial relationship) as a mediator, showing that trust-building in the relationship is the key mechanism behind this mediation effect. Second, posting more intimate information and, at the same time, posting about fewer topics increases the perceived expertise. Thus, the negative effect of breadth of self-disclosure on the engagement observed in social media field data can potentially be explained by decreased feelings of closeness to SMIs as well as by decreased perceived expertise.

### *Key Theoretical and Methodological Contributions*

In line with earlier remarks by Liu and Brown (2014), Ruppel (2017) as well as Mehumad and Meyer (2020), we find that relationship building via self-disclosing is essential in the influencer marketing context. Increasing the breadth of self-disclosure by posting about a larger number of topics had a negative effect on the perception of parasocial relationships. Revealing intimate information on social media profiles generally helps SMIs to build stronger relationships with followers and, consequently, has a positive effect on engagement. An additional study confirmed that parasocial relationship, as the main mechanism, can be replaced by trust-building. The latter is considered a more precise description of the effect that self-disclosure has on establishing parasocial relationships. Moreover, our results show that revealing negative emotions or posting content about family or friends did not strongly affect real-world social media engagement on Instagram. The results point to the importance of using an authentic writing style as well as using first person pronouns to increase engagement.

From a methodological perspective, our paper adds value to research in marketing, information systems and psychology that is interested in the measurement of the breadth of self-disclosure from social media texts. We validated our breadth of self-disclosure measure in an extended analysis of Study 1 that showed that our measure is an adequate approximation of consumers' perception of breadth of self-disclosure. It is worth mentioning that the results are not based on a manipulation (i.e., preparing a stimulus that represents different levels of breadth of self-disclosure) but on 600 observations of real social media profiles, which underlines the high external validity of our measure. Complementing the automated measure for depth of self-disclosure presented and validated by Melumad and Meyer (2020), future research can now profit from measurements of both dimensions of self-disclosure from freely available social media data.

***Managerial Implications***

Companies offering branded products have increasing interest in selecting SMIs that are not only able to reach a large number of followers, but also generate high levels of engagement among potential customers (Akpinar & Berger 2017). Consequently, understanding the drivers of engagement and, corresponding therewith, purchase intention is crucial. Accordingly, SMIs have to make two key practical decisions: First, they need to decide how intimate and personal the posted content should be (depth of self-disclosure). Second, they need to decide how broad the range of topics touched on in their posts (breadth of self-disclosure) should be. For both brands selecting SMIs as well as SMIs themselves our findings can help to adapt social media communication strategies to generate higher engagement rates and, as a consequence thereof, increase purchase intention. To further exemplify our results, we used the fitted model M2 to predict engagement rates based on mean values for control variables and 10%, 25%, 50%, 75%, and 90% quantile values from the distribution of both self-disclosure depth and self-disclosure breadth. The estimated engagement rates with confidence intervals are depicted in Table 8. Based on the estimated coefficients from our model, SMIs with a low level of depth of self-disclosure (10% quantile) and high level of breadth of self-disclosure (90% quantile) will generate an engagement rate estimate of 2.69%, while high self-disclosure depth (90% quantile) and low self-disclosure breadth (10% quantile) can increase the engagement rate to 3.60%, which equals a .91% increase. To put these values in perspective, it should be noted that industry estimates of SMI engagement rate on Instagram (with less than 100,000 followers) is 2.4% and .45% on Twitter (Influencer Marketing Hub 2020). Thus, the simulation results underline that brands might be able to increase engagement substantially by selecting the right SMIs.

**Table 8.** Estimated engagement rate for self-disclosure quantiles

| *Self-disclosure depth* (quantile) | *Self-disclosure breadth* (quantile) | | | | |
|---|---|---|---|---|---|
| | 10% | 25% | 50% | 75% | 90% |
| 10% | 3.10 | 2.97 | 2.86 | 2.76 | 2.69 |
| 25% | 3.24 | 3.11 | 3.01 | 2.91 | 2.84 |
| 50% | 3.37 | 3.24 | 3.14 | 3.04 | 2.97 |
| 75% | 3.49 | 3.36 | 3.26 | 3.16 | 3.09 |
| 90% | 3.60 | 3.47 | 3.36 | 3.26 | 3.19 |

Further, we show that breadth of self-disclosure can have a negative effect on perceived expertise of the SMI in a specific product category. While expertise is an important driver of purchase intention throughout the endorsement literature, its importance probably depends on the financial risk associated with the product category and the expertise of the consumers (Schimmelpfennig & Hunt 2020). Therefore, our findings regarding breadth of self-disclosure are of special importance for managers aiming to advertise products with a high financial risk to an audience with comparable low levels of expertise (e.g., personal computers and compact cars).

***Limitations and Future Research***

In line with SPT (Altman and Taylor 1973), we defined breadth of self-disclosure as the number of major topical areas in which a SMI posts content. We measured breadth of self-disclosure by identifying topics based on textual information. Of course, our approach could be extended by also analyzing images in terms of the variety of contexts in which a SMI influencer appears. Automatic object identification, for example, would allow analyzing how many different objects (topics) appear in SMI posted images which might be a good indicator of how many different life situations a SMI shares with her followers.

As outlined by Taffesse and Wood (2020), SMIs who share large volumes of social media content may feel that they need to post more diverse content as otherwise the posted content might lack originality. Posting frequency might thus mitigate the negative effect of breadth of self-disclosure on expertise. We ran an additional analysis with the dataset from Study 1 using model M2, but by adding an interaction effect between self-disclosure and the number of posts. We found a significant positive interaction between number of posts and the breadth of self-disclosure ($p < .05$) showing that posting frequency mitigates the negative effect of breadth of self-disclosure as expected. Future research might be necessary to investigate which influencer characteristics amplify and/or mitigate the effects of self-disclosure.

Study 1 also provided evidence that first-person pronouns and an authentic writing style are two key dimensions of depth of self-disclosure that positively affect engagement. Our analysis is limited as only texts were used when analyzing the five key dimensions of depth of self-disclosure. However, the related posted images can be very emotional and, thus, the influence of these five dimensions might change if we accounted for the influence of posted images. Accordingly, an interesting avenue for future research is to not only to additionally analyze images, but also the emotionality of video content, such as Instagram stories or YouTube videos. Face recognition algorithms would allow identifying emotional states in videos. Not only could the effect of negative emotions be tested but also other measures that are based on changing emotionality over time, such as the emotional amplitude in a YouTube video. Furthermore, Hartmann and Goldhoorn (2011) suggested that eye-gaze is a crucial determinant of viewers' parasocial experience as it can foster immediate impressions of intimacy. Accordingly, future research can investigate whether direct gaze enhances the effect of depth of self-disclosure on engagement.

Finally, validating the effects on other social media platforms is an important task for future research to determine whether the results found on Instagram are transferable to other social media platforms. The importance and effects of depth and breadth of self-disclosure for relationship building might depend on platform standards and conventions. Platforms, such as LinkedIn, are primarily used to maintain business contacts. Revealing intimate information on these business platforms might be perceived as inappropriate. We argue that the observed positive outcomes of self-disclosure are likely to be valid for platforms such as Instagram and Facebook that are primarily used for entertainment and amusement.

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# Essay B3: How can Social Media Influencers create Valuable Engagement for Endorsed Products?

# HOW CAN SOCIAL MEDIA INFLUENCERS CREATE VALUABLE ENGAGEMENT FOR ENDORSED PRODUCTS?

## ABSTRACT

Social-media-based influencer marketing has become a key component of digital marketing strategies. Influencers compete for social media users' attention by creating visually appealing content. Companies sponsor influencers in exchange for them advertising products in personal posts. To evaluate the effectiveness of influencer campaigns, marketers commonly track post engagement in the form of likes and comments that sponsored posts receive. Influencer payments are oftentimes based on post engagement (e.g., number of likes and comments), although this metric does not allow marketers to assess to what extent influencers were successful in directing attention to a product in a sponsored post. In this paper, we operationalize product engagement as the number of comments related to the product. Our analysis of more than 6,000 influencer product endorsement post on Instagram shows that some visual features that enhance post engagement decrease product engagement. Specifically, product depiction size, visual clutter of the image, and the presence of human faces have positive effects on post engagement but negative effects on product engagement. However, influencers can enhance product engagement (without diminishing post engagement substantially) by placing sponsored products more centrally and by making them more salient. Moreover, the results show that post features that direct attention toward the sponsored nature of the post positively affect both post and product engagement. We outline a theoretical framework based on vision research that helps understanding attentional processes in the influencer marketing context.

Keywords***:*** Social media influencers, sponsored posts, image processing, product engagement, post engagement, visual attention

## INTRODUCTION

Social-media-based influencer marketing has become a key component of digital marketing strategies (Hughes et al., 2019) and remains one of the most pressing research topics, as it challenges current marketing practices (Appel et al., 2019; Moorman et al., 2019). Marketers use social media influencers (SMIs) to communicate key product messages and build up brand images in sponsored posts (Hughes et al., 2019). Marketers' goal thus is to direct social media users' attention to advertised products and increase product awareness and brand knowledge.

To monitor the effectiveness and acceptance of social media influencer campaigns, many companies track consumer engagement created by the post by counting the number of interactions (likes, comments, views, clicks, shares) that the influencer posts receive (Influencer Marketing Hub 2021). In the same way, marketing academics have adopted these measures to empirically study factors that influence engagement (de Vries et al. 2012; Lie & Xie 2019; Hughes et al. 2019; Tellis et al. 2019; Rietveld et al. 2020; Valsesia et al. 2020). For example, Hughes et al. (2019) quantify the value of engagement by multiplying "the number of blog post comments and Facebook post likes, comments, and shares by an estimated dollar value for each type of engagement" (p. 16).

In this paper, we argue that the above mentioned operationalizations of consumer engagement for social media posts do not always measure "valuable engagement", as they consider engagement with the post, but do not directly reflect awareness and consideration of endorsed products. The Instagram post by the SMI Milena Karl which received around 12 thousand likes in 2017 serves as an illustrative example (see Figure 1). As can be seen on the image, there are multiple things to like or comment on, for example a handbag by Yves Saint Lauren, the dishes she ordered, her watch or sunglasses, as well as Milean Karl herself.

**Figure 1.** Example Instagram posts by a Social Media Influencer.

Instead of quantifying the undirected engagement towards the post using the number of likes and comments (now referred to as "post engagement"), we suggest measuring the engagement directed at the product by counting the post's comments that specifically refer to the product (now referred to as "product engagement"). In the given example, maybe surprisingly, the post is sponsored by Cluse, a European watch brand.

Our argumentation is in line with Akpinar and Berger (2017) who outlined that companies focus too much on generating “virality” but forget that it might not be valuable if it “does not boost brand evaluation” (p. 318). In essence, the effectiveness of SMI endorsements is expected to depend on whether the sponsored product is an important and integral part of the social media post, whether the product receives attention and whether product awareness is created. In line with this idea, the number of social media users who actively comment on a product is supposed to be a valid indicator of the users’ overall attention paid to the product in the SMIs’ posts.

The insight that post engagement and product engagement should be distinguished has important consequences for marketers and SMIs. First, given the significant marketing expenditures dedicated to influencer marketing (Hughes et al., 2019), marketers need an understanding of which factors enhance product engagement. As a consequence, they can adapt their incentive strategies to reward SMIs who create product engagement. Second, SMIs might encounter a tension between posting content that is suited to enhance post engagement and satisfying marketers’ requirements by increasing product engagement. Consequently, the goal of our paper is to investigate which visual features and post features (i.e., characteristics of the post outside the image such as the caption text) SMIs can use to enhance not only post, but also product engagement. Studying how visual features affect engagement is an important research gap worth addressing, as today’s most used social media platforms, such as Instagram, are built around visual content (Lee and Hosanagar 2018; Influencermarketinghub 2021). Thus, we present a comprehensive framework that allows for a better understanding of the attentional processes that influence post and product engagement in sponsored SMI posts.

Our theoretical basis derives from vision research (Corbetta & Shulman, 2002; Orquin & Mueller-Loose, 2013; Theeuwes, 2010) that distinguishes two main mechanisms that influence the allocation of attention, namely, top-down (endogenous) and bottom-up (exogenous) processes. This distinction depends on whether it is the observer (i.e., the subscriber of an SMI) that directs attention to the stimulus in line with personal goals or values or whether it is the stimulus (i.e. the visual features of the posted image) that attracts the subscriber’s attention. The above Instagram post may serve as an illustrative example: A company selling watches makes a contract with an SMI, for example Milena Karl, to promote a watch on her Instagram account. Milena Karl therefore posts several images of her wearing a watch and discloses her partnership with the watch maker in her posts. How much attention will the watch receive in the sponsored posts? A bottom-up process that influences the amount of attention the watch receives is, for example, how large the watch is that is shown n her posts. Previous research (e.g. Chandon et al. 2009) showed that brands with a larger number of shelf facings attracted more attention and were more often chosen. This result suggests that the size of the product in the image will influence how much attention followers will pay to the product.  Thus, if Milena Karl decided to change the layout of her post so that the watch appears larger (and not relatively small as shown in Figure 1), she might increase the amount of attention her subscribers place on the watch, and, consequently, create increased product engagement. However, if the watch was larger, the SMI or other objects of the image would take up less space of the image and, thus, receive less attention. Subscribers will be less focused on Milena Karl or the visual appeal of her post which should result in subscribers less often commenting on or liking a post. Consequently, post engagement will decrease. The example shows that SMIs face a trade-off between generating post and product engagement. Likewise, an example for a top-down process that influences the allocation of attention is sponsorship disclosure. A subscriber noticing the sponsorship with the watch maker might be more inclined to identify which brand is endorsed by the SMI and, thus, direct more attention to the watch.

Our empirical findings show that five bottom-up factors, namely product size, product centrality, product saliency, less visual clutter, and the absence of a face increase product engagement. However, when SMIs make a product larger, decrease visual clutter and when the post does not show their face, post engagement is substantially reduced. The results further suggest that making a product central and increasing its salience in the image only has minor negative effects on post engagement, which thus is a recommended tactic for SMIs. In terms of top-down processes, we also find that disclosing the sponsorship nature of a post simultaneously increases post and product engagement and it is therefore also a recommended strategy for SMIs. In contrast, mentioning the brand name in the end of the caption text and mentioning multiple brands in the same post is both associated with more post, but less product engagement.

Our paper advances prior research in two important ways. First, our research shows that visual features can have opposing effects on post and product engagement which suggests that SMIs and brands should carefully evaluate the visual design of their social-media posts as well as track both changes in post and product engagement. Second, we develop a framework based on vision research that explains why bottom-up and top-down processes of attention influence both forms of engagement. We apply established tools from vision research (Towal et al., 2013) to study bottom-up and top-down processes of attention in the social media context. This research uses real-world social media data from Instagram. We assemble two large datasets of sponsored-SMI posts for two product categories, watches and shoes, measure various visual and post characteristics, and test their effects on product and post engagement. As observed SMIs in our sample endorse products in multiple posts, our model allows to control for SMI characteristics using fixed effects. We further control for possible targeting mechanisms of the Instagram algorithm and include a rich set of control variables to our model. Our field data not only allows us to draw conclusions regarding the effectiveness of influencer marketing campaigns but also to assess the stability of the results using two different product categories.

## THEORETICAL BACKGROUND

### *Relevance of Attention Economics for Social Media Research*

With its abundance of content, attention economics is particularly relevant to today's digital (social media) environment. Lee and Hosanagar (2018, p. 5129) highlighted that "competition for consumer attention across media outlets is intense, especially on social media platforms." This scarcity mechanism of attention not only works across but also within social media platforms. As highly active SMIs create multiple posts a day, each post competes with other SMIs' posts for subscribers' attention. Consequently, gaining attention with social media posts is an SMI's central goal (Li & Xie, 2020), as being noticed is the mechanism that builds person brands on social media (Smith & Fischer, 2020). SMIs who successfully build social capital in the attention economy are attractive to companies, as those SMIs can potentially direct their subscribers' attention to sponsored products.

Smith & Fischer (2020, p. 1) see engagement as a valid "indicator of attention" (Smith & Fischer, 2020, p. 1), as liking or commenting requires more than awareness and involves mental engagement. However, given that the authors are not concerned with sponsored social media posts, they also do not discuss that different types of engagement indicate different attentional processes. Product engagement should be closely linked to attentional processes that direct the user's attention to the sponsored product in a post. On the contrary, post engagement should be linked to attentional processes that potentially direct attention towards the SMI and not necessarily towards the product. Thus, we build on Smith and Fischer's view that engagement and attention are closely linked but emphasize that a better understanding is necessary which attentional processes are linked to which types of engagement. Our paper contributes to a better understanding of which and to what extent visual and post features help SMIs in their competition for attention on social media platforms that are built around visual content.

***Prior Research on Engagement with Visual Social Media Posts***

Prior research investigated single visual features that can affect post engagement: Li and Xie (2020) found that more colorful images received increased post engagement in some product categories and that human face presence induced higher post engagement (on Twitter but not on Instagram). Rietveld et al. (2020) showed that brand-generated posts with higher brand centrality stimulated engagement in terms of the overall number of comments but not in terms of likes. Hartmann et al. (2021) compared consumer selfies, brand selfies, and packshots. They operationalize brand engagement in social media posts by the number of comments that explicitly articulate a purchase intention for the brand. The authors found that brand selfies (i.e., images of products taken by invisible consumers) attracted significantly more brand engagement than consumer selfies (i.e., images of consumers with branded products) or packshots (i.e., images only showing the product). This result suggests that faces in selfies can distract consumers, such that they focus more on the faces than the products in social media users' posts. The authors also investigated logo size, logo centrality as well as visual complexity (which is similar to visual clutter) and showed that size and centrality of the logo decreased the number of likes that posts received and visual complexity increase the number of likes that posts received.

As Table 1 shows, prior research that investigated the effect of visual characteristics on post and product engagement is still largely fragmented. Li and Xie (2020) as well as Rietveld et al. (2020) did not investigate product engagement and both groups of authors only analyzed one visual feature. The paper by Hartmann et al. (2021) is most similar to our research but is different in two important ways. First, it does not investigate sponsored SMI posts (i.e. paid media), but investigates posts shared by consumers not paid by the brand (i.e., earned media). Second, it does not investigate the visual features of product saliency, size or centrality, but instead studies the effect of logos in images. The outcome of the literature review shown in Table 1 thus underlines the need to understand the relationship between visual features, the two forms of engagement and the attentional processes that explain the respective changes in engagement.

**Table 1.** Research on engagement with visual brand-related social media posts

| | | Li & Xie 2020 | Rietveld et al. 2020 | Hartmann et al. 2021 | This study |
|---|---|---|---|---|---|
| Visual features | Product size | | | | ✓ |
| | Product saliency | | | | ✓ |
| | Product centrality | | ✓ | | ✓ |
| | Visual clutter | | | ✓ | ✓ |
| | Face presence | ✓ | | ✓ | ✓ |
| Engagement | Product/Brand | | | ✓ | ✓ |
| | Post | ✓ | ✓ | ✓ | ✓ |
| Sender | Influencer | | | | ✓ |
| | Brand | | ✓ | | |
| | Consumer | ✓ | | ✓ | |

When building Table 1, we excluded articles on video ads (e.g., Akpinar & Berger, 2017), articles in non-marketing contexts (e.g., Bagshi et al., 2014), and articles that modeled engagement on an aggregate rather than an individual-post level (Argyris et al., 2020). Additionally, Villarroel Ordenes et al. (2019) investigated how the degree of action portrayed in brand images drives engagement. However, their operationalization was based on human assessment rather than concrete visual features (that drive attention), making a comparison inconclusive. We summarize the findings of recent articles in Web Appendix Table WA1 and suggest reading Hughes et al. (2019) for a review.

***An Attention-Based View of Visual Features that Influence Post and Product Engagement***

In the vision and eye-tracking literature, attention is normally defined as selectivity in perception (Orquin & Mueller-Loose, 2013). Vision research distinguishes two main attentional processes, namely, bottom-up (exogenous) and top-down (endogenous) processes (Corbetta & Shulman, 2002; Orquin & Mueller-Loose, 2013; Theeuwes, 2010), which determine how humans allocate attention. This distinction depends on whether it is the stimulus (i.e. the visual features of an endorsed product in an image) that attracts the subscriber's attention (bottom-up process) or whether it is the observer (i.e., the subscriber of an SMI) that directs attention to the stimulus in line with personal goals or values (top-down process). Bottom-up and top-down process are described in more detail next.

***Bottom-up Processes of Visual Attention***

As exogenous factors, the bottom-up factors can be described as principles for guiding eye movement (Orquin et al., 2018). Based on a review of eye-tracking studies in the domain of decision-making, Orquin and Mueller-Loose (2013) identified four major bottom-up factors that influence attention towards products in (consumer) choice: saliency, surface size, visual clutter, and position/centrality. These four factors are in line with the six principles proposed earlier by Wedel and Pieters (2008), as visual saliency can be further elaborated into color edges, movement, and other image effects. In line with earlier research, which showed that faces can serve as a distractor in social media posts (Li & Xie, 2020; Hartmann et al., 2021), we argue that, in addition to the four factors proposed by Orquin et al. (2018), a fifth factor, a face distraction effect, should be considered in the social media context.

Each of the five factors may influence how likely it is that a key element of a sponsored social media post, such as the product, is fixated and how much post and product engagement is created. Thus, these visual features have a potential to change subscribers' perceptions of sponsored posts. Making a product larger, more salient, and more central, as well as making the image less cluttered or presenting the SMI less prominently, may increase attention to the product in a post. Increased attention to a product should increase the probability that a product is noticed and that product-related thoughts are produced. As outlined above, in line with Smith and Fischer (2020), attention is thus a necessary pre-condition to create product engagement. Processes that likely change the allocation of attention in SMI posts are expected to change product and post engagement respectively.

Researchers have argued that top-down factors are even more relevant than bottom-up factors in natural environments, as humans mostly direct their attention in line with their inner goals or motives (Hayhoe & Rothkopf, 2011; Hayhoe et al., 2003). Other studies, however, provide evidence that bottom-up factors can play a substantial role in influencing choice. Milosavljevic et al. (2012), for example, showed that bottom-up factors can have a strong influence on decision-makers' choices. When choosing from different snack items, visual saliency had a stronger effect on choice than respondents' preferences when respondents were under time pressure. Towal et al. (2013) reported that in the case of crowded shelf displays, choices were best predicted when both bottom-up factors, such as visual saliency, and top-down factors, such as preferences, were used to predict choices.

We are not aware of studies that have systematically tested the influence of bottom-up factors in sponsored SMI posts. However, we argue that bottom-up factors should have a substantial influence on both forms of engagement because the attention spans of social media users are generally quite short: a study conducted by Facebook showed that users only take around 1.7 seconds to process a single post when using the mobile feed view[24] on their mobile devices (Facebook, 2020). Although respondents do not experience time pressure when using social media, as they did in the experiments by Milosavljevic et al. (2012), most social media users do not spend much time on a single post. The shorter the amount of time that users direct their attention to a single post, the stronger the effects of bottom-up processes should be in guiding visual attention and influencing post or product engagement.

In what follows, we briefly summarize the findings from empirical studies that tested the five above-mentioned bottom-up processes in marketing contexts. We also explain how the bottom-up effects are supposed to influence how attention is directed in sponsored posts.

*Product size.* Lohse (1997) found that an enlarged display size of an ad increases the amount of attention an ad received. Chandon et al. (2009) provided supporting evidence for the effect of the size of a visual stimulus and tested it in a choice context. The authors changed the number of shelf facings and showed that brands with a larger number of facings attracted more attention

[24] The mobile feed view is used by most social media services and displays unseen content on the top. Users scroll down to see the next element, and the order of elements is determined by the service-specific algorithm.

and were chosen more often. These results suggest that larger products will receive more attention than smaller products. Increased allocation of attention to products is expected to increase product engagement, as subscribers are mentally more concerned with products shown in posts. Analogously, subscribers are less focused on other elements of the post (such as the SMI, the visual appeal of the post etc.) which should result in subscribers less often commenting on or liking a post. Thus, the result of an increased product size should be an decrease in post engagement and an increase in product engagement.

*H1: The larger the product is that is shown in a sponsored SMI post, the less post engagement is created.*

*H2: The larger the product is that is shown in a sponsored SMI post, the more product engagement is created.*

*Position and centrality effects.* Several studies (Chen & Pu, 2010; Glaholt et al., 2010; Lohse, 1997) tested position effects on attention using stimuli from various domains, such as recommender interfaces, shopping websites, yellow pages advertising, etc. These studies (mostly conducted in Western countries) found that stimuli were most often processed from top to bottom and left to right (in line with the reading patterns respondents are used to in these countries). Tests in the context of consumer choice mostly focused on centrality effects. Studies by Chandon et al. (2009) and Reutskaja et al. (2011) suggest that marketers prefer central shelf positions because a product there attracts more attention, which in turn increases the probability that a product will be chosen. Atalay et al. (2012) replicated the effect of centrality on attention and choice. They also showed that the effect does not only occur when the stimulus is in the center of the screen, but also when the choice alternatives are located on the left or the right side of the screen. Meißner et al. (2016) also found that centrally located alternatives receive increased attention when respondents choose from conjoint alternatives, but they did not find that increased attention led to a substantial increase in choice probabilities. It might be that centrality increases attention initially but only has minimal effects on choice. For social media posts, the effect of centrality should generally be stronger for short inspection times. Previous findings suggest that centrally placed products in sponsored posts receive more attention, which would be evidenced by more product engagement but less post engagement.

*H3: The more central the product is placed that is shown in a sponsored SMI post, the less post engagement is created.*

*H4: The more central the product is placed that is shown in a sponsored SMI post, the more product engagement is created.*

*Saliency.* Lohse (1997) showed that more visually salient, colored ads received more attention than non-colored ads. Bialkova and van Trijp's (2011) results reveal that more salient product attributes, such as product labels, received more attention. In the consumer choice context, Milosavljevic et al. (2012) provided evidence that more salient product alternatives receive more attention and were more likely to be chosen. A large body of research has provided overwhelming evidence for the effect that saliency has on attention (for an introduction to this field, see Frintrop et al., 2010). We therefore predict that more salient products will receive more attention in sponsored posts. In line with the above argumentation, increased product attention should reduce post engagement but enhance product engagement.

