The Role of Owned Social Media in Brand Strategy

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THE ROLE OF OWNED SOCIAL MEDIA IN BRAND STRATEGY

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Chapter I. Introduction

Many brands have established an active social media presence that allows them to interact directly with consumers. 94% of marketers worldwide use Facebook, 76% Instagram, 53% Twitter, and 53% YouTube (Guttmann 2020). Their use of social media has evolved over time. After Facebook launched, brands started joining the platform