*H5: The more salient the product is that is shown in a sponsored SMI post, the less post engagement is created.*

*H6: The more salient the product is that is shown in a sponsored SMI post, the more product engagement is created.*

*Visual clutter*. Rosenholtz et al. (2007) see visual clutter as a “stand-in for set size” which affects performs (in terms of response times) when humans are given simple search tasks. In line with that assessment, cluttered post images consist of several different visual elements that all compete for the subscribers’ attention. We can expect that less cluttered images in sponsored posts will lead to more attention on products, just because there are fewer post objects that compete for users’ attention. A marketing study that supports this idea was published by Visschers et al. (2010). The authors found that respondents paid less attention to nutrition labels in more cluttered environments. Consequently, increased product attention (resulting from less cluttered images) is expected to increase product engagement, but decrease post engagement.

*H7: The more cluttered the image in the sponsored SMI post is, the more post engagement is created.*

*H8: The more cluttered the image in the sponsored SMI post is, the less product engagement is created.*

*Distraction effects*. Several empirical studies investigated distraction effects in the context of advertisements. Severn et al. (1990), for example, concluded that an ad that includes strong sexual appeals draws attention away from the evaluation of the product. A study by Sullivan et al. (2017) provided evidence that visual elements in television ads distracted consumers from paying attention to risk information presented simultaneously. Cummins et al. (2020) recently found evidence for visual distraction effects due to sexual appeals in advertisements. When sexual appeals were used, the relative attention to the product in the ad decreased. Although SMIs in practice rarely utilize sexual appeals, mechanisms that take attention away from the product could function in a similar way. In the social media context, the SMI’s face is a potential distractor that could take attention away from the product in the sponsored post, as it is a strong attractor of attention (Tomalski et al., 2009). While Lie and Xie (2020) found that face presence increased engagement on Twitter but not on Instagram, Hartmann et al. (2020) showed that face presence on consumers’ brand-related posts led to higher engagement on both platforms and fewer statements of purchase intention by subscribers in the respective comments. Consequently, we predict that a post including a face will serve as a distractor and, thus, reduce attention to the sponsored product, which will result in less product engagement but more post engagement.

*H9: Images showing a human face in sponsored SMI posts create more post engagement (than images that do not show a human face).*

*H10: Images showing a human face in sponsored SMI posts create less product engagement (than images that do not show a human face).*

***Top-down Processes of Visual Attention***

Top-down processes allow humans to effectively interact with their surroundings (Orquin et al., 2018). For example, decision-makers focus their attention on relevant attributes or choice options according to their preferences (Meißner et al., 2016). In what follows, we briefly summarize research that has investigated top-down processes in the context of social media posts.

*Sponsorship disclosure.* In most countries, it is mandatory for SMIs to add partnership disclosures to their posts if they receive financial compensation for promoting products or brands. In some posts, the partnership disclosure statement is placed in the form of a badge above the posted image so that this disclosure element appears first in the mobile feed view. If subscribers see a partnership disclosure, it can function as an informational prime (Boerman et al., 2020) that changes how social media users process the post. Two eye-tracking studies provided initial evidence for this top-down process. Boerman et al. (2015) showed that partnership disclosures increased the amount of attention viewers paid to brands in a television program. Guo et al. (2018) investigated the effectiveness of disclosures in the context of product placements. They showed that a disclosure statement increased the relative attention to the product, which in turn increased awareness of the persuasion attempt, brand recognition, and brand attitude. A recent study by Boerman et al. (2020) showed that brand placement disclosures in ads increased brand memory in the short and long term. Akpinar and Berger (2017) argued that informational appeals (disclosures) should often bolster brand-related outcomes, such as evaluations and purchases. In sum, empirical studies investigating disclosure effects suggest that disclosure serves as an informational prime that, once activated, increases top-down allocation of attention. Consequently, we expect that prominent disclosures are likely to be looked at earlier, more likely to activate a top-down process, and therefore more likely to enhance product engagement.

The effect of disclosure on post engagement could be either positive or negative. The disclosure statement could activate persuasion knowledge (Friestad & Wright, 1994), i.e. the realization that the post is an attempt to persuade subscribers, leading to negative subscriber reactions and, consequently, less post engagement (Stubb et al. 2019; see Table WA1 in the Web Appendix for a list of studies on the outcomes of sponsorship disclosure). However, Akpinar and Berger (2017) argue that consumers should evaluate persuasion attempts as fairer and less manipulative in posts that include disclosures, which could therefore also lead to increased post engagement. Given that we focus on sponsored SMI posts in this paper and thus all of them show products, we expect that subscribers positively respond to posts from SMIs who openly disclose sponsorships.

*H11: Sponsored SMI posts that comprise a prominently shown sponsorship disclosure statement create more post engagement (than posts without prominently shown disclosure).*

*H12: Sponsored SMI posts that comprise a prominently shown sponsorship disclosure statement create more product engagement (than posts without prominently shown disclosure).*

*Brand mention.* A partner brand mention in a sponsored SMI post (i.e., a link to the account of the brand that paid the SMI for the partnership) helps social media users to recognize that the post might be sponsored by the respective brand and serves as an informational prime. Thus, we can expect that partner mentions activate top-down allocation of attention to products by the mentioned brand. SMIs are free to decide where to include a brand mention in their posts' caption (e.g., they can place the "@[brand name]" text at the beginning, middle, or at the end of the caption text). We observe whether a brand mention cue is visible without the reader having to open the caption text. In this case, subscribers are exposed to the brand mention cue regardless of their initial interest in the post that might lead them to expand the caption text and read further details. We expect that the more visible the brand mention cue is, the more it will enhance product engagement, but diminish post engagement.

*H13: Sponsored SMI posts that comprise a prominently shown brand mention create less post engagement (than posts without a prominently shown brand mention).*

*H14: Sponsored SMI posts that comprise a prominently shown brand mention create more product engagement (than posts without a prominently shown brand mention).*

However, SMI posts might include more than one link to other accounts (e.g., other persons or multiple partnering brands). When more than one partner is mentioned, multiple brand mention cues compete for attention in the caption text, as possibly more product depicted in the image compete for attention. Consequently, the number of brand mentions might have a negative effect on product engagement for the focal product. However, multiple brand mentions increase the chance that there is something to like for the subscribers, for example another product or another person.

*H15: The larger the number of brands mentioned in a sponsored SMI post, the more post engagement is created.*

*H16: The larger the number of brands mentioned in a sponsored SMI post, the less product engagement is created.*

All hypotheses are summarized in Table 2.

**Table 2.** Summary of hypotheses

| | Post engagement | | Product engagement | |
|---|---|---|---|---|
| Variables: | Hypothesis | Expected direction | Hypothesis | Expected direction |
| **Bottom-up** | | | | |
| *Product Size* | $H_1$ | - | $H_2$ | + |
| *Product Centrality* | $H_3$ | - | $H_4$ | + |
| *Product Saliency* | $H_5$ | - | $H_6$ | + |
| *Face* | $H_7$ | + | $H_8$ | - |
| *Visual Clutter* | $H_9$ | + | $H_{10}$ | - |
| **Top-down** | | | | |
| *Sponsorship Disclosure* | $H_{11}$ | +/- | $H_{12}$ | + |
| *Prominence of Brand Mention* | $H_{13}$ | - | $H_{14}$ | + |
| *Number of Mentions* | $H_{15}$ | + | $H_{16}$ | - |

## SAMPLE

To study the proposed relationships, we build a sample of SMI posts from Instagram that endorsed a watch. We find watches to be a suitable product category for our study since the ways SMIs present the product strongly differ regarding the prominence (e.g., size, centrality, saliency) of the product. Further, influencer marketing has become one of the key advertising channels for watch brands like Daniel Wellington that are allocating nearly their entire marketing communication budget to sponsored endorsements (Bloomberg 2015). In the first step, we collected a sample of 3,344 SMI accounts by searching SMI names mentioned in blog posts using Google search query “influencer list”. As these observations might in some way suffer a survivorship bias (i.e., SMI traits that increase the probability of being listed), we also collected profiles from influence.co, a large community where SMIs create a profile to connect with sponsoring brands. While these profiles might suffer a self-selection bias (i.e., SMI traits that increase the probability of creating a profile), we argue that the combination of both samples helps us to study a broad, and probably more representative, sample of SMIs than one would have using only one sampling method. For each of the SMIs, we download all Instagram posts and count the number of mentioned brands (i.e., a brand is linked in an Instagram post by adding “@[brand account name]” in the caption text). In total, we find five brands that primarily sell watches from the list of the 500 most often mentioned brands and then build a sample of Instagram posts that mention one of these brands: Daniel Wellington (n = 1735), Cluse (n = 766), Kapten & Son (n = 472), Fossil (n = 341), and MVMT (n = 310). In total, these 3,624 posts were created by 699 unique SMIs. We give further details on the sample collection as well a statistical comparison between the two sampling methods in Web Appendix A.

## VARIABLES

### *Dependent Variables*

We followed standard practice and measured post engagement by the number of likes and comments a post received. While we could not infer what drove each post to be liked (e.g., the sender itself, the content of the post, or the displayed product), comments can reveal the underlying motivation by explicitly referring to a specific element of the post. Since we focused on a single product category (i.e., watches), comments that mentioned the product (e.g., "I like your watch") could be interpreted as engagement driven by the product itself (product engagement, hereon). We consequently collect all comments and search for the term "watch" and "wristwatch" (we used the Google Translate API to translate non-English comments, which represent 14.5% of all comments). We manually checked 200 randomly chosen comments that include one of the search terms and all of them explicitly mention the product. We observe that nearly all of the comments state the product in combination with a positive description, as exemplified in Figure 2. We measure product engagement by the number of comments explicitly referring to the product.

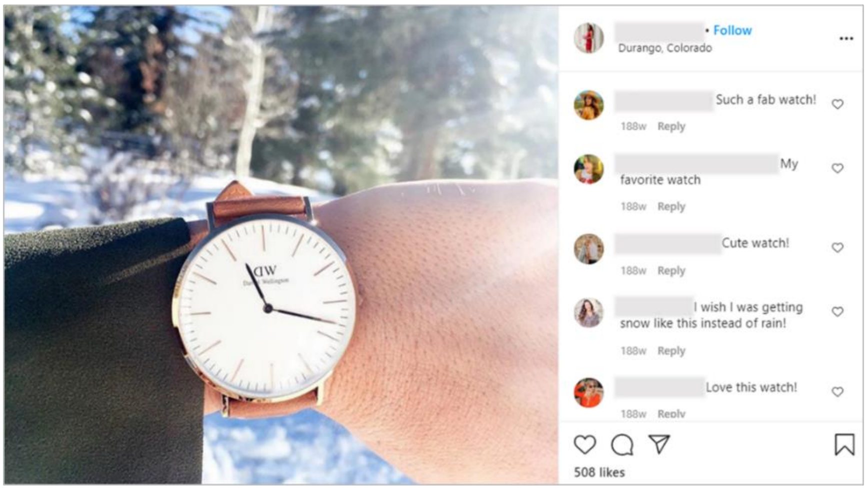


**Figure 2.** Example of comments for product engagement.

### *Features Activating Bottom-up Attentional Processes*

To measure the activation of bottom-up processes from the images, we applied a set of well-established research methods from the (computer) vision literature. The methods we chose were a compromise between performance and ease of implementation. As it is not our goal to compare the accuracy of different approaches (e.g., with respect to the determination of saliency), we instead refer to comparative studies in the literature when needed.

We first detected all objects present in images with the Google Cloud Vision API (Google, 2020a). The underlying model is based on a deep convolutional neural network (Inception-v3) and returns a list of object names and object locations for all objects, persons, and faces detected in the image. The API is very accurate when working with brand-related content and has therefore been applied in several recent marketing articles (e.g., Li & Xie, 2020; Rietveld et al., 2020).

After annotating all 3,624 posts, we kept those where a watch was detected, as some of the brands also offered other products, such as sunglasses and necklaces, and several posts do not show a product at all. To make sure that all watches were found, we partitioned the original images into images of size 299 × 299 pixels, as this is the required size for the input vector of the underlying model (Google 2020b). The Google Cloud Vision API automatically rescales input images to fit the model, but this process can lead to a less accurate detection for small objects. Partitioning the images revealed 743 images with watches that had not been detected in the images when they had the original size. We advise future researchers to keep this in mind when detecting small objects. Notably, as we show later, the watch objects we identified cover 3% of the image (calculated as the ratio of the number of pixels of the object and the number of pixels of the full image) on average. In comparison, the brand logos investigated by Hartmann et al. (2021) cover 7% of their images on average. Thus, the ratio confirms that our method is able to detect quite small watches in the images. In total, 2,729 (posted by 672 SMIs) of the 3,624 images remained in the sample, as a watch was detected. A research assistant manually annotated 100 randomly selected images from the set of images where watches were detected and 100 randomly selected images from the set of images where no watches were detected. In the former sample, all the images depict a watch. In the latter, eight images contain watches that had not been detected by the API, indicating an acceptable accuracy rate.

We used the information retrieved by the API to operationalize product size (relative size of the watch) and product centrality (one minus Euclidean distance between the center of the image and the center of the watch). We further noted the presence of a SMI if a human face was detected in the image.

A wide range of methods is available for measuring saliency (Borji, 2013). We decided to use the Adaptive Whitening Saliency (AWS) method proposed by Garcia-Diaz et al. (2012), as it has outperformed comparable models in predicting where observers look (Borji, 2013). The AWS algorithm can be used to compute a saliency map that assigns a saliency value for each pixel of the original image. We averaged the saliency values for the area of each object detected by the API in the image and then calculated the product saliency as the ratio between the watch saliency (i.e., average pixel saliency in the area of the image where we detected the watch) and the saliency of the object with the highest saliency.

To assess the visual clutter of the images, we used the method proposed by Rosenholtz et al. (2007), which quantifies clutter based on the whole image rather than based on specific objects. The authors suggested two alternate measures of clutter which they coin entropy and congestion. From a theoretical perspective, none of the two measures has clear advantages in our application context. We therefore tried both measures and used Vuong's likelihood ratio test for non-nested models (Vuong 1989). We find that clutter entropy significantly outperforms clutter congestion in predicting post engagement ($Z = -1.65$, $p < .05$) and slightly, but not significantly, in predicting product engagement ($Z = -.37$, $p = .36$). We therefore decide to use clutter entropy in our final model.

Figure 3 summarizes all visual variables and depicts example images for extreme values of each variable.

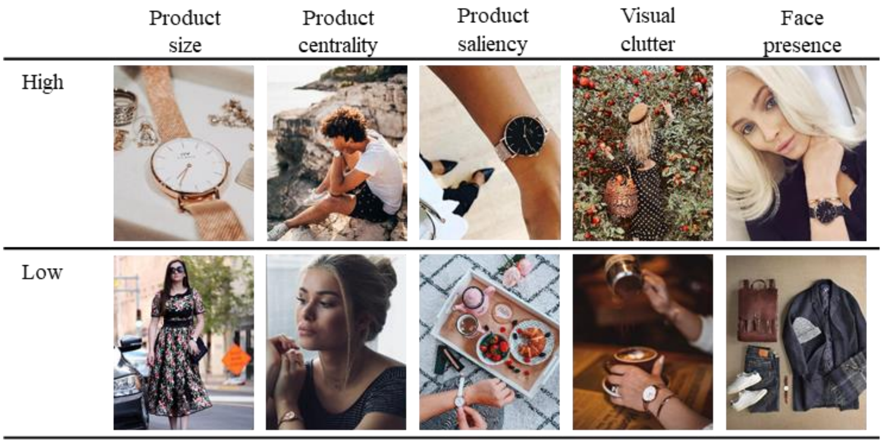


**Figure 3.** Example images for SMI posts endorsing a watch

### *Features Activating Top-down Attentional Processes*

We investigated two forms of sponsorship disclosure that differed in terms of visibility. A badged disclosure appears above the post and follows the standardized format “Paid partnership with [brand]” (Boerman, 2020). As almost all social media apps present posts in a mobile feed format, which requires scrolling down to see the next post, the badged disclosure is the first visible information besides the SMI’s name. In contrast to other forms of disclosure, the *standardized disclosure* is verified by the sponsoring brand. The most common form of sponsorship disclosure is *textual disclosure*, where the SMI discloses the sponsorship somewhere in the text. This form of disclosure typically includes the addition of an indicator word (e.g., sponsored) or the respective tag (e.g., #sponsored) to the post. We created a set of indicator words (Web Appendix Table WA3) and matched them with the text of a post to measure textual disclosure.

All posts in our sample include a mention of the brand (@[brand]) with which the SMI was collaborating. While mentioning the brand is a cue that drives attention toward the product, the position of this cue should impact its visibility. We measure the *position of the brand mention* cue as a binary variable that reflects whether the cue is within the first two lines of the caption text (Position of brand mention = 1) or not (Position of brand mention = 0). Placing the cue in the beginning of the caption increase the visibility of the cue as subscribers might stop reading the caption after the first lines. Additionally, Instagram always displays the first two lines of the caption, while the rest of the caption only becomes visible when the user “expands” the text. SMIs sometimes mentioned multiple brands and/or other user accounts in their posts when multiple products and/or other persons were present. We therefore added the *number of mentions* as a numeric variable. While the SMI is free to choose the position of the brand mention, the attention to the cue is assumed to be higher if the cue already appears in the textual preview of the post. On their feeds, users see a preview of a maximum of two rows of text without opening the post. Accordingly, we included *position of brand mention* as a dummy if the brand mention cue was placed in the first two lines of text.

Caption texts can further include information about an incentive for the subscribers such as coupons (i.e., a discount code that can be used in a shop to reduce the price) or a giveaway (i.e., the SMI gifts a copy of the product to a random or qualified set of subscribers). Both forms of incentive can increase attention toward the product and are therefore included in the model. To operationalize *coupon incentive* and *giveaway incentive,* we create a set of indicator words such as "coupon", "code", and "giveaway" (see Web Appendix Table WA3).

***Nonrandom targeting of posts***

In contrast to experimental research, where researchers can randomize stimuli across groups of participants, observations of social media behavior are always prone to potential biases, such as targeting. One concern is that SMIs target specific subscribers based on the content of their post, which will lead to biased estimates on predictors of engagement (Lee et al. 2018). However, to the best of our knowledge, Instagram does not allow SMIs or companies to choose a specific target audience for a specific post (in contrast to ads, which we do not investigate in this study) but the posts are sent to all subscribers' timelines. However, Instagram has implemented an algorithm that determines the order in which posts appear in a user's individual timeline. The algorithm also determines which posts are presented in the explore page.

While the exact mechanisms implemented in this algorithm are hidden for both SMIs and researchers, SMIs may learn over time how they can use the algorithm in their favor. For example, SMIs may observe that posts with a larger product depiction size reach fewer subscribers (and consequently get less engagement), and therefore might decide to choose a smaller depiction size in their next post. Assuming a higher engagement for the second post based on a higher reach generated by the algorithm, the researcher might erroneously infer that the higher engagement is directly caused by a smaller product size. Therefore, it is necessary to control for the targeting algorithm. According to Instagram (Costine 2018), the algorithmic targeting is based on three aspects: First, past user engagement with the sender of the post (i.e., the algorithm places the post more prominently in the timeline of a subscriber that has recently liked or commented another post of the SMI), second, past user engagement with similar content (i.e., the algorithm places the post more prominently in the timeline of a subscriber that has recently liked or commented a post with similar content), and third, how recently the post was published (i.e., the algorithm places the last post more prominently than previous posts). Our data includes post and product engagement by the respective SMI on a post-aggregate level. Therefore, we can observe the aggregate engagement with all of her posts before the sponsored post in our data. However, we cannot infer the user-individual engagement on similar posts. Nevertheless, it is important to note that our specification is formulated at the aggregate level, modeling the total number of likes and product-related comments received by a sponsored post. Accordingly, we approximate past user engagement with the sender of the post (*abnormal prior engagement*) and how recently the post was published (*recency*), as explained next.

*Abnormal prior engagement*. To control for past user engagement with the sender (i.e., the SMI), we estimate the abnormal engagement (abnormal number of likes) with the posts of the respective SMI immediately before the sponsored post. If these posts receive more engagement than one would expect by comparing them with past posts of the SMI, the algorithm might be more likely to also send the sponsored post to more users who engaged with the previous posts. To compute *abnormal prior engagement* for each sponsored post, we fit a time-series ARIMA(2,1,2) model to the series of likes for all posts before the respective sponsored post. We then record the model residuals (i.e., the part of the engagement that is not explained by the time-series structure) of all posts in a 30-days range before the sponsored post. As the residuals are measured in the same scale as the time-series (number of likes), we divide the number of likes by the expected number of likes to normalize the residual. This yields the percentage difference between the observed and the expected value. The resulting metric equals 1 if a post's residual is 0 (i.e., the observed number of likes is exactly as expected), while values higher (lower) than 1 indicate that the post received more (less) likes than expected. We multiply these normalized residuals with a carryover-coefficient of 0.5 per week, as we assume the algorithm places a stronger weight on posts that are more recent. The value of 0.5 per week is used in the literature to model the effect of past social media posts on current behavior (Kupfer et al. 2018). To compute *abnormal prior engagement*, we take the mean of the derived relative-carryover residuals. For every sponsored post, we use the following metric to compute *abnormal prior engagement*:

$$\text{Abnormal prior engagement} = \frac{1}{n}\sum_{i=1}^{i=n} \varepsilon_i 0.5^{w_i}, \tag{1}$$

where n is the number of posts in a 30-day range prior to the publication of the sponsored post, $\varepsilon_i$ is the normalized residual of the ARIMA model for post i, and $w_i$ is the number of weeks between post i and the focal sponsored post. We also estimate a model where we calculate abnormal prior engagement using the logarithm of the number of likes, which yields the same qualitative conclusions regarding our hypotheses. Further, in the product engagement model, we include *post engagement* as a predictor in order to control for the popularity of the post that might affect the targeting mechanism.

*Recency*. To control for how recently the post was published, we record the time between the post and the next post. Assuming everything else being equal, the algorithm determines the order of the post by recency. Therefore, when the same sender creates a new post after the sponsored post, the new post will appear before the sponsored post and is therefore more likely to be considered by the subscriber. We control for the duration a post is on top on a specific senders list of posts by the number of hours between the sponsored post and the following post. Doing so, we control for the time a post is considered the most recent post by a specific SMI.

### *Omitted variable bias*

Omitted variable bias occurs when variables not included in the model correlate with the dependent and independent variables in the model. Therefore, we add a rich set of observable post characteristics to our model that were also used in prior studies. From the caption text of the post we extract the length of the post, the number of hashtags, as well as the sentiment. We also control for the colorfulness and the brightness of the images[25] (Lie & Xie, 2020). To

[25] Please note that the colorfulness and the brightness of the images are not treated as product-related bottom-up effects. Brightness, for example, represents the average brightness of all pixels of an image, but does not quantify the relative brightness of the product in the image. Thus, overall brightness is not expected to influence how much attention a product receives in an image. However, the brightness of the image might increase the

measure colorfulness, we applied the method proposed by Hasler et al. (2003). Brightness was measured by the third value of the hue-saturation-value (HSV) color model (Matz et al., 2019). Additionally, we include a dummy variable if the post is created during the weekend (De Vries et al. 2012).

Still, unobserved characteristics on post-level or SMI-level might bias our estimates. For example, when SMIs infer that posting a product endorsement with high product size receives more engagement in the afternoon as subscribers interested in product endorsements are more active at that time, the researcher not controlling for (i.e., "omitting") time of day would observe a positive relationship between product size and engagement that is not causal. Additionally, in the case of more attractive SMIs, it might be more likely that they will depict their face in the images more often. If attractiveness further increases engagement, not controlling for attractiveness will lead to a biased estimate of *face* on engagement. We argue that the most concerning sources of endogeneity caused by unobserved variables either depended on experience (i.e., SMIs learn from their experience how their unobserved decisions affect post engagement) or time-invariant characteristics of the SMI (e.g., attractiveness). The second case might be extended to the subscribers of a SMI, as we assume that aggregate subscriber preferences (e.g., interest in watches) do not differ from post to post. To handle both concerns, we include the *number of product posts* as a count variable in our model that approximates how much knowledge the respective SMI has achieved regarding posts in a specific product category. For every SMI, this variable is initialized at 0 for the first post and increases by 1 unit for every additional product post in our sample. Additionally, we include *SMI fixed effects* to our model that capture SMI driven differences in engagement (Lee 2018; Lie & Xie 2019). We removed 273 SMI accounts that had a total of only one post in our sample. Accordingly, the final sample included 2,473 posts created by 399 SMIs.

We also include *brand fixed effects*, as brands might strategically influence the SMIs' decisions in the case of sponsored posts. Subscriber interest in brands might also differ over time, for example depending on a new product release. SMIs might adapt their behavior, either based on their own strategic considerations or instructed by the sponsoring brand, depending on how popular a specific brand is at the time of posting. Some SMIs might also choose to present a specific product in a post even if they are not paid for it just because it is trendy to talk about the product. To control for shocks based on time-variant brand popularity, we measure general consumer interest in the endorsed brand (*brand trend*) by taking the number of Google search queries in the month of the post. Google search data is freely available and is standardized between 0 and 100 for each brand.

Variable correlations and descriptive statistics are presented in Table 3.

relative attention paid to an image in a user's feed. Consequently, it is a factor that we need to control for on the post level.

## RESULTS

Post engagement and product engagement were both measured as nonnegative integer-valued count variables. As the normality assumption of an ordinary regression model was inadequate, a generalized linear regression model assuming a skewed distribution (e.g., Poisson or negative binomial distribution) is more appropriate. As social media count variables typically follow an overdispersed distribution (i.e., the variance is higher than the mean), we followed recent publications in the field (Hughes et al. 2019; Lie & Xie 2020) and assumed a negative binomial distribution for our dependent variables. We compute a likelihood ratio test for over-dispersion in count data with the null hypothesis that a Poisson distribution is sufficient (Cameron & Trivedi 1998). The hypothesis is rejected both in the post engagement ($X^2$ = 1,883,832, $p < .001$) and product engagement ($X^2$ = 3695, $p < .001$) models, favoring the negative binomial distribution. The coefficient estimates and model fit indices are depicted in Table 4. We first fit the model using only the SMI and brand fixed effects as explanatory variables and then fit the full model with all the explanatory variables previously discussed. Using a likelihood ratio test of nested models, we find that adding our predictors increases the model fit significantly both for post engagement ($X^2$ = 279, $p < .001$) and product engagement ($X^2$ = 37, $p < .001$).

**Table 3.** Variable correlations and descriptive statistics for final watch sample (n = 2,473)

| No. | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | *Post Engagement* | | .03 | -.09 | -.06 | .01 | .16 | .04 | .29 | -.09 | .09 | -.11 | -.10 | .02 | -.03 | -.02 | .00 | .01 | -.14 | -.11 | -.01 | -.01 | -.03 | -.02 |
| 2 | *Product Engagement* | .03 | | .10 | .06 | .15 | -.08 | -.08 | .04 | .10 | .04 | -.08 | .06 | .20 | -.03 | -.02 | -.04 | .01 | .02 | .03 | .06 | -.10 | .03 | .01 |
| 3 | *Product Size* | -.09 | .10 | | .08 | .25 | -.30 | -.14 | -.08 | .05 | .02 | -.08 | .19 | .00 | .02 | .04 | -.01 | .06 | .05 | .06 | .07 | -.10 | .04 | .00 |
| 4 | *Product Centrality* | -.06 | .06 | .08 | | .10 | .17 | -.04 | .04 | -.02 | .11 | -.03 | -.09 | .02 | -.15 | -.08 | .01 | .00 | -.12 | -.10 | -.02 | .07 | .02 | .02 |
| 5 | *Product Saliency* | .01 | .15 | .25 | .10 | | -.16 | -.10 | .03 | .10 | .11 | -.22 | .12 | -.02 | .01 | -.02 | -.02 | .04 | -.04 | -.06 | .05 | -.19 | -.01 | .08 |
| 6 | *Face* | .16 | -.08 | -.30 | .17 | -.16 | | .09 | .19 | -.01 | .08 | -.14 | -.10 | .00 | -.06 | -.06 | -.01 | .04 | -.12 | -.15 | .00 | -.09 | .01 | .00 |
| 7 | *Clutter* | .04 | -.08 | -.14 | -.04 | -.10 | .09 | | .03 | .00 | .03 | -.17 | -.07 | -.03 | .17 | .29 | -.01 | -.02 | -.03 | -.11 | .00 | -.04 | .00 | -.04 |
| 8 | *Standardized Disclosure* | .29 | .04 | -.08 | .04 | .03 | .19 | .03 | | .01 | .04 | -.12 | -.11 | .00 | -.03 | -.06 | .00 | .01 | -.15 | -.07 | .04 | .06 | -.01 | .04 |
| 9 | *Textual Disclosure* | -.09 | .10 | .05 | -.02 | .10 | -.01 | .00 | .01 | | -.02 | -.23 | .29 | -.02 | .05 | .04 | -.03 | .08 | .05 | .07 | .15 | -.22 | -.04 | .10 |
| 10 | *Prominence of Brand Mention* | .09 | .04 | .02 | .11 | .11 | .08 | .03 | .04 | -.02 | | -.29 | -.04 | -.08 | .00 | -.04 | .00 | -.02 | -.16 | -.46 | -.19 | -.12 | .02 | -.01 |
| 11 | *Number of Mentions* | -.11 | -.08 | -.08 | -.03 | -.22 | -.14 | -.17 | -.12 | -.23 | -.29 | | -.16 | .22 | -.15 | -.07 | .05 | -.09 | .20 | .45 | -.01 | .45 | -.03 | -.03 |
| 12 | *Coupon Incentive* | -.10 | .06 | .19 | -.09 | .12 | -.10 | -.07 | -.11 | .29 | -.04 | -.16 | | -.03 | .12 | .07 | .00 | .13 | .13 | .18 | .23 | -.29 | .01 | .17 |
| 13 | *Giveaway Incentive* | .02 | .20 | .00 | .02 | -.02 | .00 | -.03 | .00 | -.02 | -.08 | .22 | -.03 | | -.05 | -.02 | .02 | -.04 | .05 | .22 | .12 | .10 | .01 | .00 |
| 14 | *Colorfullness* | -.03 | -.03 | .02 | -.15 | .01 | -.06 | .17 | -.03 | .05 | .00 | -.15 | .12 | -.05 | | .21 | .00 | .05 | .07 | .02 | .09 | -.16 | .02 | .08 |
| 15 | *Brightness* | -.02 | -.02 | .04 | -.08 | -.02 | -.06 | .29 | -.06 | .04 | -.04 | -.07 | .07 | -.02 | .21 | | -.01 | .04 | .03 | .00 | .07 | -.18 | .00 | -.08 |
| 16 | *Weekend* | .00 | -.04 | -.01 | .01 | -.02 | -.01 | -.01 | .00 | -.03 | .00 | .05 | .00 | .02 | .00 | -.01 | | .00 | .01 | .02 | .01 | .04 | .00 | -.02 |
| 17 | *Recency* | .01 | .01 | .06 | .00 | .04 | .04 | -.02 | .01 | .08 | -.02 | -.09 | .13 | -.04 | .05 | .04 | .00 | | .01 | .00 | .03 | -.12 | -.06 | -.02 |
| 18 | *Number of Hashtags* | -.14 | .02 | .05 | -.12 | -.04 | -.12 | -.03 | -.15 | .05 | -.16 | .20 | .13 | .05 | .07 | .03 | .01 | .01 | | .60 | .16 | -.03 | .02 | -.01 |
| 19 | *Text length* | -.11 | .03 | .06 | -.10 | -.06 | -.15 | -.11 | -.07 | .07 | -.46 | .45 | .18 | .22 | .02 | .00 | .02 | .00 | .60 | | .38 | .14 | .00 | .06 |
| 20 | *Text Sentiment* | -.01 | .06 | .07 | -.02 | .05 | .00 | .00 | .04 | .15 | -.19 | -.01 | .23 | .12 | .09 | .07 | .01 | .03 | .16 | .38 | | -.06 | .04 | .08 |
| 21 | *Prior Product Posts* | -.01 | -.10 | -.10 | .07 | -.19 | -.09 | -.04 | .06 | -.22 | -.12 | .45 | -.29 | .10 | -.16 | -.18 | .04 | -.12 | -.03 | .14 | -.06 | | -.03 | -.02 |
| 22 | *Abnormal prior Engagement* | -.03 | .03 | .04 | .02 | -.01 | .01 | .00 | -.01 | -.04 | .02 | -.03 | .01 | .01 | .02 | .00 | .00 | -.06 | .02 | .00 | .04 | -.03 | | -.05 |
| 23 | *Brand Trend* | -.02 | .01 | .00 | .02 | .08 | .00 | -.04 | .04 | .10 | -.01 | -.03 | .17 | .00 | .08 | -.08 | -.02 | -.02 | -.01 | .06 | .08 | -.02 | -.05 | |
| | Descriptive Statistics | | | | | | | | | | | | | | | | | | | | | | | |
| | Type[a] | C | C | N | N | N | B | N | B | B | B | C | B | B | N | N | B | C | C | C | N | C | N | C |
| | Mean | 11k | 5 | 0.03 | 0.77 | 0.75 | 0.43 | 3.64 | 0.12 | 0.46 | 0.52 | 2 | 0.54 | 0.03 | 37 | 153 | 0.22 | 2k | 6 | 361 | 0.65 | 10 | 0.32 | 51 |
| | Median | 2.3k | 1 | 0.01 | 0.78 | 0.78 | 0 | 3.66 | 0 | 0 | 1 | 1 | 1 | 0 | 35 | 155 | 0 | 1.4k | 3 | 284 | 0.8 | 4 | 0.31 | 46 |
| | Minimum | 36 | 0 | 0.00 | 0.40 | 0.11 | 0 | 1.63 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 28 | 0 | 1 | 0 | 43 | -0.86 | 1 | 0.00 | 18 |
| | Maximum | 460k | 265 | 0.81 | 1.00 | 1.00 | 1 | 4.88 | 1 | 1 | 1 | 30 | 1 | 1 | 119 | 245 | 1 | 51k | 35 | 1987 | 1.00 | 123 | 1.02 | 100 |

Notes: a) C = Count, B = Binary, N = Numeric;

The coefficient estimates show that some of the drivers of greater post engagement reduce product engagement and vice versa. Specifically, subscribers are more prone to like posts when the product is smaller ($b = -.05$, $p < .001$), less central ($b = -.01$, $p < .10$), and less salient ($b = -.01$, $p < .10$), a face is visible ($b = .14$, $p < .001$) and when the image is more cluttered ($b = .03$, $p < .01$). In contrast, product engagement exhibits an opposite pattern and is driven by high product size ($b = .15$, $p < .001$), centrality ($b = .06$, $p < .05$), and saliency ($b = .25$, $p < .001$). Further, both a face ($b = -.34$, $p < .001$) and visual clutter ($b = -.20$, $p < .001$) reduce product engagement as they might distract from the product. Overall, these results are consistent with hypothesis $H_1$-$H_{10}$.

In terms sponsorship disclosure (H11), we find that a standardized disclosure is associated with both post engagement ($b = .13$, $p < .001$) and product engagement ($b = .77$, $p < .001$). Textual disclosure, however, is neither significantly associated with post nor with product engagement.

Not only post features that evoke bottom up processes have an effect on engagement. The results show that post captions can help increase product engagement when the number of mentioned brands is low ($b = -.18$, $p < .01$) and when the focal brand is mentioned at the beginning of the post ($b = .15$, $p < .05$). However, both mechanisms affect post engagement in the opposite direction (number of mentions: $b = .04$, $p < .01$; position of brand mention: $b = -.05$, $p < .01$). These results are consistent with hypotheses $H_{13}$-$H_{16}$.

**Table 4.** Regression results for watch post sample

| | Post Engagement | | | | Product Engagement | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Est. | SE | p | Hyp. | Est. | SE | p | Hyp. |
| *(Intercept)* | **5.47*****| .16 | .00 | | **-2.67**** | .92 | .00 | |
| **Bottom-up** | | | | | | | | |
| *Product Size* | **-.05*****| .01 | .00 | **$H_1$: -** | **.15*****| .03 | .00 | **$H_2$: +** |
| *Product Centrality* | **-.01†** | .01 | .08 | **$H_3$: -** | **.06*** | .03 | .05 | **$H_4$: +** |
| *Product Saliency* | **-.01†** | .01 | .09 | **$H_5$: -** | **.25*****| .03 | .00 | **$H_6$: +** |
| *Face* | **.14*****| .02 | .00 | **$H_7$: +** | **-.34***** | .07 | .00 | **$H_8$: -** |
| *Visual clutter* | **.03**** | .01 | .00 | **$H_9$: +** | **-.20***** | .03 | .00 | **$H_{10}$: -** |
| **Top-down** | | | | | | | | |
| *Standardized Disclosure* | **.13*****| .03 | .00 | **$H_{11}$: +** | **.77***** | .11 | .00 | **$H_{12}$: +** |
| *Textual Disclosure* | .01 | .02 | .79 | $H_{11}$: + | .11 | .07 | .13 | $H_{12}$: + |
| *Prominence of Brand Mention* | **-.05**** | .02 | .01 | **$H_{13}$: -** | **.15*** | .06 | .02 | **$H_{14}$: +** |
| *Number of Mentions* | **.04**** | .01 | .00 | **$H_{15}$: +** | **-.18**** | .06 | .00 | **$H_{16}$: -** |
| **Control variables** | | | | | | | | |
| *Coupon Incentive* | -.02 | .02 | .29 | | .10 | .08 | .23 | |
| *Giveaway Incentive* | **.18***** | .05 | .00 | | **1.16***** | .16 | .00 | |
| *Colorfullness* | .00 | .01 | .59 | | -.01 | .03 | .81 | |
| *Brightness* | .00 | .01 | .84 | | .05 | .03 | .12 | |
| *Weekend* | .00 | .02 | .85 | | .02 | .06 | .73 | |
| *Recency* | **.02*** | .01 | .04 | | .02 | .03 | .45 | |
| *Number of Hashtags* | .00 | .01 | .90 | | -.03 | .06 | .62 | |
| *Text length* | -.02 | .02 | .27 | | .03 | .05 | .61 | |
| *Text Sentiment* | .00 | .01 | .84 | | .02 | .03 | .54 | |
| *Prior Product Posts* | **.07***** | .01 | .00 | | **-.20***** | .05 | .00 | |
| *Abnormal prior Engagement* | **.03***** | .01 | .00 | | .03 | .03 | .24 | |
| *Brand Trend* | **.02*** | .01 | .03 | | .00 | .03 | .91 | |
| *Post engagement* | | | | | **.17*** | .07 | .02 | |
| **Fixed effects** | | | | | | | | |
| *SMI* | Yes | | | | Yes | | | |
| *Brand* | Yes | | | | Yes | | | |
| **Fit** | | | | | | | | |
| Nagelkerke $R^2$ | .97 | | | | .62 | | | |
| LLH | -20634 | | | | -4656 | | | |
| LLH (Fixed effects only) | -20773 | | | | -4842 | | | |
| $Chi^2$ (vs. fixed effects only) | **279***** | | .00 | | **37***** | | .00 | |

Notes: Significant estimates (p < .10) are bold. † p < .10; * p < .05; ** p < .01; *** p < .001.

In terms of incentives, we find a positive significant effect on post engagement ($b = 18$, $p < .001$) and product engagement ($b = 1.16$, $p < .001$) for posts that include a giveaway, but no significant effect of coupons ($p > .23$).

In summary, we see that the SMI's decision of how to visually present the product within her posts has opposing effects on post and product engagement. Thus, SMIs can use visual features to enhance product engagement, but at the expense of creating less post engagement. The same applies to the way the brand is mentioned in the preview text. Interestingly, posts with standardized disclosure and giveaway incentive generate both more post and product engagement. Additionally, repeatedly endorsing products from the same category (i.e., number of prior product posts) has a positive effect on post engagement ($b = .07$, $p < .001$), but a negative effect on product engagement ($b = -.20$, $p < .001$). Lastly, while post engagement is a significant driver of product engagement ($b = .17$, $p < .05$), the effect size is relatively small and does not counterbalance the negative effects of the proposed top-down and bottom-up processes on product engagement. Additionally, most variables in the model have a stronger effect size on product than on post engagement. For example, adding a face to the image decreases product engagement directly with $b = -.34$ and indirectly (through post engagegment) by $b = .024$, which does not compensate the negative direct effect.

Accordingly, the empirical results clearly support the paper's key proposition that SMIs face a trade-off between optimizing post and product engagement.

## REPLICATION STUDY WITH SHOES

To assess whether the relationships found for watches extend to other product categories, we build a second sample with shoes, following the same procedure as outlined previously. Similar to watches, shoes are rather small products and the SMI has to choose how to present them regarding size, centrality, saliency, and other key variables identified in the previous model. The final sample includes 3599 posts by 460 different SMIs and 14 brand: Adidas Originals (n = 667), Aldo (n = 294), Allbirds (n = 20), Asics (n = 132), Converse (n = 548), Dr. Martens (n = 155), Hunter Boots (n = 108), Loubtin World (n = 475), Nike Football (n = 127), Puma (n = 376), Reebok Classics (n = 126), Skechers (n = 79), Toms (n = 110), and Vans (n = 382). Similar as before, we aim to estimate a model with SMI-fixed effects, and therefore removed SMIs with only one post from the sample. Further, our variable operationalization for the sample of watches was based on the idea that sponsored post for watches most often will show only a single watch, while shoes are often presented in pairs. If more than one watch appeared in the sample (4.6% of the observations) we used the watch object that was largest as the endorsed product. In the shoe sample, 16.2% of the observations in the original sample have more than two shoe objects. This finding is not surprising since shoes are bigger and more visible (e.g., they are not covered by a jacket) than watches. For example, an image of a group of people walking across the street might contain several shoes, while it is unlikely that the watches of all persons are visible. To identify the correct pair of shoes as the endorsed product, we remove images with more than two shoes from the sample and keep a final sample of 3599 posts. In case we find two shoe objects in an image, we calculated product size as the sum of the sizes of both object while we average the scores of centrality and saliency to calculate the respective measures.

Variable correlations and descriptive statistics are depicted in Table 5. The correlations and descriptive statistics show several differences across the two samples. First, we find very strong correlations (i.e., $r > .50$) between product size and centrality ($r = .69$), product centrality and saliency ($r = .52$), face and product centrality ($r = -.63$), and face and product size ($r = -.56$). In comparison, the strongest correlation among these factors in the watch sample was between face and product size ($r = -.30$). We argue that these differences are caused by the nature of how watches and shoes are presented by the SMIs. For example, one could imagine an image of a person with a relatively small watch in the center of the image. However, in the same image, it is very unlikely that the shoes of the person appear in the center of image, but rather at the bottom. Accordingly, a possible image composition with a small shoe object in the center of the image is simply unlikely to appear. We first estimated the model with the same set of predictors as in the watch sample but unsurprisingly find less strong effects for the highly correlated predictors (product size, product centrality, product saliency, face) as high correlation among explanatory variable can lead to a lack of statistical power. The full results can be seen in Web Appendix Table WA3. In the following analysis, we summarize these variables into a factor labeled as “Visual product focus”. Precisely, “Visual product focus” is the sum of the standardized values of product size, product centrality, and product saliency, minus the standardized value of face, since the face variable is expected to affect the dependent variables in an opposing direction. We further conduct an exploratory factor analysis, also including the clutter variable. These results are displayed in Web Appendix Table WA4 and show that two factors are sufficient ($X^2 = 12.13$, $p < .001$) where one factor can be interpreted as “Visual product focus” (product size, centrality, and saliency have a loading above .59, face has a loading of -.72) and the other as visual clutter with a loading of .98. For simplification, we report in the following the model with “Visual product focus” as defined above, but note that using the factor scores leads to the same qualitative results.

Second, posts in the shoe sample only rarely contain a disclosure statement compared to the watch sample. In the watch sample, we observed a standardized disclosure and a textual disclosure in 12.1% and 46.1% of all posts, respectively. In contrast, in the shoe sample only 2.6% of the posts have a standardized disclosure and 7.2% of the posts have a textual disclosure. The most obvious reason for this observation is that some SMIs post images of their shoes even if they are not rewarded by the brand and therefore have no sponsorship to disclose. To verify if these lower disclosure levels in the shoe category are due to differences in the set of influencers for each product category, we consider the sub-sample of SMIs in the shoe sample that are also included in the watch sample (112 SMIs, 1295 posts) and observe a standardized disclosure in the shoe category of 3.4% and textual disclosure in 7.8% of the posts, showing only a marginal difference with the full shoe sample. Accordingly, the differences in the two samples are not due to SMI selection but due to the product category itself. Similar differences can be observed regarding the frequency that coupons (54.2% vs. 2.8%) and giveaway incentives (2.7% vs. 1.2%) are used.

**Table 5.** Variable correlations and descriptive statistics for final shoe sample (n = 3,599)

| No. | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | *Post Engagement* | | .17 | -.02 | -.01 | .01 | .07 | -.04 | .12 | -.01 | .04 | -.02 | -.01 | -.01 | .04 | -.02 | -.01 | .01 | -.07 | -.02 | -.04 | .00 | .05 | .02 |
| 2 | *Product Engagement* | .17 | | .05 | .09 | .06 | -.03 | .00 | .04 | .06 | .06 | -.05 | .01 | .03 | -.02 | -.01 | -.02 | -.01 | -.07 | -.04 | -.03 | .04 | .02 | .03 |
| 3 | *Product Size* | -.02 | .05 | | .68 | .45 | -.56 | -.22 | -.07 | -.11 | .33 | -.02 | -.07 | -.01 | .07 | .02 | -.02 | -.12 | -.13 | -.15 | -.13 | .11 | .01 | .04 |
| 4 | *Product Centrality* | -.01 | .09 | .68 | | .52 | -.63 | -.31 | -.04 | -.08 | .34 | -.08 | -.08 | .00 | -.02 | .08 | -.01 | -.15 | -.17 | -.17 | -.16 | .24 | -.01 | .03 |
| 5 | *Product Saliency* | .01 | .06 | .45 | .52 | | -.46 | -.14 | -.01 | -.04 | .24 | -.05 | -.02 | .01 | .00 | .06 | .01 | -.10 | -.13 | -.11 | -.12 | .15 | .00 | .07 |
| 6 | *Face* | .07 | -.03 | -.56 | -.63 | -.46 | | .23 | .12 | .15 | -.22 | -.05 | .06 | -.01 | .01 | -.02 | -.03 | .14 | .09 | .10 | .15 | -.21 | .01 | -.06 |
| 7 | *Clutter* | -.04 | .00 | -.22 | -.31 | -.14 | .23 | | .02 | .10 | -.17 | .03 | .07 | -.01 | .11 | .06 | -.01 | .07 | .11 | .09 | .09 | -.16 | .00 | -.07 |
| 8 | *Standardized Disclosure* | .12 | .04 | -.07 | -.04 | -.01 | .12 | .02 | | .18 | -.02 | -.05 | -.03 | .00 | .00 | -.04 | .00 | .04 | -.05 | -.01 | .05 | -.03 | .00 | .05 |
| 9 | *Textual Disclosure* | -.01 | .06 | -.11 | -.08 | -.04 | .15 | .10 | .18 | | -.08 | -.06 | .11 | .01 | -.01 | .02 | .01 | .06 | .12 | .14 | .16 | -.05 | .01 | .07 |
| 10 | *Prominence of Brand Mention* | .04 | .06 | .33 | .34 | .24 | -.22 | -.17 | -.02 | -.08 | | -.28 | -.10 | -.01 | .01 | -.01 | -.05 | -.10 | -.31 | -.45 | -.32 | -.03 | .02 | -.04 |
| 11 | *Number of Mentions* | -.02 | -.05 | -.02 | -.08 | -.05 | -.05 | .03 | -.05 | -.06 | -.28 | | .00 | -.01 | -.02 | .05 | .01 | -.07 | .47 | .60 | .24 | .19 | .00 | .09 |
| 12 | *Coupon Incentive* | -.01 | .01 | -.07 | -.08 | -.02 | .06 | .07 | -.03 | .11 | -.10 | .00 | | .00 | .01 | .04 | .02 | .03 | .10 | .13 | .11 | .09 | -.02 | .03 |
| 13 | *Giveaway Incentive* | -.01 | .03 | -.01 | .00 | .01 | -.01 | -.01 | .00 | .01 | -.01 | -.01 | .00 | | -.02 | -.05 | .00 | .00 | -.02 | .06 | .06 | .01 | .01 | .02 |
| 14 | *Colorfullness* | .04 | -.02 | .07 | -.02 | .00 | .01 | .11 | .00 | -.01 | .01 | -.02 | .01 | -.02 | | .09 | -.02 | .01 | .04 | .03 | .06 | -.12 | .02 | -.05 |
| 15 | *Brightness* | -.02 | -.01 | .02 | .08 | .06 | -.02 | .06 | -.04 | .02 | -.01 | .05 | .04 | -.05 | .09 | | -.04 | -.03 | .06 | .04 | .02 | .06 | -.04 | -.03 |
| 16 | *Weekend* | -.01 | -.02 | -.02 | -.01 | .01 | -.03 | -.01 | .00 | .01 | -.05 | .01 | .02 | .00 | -.02 | -.04 | | .02 | .04 | .03 | .04 | -.03 | .03 | .00 |
| 17 | *Recency* | .01 | -.01 | -.12 | -.15 | -.10 | .14 | .07 | .04 | .06 | -.10 | -.07 | .03 | .00 | .01 | -.03 | .02 | | .02 | .03 | .07 | -.08 | -.01 | -.01 |
| 18 | *Number of Hashtags* | -.07 | -.07 | -.13 | -.17 | -.13 | .09 | .11 | -.05 | .12 | -.31 | .47 | .10 | -.02 | .04 | .06 | .04 | .02 | | .65 | .36 | .00 | .02 | .07 |
| 19 | *Text length* | -.02 | -.04 | -.15 | -.17 | -.11 | .10 | .09 | -.01 | .14 | -.45 | .60 | .13 | .06 | .03 | .04 | .03 | .03 | .65 | | .50 | .09 | -.04 | .08 |
| 20 | *Text Sentiment* | -.04 | -.03 | -.13 | -.16 | -.12 | .15 | .09 | .05 | .16 | -.32 | .24 | .11 | .06 | .06 | .02 | .04 | .07 | .36 | .50 | | -.07 | .01 | .03 |
| 21 | *Prior Product Posts* | .00 | .04 | .11 | .24 | .15 | -.21 | -.16 | -.03 | -.05 | -.03 | .19 | .09 | .01 | -.12 | .06 | -.03 | -.08 | .00 | .09 | -.07 | | -.07 | .18 |
| 22 | *Abnormal prior Engagement* | .05 | .02 | .01 | -.01 | .00 | .01 | .00 | .00 | .01 | .02 | .00 | -.02 | .01 | .02 | -.04 | .03 | -.01 | .02 | -.04 | .01 | -.07 | | .00 |
| 23 | *Brand Trend* | .02 | .03 | .04 | .03 | .07 | -.06 | -.07 | .05 | .07 | -.04 | .09 | .03 | .02 | -.05 | -.03 | .00 | -.01 | .07 | .08 | .03 | .18 | .00 | |
| | Descriptive Statistics | | | | | | | | | | | | | | | | | | | | | | | |
| | Type[a] | C | C | N | N | N | B | N | B | B | B | C | B | B | N | N | B | C | C | C | N | C | N | C |
| | Mean | 14k | 2 | .15 | .68 | .75 | .51 | 3.54 | .03 | .07 | .48 | 5 | .03 | .01 | 34 | 153 | .24 | 1373 | 8 | 32 | .39 | 33 | .33 | 66 |
| | Median | 2k | 1 | .05 | .65 | .8 | 1 | 3.6 | 0 | 0 | 0 | 3 | 0 | 0 | 30 | 153 | 0 | 925 | 4 | 226 | .44 | 9 | .32 | 70 |
| | Minimum | 6 | 0 | .01 | .39 | .05 | 0 | 1.13 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 19 | 0 | 1 | 1 | 19 | -.93 | 1 | .08 | 8 |
| | Maximum | 1843k | 626 | 1.38 | 1.00 | 1.00 | 1 | 5.23 | 1 | 1 | 1 | 99 | 1 | 1 | 153 | 248 | 1 | 41k | 33 | 2k | 1.00 | 264 | 1.11 | 100 |

Notes: a) C = Count, B = Binary, N = Numeric;

The results of the negative binomial regression model for the shoe sample are depicted in Table 6. The estimated effects are similar to those in the watch sample. Posts with a prominent visual product focus (high product size, centrality, saliency, not showing a face) get lower post engagement ($b = -.05$, $p < .001$) and stronger product engagement ($b = .42$, $p < .001$), which is in line with $H_1$-$H_8$. Images with higher clutter again receive more post engagement ($b = .05$, $p < .001$). However, the negative effect of clutter on product engagement could not be replicated in the shoe samples ($b = .03$, $p = .31$). Therefore, we confirm $H_9$ and only partially confirm $H_{10}$. Similar to the watch sample, post with a higher number of mentions get more post ($b = .10$, $p < .05$) and less product engagement ($b = -.32$, $p < .01$), while positioning the brand cue at the beginning of the caption decreases post ($b = -.09$, $p < .01$) but increases product engagement ($b = .22$, $p < .001$). Additionally, similar to watches, shoe endorsements that have a standardized disclosure simultaneously get more post ($b = .18$, $p < .05$) and product engagement ($b = .44$, $p < .001$).

**Table 6.** Regression results for shoe post sample

| | Post Engagement | | | | Product Engagement | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Est. | SE | p | Hyp. | Est. | SE | p | Hyp. |
| *(Intercept)* | **3.97***** | .19 | .00 | | **-5.03***** | .51 | .00 | |
| **Bottom-up** | | | | | | | | |
| *Visual product focus* | **-.05***** | .01 | .00 | **$H_{1,3,5,7}$: -** | **.42***** | .03 | .00 | **$H_{2,4,6,8}$: +** |
| *Visual clutter* | **.05***** | .01 | .00 | **$H_9$: +** | .03 | .03 | .31 | $H_{10}$: - |
| **Top-down** | | | | | | | | |
| *Standardized Disclosure* | **.18*** | .08 | .02 | **$H_{11}$: +** | **.44**** | .14 | .00 | **$H_{12}$: +** |
| *Textual Disclosure* | **.25***** | .05 | .00 | **$H_{11}$: +** | .01 | .10 | .93 | $H_{12}$: + |
| *Position of Brand Mention* | **-.09**** | .03 | .00 | **$H_{13}$: -** | **.22***** | .06 | .00 | **$H_{13}$: +** |
| *Number of Mentions* | **.10*** | .04 | .02 | **$H_{15}$: +** | **-.32**** | .10 | .00 | **$H_{15}$: -** |
| **Control variables** | | | | | | | | |
| *Coupon Incentive* | .03 | .07 | .70 | | .05 | .13 | .69 | |
| *Giveaway Incentive* | -.16 | .10 | .11 | | **.37†** | .19 | .05 | |
| *Colorfullness* | -.02 | .01 | .18 | | **-.06*** | .03 | .02 | |
| *Brightness* | **.03**** | .01 | .01 | | -.02 | .02 | .36 | |
| *Weekend* | .02 | .02 | .33 | | **-.15**** | .06 | .01 | |
| *Recency* | **.06***** | .01 | .00 | | -.02 | .02 | .34 | |
| *Number of Hashtags* | **-.08***** | .02 | .00 | | **-.09*** | .04 | .04 | |
| *Text length* | **.15***** | .02 | .00 | | .03 | .05 | .53 | |
| *Text Sentiment* | .01 | .01 | .58 | | .03 | .03 | .38 | |
| *Prior Product Posts* | **.39***** | .02 | .00 | | **-.11**** | .04 | .00 | |
| *Abnormal prior Engagement* | .01 | .01 | .30 | | -.01 | .03 | .71 | |
| *Product Category Trend* | .02 | .02 | .18 | | -.01 | .04 | .87 | |
| *Post engagement* | | | | | **.87***** | .04 | .00 | |
| **Fixed effects** | | | | | | | | |
| *SMI* | Yes | | | | Yes | | | |
| *Brand* | Yes | | | | Yes | | | |
| **Fit** | | | | | | | | |
| Nagelkerke $R^2$ | .94 | | | | .61 | | | |
| LLH | -30477 | | | | -5064 | | | |
| LLH (Fixed effects only) | -30965 | | | | -5441 | | | |
| $Chi^2$ (vs. fixed effects only) | **976***** | | .00 | | **754***** | | .00 | |

Notes: Significant estimates (p < .10) are bold. † p < .10; * p < .05; ** p < .01; *** p < .001.

Compared to the watch sample, the positive effect of textual disclosure on post engagement is much stronger in the shoe sample (b = .25, p < .001), which might be explained by the lower frequency of textual disclosure in the shoe sample. In summary, these findings again support $H_{11}$-$H_{15}$. We also find a marginal significant effect for giveaway incentive on product engagement ($b = .37, p < .10$). Interestingly, we find the same positive effect of prior product posts on post engagement ($b = .39, p < .001$) and negative effect on product engagement ($b = -.11, p < .001$).

## GENERAL DISCUSSION

Using SMI campaigns, companies aim to create valuable engagement for their products and brands. It is common marketing practice to track how many subscribers like, share and comment on SMI posts and this way to quantify how much post engagement is created. The post engagement measure, however, does not reflect awareness and consideration of endorsed products in sponsored post and, thus, is rather a weak indicator of valuable product engagement. In this paper, we argue that instead of just tracking post engagement, companies should also measure product engagement, as this measure reflects whether the product receives attention and whether product awareness is created. In essence, this claim is in line with Akpinar and Berger (2017) who warned that focusing on generating "virality" (i.e. post engagement) is not a suitable strategy to enhance brand evaluation (i.e. product engagement).

Our paper thus investigates bottom-up and top-down processes that have opposing effects on post and product engagement in sponsored SMI posts. We propose using a well-established framework from vision research to examine visual social media content. We introduce this framework and explain how bottom-up and top-down processes of visual attention influence post and product engagement. The resulting model was then validated using two large sets of sponsored SMI posts. We offer novel theoretical contributions and managerial implications that are outlined next.

### *Theoretical Contributions*

First, our research contributes to the literature by pointing out that distinguishing post and product engagement effects is important. While post engagement is primarily intended to build the SMI's social capital and establish close relationships with subscribers, product engagement allows brands to understand interactions with sponsored content. Our empirical results show that bottom-up and top-down processes affect post and product engagement differently. Bottom-up processes, which direct attention to the sponsored product, potentially decrease post engagement but can increase product engagement. From an SMI's perspective, post and product engagement goals conflict. The empirical results suggest that this conflict can be partly resolved by changing the visual features (centrality and saliency), which increase product engagement but do not as strongly decrease post engagement.

Second, to the best of our knowledge we are the first to systematically investigate five bottom-up factors of attention that influence post and product engagement. Given that the literature so far has largely focused on examining textual post elements, we broaden this focus on visual content using insights from vision research. The empirical results show that size, centrality, saliency, visual clutter, and face presence substantially influence post and product engagement processes. We further showed that certain top-down processes triggered, for example, by visible cues of sponsorship disclosure, can simultaneously increase post and product engagement.

### *Managerial Implications*

Our study has important implications for the interaction between social media managers and SMIs. A key point of friction in this relationship concerns creative control: While marketers want to control the visual presentation of their products to generate product engagement, SMIs strive for authentic content that engages their subscribers (Takumi, 2019). Our findings reveal that these goals may conflict, as several bottom-up processes (product size, less clutter, and no face presence) and top-down processes (prominence of brand mention and number of brand mentions) that direct attention to the product increased product engagement but decreased post engagement.Table 7 illustrates our findings regarding two predictors that have a significant effect on product engagement, but not a strong impact on post engagement: Product saliency and product centrality. Increasing product saliency and centrality is expected to boost product engagement while not severely hurting post engagement. As can be seen in image A, other objects that are highly salient can reduce the saliency of the focal product as they compete for attention. In comparison, image B has a high value of saliency, while it is similar in all other dimensions. Comparing estimated engagement between A and B, image B is predicted to achieve a 81% greater level of product engagement, while post engagement is only slightly lower than that of image B (-3%). Following these results, SMIs should consider not adding very salient objects to the images, like a dish with a food item that stands out in color as depicted in image A. Following the same argumentation on comparing images C and D, we see how placing a product in a more central spot can increase product engagement by 29%, while only reducing post engagement by 5% (even with a lower product size in image D compared to C, note that the difference in product size between the two images is less than 0.5 standard deviation).

**Table 7.** Effect of saliency and centrality on engagement

| Image | A | B | C | D |
|---|---|---|---|---|
| |  |  |  |  |
| Description | Low saliency | High saliency | Low centrality | High centrality |
| Product size[a] | 0.22 | 0.18 | 1.32 | 0.65 |
| Product centrality | 0.96 | 0.96 | 0.40 | 0.86 |
| Product saliency | 0.19 | 0.80 | 0.64 | 0.60 |
| Visual clutter | 3.62 | 3.72 | 4.41 | 4.29 |
| Face | Yes | Yes | No | No |
| Post engagement[b] | 2403 | 2327 (-3%)[d] | 2244 | 2131 (-5%) |
| Product engagement[c] | 11 | 20 (+81%) | 14 | 18 (+29%) |

Notes: a) Percentage share of watch size compared to whole image; b) Number of likes and comments; c) Number of product related comments; d) Percentage change compared to left image. All variables not listed are set at their respective medians.

Additionally, we investigated several top-down processes that could further help SMIs to increase product engagement without reducing post engagement. One robust finding of our analysis is the positive effect of standardized sponsorship cues on engagement. While the investigated disclosure cues (standardized disclosure and textual disclosure) are partially specific to Instagram, our findings suggest that the higher the visibility of the cue the more engagement toward the post and the product can be expected. An explanation for the former might be that subscribers evaluate a persuasion attempt as fairer and less manipulative if the post includes a disclosure (Akpinar & Berger, 2017).

***Limitations and Further Research Directions***

*Investigating the relationship between engagement and return on investment.* In this study, we focus on post and product engagement as the depended variables. A few papers investigated the relationship between post and product engagement and the return on investment (ROI) outside the influencer marketing context. Kumar et al. (2013), for example, showed that both social media and customer word-of mouth increase ROI. Moreover, Pansari and Kumar (2017) found that incentivized referrals, social media conversations about products and brands, as well as feedback provided by customers are positively related to a firm's revenue. Based on these earlier findings, we argue that increasing product engagement should be more effective than increasing post engagement in enhancing ROI. However, given that that data to test this hypothesis is not publicly available, we have to leave this test to future research.

*Measuring attention via eye-tracking.* Our research framework is unique in that it tests several effects of bottom-up and top-down attentional processes on engagement. As the literature provides strong empirical evidence that the respective bottom-up and top-down processes increase relative attention to a target object (i.e., the sponsored product), we did not rely on measuring attention directly via eye-tracking. Measuring eye movements requires conducting empirical studies in a lab, which would preclude an investigation of post and product engagement in a real-world social media context. Thus, our framework constitutes a bridge between vision research and research that examines engagement effects with social media data without measuring attention directly. However, conducting additional empirical eye-tracking studies in a lab could lead to further interesting insights. For example, the saliency of sponsored products and distractors, such as faces, could be manipulated to test how these factors change users' attitudes toward posts and their behavioral intentions. Other bottom-up factors, such as centrality or visual clutter, could be manipulated analogously. We are not aware of lab studies that have manipulated bottom-up processes of attention and tested their respective effects in the context of social media posts, leaving room for future comprehensive empirical work. Moreover, eye movement data might be readily available in the years to come once built-in eye-tracking technology is standard in devices such as smartphones and desktop computers (Van der Lans & Wedel, 2017). As soon as eye movement data are available on a broad scale, users' social media behavior can be monitored more closely. This would enhance our ability to understand and predict in even more detail which attentional patterns increase post and product engagement or impact related behavioral variables, such as SMI loyalty.

*Investigating parasocial relationships between SMIs and their subscribers.* In this article, we use a sample of field observations to study the proposed hypotheses on a post-aggregate level. However, it is likely that subscribers are heterogeneous and react differently toward product endorsements. In particular, digital marketing strategies that use SMIs to advertise products and brands seem to be successful because they harness the social capital of SMIs, which comprises close (parasocial) relationships with their subscribers. Several papers have emphasized that SMIs who create intimate, frequent, and highly confessional social media posts that are rich in personal detail are more successful in building close relationships with their subscribers (e.g., Chung & Cho, 2017). An interesting topic for future research, therefore, is how the engagement process changes in close parasocial relationships. The creators of the persuasion knowledge model, Friestad and Wright (1994), have suggested that allocation of attention to advertisements (i.e., sponsored posts) could be an important defense mechanism to persuasion attempts (tactics). They have stated that adults learn to "cope with a tactic by withdrawing their attention from the part of a message that contains it but refocusing attention when they choose to" (p. 12). However, such defense mechanisms might be less effective once a close relationship with an SMI is established. Not only could research investigate whether withdrawing attention is a coping tactic used frequently in social media contexts, but also whether the effectiveness of this mechanism depends on the closeness of the relationship.

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# Essay C1: The Price of Popularity: Why Consumers Share More Negative Electronic Word of Mouth for Big Brands

# The Price of Popularity: Why Consumers Share More Negative Electronic Word of Mouth for Big Brands


## Abstract

Increasing market share and awareness is among the cornerstones of each business strategy. In this article, however, the authors show that becoming popular may come at the price of receiving more negative electronic word of mouth (eWOM) on social media and online review platforms. In a field study on 133 chain restaurant brands, controlling for representative consumer brand ratings using panel data, we reveal more negative valence in brand-related social media posts and lower star ratings on online review platforms for big (vs. small) brands. Subsequent experiments reveal that consumers are more likely to share a positive experience they had with a small (vs. big) brand. Furthermore, small brand size improves the valence of intended eWOM articulations. Two mediators can explain this relationship. First, small (vs. big) brands evoke a stronger need to help those same brands, which leads to more positive eWOM valence. Second, consumers perceive sharing eWOM about small (vs. big) brands as more directly communicating with these brands, which hinders consumers from sharing eWOM with negative valence. The article concludes with a discussion of theoretical contributions and managerial implications of how big brands can counteract the negative effects of popularity.



Keywords: online reviews, social media, brand size, brand management, consumer behavior


## Statement of Intended Contribution

In this article, we address whether and why big brands receive more negative electronic word-of-mouth (eWOM) ratings than small ones. Conducting a field study with more than hundred brands, we discovered that the average valence of brand related tweets and the average star ratings on Yelp are more unfavorable for big (vs. small) brands. To examine the causal relationship between brand size and eWOM ratings, we perform two experiments and test two mediators that potentially explain why big (vs. small) brands receive more negative eWOM ratings.

Through our findings, we complement academic marketing research on eWOM. We examine the influence of a brand characteristic previously neglected in this context (brand size) and show how it affects customers' decisions regarding the intention to share eWOM and the valence of their eWOM articulations. We study these mechanisms for eWOM ratings on both social media and online review platforms. We add to existing knowledge on eWOM motivations by showing that high "perceived need for help" for a brand leads to more positive eWOM related to this brand and that this motive is elicited by small brands. Additionally, we extend recent findings of Hydock et al. (2020) by showing that big brands trigger perceptions of not sharing eWOM directly with them. As a result, consumers are more likely to share negative eWOM about big (vs. small) brands.

Our findings can provide valuable implications for managers of "big brands" that face more negative eWOM ratings than their smaller competitors. Big brands ought to be mindful that more negative eWOM ratings do not always reflect dissatisfied customers, but can instead be driven by brand size. Furthermore, big brands can build on the mediators studied to mitigate the negative effect of brand size, for example, by communicating required help in form of positive eWOM articulations.

**Introduction**

In the last decades, marketing scholars and practitioners have been keen on understanding what motivates consumers to use the internet (e.g., social media and review platforms) to articulate their opinions on products, services, and brands publicly. Academic literature refers to this as electronic word of mouth (eWOM). The importance of understanding when and why consumers voluntarily share eWOM is substantiated in a wealth of empirical research that finds a strong link between eWOM and sales (e.g., Chevalier and Mayzlin, 2006; Babić Rosario et al. 2016). In a recent consumer survey, 93% of participants said that online reviews affected their purchasing decisions (Fullerton 2017). Therefore, it is not surprising that brands have a particular interest to be portrayed favorably on the Internet—through, for example, positive customer reviews or favorable social media posts. Brands also utilize eWOM to infer consumers' attitudes toward their brand and products in terms of satisfaction (Tirunillai and Tellis 2014), needs (Timoshenko and Hauser 2019), preferences (Decker and Trusov 2010), and brand perception (Schweidel and Moe 2014; Rust et al. 2021).

The two aforementioned functions (i.e., positively affecting consumers and helping the company understand consumers) require that a brand thoroughly understands what motivates consumers to articulate negative and positive eWOM. Considering the first function mentioned, this knowledge can be used to make marketing decisions that motivate (prevent) consumers to share their positive (negative) experiences about the brand online. Related to the second function, companies can only infer the actual brand ratings from eWOM if they know when and why consumers share their opinion (Hydock et al. 2020). For example, changing a brand logo based on negative eWOM about the old logo could be a mistake if the observed eWOM does not adequately represent the customers of the brand.

In this research, we investigate if and why eWOM ratings differ for small and big brands. While one intuitively expects that big brands receive a higher volume of articulations, given their higher market share and awareness among consumers, do big brands receive more positive or more negative eWOM ratings[26] compared to their smaller competitors?

[26] In the following, we use the term "eWOM rating" when we refer to the aggregate valence of all online articulations regarding a brand.

While the relationship between specific brand characteristics and eWOM has received relatively little attention in the academic literature, a couple of studies in the last decade have shed light on how brand characteristics affect eWOM. For example, Lovett et al. (2014) studied the relationship between brand characteristics and eWOM volume. Among others, they showed that eWOM volume (i.e., the number of online articulations related to the brand) is higher for brands with high levels of “differentiation,” “esteem,” and “excitement”. Another study by Paharia et al. (2014) found that consumers with positive brand experiences were more likely to create eWOM for a small brand when they knew that the brand was competing with a big brand. We build on this study to investigate whether small brands, regardless of the saliency of a competitor, evoke more positive eWOM compared to bigger brands in the same industry.

Different predictions can be made regarding the size of a brand and its effect on eWOM ratings. For example, consumers are more likely to share content that makes them look good rather than bad (i.e., self-enhancement; Berger 2014). Taking brand size as a cue for a brand’s success, consumers might be more likely to share their positive experiences with a popular brand compared to a less known and less successful brand. On the other hand, given that consumers might perceive big brands as already successful, consumers with positive experiences might not feel the need to help these brands with positive articulations (i.e., emotion-regulation; Berger 2014).

To study the effect of brand size on eWOM ratings, we conducted a field study and two experiments. In Study 1, we compare a sample of 133 chain restaurant brands from the United States regarding their brand size (i.e., market share and brand awareness), brand rating (i.e., consumer ratings on brand impression, reputation, quality, and satisfaction), and their corresponding brand-related eWOM ratings across social media (gathered from Twitter.com) and online product reviews (gathered from Yelp.com). After controlling for several factors related to the product category and social media behavior of the respective brands, we consistently found a strong and significant negative effect of brand size on eWOM ratings. While, not surprisingly, brand rating positively predicts eWOM rating, the effect size of brand size is comparably strong, indicating the important role of brand size for eWOM ratings. To investigate the causal nature of this relationship, we conducted a 2 (brand size: big vs. small) × 2 (brand rating: negative vs. positive) scenario experiment (Study 2) with n = 113 participants with eWOM sharing intention as the dependent variable. The results show that consumers’ intention to share a positive (negative) brand experience is higher if the respective brand is small (big). In a third study (n = 303), we revealed that eWOM valence in the case of an articulated experience (e.g., the sentiment of a tweet or the star rating of a review) was more positive for small brands. We identified two mediators that explain the phenomenon. First, consumers support smaller brands, as they perceive them to be in a higher need for help. Second, consumers perceive sharing eWOM about small brands as more directly communicating with these brands. As consumers are less likely to share negative eWOM directly with a brand, small brands receive less negative eWOM (Hydock et al. 2020).

This research contributes to theory and practice. First, we empirically explore the relationship between brand size and eWOM ratings and consistently find that eWOM ratings are more negative for big brands. This result may help managers understand that a possible reason for a decline in eWOM ratings might be an increase in brand size rather than a decline in actual consumer brand perception. Second, we show that the perceived need for help of a brand (i.e., consumers' perception of the brand's need to be supported by them) and perceived directness when sharing eWOM about the brand (i.e., perception of eWOM authors on whether their articulations directly reach the brand in question) are important mediators of the effect of brand size on eWOM ratings. Brands can utilize both mediators strategically by, for example, communicating their need for help and directness in order to improve their eWOM ratings. Both contributions further extend academic research on understanding why brand rating in reality (i.e., measured by asking a random sample of consumers) and a brand's eWOM rating observed online (i.e., measured by aggregating all online articulations of consumers) differ strongly (Moe and Schweidel 2012; Schoenmueller 2020). Third, we build on the recent findings of Hydock et al. (2020) and show that the feeling of sharing "with" vs. "about" a brand might not depend only on the channel of communication (e.g., a customer survey vs. word of mouth) but also on brand characteristics that trigger the perception of more directly communicating with the brand in a social media or online review environment.

In the following, we summarize the theoretical background of this study. Since previous research efforts have in many cases focused on the volume of eWOM and often ignored the valence of the communication, we explain the importance of analyzing this factor in the next section. We then discuss related work, and derive a set of hypotheses for the expected relationships between brand size and eWOM. We subsequently describe our three studies and their results and discuss their implications for theory and practice, limitations, and suggestions for future research.

## Theoretical Background

### *How Electronic Word of Mouth Ratings Influence Consumer Behavior*

While in its origins, word of mouth (WOM) was used by humans to, for example, prevent others from eating toxic berries, the dynamic development of trade and marketing influences today's communication conditions. Research on WOM has shown that this form of direct personal communication is more effective than traditional marketing tools, such as personal selling, and even more effective than conventional advertising media (Katz and Lazarfeld 1955). WOM stimulates consumer spending and accounts for two-thirds of consumer product sales (Solomon 2015). Through the implementation of Web 2.0, WOM has become more topical than ever, and the arrival of the Internet age has led to the birth of electronic word of mouth (eWOM) communication. In their work from 2004, Hennig-Thurau et al. defined eWOM as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (p. 39). Information via eWOM comes at a minimal search cost to potential recipients (Bakos, 1997); moreover, this easily accessible information on products and services can greatly affect online consumption decisions (Cheung et al. 2008). Due to its high credibility and independence from marketers' interests (Choi et al. 2013), eWOM is considered highly influential (Kim et al.

2018). There are two key metrics to consider when examining eWOM communications: volume and valence. By eWOM volume, one designates the disseminated amount of eWOM. The idea that eWOM can be either positive, negative, or neutral is called valence (Liu 2006). Other words for valence are “favorability” or “sentiment.[27]”

While a positive association was shown between eWOM volume and product sales (Liu 2006; Keller 2007; Babić Rosario et al. 2016), there have been mixed results on the relation of eWOM valence and sales. When analyzing the effect of consumer reviews on the relative sales of books at two leading online booksellers, Chevalier and Mayzlin (2006) showed a link between book sales and eWOM valence and found that sales increase when a book’s online review rating improves. Additionally, Park and Lee (2009) demonstrated that the valence of product reviews affects consumers’ purchase behavior during the decision phase, with negative product reviews having a higher influence on consumers’ purchases than positive product reviews. Chintagunta et al. (2010) showed that the average rating of online reviews until movie release positively affects movies’ opening box office earnings. Studying four million microblogging WOM messages shared through Twitter, Hennig-Thurau et al. (2014) reported that eWOM influences the early adoption decisions of active Twitter users. They found an effect of negative eWOM on the early adoption of movies, with negative eWOM reducing the intention to see a new movie. In 2016, Kostyra et al. analyzed the effects of customer online reviews on consumers’ consumption choices. In contrast to previous findings, their results show that the volume and variance of online customer reviews do not directly influence customers’ decisions but moderate the influence of valence on their decisions. Babić Rosario et al. (2016) conducted a meta-analysis and confirmed the significant positive effect of eWOM valence on sales. The authors further concluded that researchers often mix up volume and valence—for example, by counting the number of positive online reviews as a measure of valence—and thus overestimate the role of valence. After carefully separating the two dimensions, they found that eWOM valence still matters and demonstrated that positive eWOM metrics have a greater effect on sales than negative eWOM metrics. In a series of seven studies, Watson et al. (2018) recently found that valence is more important than the volume of product ratings when consumers assess product quality. They showed that the number of reviews has a greater impact on clients’ consumption decisions when (1) the average product ratings are negative or neutral and (2) the level of review numbers is low. These results show that the two metrics interact in terms of their impact; therefore, it is not directly possible to make statements about whether one of the two metrics has a higher importance.

In addition to the described increase in sales, another consequence of positive eWOM is the ability to drive brand equity. Tirunillai and Tellis (2012) aggregated eWOM from multiple websites over a four-year period across 6 markets and 15 firms and found asymmetric impacts of eWOM valence on firm sales and stock trading outcomes. The erosion of value in returns due to negative eWOM was greater in absolute terms than the gain in value due to positive eWOM. Showing how eWOM valence can affect businesses, Hansen et al. (2018) analyzed the destructive potential of social media firestorms. Negative information about a brand can be the

[27] The term “sentiment” is mostly used in the domain of natural language processing where sentiment analysis refers to models that extract the valence of a textual articulation.

most impactful in terms of negative brand perception changes (Hansen et al. 2018). Considering the characteristics of online communication, it becomes clear that marketers and researchers should notice eWOM valence and that it could be of great value for brands to maintain positive eWOM and reduce the amount of negative eWOM.

### *Electronic Word of Mouth as a Portrayal of Consumers' Brand Ratings*

While one could assume that brands evoking positive (negative) brand ratings—by generating a satisfying customer experience, for example—will, in turn, be fairly and equally rewarded with positive (negative) eWOM, several articles in the marketing literature provide evidence that eWOM ratings are a "biased" portrayal of actual consumer attitude toward the brand in question. The main reason for this observation is that consumers self-select whether to articulate eWOM, whereas traditional surveys on brand ratings utilize a random sample of consumers. Accordingly, one would observe a biased portrayal of a brand when there is a relationship between brand rating and the self-selection process (e.g., consumers rating a brand positively are more likely to articulate eWOM for the respective brand than those rating a brand negatively). Berger (2014) argued that WOM is goal-driven and serves key functions (e.g., emotion regulation); thus, consumers' self-selection process can depend on an interplay of (i) the actual experience, (ii) personal attributes of the consumer, and (iii) characteristics of a product or brand. As examples regarding (i), several studies show that consumers with extreme (vs. neutral) experiences are more likely to provide eWOM (Moe and Schweidel 2012; Schoenmueller 2020). One reason could be that extreme experiences, in contrast to neutral ones, evoke a desire to regulate emotions by venting negative or reciprocating positive feelings (Hydock et al. 2020). The aforementioned study by Moe and Schweidel (2012) further shows that consumers' personal attributes (ii) can affect the self-selection process. For example, the researchers identified some contributors to online review platforms as "activists" that generally differentiate eWOM valence from the majority. A recent study by Olsen and Ahluwalia (2021) showed that consumers might even share favorable WOM about unsatisfactory purchases. Building on previous work, the authors were able to show that consumers view their own personal failures more positively through relative comparisons with others who fare similarly or worse. Accordingly, they spread positive WOM about unsatisfactory purchases to encourage others to make the same poor choices, as they seek to improve post-purchase feelings toward their own unsatisfactory outcomes. Additionally, De Angelis et al. (2012) revealed that consumers motivated by self-enhancement are more likely to share positive experiences to maintain a positive self-view. Regarding (iii), a study by Paharia et al. (2014) found that consumers with positive experiences are more likely to contribute eWOM for a brand when a larger dominant competitor is salient (i.e., when the existing competition is obviously recognizable to the consumer). The researchers attributed their findings to the fact that consumers classify the respective brand as an "underdog" that is more worth supporting and more likely for consumers to identify with. In the next chapter, we build on the study by Paharia et al. (2014), but instead of investigating eWOM motivation in the presence (vs. absence) of a larger competitor, we argue that brand size affects eWOM ratings in general and theoretically explain how brand size can affect the self-selection mechanism.

### *Brand Size and Electronic Word of Mouth Ratings*

An emphasis on business size has become more overt, and recent research has explored the underlying factors driving consumers' support for small (vs. big) companies (Yang and Aggarwal 2019). The perceived power disadvantages of small brands (compared to big brands) shape consumer attitudes regarding these brands (ibid.). Small brands are more dependent on building good relationships with their customers than big brands because they need to consolidate and grow their customer base (Ailawadi et al. 2010). Some studies distinguish small companies from bigger companies based on criteria such as financial turnover, assets, market share, number of employees, and ownership structure (Curran and Blackburn 2001). The size of a brand is frequently associated with the market share of that brand. For consumers, however, market share is difficult to observe directly, so they might infer the size of a brand from advertising awareness and other forms of exposure. Rather than a brands' true market position, it is consumers' perception of brand size that influences the mental classification of the concerned brand by the consumer (Paharia et al. 2014). While research on brand size is still scarce in the marketing literature, a couple of studies have demonstrated how the size of a brand affects consumer behavior. For example, Yang and Aggarwal (2019) investigated the effect of size on consumers' expectations of company behavior and found that consumers expect higher communion behavior from small (vs. big) companies. The authors demonstrated via five studies that the perceived size of a company influences consumer expectations and subsequent evaluations. The size of a brand could also be associated with popularity—gained, for example, by winning an award. Kovacs and Sharkey (2013) compared thousands of reader ratings of books that had won an award and found that popularity had a negative impact on reader ratings. In addition to the expectations that consumers develop in relation to the behavior of a brand, brand size also influences consumers' attitudes toward brands. For example, the disadvantaged position of small companies often draws consumer support (Paharia et al. 2011). Accordingly, we assume that:

**$H_1$:** eWOM ratings for big brands are more negative, on average.

*Perceived Need for Help.* One motivation for engaging in eWOM activities can be to help the company. As early as 1989, Sundaram et al. found that consumers share positive WOM to support companies. Customers can be motivated to engage in eWOM communication to give the company "something in return" for a good experience (Hennig-Thurau et al. 2004). The desire to help a brand may stem from general moral principles (Minestero et al. 2018). Wilhelm and Bekkers (2010) outlined the moral position that one should help those in need and revealed that people show helping behavior for those who really seem to need help. Feeling that it is important to help others who are in need (Minestero et al. 2018), consumers may intend to help smaller brands, which they perceive as having fewer resources.

Consumers attribute some characteristics to small brands, which they also attribute to brands that they classify as "underdogs." Small brands usually have a weaker market position and fewer resources than their bigger competitors do. Hoch and Deighton (1989) classified brands as "underdogs" and "top dogs" based on their market shares compared to other brands in their category. Additionally, some brands strategically position themselves as underdogs by using an "underdog brand biography" that highlights the brand's external disadvantage, passion, and determination, which can positively affect consumer loyalty (Paharia et al. 2011; Paharia et al.

2014). In 2013, Cambridge University Press defined an underdog[28] as “a person or a group of people with less power, money, and so forth than the rest of society” and “in competition, a person or a team considered to be the weakest and the least likely to win.” Applying this to a marketing context, one can say that a brand positioned as an underdog is a brand that emphasizes its fewer resources compared to other brands and underlines its weak market position (Avery et al. 2010). Delgado-Ballester (2020) cites as examples of characteristics of brands in underdog positions an involvement in unbalanced battles (big brands dominating smaller rivals or insurgent brands against incumbents). From a business perspective, the distinction between brands with underdog and brands with top-dog positioning is rooted in the hierarchical structure of the market and the power imbalance between competitors (Jin and Huang 2019). In a study from 2020, He et al. highlighted that consumers can relate to the inspiring stories of brands with underdog biographies. The fact that consumers can relate to the plight of such weaker brands may be one driving motive for consumers to support such perceived disadvantaged brands (McGinnis et al. 2009). Participants in a study by McGinnis et al. (2009) stated that the support of a less privileged brand would maintain balance and fairness by keeping bigger businesses and established brands at bay. Additionally, the authors talk about an “anti-elite fanaticism,” finding that the informants defied the paternalism of large corporate attempts at persuasion by supporting small brands. Since smaller brands usually have fewer resources than bigger brands, one can assume that consumers classify them as needing more help. Following the reasoning above, consumers should thus have a tendency to show higher support for small (vs. big) brands. This support can manifest in a higher likelihood of sharing a positive experience or a lower likelihood of sharing a negative experience. Furthermore, after a consumer decides to articulate via eWOM, the evaluation might be more positive if the consumer wants to support the brand. In terms of valence, both the decision of whether to share and the decision of what to share influence the eWOM rating observed by others on social media and online review platforms. In light of the relationships just presented, we developed the following hypotheses:

**$H_{2a}$:** Perceived need for help is higher for small (vs. big) brands.

**$H_{2b}$:** Perceived need for help has a positive effect on eWOM ratings.

*Perceived directness.* When consumers post something online about a brand, it is usually not clear in advance who exactly will read that post. Nevertheless, before one puts up a post, the author is likely to have a recipient in mind to whom she wants to address her post. When posting about a brand, writers may assume that either other consumers of the brand or an employee of the company will read their post. The way consumers express themselves about a brand may also depend on whom they see as the likely recipients of this expression. Rosen and Tesser (1970) described a tendency to avoid the communication of unpleasant information (the “MUM effect”). One explanation for this tendency is the anticipated discomfort from conveying bad news (Tesser and Rosen, 1975). Often people strive to make an unpleasant message more palatable to the recipient (Sussman and Sproull 1999). Reluctance to transmit bad news may come from a concern with the recipient (Folger and Skarlicki 2001). Therefore, sharing a

[28] The term “underdog” refers to someone who is inferior to another. We do not equate a small brand with brands with underdog biographies, but draw parallels between small brands and brands that emphasize such positioning.

negative experience directly with the brand in question can lead to negative emotions in consumers. In the present study, we examine perceptions of the directness of communication with a brand and consider a construct we call "perceived directness." A high level of perceived directness means that a consumer assumes that employees of the brand are likely to read their post. Hydock et al. (2020) showed that unhappy customers are unlikely to share their opinions directly "with" brands, while they are likely to share indirectly "about" brands. Consumers with positive (vs. neutral) attitudes are more likely to articulate these attitudes, but those with negative attitudes do not show a similar increase in sharing (Hydock et al. 2020). The authors explain this behavior by the fact that for consumers with positive (vs. neutral) attitudes toward a brand, reciprocity norms increase sharing, but for consumers with negative (vs. neutral) attitudes, reluctance to criticize others discourages them from sharing the experience. Since there is an aversion to sharing a negative experience directly with the brand in question, we assume that perceived directness reduces the chance that consumers will share negative eWOM about the brand. If a consumer feels that a negative utterance on his part will resonate directly with the people affected by that utterance, the aversion to criticizing them should prevent him from articulating his negative experience. Following this line of reasoning, it seems logical that consumers may shy away from directly criticizing brands online if they feel that the concerned brand will see their criticism directly, but at first glance, the correlations between the directness of communication and brand size are less clear. We question whether the perceived directness of communication may be a factor influencing consumers' intentions to share eWOM in the context of brand size.

Consumers interact with brands in ways similar to how they interact with people in social situations (Yang and Aggarwal 2019). As illustrated in the preceding discussion, consumers identify more readily with underdog (vs. top-dog) brands, and small brands share many of the characteristics of underdog brands. By identifying more intensively with a brand, consumers should also perceive the brand as "closer" to themselves. Since consumers see smaller brands as more accessible, the aversion to criticizing them directly should be stronger (than with big brands). Yang and Aggarwal (2019) proposed that consumers expect small companies to be more communal. Previous literature supports this conjecture and has found that low power is associated with communion (Galinsky et al. 2003). Small companies have to take a close look at customers' needs and build brand loyalty by creating warm and trust-based relationships (Malone and Fiske 2013), which is why they may have closer connections to their customers; thus, when communicating with the brand, consumers might perceive the communication as more direct (than when communicating with a big brand). Additionally, big brands already have a larger consumer base and more eWOM in circulation. This means that there are already many reviews of the big brands on review and social media platforms. Therefore, such brands can seem more distant to individual consumers, who may suspect that they will be lost in the mass of consumers of a popular brand. Furthermore, clients might assume that big brands have their own professional and centralized social media team that deals with brand-related eWOM, rather than employees or managers working at a local branch. Accordingly, they might suspect that eWOM articulations are handled in an automated fashion and do not receive direct attention from these bigger brands. Considering the outlined mechanisms that affect online consumer articulations, we arrive at the following hypotheses:

**$H_{3a}$:** Perceived directness is higher for small (vs. big) brands.

**$H_{3b}$:** Perceived directness has a positive effect on eWOM ratings.

We present the conceptual model of this study in Figure 1.

***Insert Figure 1 about here***

To test the conceptual model, we ran three studies. In the first study (Study 1), we used observed eWOM ratings from social media posts on Twitter and online reviews on Yelp. These ratings combine, per definition, the decision to share (sharing intention) and the decision on how positively or negatively to articulate (valence). To verify the causal nature of the findings resulting from Study 1, we conducted an online experiment (Study 2) where we stimulated brand size and brand rating and measured the effect on eWOM sharing intention. In Study 3, we investigated the effect of brand size on eWOM valence and tested two mediators (perceived need for help and perceived directness) to infer the possible underlying reasons that lead to the negative effect of brand size on eWOM ratings.

## Study 1: Field Study of Brand Size and eWOM Ratings

The aim of Study 1 was to investigate the relationship between brand size and eWOM rating in various real-world settings after controlling for brand rating (i.e., the aggregation of individual direct or indirect experiences with the brand). To investigate this relationship, we first built a list of suitable brands. We found restaurant chains to be a good fit for our research goals for two reasons: first, restaurant chains are well represented on review sites (e.g., users posting a restaurant recommendation on Yelp) and social media sites (e.g., people tweeting about a consumption experience); and second, as restaurant brands are primarily service providers, they are less likely to sell products that strongly differ according to their quality and resulting brand perception. While, for example, an electronic brand might receive higher variation in its eWOM ratings depending on the specific product the consumer purchased (e.g., Sony PlayStation and Sony earbuds), the content of restaurant reviews focuses more on the overall experience rather than on the specific product. Therefore, modeling the relation between restaurant chain brand ratings and restaurant experiences as depicted in eWOM is less biased by product-specific heterogeneity in individual brand ratings.

We took a sample of 133 restaurant-chain brands that were included in the YouGov brand panel[29] and had received more than 1,000 consumer-day observations in the respective time windows, as explained in the following (our final sample contained a mean of 10,746 consumer-day observations per brand, ranging from a minimum of 4,360 to a maximum of 14,509, depending on how many panelists were aware of the respective brand). For each of these brands, we collected a comprehensive set of Twitter posts as a social media sample for brand-related

[29] YouGov maintains a dedicated panel of respondents who have explicitly chosen to participate in online research activities. The YouGov U.S. panel includes 2 million respondents.

articulations. For the Twitter platform, we analyzed the data based on @-mention usage and hashtag (#) usage. Launched in 2006, Twitter is a real-time Internet service used to share text messages (tweets) limited to 140 characters in a personalized, public-message stream (Jürgens and Jungherr 2011). Users of Twitter can target a conversation to or reference a particular user by using a convention called @reply (Honey and Herring 2009). The primary way to organize tweeted information is the hashtag. Using hashtags, users can find tweets on a specific subject more easily (Chang 2011). However, hashtags may suffer from their fragmentary and redundant nature (ibid.). We collected all tweets directed at the brand (i.e., including "@[brand name]") or used the brand-specific tag (i.e., including "#[brand name]"). As Twitter allows setting the time window when searching for tweets, we collected all tweets posted in 2019 for each brand.

To cover the format of the online reviews, we crawled data from the Yelp platform with respect to our brand sample. Founded in 2004, Yelp.com enables consumers to read and write reviews of all kinds of services and products. Yelp's growth in value and number of customer reviews has shown just how influential the site has become. It is customers (who are not directly compensated for their reviews) and not business owners who write reviews on Yelp.com. To collect a representative set of reviews for each of the brands in our sample, we first created a set of 49[30] major US cities and then compiled all reviews posted in 2019 for each restaurant of each brand in these cities. In total, we extracted 438,000 reviews from Yelp.com.

Although we modeled the effects of brand rating and brand size on eWOM ratings, there might also be a reversed effect of eWOM ratings on brand rating and brand size. For example, more favorable eWOM ratings might increase the number of sales and, in the long term, increase brand size (Duan et al. 2008). To correct for this problem, we measured brand rating and brand size for the last quarter of 2018, while we observed eWOM ratings for the whole year or 2019. Doing so, we eliminate a potential reversed causality bias.

***Variables***

*eWOM Rating.* To measure the valence of a rating, we first need to define the valence of each articulation separately before aggregating at the brand level. For the review data, we took the mean of the review ratings (ranging from 1 to 5) as a measure of eWOM rating. For the social media data, we first extracted the valence for the text of each post using VADER (Hutto and Gilbert, 2014), a rule-based model that is specifically attuned to sentiment analysis in tweets. The model returns three standardized metric values between 0 and 100 to represent the positive, neutral, and negative dimensions of a given text (the values sum up to 100). We classified a social media post according to the dimension with the highest value, but only classified a post as neutral if the positive and negative dimensions were equally 0 (i.e., the neutral dimension has a value of 100). We then calculated the mean eWOM rating for each brand as the difference between positive and negative posts divided by all posts (i.e., positive, negative, and neutral). We included in the model only brands for which we were able to collect more than 100 Twitter posts and more than 10 online reviews. Table 1 provides details about the extracted social media and review data, as well as the distribution of eWOM valence. We find a u-shape distribution

[30] These are the 49 largest cities in the U.S. based on population as of 2019. We were able to utilize sufficient reviews of these cities for the analysis.

of review ratings (Moe and Schweidel, 2012; Hydock et al. 2020), but, in contrast to Schoenmueller et al. (2020), we do not see a higher number of positive (vs. negative) reviews. Additionally, neutral or positive social media posts outnumber the negative ones. However, one should note that the methods used to infer eWOM valence are quite distinct in the social media and review samples, and we do not intend a direct comparison.

***Insert Table 1 about here***

*Brand Rating and Size*. We utilize YouGov's BrandIndex panel, which is based on more than 5,000 daily interviews for more than 1,500 brands (YouGov 2021). The sample is weighted to be representative for the population of the United States. YouGov collects consumer responses on several variables related to how favorable consumers perceive a brand (6 items; e.g., satisfaction, reputation), how present the brand is (4 items; e.g., advertising awareness, word of mouth conversations about the brand), and the purchasing behavior toward the brand (4 items; e.g., purchase intention, customer status). We follow Luo et al. (2013) and operationalize brand rating as a latent variable by averaging the six brand rating items (impression, recommendation, quality, value, reputation, and satisfaction; Cronbach's $\alpha = .94$). Across the literature, there is no consistent operationalization of brand size. For example, Paharia et al. (2014) used the terms "small brand" and "low-share brand" concurrently when referring to the market share of the brand. They also noted that consumer behavior is driven by the "perceptions of whether a brand is smaller, rather than the brand's true market position" (p. 655). Yang and Aggarwal (2019) used the terms "company" and "brand" interchangeably and operationalized size by revenue, net income, and number of employees. We argue that consumers possess different levels of knowledge regarding the actual market share or revenue of a brand and are more likely to perceive a brand as a "big player" if a brand is very present—for example, because a lot of consumers talk about this brand or consumers are exposed to this brand through advertising channels frequently. Accordingly, we operationalize brand size as a latent variable by the mean of the four items related to purchase behavior (consideration, purchase intention, current customer, and former customer) and the four items related to brand presence (awareness, attention, ad awareness, and WOM exposure through friends and family). We find a high internal consistency with Cronbach's $\alpha = .90$. A subsequent maximum-likelihood factor analysis confirms these findings and shows that the items related to brand presence and purchase behavior load on the same factor, while items related to brand rating load on a second factor.

*Control Variables.* Brands follow different social media strategies that, in turn, might affect brand-related eWOM ratings. For example, brands that create more posts, either on their own accounts or in response to consumer tweets, are more likely to build loyal followers that create positive eWOM on their own (Colliander and Wien 2013). Ma et al. (2015) found that service intervention on Twitter improves relationships but also encourages more complaints later. Big brands might be more likely to have their own social media team that is able to affect eWOM ratings positively by, for example, replying to tweets, incentivizing positive eWOM, or creating content that leads to positive eWOM. Accordingly, not controlling for brand-specific differences in the social media strategy might lead to an omitted variable bias. We therefore include the number of posts generated by a brand as a control variable. We also consider the number of users the brand follows (followees) as a control variable, as it might reflect how much effort a brand invests in building relationships on a social network. Since there are no such separate profiles for brands on online customer review platforms, at least not on Yelp, we do not include comparable control variables in the model. However, as the number of restaurants within the same geographic area differs between brands, we incorporate it as a control variable (Liu et al. 2018). We further control for the price tag[31] associated with a brand's restaurants. While all brands in our sample are restaurant-chain brands, we use YouGov's more detailed classification of brand as "Fast Food," "Fast Casual Dining," "Top Casual Dining," "Casual Dining," and "Specialty" to account for unobserved category-specific effects.

### *Results and Discussion*

To estimate the effects, we use ordinary least squares regression, as the dependent variable (eWOM rating) is a continuous measure. We provide the results in Table 2. All models are significant ($p < .001$) and explain between 28% and 47% of the variance in eWOM rating. As expected, all three samples show a significant positive effect of brand rating on eWOM rating ($p < .01$), as well as a significant negative effect of brand size on eWOM rating ($p < .01$).

***Insert Table 2 about here***

In the sample with tweets directed at a brand (including @brand in the post), the negative effect of brand size ($b = -.412$) is larger than the positive effect of brand rating ($b = .261$), while in the other samples, brand rating has a slightly larger effect. The results support hypothesis $H_1$.

*The Confounding Effect of eWOM Volume.* One might argue that the effect of brand size on brand rating is confounded by eWOM volume. For example, Moe and Schweidel (2012) showed that rating environments become more negative over time (i.e., with the number of articulations). They showed that consumers adapt their eWOM sharing intention and sharing valence based on the eWOM environment (i.e., the volume and average valence they observe from the eWOM platform) and that some users (i.e., "activists") are more likely to share a negative opinion when the volume of positive articulations is high. While their study was based on a sample of online reviews, it is questionable to what extent consumers can evaluate the eWOM environment on Twitter, as there are no summary statistics on the volume and valence available for the user. We observe a strong correlation between brand size and eWOM volume (the log number of articulations in our sample, see Table 1): $r = .74$ for the @brand tweets, $r = .67$ for the #brand tweets, and $r = .61$ for the Yelp reviews. We therefore estimate the models but replace brand size with eWOM volume. The effect of eWOM volume on eWOM valance is significantly positive in the @brand sample ($b = -.34$, $p < .001$) and in the #brand sample ($b = -.23$, $p < .001$) but is not significant in the Yelp sample ($b = .19$, $p = .38$). Accordingly, eWOM volume might confound the effect of brand size on eWOM valence for social media posts but not for online reviews.

[31] Yelps asks reviewers to indicate the price per person. The number of "$" signs next to the restaurant name indicates the price level.

**Study 2: Effect of Brand Size on eWOM Sharing Intention**

***Method***

One explanation for the relationship found in Study 1 is that the size of a brand affects consumers' decision to articulate negative or positive experiences with this brand. For example, consumers might form a stronger eWOM sharing intention after a negative experience with a big (vs. small) brand. Accordingly, the interaction effect of brand size and brand rating on eWOM sharing intention might help explain why we observed more negative eWOM ratings for big brands.

To test the causal relationship between brand size, brand rating, the interaction effect between brand size and brand rating, and eWOM-sharing intention, we conducted an online experiment with a 2 (brand size: big vs. small) × 2 (brand rating: positive vs. negative) between-subjects design. The participants were allocated randomly to the four conditions. First, the subjects read a short text about the fictitious restaurant-chain brand "SOUL," which was described as either a big or small brand following the variables from Study 1 (see Factor 1 in Table 1). As noted by Paharia et al. (2014), "[i]t is, after all, consumers' perceptions of whether a brand is smaller, rather than the brand's true market position" (p. 655). We therefore stimulate all dimensions included in Study 1 rather than solely referring to the market share of the brand. In the big brand condition, the participants read the following brand manipulation:

"*Imagine a fictious brand named SOUL, a casual dining restaurant chain. SOUL has a <u>high market</u> share and is considered as a "<u>big player</u>" in the chain restaurant industry. <u>Many</u> people are current or former customers of SOUL and have visited a SOUL restaurant at least a couple of times in their life. Additionally, <u>many</u> people talk about SOUL with their friends and family and it is <u>very likely</u> that one is aware of an advertisement from the SOUL company."*

Next, we replaced all underscored words with their opposites to stimulate a small brand in the respective condition. We instructed the participants to write a short text about the "SOUL" brand using their own words in order to stimulate a deeper thought process. Across all responses, we could surmise a more intense engagement with the situation based on the thoughts formulated. Afterward, the respondents read a short text about a fictitious experience with the "SOUL" brand in terms of visiting one of their restaurants. We framed the experience as either a positive brand rating or a negative brand rating with the following text for the positive brand rating (i.e., a positive experience with the brand) manipulation:

"*Imagine that one day you yourself visit the restaurant of the SOUL chain for the first time. The table you reserved was available <u>immediately</u>. The service was very <u>friendly</u> and your order was prepared <u>quickly</u>. The food and drinks were <u>great</u>. Overall you are very <u>satisfied</u> with the experience when leaving the restaurant."*

Again, we replaced the underscored words in the negative brand rating condition. The participants were subsequently asked about their intention to share their experience with the

"SOUL" brand on social media (7-point Likert scale, 3 items by Picazo-Vela et al. 2010, Cronbach's $\alpha = 0.97$) or by posting an online review (Cronbach's $\alpha = 0.96$). We also asked the subjects to indicate their general likelihood of sharing brand experiences online to account for their baseline sharing intention in the model. The survey was completed by 113 participants from the United Kingdom (44 males, 69 females, average age = 34, 27% students) using the Prolific[32] online panel. To ensure that the context of the study was sufficiently familiar to the respondents, we recruited only those who indicated that they used social media platforms at least once a month.

***Results and Discussion***

We first used a pairwise t-test to compare the mean eWOM sharing intention across the brand size manipulations. We observed that a small brand size leads to higher eWOM sharing intentions in the case of positive brand ratings. For negative brand ratings, while not significant, we observed an increase in eWOM sharing intentions for big brands. The findings support $H_1$.

***Insert Table 3 about here***

Next, we estimated two linear models with social media and online review sharing intention as the dependent variables. We used brand size, brand rating, and the interaction term as explanatory variables and further controlled for the baseline sharing intention of a participant ("In general, how often do you post about one of your consumption experiences on a review/social media platform?"). We present the results in Table 4.

We find a significant positive main effect of brand rating for social media posts ($b = 1.381$, $p < .01$) and online reviews ($b = 1.033$, $p < .05$). This effect is in line with the literature, which shows a positivity bias for shared brand ratings (Schoenmueller et al. 2020). Furthermore, we identify a significant negative interaction effect between brand size and brand rating for social media posts ($b = -1.215$, $p < .05$) and online reviews ($b = -1.497$, $p < .01$), indicating that a positive rating is less likely to be articulated for big brands than for small brands. Brand size does not show a significant effect on eWOM sharing intentions ($p > .212$).

***Insert Table 4 about here***

The results are in line with Study 1, we can confirm the insights through the previously analyzed data from the field with our experiment and at the same time, control for external influences through the experimental framework. We show that big brands' more negative eWOM ratings might stem from consumers' lower intention to articulate positive experiences with big brands or higher intention to share positive experiences with small brands. The results support hypothesis $H_1$.

[32] Prolific is an on-demand survey platform located in Oxford, United Kingdom. Several studies showed that Prolific allows collecting high quality data. Peer et al. (2017), for example, showed that Prolific has several advantages and no major disadvantages compared to heavily used alternatives, such as Amazon's Mechanical Turk.

## Study 3: Mediated Effect of Brand Size on eWOM Valence

### *Method*

The aim of Study 3 was to extend Study 2 by including two possible mediators: the perceived need for help and perceived directness. We also used eWOM valence (i.e., sentiment of the post) as the dependent variable. Following the removal of the participants who failed the attention check questions, we recruited n = 303 respondents (85 males, 218 females, average age = 45, 24% students) from the United Kingdom using the same panel as in Study 2. After reading the brand manipulation, the participants were asked to indicate the perceived need for help of the brand using four items we designed based on the motive of helping others found in the eWOM literature (Hennig-Thurau et al., 2004): "I want to help [brand] to be successful."; "In my opinion, [brand] should be supported."; "[Brand] arouses my desire to help the company."; and "I feel motivated to help [brand]." The items showed high reliability ($\alpha = .92$). The respondents were subsequently asked to rate their perceived directness when communicating with the brand via social media or an online review. We designed four items for this study based on Hydock et al. (2020): "When posting on social media about [brand], it would probably feel like directly communicating with the brand."; "When posting on social media about [brand], it would probably feel like telling an employee about my experience."; "When posting on social media about [brand], it would be likely that an employee will read the post."; and "When I express my opinion about the [brand] in a social media post, I feel like I am personally interacting with the brand." The items showed sufficient reliability ($\alpha = .86$). We then used the same items but replaced social media with online reviews, as there can be differences across the two venues. Again, the item correlation was sufficient ($\alpha = .85$). In the next step, the participants read the brand rating manipulation as in Study 2. We then asked the subjects to indicate the valence of articulation in the case of eWOM contribution for both venues by asking, "Suppose you were to post on social media about your experience at [brand], what would the sentiment of that post be?" (on a scale from 1 = "very negative" to 7 = "very positive"). We further controlled for the baseline sharing intention of the participants in the same way as in Study 2, as there might be a relation between posting frequency and sharing valence (Moe and Schweidel 2012).

### *Results and Discussion*

First, we estimated the mean eWOM valence across the four experimental groups and presented the results, as well as the p-value of a pairwise t-test regarding the brand size condition, in Table 5. As can be seen, the participants in the small brand size condition would share eWOM with more positive valence ($p < .10$), with the exception of social media eWOM valence under the negative brand rating scenario ($p = .190$). The findings support hypothesis $H_1$.

***Insert Table 5 about here***

Second, we estimated a mediation model using the Lavaan R package using a maximum likelihood estimator and bootstrap standard errors. We used brand size, brand rating, and baseline sharing intention as the explanatory variables and eWOM valence for social media and online reviews as the dependent variables. Furthermore, perceived directness and the need for help served as mediators between brand size and eWOM valence. The model was significant ($X^2 = 538.373$, $p < .001$). The estimated path coefficients are depicted in Figure 2. Note that while we only estimated one model, we report the findings separately regarding the two dependent variables for the sake of clarity.

***Insert Figure 2 about here***

The results of the mediation model show that brand size has a significant negative total effect on eWOM valence for both social media posts ($b = -.218$, $p < .01$) and online reviews ($b = -.250$, $p < .01$). In both cases, we observe a full mediation, with a non-significant direct effect of brand size (social media: $b = .009$, $p = .921$; online reviews: $b = .049$, $p = .601$) and a significant indirect effect (social media: $b = -.227$, $p < .001$; online reviews: $b = -.299$, $p < .001$). Regarding the two mediators, we observe that the perceived need for help is significantly lower for big brands ($b = -.948$, $p < .001$), which supports $H_{2a}$. In turn, the perceived need for help increases eWOM valence in a significantly positive way (social media: $b = .140$, $p < .001$; online reviews: $b = .220$, $p < .001$). In both cases, the perceived need for help significantly mediates the effect of brand size on eWOM valence (social media: $b = -.133$, $p < .01$; online reviews: $b = -.208$, $p < .001$). Additionally, perceived directness is lower when contributing eWOM about a big brand (social media: $b = -1.339$, $p < .001$; online reviews: $b = -1.397$, $p < .001$), supporting $H_{3a}$. However, perceived directness only slightly affects eWOM valences on social media ($b = .067$, $p < .10$) and, as a result, only slightly mediates the effect of brand size on eWOM valence for social media ($b = -.094$, $p < .10$). For online reviews, we observe a positive effect of perceived directness on eWOM valence ($b = .065$, $p < .05$) and a significant mediation ($b = -.091$, $p < .05$). In summary, big brands experience more negative eWOM valences via both venues, supporting $H_1$. The perceived need for help explains this relationship in both cases (supporting $H_{2b}$), while perceived directness seems to play a more significant role only for online reviews (supporting $H_{3b}$ only partially). An explanation for this finding could be that negative articulations on social media platforms may create lower discomfort than articulations on online review platforms because social media platforms are less formal concerning the way of communicating. In the case of informal and casual communication, consumers might assume that less specific intentions are attributed to them with regard to their articulations and that criticism therefore has less of an attacking effect than on review platforms, where articulations are necessarily planned.

## General Discussion

We present three studies to examine how brand size affects consumers' eWOM ratings. All studies are summarized in Table 6.

***Insert Table 6 about here***

In the field study, we consider brand-related eWOM ratings on social media and review platforms and compare a sample of 133 chain restaurant brands from the US. We show that big brands receive more negative eWOM ratings compared to small brands. To shed light on the causal nature of this relationship, we conducted a 2 (brand size: big vs. small) × 2 (brand rating: negative vs. positive) scenario experiment (Study 2) with eWOM sharing intention as the dependent variable and showed that consumers exhibit a higher intention to share a positive (negative) brand experience when the respective brand is small (big). Through the third study, we identified the perceived need for help and perceived directness as mediators that explain why brand size has a negative effect on eWOM ratings. The participants perceived that the small (vs. big) brand was in greater need for help and rated the perceived directness of communication higher with the small brand than with the big brand. While the perceived need for help positively affects eWOM valence on social media and online review platforms, we found that perceived directness only affects eWOM valence on online review platforms.

### *Theoretical Contribution*

Our theoretical contributions come in several areas. Moe and Schweidel (2012) emphasized that it is critical for marketers to understand what consumers' motives are for expressing their opinions online and what influences their behavior. We add to the existing literature on eWOM by focusing on eWOM ratings and looking at the relationship between brand attributes and eWOM ratings. Building on the literature on consumers' reactions with respect to brand size (Paharia et al. 2014; Yang and Aggarwal 2019), we found a negative effect of brand size on eWOM ratings, which adds to previous research on the relationship between brand size and eWOM (Paharia et al. 2014). We further show that consumers are more likely to post positive ratings for small (vs. big) brands. This finding expands our understanding of how brand size drives eWOM sharing and extends previous work that has focused on documenting the frequency of positive (vs. negative) eWOM (Schoenmueller et al. 2018; Wangenheim and Bayon 2007).

Our studies also provide some evidence that individuals' perceptions of factors perceived in connection with brand size affect eWOM contribution. For example, the perceived need for help has an influence on eWOM ratings. We extend studies that look at consumers' motivation to support brands with eWOM articulations (Hennig-Thurau et al. 2014; Minestero et al. 2018) and show that consumers feel more strongly that small (vs. big) brands need help. In addition to the increased perception of the need for help of a small (vs. big) brand, we showed that participants who perceive a higher need for help show a higher intention to share positive eWOM for the brand in question and a lower intention to share negative eWOM for this brand.

We also revealed a to date hardly considered effect, that discourages dissatisfied customers from interacting with small brands more than with big brands. The feeling of communicating directly with a brand can, on the one hand, lead consumers to share more positive eWOM after a positive experience and, on the other hand, reduce the likelihood of a negative comment. We extend the findings of Hydock et al. (2020) by showing that the feeling of communicating "with" vs. "about" a brand depends not only on the channel of communication but also on the perceived size of the corresponding brand, which triggers the perception of more direct communication with this brand. The size of a brand can influence consumers' assumptions about who receives their articulations. The depicted effect of perceived directness is stronger for small (vs. big) brands. One reason for the higher perceived directness of eWOM communication for small (vs. big) brands could be that consumers do not feel that their statements are lost in a crowd of opinions. Expectations of the behavior of small (vs. big) brands can also change the perceived directness. Interestingly, the found effect of perceived directness is more significant for review platforms (compared to social media platforms), which can provide a good starting point for further research.

In addition, we gained new insights by comparing social media platforms and review platforms. Many studies have used consumer reviews from websites such as Amazon.com to collect data for analysis (e.g., Chakraborty 2019; Kordrostami and Rahmani 2020). In our studies, we used real data from a review platform, Twitter posts, and query-sharing intentions for the different platforms. We were thus able to demonstrate how the sharing behavior of consumers regarding a brand differs on the two platforms. For both social media and reviews, consumers are less likely to feel that they are communicating directly with big (vs. small) brands. We found a negative indirect effect of brand size on eWOM ratings for both platform types.

### ***Managerial Implications***

This research yields two important implications for marketing decision makers. First, we identified a negative relationship between brand size and eWOM ratings. While increasing brand size in terms of market share and awareness is the top priority goal of almost every business, negative eWOM ratings counteract brand growth, as they reduce sales (Rosario et al., 2016). The main implication of this observation is that big brands need to invest more in eWOM marketing (e.g., incentivizing positive eWOM) in order to compensate for the negative effect of their size. We study two mechanisms that explain why big brands suffer from negative eWOM, and one can translate both mechanisms into actionable strategies. On the one hand, we show that consumers are less motivated to help big brands, likely because big brands are considered as already successful and less in need of help than small brands. Consequently, big brands should focus on convincing their customers that their help in terms of positive eWOM ratings is important and helpful for the brand. For example, employees might allude to customers that a positive review would be very helpful. On the other hand, we show that consumers who feel that they are communicating directly with a particular brand are less likely to share negative eWOM about that brand. Brands can potentially utilize consumers' aversion to directly criticizing the brand by communicating that the brand makes huge efforts to read all brand-related eWOM. For example, when brands often reply to tweets and online reviews, it might evoke a consumers' feeling of directly communicating with the brand (Labrecque, 2014); as a consequence, some consumers might abstain from giving a negative eWOM rating. Going further, the use of chatbots with artificial intelligence could be helpful, as their responses should give consumers a sense of direct communication when the chatbot is perceived as a real person.

Second, brands often gather brand-related eWOM data to infer consumers' needs, preferences, and brand perception. Additionally, brands might use eWOM ratings on social media to approximate how successful a social media marketing campaign is. In both cases, variations in brand size might lead to misleading observations and conclusions. For example, if the observed eWOM ratings decline, marketers might conclude that consumers perceive their brand as less positive, while the real reason for this change might be an increase in brand size and a constant, or even slightly increasing, brand perception. Additionally, comparing the focal brand's eWOM ratings with those of a smaller competitor might lead to the conclusion that the social media strategy of the competitor is superior or that customers have more positive brand perceptions about the competitor, while, in fact, the difference in eWOM ratings might be a simple consequence of the difference in brand size. We therefore suggest controlling for brand size if the dependent variable is related to average eWOM ratings.

***Limitations and Future Research***

The aim of the present work was to present the relationship between the size of a brand and eWOM ratings. By doing so, we add new insights to the research area of eWOM communication. However, the findings are subject to at least three limitations, which could provide directions for further research.

First, the present study focuses on chain restaurant brands. While eWOM ratings play an important role in this domain, emphasizing the relevance of our research, future studies might investigate how far they can translate our findings to other business categories. While restaurants are service providers that typically include some sort of human interaction with an employee, the mediators we identified might be less predictive for a business category where less human interaction is required-for example, e-commerce brand categories where consumers order partially anonymously and the service component and communication is eliminated. Moreover, even in the restaurant industry, many chains (such as McDonald's) have started to install self-order terminals, which reduce the interaction with employees. Does using a terminal decrease the brand's perceived need for help or perceived directness when articulating an opinion about the brand online?

A second limitation of our first study is that we do not investigate different branding strategies. Several interesting research questions arise from our findings: How does an underdog brand positioning affect the perceived brand size and hence, for example, the perceived need for help? How does the perceived brand size of the parent brand affect brand extensions? For example, do McCafé customers perceive the brand as big with a low need for help given the size of the parent brand, McDonald's?

Furthermore, it is worth mentioning that we looked at eWOM on the social media platform Twitter and the review platform Yelp. However, there are numerous other platforms on which eWOM is shared. Future research should further develop and confirm our initial findings by addressing the generalizability of the results to other platforms. As we found only partial support for hypothesis $H_3$, future studies could fruitfully explore this issue further by investigating why the influence of perceived directness of communication on review platforms differs from the influence on social media platforms.

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**Tables**

**Table 1.** Social media and online review data

| Variable | Mean | Share[a] | Median | Minimum | Maximum |
|---|---|---|---|---|---|
| | **Tweets @brand (n = 127 brands[b])** | | | | |
| Number of tweets | 25,860 | | 9,501 | 170 | 155,638 |
| Negative tweets | 5,277 | 20% | 1,432 | 18 | 33,265 |
| Neutral tweets | 8,552 | 33% | 2,952 | 47 | 50,484 |
| Positive tweets | 12,031 | 47% | 4,855 | 60 | 73,493 |
| | **Tweets #brand (n = 111 brands)** | | | | |
| Number of tweets | 6,279 | | 1,080 | 103 | 132,546 |
| Negative tweets | 1,098 | 17% | 104 | 2 | 17,880 |
| Neutral tweets | 2,279 | 36% | 302 | 14 | 48,361 |
| Positive tweets | 2,902 | 46% | 462 | 59 | 66,305 |
| | **Yelp reviews (n = 115 brands)** | | | | |
| Number of reviews | 1,350 | | 867 | 23 | 11,655 |
| 1-star reviews | 573 | 42% | 243 | 5 | 6,784 |
| 2-star reviews | 159 | 12% | 100 | 1 | 1,098 |
| 3-star reviews | 136 | 10% | 92 | 1 | 880 |
| 4-star reviews | 178 | 13% | 121 | 1 | 1,013 |
| 5-star reviews | 304 | 23% | 216 | 5 | 2,383 |
| Number of restaurants | 200 | | 119 | 3 | 4,153[c] |

Notes: [a] Percentage share of all observations in the particular sample; [b] From the total sample of 133 brands, we were able to extract more than 100 tweets for 127 brands; [c] Subway restaurants (n = 4,153) and Dunkin Donuts restaurants (n = 1,952) are the two brands with more than 1,000 locations.

**Table 2.** Regression results for eWOM rating

| Variable | Est. | SE | p |
|---|---|---|---|
| Sample: Tweets @brand (n =127 brands)<br>$R^2$ = .343; BIC = 356, F = **7.878*** | | | |
| *Intercept* | **−.513**† | .294 | .083 |
| *Brand Rating* | **.261** | .087 | .003 |
| *Brand Size* | **−.412*** | .084 | .000 |
| *Category: Fast Casual Dining*[a] | −.335 | .216 | .124 |
| *Category: Fast Food*[a] | **−.418**† | .238 | .082 |
| *Category: Specialty*[a] | −.033 | .225 | .882 |
| *Category: Top Casual Dining*[a] | −.123 | .282 | .664 |
| *Log(Twitter Followees)* | **.057**† | .031 | .072 |
| *Log(Brand Tweets)* | **.072**† | .038 | .063 |
| Sample: Tweets #brand (n = 111 brands)<br>$R^2$ = .280; BIC = 349; F = **5.488*** | | | |
| *Intercept* | −.311 | .308 | .315 |
| *Brand Rating* | **.338*** | .090 | .000 |
| *Brand Size* | **−.282** | .087 | .002 |
| *Category: Fast Casual Dining*[a] | −.208 | .225 | .357 |
| *Category: Fast Food*[a] | −.362 | .248 | .147 |
| *Category: Specialty*[a] | .006 | .234 | .980 |
| *Category: Top Casual Dining*[a] | −.264 | .304 | .387 |
| *Log(Twitter Followees)* | **.060**† | .033 | .069 |
| *Log(Brand Tweets)* | .014 | .041 | .726 |
| Sample: Yelp reviews (n = 115 brands)<br>$R^2$ = .471; BIC = 296; F = **11.800*** | | | |
| *Intercept* | **−.880**† | .505 | .084 |
| *Brand Rating* | **.320*** | .080 | .000 |
| *Brand Size* | **−.308*** | .083 | .000 |
| *Category: Fast Casual Dining*[a] | .018 | .256 | .945 |
| *Category: Fast Food*[a] | .168 | .295 | .570 |
| *Category: Specialty*[a] | .273 | .278 | .328 |
| *Category: Top Casual Dining*[a] | .075 | .280 | .789 |
| *Yelp Price Tag* | **.568*** | .241 | .020 |
| *Log(Number of restaurants)* | **.000**† | .000 | .098 |

Notes: [a] Reference category is "Casual Dining"; †p < .100; * p < .050; ** p < .01; *** p <. 001.

**Table 3.** Mean eWOM sharing intention across experimental conditions.

| | Social media | | | Online review | | |
|---|---|---|---|---|---|---|
| | *Brand size*: Small | *Brand size*: Big | p | *Brand size*: Small | *Brand size*: Big | p |
| *Brand rating*: Positive | **5.619** | **4.744** | < .10 | **5.679** | **4.556** | < .05 |
| *Brand rating*: Negative | 3.951 | 4.321 | .451 | 4.383 | 4.929 | .220 |

Note: Bold values are significantly different across brand size conditions

**Table 4.** Effect of brand size and brand rating on eWOM sharing intention

| | Social media | | | Online reviews | | |
|---|---|---|---|---|---|---|
| Variable | Est. | SE | p | Est. | SE | p |
| *(Intercept)* | **1.928***** | .381 | .000 | **2.786***** | .392 | .000 |
| *Baseline sharing intention* | **.718***** | .092 | .000 | **.560***** | .097 | .000 |
| *Brand size*[a] | .494 | .394 | .212 | .423 | .391 | .282 |
| *Brand rating*[b] | **1.381**** | .395 | .001 | **1.033*** | .393 | .010 |
| *Brand size × rating* | **-1.215*** | .549 | .029 | **-1.497**** | .546 | .007 |
| Adjusted $R^2$ | .409 | | | .275 | | |

Notes: [a] 0 = “small,” 1 = “big”; [b] 0 = “negative,” 1 = “positive.” * p < .050; ** p < .01; *** p <. 001.

**Table 5.** Mean eWOM valence across experimental conditions

| | Social media | | | Online reviews | | |
|---|---|---|---|---|---|---|
| | *Brand size*: Small | *Brand size*: Big | p | *Brand size*: Small | *Brand size*: Big | p |
| *Brand rating*: Positive | **6.692** | **6.400** | < .01 | **6.654** | **6.440** | < .100 |
| *Brand rating*: Negative | 2.208 | 2.077 | .190 | **2.500** | **2.192** | < .050 |

Note: Bold values are significantly different across brand size conditions

**Table 6.** Summary of conducted studies

| Study | Method | Sample | Main variables | Findings |
|---|---|---|---|---|
| 1 | Field study | 127 chain restaurant brands | *Brand size*<br>*Brand rating*<br>*eWOM rating* | Negative effect of brand size on eWOM ratings. |
| 2 | Experiment | 113 participants | *Brand size*<br>*Brand rating*<br>*eWOM sharing intention* | Higher sharing intention for positive brand ratings for small (vs. big) brands. |
| 3 | Experiment | 303 participants | *Brand size*<br>*Brand rating*<br>*Perceived need for help*<br>*Perceived directness*<br>*eWOM valence* | Negative effect of brand size on eWOM valence.<br>Negative effect is mediated by perceived need for help and perceived directness. |

## Figures

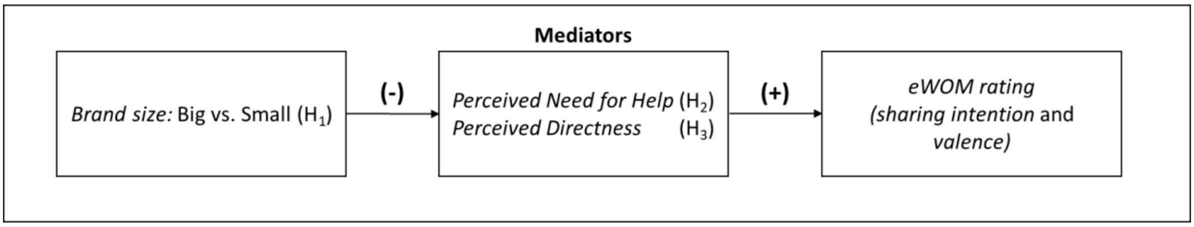


**Figure 1.** Conceptual model.

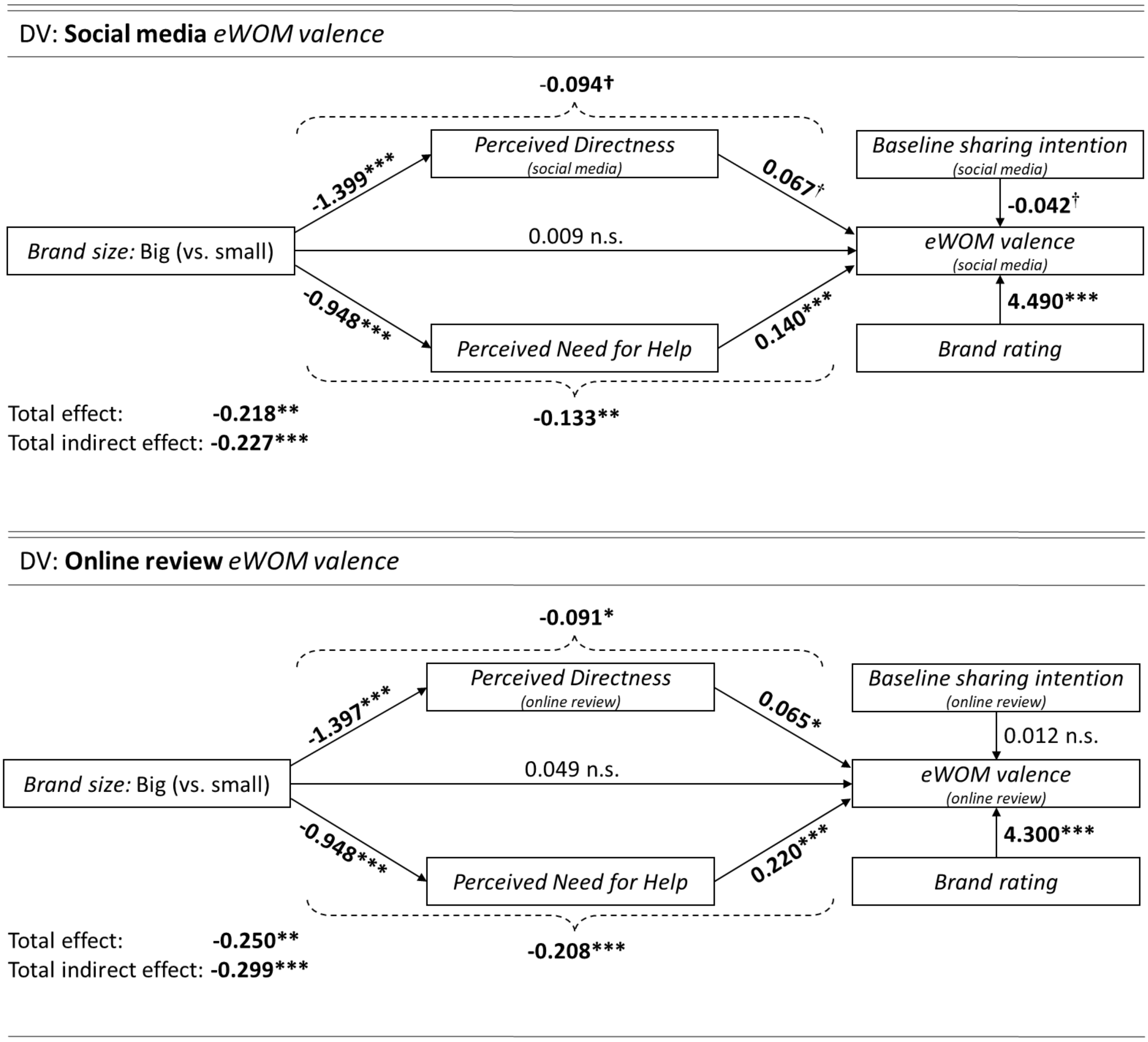


**Figure 2.** Mediation model results

Notes: We estimate a single model but report the results separately for the sake of clarity. We allowed for the residual variances of the two dependent variables to be correlated.

† p < .100; * p < .050; ** p < .01; *** p <. 001.

# Essay C2: The Effect of Corporate Political Advocacy on Brand Perception: An Event Study Analysis

## The Effect of Corporate Political Advocacy on Brand Perception: An Event Study Analysis


## Abstract

**Purpose –** In recent years, brands have increasingly engaged in corporate political advocacy (CPA; also termed brand activism or corporate sociopolitical activity) by taking positions on polarizing sociopolitical issues. Recent experimental research suggests that consumers respond to CPA based on its alignment with their own values, and that it typically induces an overall negative response. This research provides additional insights by exploring consumer brand perceptions following CPA.

**Design/methodology/approach –** An event study of 106 CPA events and weekly consumer brand perception data was conducted. A regression model was used to investigate the moderating effects of CPA effort, concurrence, and the strength of the online protests evoked by the CPA.

**Findings –** The results show that CPA had a negative effect on consumers' brand perceptions and that the effect was stronger for customers relative to non-customers. The negative effect was attenuated by CPA concurrence and amplified by effort. Additionally, online protests were driven by CPA effort and had a strong negative effect on brand perception. Online protests were stronger in the past, and in turn, the negative effects of CPA on brand perceptions have slightly weakened in recent years.

**Originality/value –** This article contributes to the existing literature by highlighting the role of online protests following CPA and distinguishing consumer and customer responses. This study also provides converging evidence of the moderating effects of effort and concurrence identified in previous studies.


## Introduction

In recent years, researchers have noted a new trend whereby companies weigh in on divisive political issues. For example, Delta Airlines and Dick's Sporting Goods cut ties with the National Rifle Association following its fight against laws regulating gun ownership; Apple, Google, and Facebook openly opposed former U.S. president Donald Trump's immigration ban; and Nike made Colin Kaepernick, the leader of a controversial national anthem protest over social injustice, the face of an advertising campaign. These examples of corporate participation in polarizing political debates that seemingly have no direct link to the firms' bottom line are termed corporate political advocacy (CPA), i.e., a brand's public engagement on a controversial sociopolitical issue (Hydock *et al*. 2020; Hydock *et al*. 2019; Wettstein and Bauer 2016; see also Bhagwat *et al*. 2020[33]).

[33] In this paper, the CPA label is used to refer to brands' engagement in controversial political issues (Hydock *et al*. 2020; Hydock *et al*. 2018; Wettstein and Baur 2016). However, at least five labels have emerged to describe the same phenomenon: brand activism (Mukherjee and Althuizen 2020), corporate sociopolitical activity (Bhagwat et al. 2020), sociopolitical activism (Nalick et al. 2016), and corporate social advocacy (Dodd and Supa 2014). Additionally, it is not differentiated between brands and companies.

Current research suggests that CPA, at least in part, stems from consumers' increasing expectations that brands help spur social change (Austin *et al*. 2019; Bravo and Lee 2019; Coombs and Holladay 2018). These expectations present a challenge for brands because the population (at least in America) is increasingly polarized (Weber *et al*. 2021), which means that CPA might elicit competing positive and negative responses. In fact, researchers have found that consumers respond to CPA based on its overlap with their own values (Bhagwat *et al*. 2020; Bravo and Lee 2019; Dodd and Supa 2014; 2015; Hydock *et al*. 2020); that is, when consumers support (oppose) a brand's CPA, they express more (less) favorable attitudes toward the brand. This suggests that the overall effect of CPA depends on the portion of consumers who support (vs. oppose) the action and, therefore, that a brand's decision to engage in CPA should be a function of the political leanings of their customers.

Research also suggests that, in most cases, the net response to CPA (i.e., the change in average brand perception) might be negative because consumers respond more negatively to brand actions they oppose than to brand actions they support (Hydock *et al*. 2020) and because some consumers oppose any form of CPA (Morning Consult 2018). Furthermore, existing research points to several factors that moderate the effects of CPA, including a brand's market share (Hydock *et al*. 2020), as well as the CPA source, its form (action vs. statement), the existence of a coalition, and its authenticity and fit with the brand (Bhagwat *et al*. 2020; Vredenberg *et al.* 2020; Schmidt *et al.* 2021).

Despite these initial insights, many questions remain regarding responses to CPA, and a more nuanced understanding of its effects is necessary from both an academic and a practitioner perspective. For instance, while Hydock *et al*. (2020) focused on how CPA affects choice share among consumers generally, Bhagwat *et al*. (2020) and Villagra *et al.* (2021) focused on the initial stock market response, and Mukherjee and Althuizen (2020) investigated the differences between consumers who agreed and those who disagreed with CPA regarding brand attitude in an experimental setting. However, to the best of the authors' knowledge, no research has examined (i) the effect of CPA on brand perceptions with real in-market consumer response data, (ii) the specific effects of CPA on customers' (vs. non-customers'[34]) brand perceptions, and (iii) the role of online protests. The current study seeks to fill these three gaps.

First, consistent with previous existing work (Bhagwat *et al*. 2020; Mukherjee and Althuizen 2020), this paper finds that CPA has a negative effect on consumers' brand perceptions; however, it builds on this work by showing that this effect is actually stronger for customers relative to non-customers (research gap (i)). Second, it is found that two moderators of CPA's effect on stock price identified by Bhagwhat *et al.* (2020) extend to consumer perceptions (effort and concurrence) (research gap (ii)). Third, the paper shows that online protests are primarily driven by the effort put into the CPA, and in turn have a strong negative effect on brand perception. Initial evidence is found that online protests were stronger in the past and, in turn, that the negative effects of CPA on brand perception have slightly weakened in recent years (research gap (iii)).

In what follows, first, the relevant literature is reviewed and a set of hypotheses is derived to motivate the conceptual model of CPA's impact on brand perception. The model, as well as the

[34] Non-customers are defined as all consumers that have never been a customer at the respective brand.

corresponding hypotheses, was operationalized and tested through aggregated data on over 100 CPA events, daily consumer panel data, social media data, and brand attributes. By examining representative consumer responses to corporate behavior, this study provides unique insights into CPA's effects on consumer perceptions. Following the reporting of these results, implications for corporate decision-making, the theoretical understanding of CPA, and directions for future research are discussed.

## Theoretical Background

### *Corporate Political Advocacy and Consumer Response*

An emerging body of literature on the intersection of politics and marketing (e.g., Jung and Mittall 2020; Schweidel and Bendle 2019) has sought to explain the recent phenomenon of brand engagement in divisive sociopolitical issues. A 2018 survey of 324 marketing managers from the United States showed that a company's ability "to attract new and retain current customers" is an important reason that influenced the willingness to take a stance (Deloitte 2018). Interestingly, the above mentioned reason was stated by 69.7% of those managers who are willing to take a stance but also by 67.8% of those who are unwilling, showing the opposing predictions regarding this issue. The study also found that managers who took a stance wanted to show that their company cares about more than making profits. In this regard, CPA is not only motivated by customer pressure, but might also be pushed by decision makers' (e.g., chief executive officers') willingness to take the lead on issues that are seen as socially important (Chatterji and Toffel 2018; Hambrick and Wowak 2021). Researchers note that despite the obvious risks involved (Weinzimmer and Esken 2016), CPA can be motivated by consumers and other stakeholders pressuring companies to engage in polarizing sociopolitical issues (Austin *et al*. 2019; Bravo and Lee 2019; Coombs and Holladay 2018; Schmidt *et al.* 2021). Not only is it risky, but CPA represents a departure from brands' historically safer interactions with stakeholders (van Marrewijk 2003) through corporate social responsibility (CSR). While CSR initiatives typically elicit a positive or ambivalent response to philanthropically oriented actions (Weinzimmer and Esken 2016), CPA involves taking a stance on polarizing (Hydock *et al*. 2019; Hydock *et al*. 2020) and controversial sociopolitical issues (Bhagwhat *et al.* 2020) that elicit dissensus (Ciszek and Logan 2018) through support of one group over another (Wettstein and Bauer 2016). Accordingly, CPA is defined as a form of brand activism in which a brand takes a public stance on a controversial sociopolitical issue.

### *Brand–Consumer Value Overlap*

Given that CPA involves polarizing sociopolitical issues that induce both support and opposition, it follows that an individual consumer's attitude toward the brand will depend on their political beliefs (Hambrick and Wowack 2021). This conclusion stems from the fact that political ideology can comprise part of a brand's image (Jung and Mittal 2020); brand perceptions depend not only on a brand's functional benefits but also on its symbolic values, which facilitate identity expression (Aaker 1997); and consumers prefer brands whose self-concept is congruent with their (Malhotra 1988). Research has even found that alignment between a consumer's and a brand's sociopolitical values explains brand perceptions and purchase intentions (Shepherd *et al*. 2015), including in the specific context of CPA (Bravo and Lee 2019; Bhagwhat *et al*. 2020; Dodd and Supa 2014; 2015; Hydock *et al*. 2020). Given that consumers' brand perceptions are a function of the alignment between their own beliefs and a brand's CPA, one might anticipate a null net effect of CPA for issues with similar levels of support and opposition and, intuitively, a positive (negative) effect if the majority of consumers support (oppose) the advocated position. However, there are two reasons for expecting a negative attitudinal response to CPA.

***Negative Effects of CPA***

First, research indicates that negative (vs. positive) information is more diagnostic in decision making and impression formation (Rozin and Royzman 2001). In fact, research has explicitly found that consumers react more negatively to CPA they oppose than positively toward CPA they support (Hydock *et al*. 2020; Mukherjee *et al*. 2020). The increased weight assigned to negative (vs. positive) information also extends to word-of-mouth (WOM) communication, which consumers disseminate with more detail, more often, and to a greater number of recipients, all over a longer period (Hornik *et al*. 2015). Second, the consumer response to CPA is more likely to be negative because research has found that while many consumers increasingly support brand engagement in sociopolitical issues, others oppose it. A survey by Morning Consult (2018) of 2,200 consumers from the United States showed that only 22% of all participants (36% of participants younger than 21 years) thought brands should engage in CPA, while 60% of all participants indicated that brand should not get involved in CPA. While other research has found greater support for CPA (e.g., Sprout Social 2017), it is notable that the combination of customers who generally oppose CPA and customers who disagree with a given CPA position is likely to induce an overall negative response (when support and opposition are approximately equal). Together, these forces mean that when the population is divided between support for and opposition to a brand's CPA, the net effect on brand perceptions should be negative.[35] Therefore, it is expected that:

**$H_{1a}$:** CPA has a negative effect on consumer brand perception.

While previous research has provided evidence of a negative effect on consumer brand perception in general (Hydock *et al*. 2020; Mukherjee *et al*. 2020), as well as stock prices (Bhagwat 2020), researchers have yet to explicitly examine the effects of CPA on customers vs. non-customers (i.e., consumers who have not yet purchased anything from the brand). On the one hand, it is possible that customers might be less reactive in response to a brand's CPA due to a greater level of loyalty (Ahluwalia *et al*. 2000). On the other hand, customers with a closer connection to the brand are more likely to feel betrayed by a brand whose CPA they oppose (Reimann *et al*. 2018). Mukherjee and Althuizen (2020) argued that "CPA provides an opportunity to assess the level of self-brand similarity in the context of moral judgments" (p.773). As self-brand similarity is, in general, assumed to be higher for customers (vs. non-customers) of a brand, customers would see a stronger reason to change their brand perception and switch to a competitor in case they oppose the stance of a brand. In contrast, when they support the stance, their likely positive brand perception will remain positive but will not change to a significant degree (Mukherjee and Althuizen 2020). Furthermore, a brand's CPA

[35] While support for a particular CPA action can vary, given that CPA is defined by its polarizing nature, with a large sample of CPA events, the average level of support and opposition coalesces, and therefore the net effect of CPA should be negative.

might be less personally relevant to non-customers compared to customers, resulting in less motivation to elaborate on the information and change attitudes (Petty and Cacioppo 1986). Therefore, is assumed that:

**$H_{1b}$:** CPA has a negative effect on customer brand perception.

**$H_{1c}$:** The negative effect of CPA on brand perception is stronger for customers than for non-customers.

***Online Protests***

Online protests, or "firestorms," are a digital kind of brand crisis that has recently emerged on several social media platforms, such as Twitter (Hansen *et al*. 2018). Conceptually, online protests can be seen as a large number of negative electronic word-of-mouth (eWOM) statements spread over a short period of time regarding a specific issue that concerns one or multiple brands. Several studies have shown that negative eWOM can affect brand perception and moderate the negative consequences of negative brand information. For example, Hsu and Lawrence (2016) showed that the volume of eWOM can exacerbate the negative effect of product recall announcements on shareholder value. Hansen *et al*. (2018) found that the number of negative tweets triggered by brand failure significantly increased the negative effect on company perceptions. In an experiment conducted by van Den Broek *et al*. (2017), exposure to an online protest negatively affected consumers' brand perception. Furthermore, they found evidence that the number of consumer actions (e.g., online petition signatures, Facebook likes, or YouTube views) surrounding digital protests had a significantly negative moderating effect on a brand's financial value. In the case of CPA, online protests might be initiated by those who oppose the stance in question, whereas consumers with high brand identification who also agree with the stance might defend the brand (Mukherjee and Althuizen 2020). However, Mukherjee and Althuizen's (2020) results indicate that a public backlash, such as an online protest, has a stronger negative effect on consumers' brand attitudes who disagree than the positive effect on those who agree. Therefore, it is expected that:

**$H_2$:** The negative effect of CPA on brand perception is amplified by the strength of online protests that immediately follow the CPA.

Online protests, in turn, might depend on the characteristics of the CPA event and the brand taking a stance. While Hansen *et al*. (2018) found no significant relationship between a brand's failure type (product or service vs. social vs. communication failure) and the strength[36] of the online protest, they did not control for brand characteristics (e.g., brand awareness), and the events they investigated were quite different, even within the categories of failure types. Following the theoretical considerations above, several expectations regarding the strength of the online protest can be made. As greater effort signals greater commitment, consumers opposing the stance might be more likely to engage in an online protest to vent their negative feelings associated with the brand's decision (Hennig-Thurau *et al*. 2004). The same mechanisms could drive the strength of the protest based on low levels of brand alignment. For example, Dick's Sporting Goods might be favored by more Republican than Democrat

[36] They define strength of an online protest as the number of tweets, which is the same operationalization used in the model.

consumers, so taking a more liberal stance might result in a stronger online protest than a brand that is already associated with a liberal stance.

***Effort***

Any action an entity takes can be characterized by the amount of effort it requires. Weiner (1970) classified effort as an internal cause for observed behavior. Effort signals one's commitment to a goal (Novacek and Lazarus 1990) and internal motivation (Dik and Aarts 2007), and the extent to which consumers adjust their perceptions of an entity depends on what inferences are drawn about the link between an action and the actor's underlying dispositions (Jones and Davis 1965). A high-effort action can also be perceived as unexpected and extreme behavior, which is more likely to be attributed to internal disposition. Thus, it follows that brand actions exhibiting greater effort will have a stronger effect on brand perceptions.

An example of low-effort CPA would be a verbal statement by a spokesperson (e.g., chief executive officers, public relations managers) or a tweet indicating the brand's stance, whereas high-effort CPA might be exemplified by a change in policy, reallotment of resources (e.g., removing an advertisement from a TV show), donating money to support a cause, or canceling a discount program with a political organization. In fact, research shows that CSR only impacts brand perception if attributed to internal dispositions (Yoon *et al*. 2006), greater CSR investment signals greater effort and induces more favorable brand perceptions (Ellen *et al*. 2000), and that high-effort CPA (e.g., prioritizing the hiring of immigrants) has a stronger effect on stock prices than low-effort CPA (e.g., only voicing support for immigrants) (Bhagwat *et al*. 2020). Additionally, Mukherjee and Althuizen (2020) showed that when consumers perceive the relationship between the brand and the source of the stance to be more distant, the negative effect of CPA is weaker, because it allows consumers to morally decouple the brand from the stance. Accordingly, it is expected that:

**$H_{3a}$:** The negative effect of CPA on brand perception is amplified by high (vs. low) effort.

Is it also expected that high-effort CPA will result in stronger online protests. One of the main motivations for engaging in negative eWOM is to vent negative feelings about a brand and regulate one's own negative emotions (Hennig-Thurau 2004). In the case of low-effort CPA, consumers might be able to reappraise thoughts to regulate emotions (Sheppes *et al*. 2011), as they "morally decouple the brand from the stand" (Mukherjee and Althuizen 2020, p.772). However, this mechanism is not sufficient when high-effort CPA is attributed to internal dispositions, leading to the articulation of negative eWOM as an alternative way to regulate emotions. Accordingly, it is supposed that:

**$H_{4a}$:** High (vs. low) effort CPA will be followed by a stronger online protest.

***Concurrence***

When a brand engages in CPA concurrently with other brands, two psychological mechanisms are likely to mitigate its effect on brand perception. First, when a group takes actions, people are less likely to attribute responsibility to individuals (Waytz and Young 2012). According to the covariation principle (Kelly 1973), a certain behavior is attributed to potential causes that appear at the same time. Attribution is, among other factors, based on concurrence (i.e., covariation of behavior across different people), where high concurrence increases the chance that an observer attributes behavior to situational explanations and low concurrence to internal disposition. Second, consumers are susceptible to conformity and are likely to adopt the opinions held by the majority in a group (Asch 1956). In the context of CPA, experimental work has found that the number of brands taking a position influences attitude change on that issue (Parcha and Kingsley 2020). Additionally, shareholders react less negatively to CPA if multiple brands take the same position at the same time (Bhagwhat *et al*. 2020). It is contend that when a brand engages in the same form of CPA as other brands (i.e., concurrence), its effect on brand perception should be lessened. Therefore, it is hypothesized that:

**$H_{3b}$:** The negative effect of CPA on brand perception is attenuated by high concurrence.

Following the above argument, concurrence can be used as a cue to decouple the brand from the stance. For example, the brand's behavior can be reappraised by attributing responsibility to other brands, and consumers might feel less inclined to articulate negative eWOM. Furthermore, when multiple brands take a stance simultaneously, potential protestors need to allocate their attention and effort and might decide to focus on the most prominent brand instead of risking diluting the protest by charging multiple brands at the same time. Thus, it is assumed that:

**$H_{4b}$:** High (vs. low) concurrence of CPA will be followed by a less strong online protest.

***Event Study Analysis and Conceptual Framework***

To investigate the proposed hypotheses, an event study is conducted to test the effect of CPA on brand perception (Ball and Brown 1968; Sorescu *et al*. 2017; Hansen *et al.* 2018). Afterwards, the magnitude of this effect is determined with a set of moderating factors related to the theoretical drivers discussed in this section (see Bhagwat *et al*. 2020 for a similar model). As the online protest following the CPA event is expected to be affected by CPA behavior and, in turn, to affect the relationship between CPA and brand perception, a mediation model is used to test the relationships discussed above. Given its high ecological validity, which stems from using real-world events in contrast to experimental scenarios, the event study methodology has often been used in marketing research to study the effect of brand-related events like CPA (Bhagwat *et al.* 2020), product recalls (Hsu and Lawrence 2016), and social media firestorms (Hansen *et al.* 2018) on stock returns and brand perception. Note that compared to an experiment in which the researcher assigns participants to an experimental (brand that engages in CPA) and control (brand that does not engage in CPA) group, the researcher can only observe actual CPA behavior in the real world, i.e., the experimental group. To infer the causal effect of the treatment (CPA), the event study methodology compares the expected outcome[37] of the dependent variable (i.e., the expected brand perception given no CPA) with the actual outcome of the dependent variable (i.e., the observed brand perception after CPA). This difference is called the "abnormal" value of the dependent variable, and in this paper, abnormal brand perception (ABP). The difference is then assumed to be caused by the treatment, i.e., the brand's decision to engage in CPA. The ABP can then be measured for each event for each time unit in

[37] In this study, a time-series model is fitted to the weekly observations of brand perception and use the model predictions for the weeks surrounding the CPA event.

a pre-defined time window. As the measure of brand perception will be on a weekly scale, ABP is reported for the first two weeks after the event. The average of these two weeks then serves as the cumulated ABP (CABP) (see Figure 1). This variable is then used as a dependent variable in a separate model in which CPA behavior and control variables are explanatory variables and online protest is a mediator. Note that this model is formally a standard mediation model, as one would estimate for classical survey data, and the dependent variable (CABP) is not directly measured but inferred from the event study model. The conceptual model is depicted in Figure 1. Besides factors describing specific CPA behavior, this research investigates the effects of four control variables that might directly and indirectly affect the relationship between CPA and brand perception through their effects on online protests.

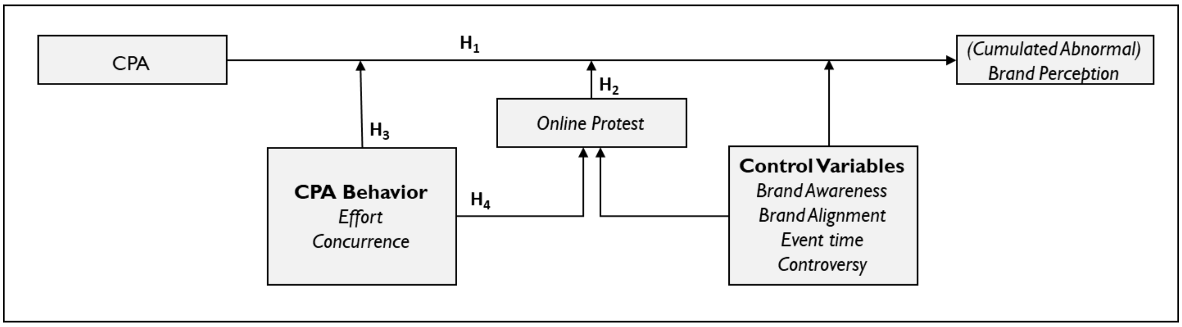


**Figure 1.** Conceptual framework.

Consumers might react differently depending on their prior knowledge about the brand taking the stand. For example, brands with high awareness (i.e., established brands with a high market share that are familiar to most consumers) might face stronger online protests, as more consumers are aware of the brand and can contribute to the protest via negative WOM. Another factor at the brand level is the alignment between the brand and the political direction of the CPA. Bhagwat *et al.* (2020) showed that the alignment between the CPA's direction and the political preferences of customers, employees, and the government has a positive effect on the company's share price after the event. However, they did not find an effect due to the fit between brand image and CPA.

The time of the event might also affect how strongly CPA affects brand perception. Schoenmueller *et al*. (2019) found an increasing polarization in preference partisanship (i.e., a correlation between brand and political preferences) since Donald Trump became the President of the United States. Accordingly, opposing predictions can be made: while consumers' political polarization might have increased in recent years, CPA might become less extraordinary over time, and thus consumers' reactions to it might either intensify or abate. For example, 50% of consumers indicated that too many brands use societal issues as a marketing ploy to sell more products (Edelman 2019), which could increase negative responses over time. Alternatively, consumers might become less motivated to protest online, as a multitude of brands taking controversial stances might lead to habituation.

It is also controlled for the extent to which CPA is controversial by measuring consumers' perceptions of anonymized versions of each CPA event. What differentiates CPA from CSR is that the former is controversial; it induces strong support and opposition (Bhagwat *et al*. 2020; Hydock *et al*. 2020). However, this dimension is not binary; it exists on a continuum. Therefore, with some CPA issues, the variance in consumer responses may be explained by their being less controversial and thus more aligned with CSR, which typically evokes a positive consumer response (van Marrewijk 2003; Yoon *et al*. 2006).

## Empirical Study

### *Variables*

*Brand Perception*. Brand perception measures are obtained from YouGov's BrandIndex (YouGov 2020), which is based on more than 5,000 daily interviews about more than 1,500 brands, including several brand perception indicators. The sample was weighted to be representative of the population of the United States, which was the focus of the analysis. Brand perception was measured by the question, "Overall, of which of the following brands do you have a positive/negative impression?" Only participants who were aware of the brand were considered. To measure daily brand perception, this paper followed Luo *et al*. (2013) and used the mean of the survey question response by taking the difference between the number of respondents with positive responses and the number of respondents with negative responses divided by the number of all respondents (i.e., positive, negative, and neutral).[38] Daily measures were cumulated to weekly measures to reduce volatility and increase the sample size, which could be rather low (on a daily basis) for companies with low awareness. To account for differences between consumers (i.e., those aware of the brand that had never purchased from the brand) and customers, reflexive filters based on participants' self-declarations about their customer status regarding past purchases of a brand's products were used.

*Online Protest.* To account for the magnitude of an online protest after a CPA event, social media data from Twitter, the most prominent public platform on which consumers protest corporate actions (see Berman *et al*. 2019 for a review), is used. Protests of CPA can be seen as a special case of negative eWOM (Hansen *et al*. 2018). To measure the volume of negative eWOM, all tweets that belonged to an online protest of a brand as a consequence of CPA by using the tag "#boycott[brand]" were collected. This approach is commonly used to identify events in the online protest literature (Makarem and Jae 2016; Hansen *et al*. 2018). To account for a skewed distribution typical of social media metrics, the log of the number of tweets for the week after the event was used as a measure of online protest.

*Effort*. CPA effort is defined as high when a brand not only issued a verbal or textual statement but also took action (Bhagwat et al. 2020). Applying this definition, two research assistants, blind to the goal of the study, coded CPA behavior using a binary system (low vs. high) and agreed in 96% of the cases. A subsequent discussion led to a consensus on all events.

*Concurrence*. CPA events are treated as concurrent if at least two companies took the same position (i.e., taking a stance in the same direction) on the same political issue within one week.

*Brand Awareness*. Participants in YouGov's BrandIndex indicated whether they were aware of a brand or not. For each brand, the data includes weekly measures between 0 and 1 according

[38] This calculation equals the mean of a numerical variable with "$positive$" $= 1$, "$neutral$" $= 0$ and "$negative$" $= -1$.

to the share of consumers who were aware of the brand. To measure brand awareness prior to the event, this score was averaged over four weeks prior to the event.

*Brand Alignment*. To measure the alignment between the brand and the political stance of the CPA, this papers follows Schoenmueller *et al*. (2019) and measures brand preference partisanship as the difference in brand perception based on the political preference of the consumer. The same brand perception data from YouGov for the dependent variable was used and panelists were separated according to their political identifications. More precisely, consumers were first split into two groups depending on their self-identification as a "strong Democrat/Republican," "not very strong Democrat/Republican," or "lean Democrat/Republican." Consumers who answered the question with "independent" or "not sure" were not taken into account. The brand perception measures, as discussed above, were then calculated in a timeframe six months before an event for both groups and took the difference to calculate the brand preference partisanship. Table I reports the brands with extreme values of preference partisanship (i.e., the differences between Democrat and Republican perceptions).

**Table I.** Brand perception by political preference

| Brand | Democrat Perception | Republican Perception | Difference |
|---|---|---|---|
| Uber | .47 | .40 | .07 |
| JPMorgan Chase | .34 | .28 | .06 |
| Google | .77 | .71 | .06 |
| Morgan Stanley | .29 | .23 | .06 |
| Twitter | .45 | .39 | .06 |
| … | … | … | … |
| Under Amour | .46 | .54 | -.08 |
| IBM | .33 | .40 | -.07 |
| Dick's | .37 | .46 | -.09 |
| Campbells | .62 | .72 | -.10 |
| Ford | .53 | .63 | -.10 |

To measure brand alignment, the difference value in the last column of Table I was multiplied by -1 in case the position taken by the brand was a Republican standpoint.

*Time*. Changing responses to CPA events over time were controlled for by including the number of days since the first event in the event list. Accordingly, the time variable controlled for a time-dependent linear shift in consumer reactions to CPA.

*Controversy*. Recent work examining brands' interactions with stakeholders highlights that CPA differs from other corporate actions such as CSR because it involves a brand taking a stance on a controversial issue, as opposed to supporting a cause that receives universal support or a mix of support and ambivalence (Bhagwat *et al.* 2020; Hydock *et al*. 2020; Weinzimmer and Esken 2016). The controversial nature of CPA is critical to understanding the consumer response. Although some consumers support CPA, those who oppose a stance have a stronger reaction, which is why there is typically a negative response to CPA (Hydock *et al*. 2020). In contrast, CSR typically (but not always) induces a positive response because it is uncontroversial and viewed as socially responsible (van Marrewijk 2003; Yoon *et al*. 2006). However, CPA and CSR are not binary constructs; they exist on a continuum. Consider a company's response to the Black Lives Matter movement: At the controversial end of the continuum (CPA), the company might support defunding the police, which is likely to induce strong support and opposition. On the uncontroversial end of the spectrum (CSR), the company might support hate crime legislation, which is likely to induce strong support and limited opposition. In the middle of the spectrum, the company might support police reform, which might invoke more opposition than hate crime legislation, but less opposition than defunding the police. As stated previously, because a negative response to CPA is a function of its controversial nature, which induces similar amounts of support and opposition (the latter of which is stronger), the results were expected to be contingent on the identified events actually being CPA rather than CSR (i.e., controversial). Accordingly, the extent to which each CPA issue was seen as controversial was measured in a pretest. Specifically, workers from MTurk ($M_{age}$ = 38.90; 52% male; US residents with 95% HIT approval rate) were recruited to rate the CPA events in terms of how controversial, political, socially responsible, and charitable they were on a 7-point scale (1 = "strongly disagree"; 7 = "strongly agree"). To control for possible correlations between the workers' political attitudes and the four items mentioned above (e.g., supporters of a CPA action might be more likely to deem it socially responsible), a politically balanced sample was recruited ($M_{political\ orientation}$ = 4.06) using a pre-screen that employed quota sampling based on participants' political orientation (7-point scale, very liberal to very conservative). Furthermore, the event descriptions were anonymized by removing the explicit names of politicians and brands. This dataset served as a manipulation check: workers agreed that the CPA events (averaging across events) were political ($M = 5.43$, $SD = 1.51$ $t(34) = 18.49$, $p < .001$) and controversial ($M = 5.33$, $SD = 1.47$, $t(34) = 22.81$, $p < .001$) but neither agreed nor disagreed that the events were socially responsible ($M = 3.90$, $SD = 1.86$, $t(34) = -.93$, $p > .1$) and disagreed that they were charitable ($M = 3.20$, $SD = 1.75$, $t(34) = -9.75$, $p < .001$). A principal component analysis (PCA) shows two components that accounted for 82% of the variance, with the first component receiving high factor loadings from political (.85) and controversial (.90), while socially responsible (.76) and charitable (.91) loaded on the second component. According to the highest loading items, these components were labeled controversial and charitable. See the details of the results in Web Appendix Table WA1. As the controversial nature of CPA is critical to distinguishing it from CSR, controversy was also included as a covariate in the models. It should be noted that similar results were found when charitable was included as a covariate.

Table II summarizes all variables, their operationalization, and the source used to obtain the data.

**Table II.** Variables for the regression model.

| Variable | Operationalization | Source |
|---|---|---|
| *Cumulated Abnormal Brand Perception* | Difference between expected and actual brand perception in the first two weeks after the event; outcome of the event study | YouGov |
| *Online Protest* | Number of tweets with stated boycott intention related to the brand | Twitter |
| *Effort* | Whether the CPA action required effort (1) or not (0) | Coded |
| *Concurrence* | Whether multiple brands (1) or a single brand (0) conducted a similar CPA action around the same time (i.e., not more than one week between the events) | Coded |
| *Brand Awareness* | Average share of consumers who were aware of the brand four weeks before the CPA event | YouGov |
| *Brand Alignment* | Difference in brand perception of liberal vs. conservative consumers | YouGov |
| *Time* | Time of the CPA event measured in days since the first event of the sample | Coded |
| *Controversy* | How controversial and political a CPA action was perceived to be | MTurk |

***Sample***

To empirically study the hypothesized effects of CPA, a broad sample of brands engaging in polarizing sociopolitical issues was collected (Hydock *et al*. 2009; Wettstein and Bauer 2016). To generate this sample, an extensive newspaper search using LexisNexis and Google News on articles published in 2016, 2017, and 2018 was conducted. As there is no uniform vocabulary signaling CPA, this research focuses on a set of polarizing and controversial issues: gun control policy, immigration policy, abortion policies, transgender rights, campaigns of Democratic/Republican lawmakers, and protestors kneeling during the national anthem (Morning Consult 2018). To identify brand involvement with these polarizing issues, search terms representing polarizing issues were combined with search terms for brand involvement (i.e., “brand/company/CEO” + “endorse/take a stand/support”). This yielded 172 events. 48 events in which the brand was generally not included in the YouGov consumer panel, 16 for which there were insufficient weekly interviews in the panel, and two that were directed at a business unit of the brand operating in a country other than the United States were then removed. This left 06 CPA events for the analysis involving 92 companies. A list of all the events can be found in Web Appendix Table WA2. In the sample, 60% of the events were high-effort CPA, and for 81% of the events concurrence was observed. Online protests after CPA ranged from a minimum of 11 tweets to a maximum of 44,720 tweets, with an average (median) of 1,410 (145) tweets.

***Methodology***

To model the effect of CPA on brand perception, this paper follows the event study regression approach (Ball and Brown 1968; Sorescu *et al*. 2017). For example, Hansen *et al*. (2018) used the event study methodology to analyze the impact of social media firestorms on brand perception. For each CPA event, the expected brand perception was estimated for the two weeks after the event and compared with the actual brand perception to determine the abnormal change in brand perception as a temporal consequence of the CPA event. A mediation model was then used to explain abnormal changes in brand perception using the variables discussed above.

The univariate time series of weekly brand perceptions was indexed by $t$, where $t < 0$ reflects all weeks before the event, $t = 0$ is defined as the week in which the last day is the event day, and $t > 0$ are all weeks following the event.

To predict univariate time-series brand perception data, ARIMA($P_m, D, Q_m$) is applied. *Brand perception* for event $m$ is thereby explained by its own $P_m$ lagged values, $Q_m$ lagged values of the error, a constant $c$, and an error term $\varepsilon$. As the autoregressive and moving-average structure are assumed to differ between companies, the model allows flexible model specifications (i.e., choose $P_m$ and $Q_m$ for each event $m$). By checking for the best fitting model with a minimum Bayesian information criterion (BIC) for each event, a more accurate prediction compared to a single prediction model covering all brands is enabled. In the simplest case, the model predicted brand perceptions as the mean of past values ($P_m = Q_m = 0, c_m \neq 0$). Formally, the model was given by

$$\Delta BP_{m,t} = c_m + \varepsilon_{t,m} + \underbrace{\sum_{i=1}^{P_m} \varphi_i \Delta BP_{m,t-i}}_{\mathrm{AR}(P_m)} + \underbrace{\sum_{j=1}^{Q_m} \chi_i \varepsilon_{t-j}}_{\mathrm{MA}(Q_m)}, \tag{1}$$

where $\mathrm{BP}_{m,t}$ represents *brand perception* in connection with event $m$ in week $t$. The $\mathrm{AR}(P_m)$ component of Equation 1 accounts for the autoregressive part of the model with unknown parameters $\varphi_1, \ldots, \varphi_{P_m}$ for order $P_m$, and $\mathrm{MA}(Q_m)$ represents the moving-average part with unknown parameters $\chi_1, \ldots, \chi_{Q_m}$ for order $Q_m$, and $\epsilon_{t,m}$ is the residual. Due to the fact that ARIMA models are defined for stationary time series, in the case of a non-stationary time series, first differences have to be used in order to satisfy stationarity conditions, i.e., $\Delta BP_{m,t} = BP_{m,t} - BP_{m,t-1}$.

The ABP was then calculated as the difference between the actual brand perception and the predicted brand perception from Equation 1:

$$ABP_{m,t} = BP_{m,t} - E\left(BP_{m,t}\right). \tag{2}$$

CABP was calculated for the first two weeks after the event by averaging the ABPs:

$$CABP_m = (ABP_{m,1} + ABP_{m,2})/2. \quad (3)$$

In the next step, the model as depicted in Figure 1 was estimated using the R package lavaan. Bootstrap standard errors were computed given the small sample size of n = 106 events. All variables except the binary predictors *consensus* and *effort* entered the model z-standardized. In addition, the number of tweets underlying the *online protest* variable was log-transformed.

## *Results*

*Event Study*. The ARIMA model from Equation 1 was fit to the n = 106 CPA events. The minimum number of respondents per week was 93, which was sufficient to obtain robust weekly estimates. Note that only respondents who were aware of the brand were asked about their perceptions, which resulted in smaller sample sizes underlying weekly brand perception. To estimate the model, weekly brand perception data starting from 2016 was used. Accordingly, the number of observations before the event differed depending on the date of the event and the time point at which the brand was included in the panel survey. Figure 2 depicts the histogram for the mean sample size, as well the number of observations (i.e., weeks) before the event.

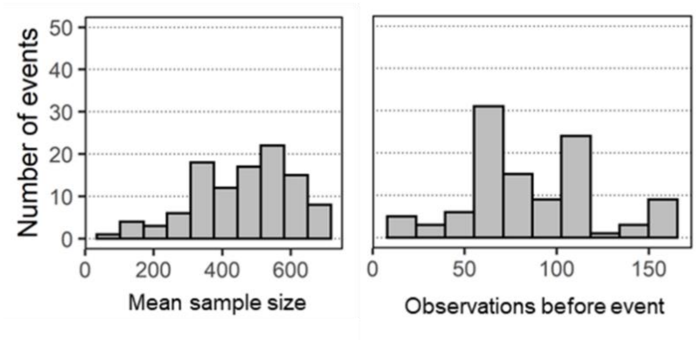


**Figure 2.** Histogram for mean sample size and number of observations before the event for weekly brand perception.

To check the stationarity of the univariate brand perception time series, a Dickey–Fuller test for the null hypothesis that a unit root is present in the process was conducted. The process proved not stationary for most of the events.[39] Accordingly, to achieve the highest comparability among brand-level predictions, all ARIMA models used the first difference $\Delta BP_{m,t}$ instead of $BP_{m,t}$. Table III depicts the event individual model specifications. The mean ABP, standard error, p-value, and the share of companies with negative perceptions are depicted in Table IV. Evidently, ABPs were significantly negative after the event, which confirms $H_{1a}$.

[39] The time series for brand perception (brand awareness) was stationary for 38 (32) companies ($p \leq .01$), while the others 68 (74) models proved to be not stationary ($p > .01$).

**Table III.** ARIMA model specifications.

| Order | AR | MA | AR+MA |
|---|---|---|---|
| 0 | .83 | .12 | .07 |
| 1 | .04 | .79 | .72 |
| 2 | .07 | .03 | .09 |
| 3 | .05 | .02 | .09 |
| 4 | .02 | .02 | .05 |
| 5 | .00 | .02 | .05 |

Notes: The numbers represent the relative share of models with the specific order.

**Table IV.** Main effects of CPA on abnormal brand perception (ABP).

| Week | *ABP* | SE | p | Negative perception (% of events) |
|---|---|---|---|---|
| 0 | -.278 | .369 | .452 | 49.1 |
| 1 | **-1.710**** | .516 | .001 | 60.4 |
| 2 | **-2.291**** | .545 | .000 | 68.9 |

Notes: **p < .01.

*Mediation Model*. In the next step, all $ABP_m$ were cumulated for the first two weeks after the event to compute $CABP_m$ as the dependent variable. The R package lavaan was then used to estimate a mediation model with maximum likelihood estimator and bootstrap standard errors. The fitted model was significant ($\chi^2$ = 67.445, p < .001) with a log-likelihood of -49.810, Akaike information criterion (AIC) of 129.620, and BIC of 169.571. The results of the parameter estimated are summarized in Table V. All non-binary variables were z-standardized except online protest. The estimated effects on online protest can therefore be converted to a percentage change in the number of tweets given a change in the explanatory variable of one standard deviation.

The strength of the online protest had a significant negative effect on brand perception (b = -.006, p < .01), which confirms $H_2$. The results also show a significant negative direct effect of effort (b = -.032, p < .01) and a significant positive direct effect of concurrence (b = .031, p < .050), which confirms $H_{3a}$ and $H_{3b}$.

**Table V.** Regression results.

| Estimate | Estimate | SE | p-value | Hyp. |
|---|---|---|---|---|
| Direct effect on CABP | | | | |
| *Online Protest* | **-.006**** | .002 | .005 | **$H_2$: -** |
| *Effort* | **-.032**** | .011 | .003 | **$H_{3a}$: -** |
| *Concurrence* | **.031*** | .015 | .035 | **$H_{3b}$: +** |
| *Brand Awareness* | -.005 | .005 | .335 | |
| *Brand Alignment* | -.003 | .004 | .459 | |
| *Time* | .008 | .006 | .156 | |
| *Controversy* | **-.007**† | .004 | .079 | |
| Direct effect on online protest | | | | |
| *Effort* | **2.156***** | .611 | .000 | **$H_{4a}$: -** |
| *Concurrence* | -1.119 | .701 | .110 | **$H_{4b}$: +** |
| *Brand Awareness* | **.419**† | .235 | .074 | |
| *Brand Alignment* | .130 | .214 | .542 | |
| *Time* | **-.700*** | .309 | .023 | |
| *Controversy* | .340 | .311 | .275 | |
| Indirect effect on CABP via online protest | | | | |
| *Effort* | **-.012*** | .006 | .038 | |
| *Concurrence* | .007 | .005 | .187 | |
| *Brand Awareness* | -.002 | .002 | .172 | |
| *Brand Alignment* | -.001 | .001 | .578 | |
| *Time* | **.004**† | .002 | .071 | |
| *Controversy* | -.002 | .002 | .338 | |
| Total effect on CABP | | | | |
| *Effort* | **-.044***** | .011 | .000 | |
| *Concurrence* | **.037*** | .017 | .031 | |
| *Brand Awareness* | -.007 | .006 | .189 | |
| *Brand Alignment* | -.003 | .004 | .397 | |
| *Time* | **.012*** | .006 | .026 | |
| *Controversy* | **-.009*** | .005 | .048 | |

Notes: †p < .10, *p < .05, **p < .01, ***p < .001.

Regarding effects on online protest strength, only effort has a significant effect (b = 2.156, p < .01), which confirms $H_{3b}$. As this relation was log-linear, the actual effect size of effort was $(e^{2.156} - 1)$ = 7.637, indicating a more than seven times increase in protest strength for high-effort CPA. The indirect effect of effort on brand perception through online protest was also significant (b = -.012, p < .05). The effect of concurrence on online protest was not significant (b = -1.119, p = .110). Therefore, $H_{4b}$ is rejected. However, the total effects of concurrence (b = .037, p < .50) and effort (b = -.044, p < .001) significantly affected brand perception.

Regarding the control variables, time had a significant positive total effect on brand perception (b = .012, p < .50), which was significantly mediated via online protests (b = .004, p < .10) but with no significant direct effect (b = .008, p = .156). The effects of brand awareness (b = -.007, p = .189) and brand alignment (b = -.003, p = .397) were not significant, even though brand awareness had a slightly significant positive effect on online protest (b = .419, p < .10).

### *Alternate Models*

Two alternate models were tested. First, traditional linear regression without online protest as a mediator was used. The results were similar, although controversy had no significant effect. Second, following Hansen *et al*. (2018), a model that did not include online protest strength as observed (i.e., the number of tweets) but as estimated from an auxiliary regression model[40]. The auxiliary model includes online protest as the dependent variable, and all other variables as explanatory variables. The residuals of online protest (i.e., the variance in the online protest variable that was not explained by the rest of the variables) was then used as a predictor of ABP. The models show similar results, supporting the same hypotheses as above. Both models are depicted in Web Appendix Table WA3.

### *Alternative Dependent Variables for Customers*

To test the effect of CPA on customer brand perception, the same methodology explained in Equations 2 and 3 was used but the explained variable was restricted to customers rather than all consumers. Respondents of the YouGov survey were filtered according to their self-declarations about their customer status regarding past purchases of the companies' products. As some companies represented in the panel had few customers, 11 events with a mean sample size of less than n = 30 weekly observations were removed, as the resulting metric was highly volatile when the underlying sample was too small. In comparison, the minimum mean sample size for all consumers was n = 93 (see Figure 2). The results for the segment of non-customers who stated that they had never purchased a product from the respective brand was also recorded. The model used the aforementioned perception metric to measure ABP for both segments (i.e., customers and non-customers). As shown in Table VI, the main effects of CPA were stronger only when considering customers compared to non-customers and all consumers. The model confirmed $H_{1b}$, as CPA had a significant negative effect on customer brand perception in the first ($CABP_{customer}$ = -3.878, p < .01) and second weeks ($CABP_{customer}$ = -3.868, p < .01) after a brand's CPA. To test $H_{1c}$, a t-test to determine whether the difference between $CABP_{customers}$ and $CABP_{non\text{-}customers}$ was unequal to zero was used. The results are reported in Table VI and indicate that there was a significant difference in the first ($CABP_{difference}$ = -2.734, p < .01) and second weeks ($CABP_{difference}$ = -2.228, p < .05) after the event. Therefore, also $H_{1c}$ was confirmed.

[40] Note that technically this auxiliary model yields the same estimates as the direct effect on online protest in Table V.

**Table VI.** Main effects of CPA on abnormal brand perception by segment.

| Week | Cumulated abnormal brand perception (CABP) | | | |
|---|---|---|---|---|
| | Consumer (n=106) | Customer (n=95) | Non-customer (n=106) | Difference |
| 0 | -.278 | -.539 | -.224 | -.315 |
| 1 | **-1.710**** | **-3.870**** | **-1.136*** | **-2.734**** |
| 2 | **-2.291**** | **-3.868**** | **-1.640**** | **-2.228*** |

Notes: *$p < .05$, **$p < .01$.

## Discussion

Through the analysis, this paper provides insight into how consumer brand perception is affected by CPA and documented moderating effects. It contributes to the literature on CPA by filling three research gaps: The model showed a negative main effect of CPA on brand perception among consumers and that it is greater for customers than for non-customers (research gap (i)). It also showed that the effect of CPA depends on several key characteristics of the CPA event (research gaps (ii) and (iii))—namely, concurrence (i.e., multiple brands taking a similar stance simultaneously), which reduces negative outcomes directly, and the effort put into the CPA, which negatively affects brand perception and further increases the strength of the subsequent online protest, which in turn has a negative effect on brand perception. Third, the more controversial the CPA is perceived, the more negative is the change in consumer brand perception. Lastly, it was found that over the considered period, the negative effect of CPA on brand perception decreased slightly. The data suggests that this decrease might be due to the decreasing strength of online protests associated with CPA, perhaps because consumers are becoming more habituated to this form of brand positioning.

### *Theoretical and Empirical Implications*

Through the investigation of CPA's effects on brand perception, as well as the moderators of these outcomes, this paper builts on previous research. Theoretically, it first explores the moderating effect of online protest and the fact that protests mediate the relationship between effort and brand perception. Specifically, this paper uniquely shows that online protests amplify the negative impact of CPA on brand perception. It also contributes to the literature by showing that effort also increases the strength of social media protests following CPA.

Second, it was demonstrated that customers and non-customers differentially respond to CPA, finding that the former respond more negatively than the latter. This provides nuance to the existing research on CPA, which has until now only revealed an overall negative effect (Bhagwhat *et al*. 2020; Hydock *et al*. 2020).

This paper also contributes empirically by providing converging evidence for several moderators of CPA's impact on consumer brand perception. Specifically, recent work was extended by showing that concurrence mitigates and effort amplifies the negative effect of CPA on brand perception as they do with stock price (Bhagwat *et al.* 2020).

### ***Managerial Relevance***

An important aspect of marketing is to build a strong brand image with favorable perception (Keller 1993). Consumer brand perception directly affects buying behavior, market share, and the profitability of a brand, which subsequently is the basis for investment decisions that increase shareholder value (Luo *et al*. 2013). As the systematic building of positive brand perception requires a long-term strategy, it is crucial to understand how it is affected by targeted actions such as CPA.

The empirical analysis conducted in this study provides initial evidence for a mostly negative effect of CPA on brand perception. Thus, despite the documented calls by consumers for brands to engage in divisive sociopolitical topics (Austin *et al*. 2019; Bravo and Lee 2019; Coombs and Holladay 2018), brand managers should think very carefully about the risks involved. That said, it is possible that a brand with a very homogenous customer base in a political respect might be able to safely engage in CPA, as the portion of customers supporting the CPA might outweigh the relatively stronger responses of those who oppose it and CPA in general.

For brands with politically heterogeneous customer bases that still wish to engage in CPA, considering the findings of this paper can help reduce CPA's negative effects on brand perception. Specifically, the findings suggest that companies should follow other brands or even collaborate with other brands when implementing their CPA strategy, as acting concurrently can reduce its negative effect on brand perception. Furthermore, given that greater CPA effort can amplify its effects on brand perception, a brand that seeks to engage in CPA is advised to do so with less effort (e.g., via a statement rather than a donation). These findings are in line with those of Bhagwhat *et al*. (2020), which showed that concurrence positively and effort negatively affect shareholder reactions to CPA two days after the event. Notably this finding on effort contrasts with some research, and the resulting managerial implications for CSR, which states low (vs. high) effort initiatives can be less successful (Schons and Steinmeier 2015).

It was found that online protest is a strong predictor of ABP. From a managerial point of view, the strength of an online protest is not controlled by the brand. While Hansen *et al*. (2018) showed that online protests can have short- and long-term effects on brand perception and consumer memory, the findings showed that high-effort CPA can be even more dangerous, since greater effort translates into greater online protest strength.

This paper does not find that brand alignment had a significant moderating effect. Accordingly, brands that are perceived as positive (negative) by consumers who share (do not share) the political direction of the CPA before the event will still suffer a net decline in consumer brand perception. The operationalization most closely matches the "brand deviation" variable in Bhagwat *et al*. (2020), for which the authors did not find a significant effect on stakeholder decisions. Therefore, brands associated with a specific political stance will still provoke negative consumer reactions, on average.

It should be noted that the findings regarding the effect of CPA warrant long term investigation. This need emerges from the fact that over time (2016-2018), the direct effect of CPA on online protest decreased, raising the possibility that the negative response to CPA may diminish as they become more familiar with this relatively new brand action.

***Limitations and Future Research***

This study has several limitations that suggest directions for future research. These can be roughly placed into three categories: issues related to CPA motivation and main effects, CPA context, and CPA moderators.

*Motivation and Effects.* While this study focuses on the implementation and outcome of CPA, future research might investigate the motivation to explain why brands decide to take a stance. While some brands see CPA as an integral part of their positioning strategy, the majority of brands might be following bandwagon behavior, which might be perceived as inauthentic "woke washing" (Vredenburg *et al.* 2020; Schmidt *et al.* 2021). A challenging but potentially valuable contribution would be to operationalize authenticity (i.e., define a measure to quantify how authentic a CPA action is) and test this moderator in the framework provided in the empirical analysis of this paper.

In addition, CPA might have impacts on brand image that go beyond the immediate attitudinal responses elicited in consumers. For instance, CPA could induce positive associations (e.g., courageous, authentic, or principled) that generate longer-term positive attitudes and help consumers identify with the brand, making it a potential strategy to induce loyalty (Watson *et al*. 2015). While the analysis focuses on short-term consumer reactions, companies might also consider the long-term effects of CPA and effects of CPA on their employees and other stakeholders. Studying the long-term effects of CPA might also help academics understand the impact of brand actions on the dynamic nature of sociopolitical issues. For instance, in light of the omnipresence of brands (Swaminathan *et al*. 2020), it is possible that brand actions might be instrumental in changing public opinion on controversial issues.

*Context.* While this study yields high validity, given the real-life observations of the data, the utilized consumer panel is not suitable for inferring consumers' individual reactions to CPA. Continued research (based on tailor-made experiments, for instance) might seek to understand how the presented moderators impact individual responses (as opposed to the net effect) of CPA on brand perception and attitude. Further, this research might seek to measure consumers perceptions of CPA with an even larger sample (the pre-test was politically balanced but small in size). Such an investigation might uncover differences in how segments respond to and perceive CPA.

In the empirical analysis, it was found that the negative effect of CPA on brand perception has decreased slightly over time, indicated by a decreasing strength of online protests. One reason for this observation could be that CPA has become more commonplace in recent years, and consumers' motivations to participate in online protests have been driven by the novelty of CPA. Future research could use this observation as a starting point to evaluate consumers' online protest behavior over time.

It was also found that CPA has a more positive effect on brand perception if it is perceived as less controversial. Follow-up studies could build on this by considering how and under which conditions framing the CPA message as less controversial can elicit the most positive response.

*Moderators.* Future research might also consider how consumer–brand relationships and expectations impact consumer response to CPA. For example, in this study, a trend whereby the negative effect in the weeks after CPA were even more negative for customers relative to non-customers was observed (see Table VI). This finding suggests that the response to a brand's CPA can be impacted by existing relationships between the brand and its (potential) customers. While this paper documents a stronger effect of CPA on customer vs. non-customer responses, the current research was unable to parse the extent to which online protest was driven by customers vs. non-customers. Future research could explore which brands are most likely to be harmed by CPA as a function of their customers' social media use.

Future research might also examine how CPA and associated online protests affect brand awareness (i.e., the share of consumers who are aware of the brand). While past research has documented the beneficial effects of negative publicity, the ability of a brand to encourage protests through its own online presence (creating a persona that invites protest) presents an opportunity for (low-awareness) brands that seek to increase awareness through CPA. Future research might also consider how and whether other forms of protest (e.g., pickets and boycotts) impact the response to CPA.

In the current research, it was found that concurrence had a positive effect on brand attitudes but no effect on protest. While it is difficult to draw strong conclusions from such a null result, this suggests that protests might not lead to less favorable attitudes in all conditions. Future research with more statistical power might be able to clarify this result.

This research is among the first to empirically investigate the effect of CPA on brand perception, especially highlighting the role of online protests. The authors hope that this contribution serves as a platform for future research and discussion among academics and practitioners.

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## Education

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| • Business Administration and Economics (B. Sc.). Thesis: “A comparison between quantile and expectile regression models”. Overall grade: 1.9. | Bielefeld University | 2011 – 2014 |
| • Business Administration and Economics (M. Sc.). Thesis: “A method to analyze brand perceptions using user-generated content”. Overall grade: 1.6. | Bielefeld University | 2014 - 2017 |
| • Ph. D. (Dr. rer. pol.). Thesis: “Essays on Brand-Related User-Generated Content in Online Social Networks”. Summa cum lauda. | Bielefeld University | 2017 - 2022 |

## Employment

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| • Internship Market Research | TNS Infratest | 2012 (4 month) |
| • Working Student Market Research | Interrogare | 2014 - 2015 |
| • Internship Marketing Strategy and Insights | McDonald’s Germany | 2016 (6 month) |
| • Research Assistant | Bielefeld University | 2017 – 2022 |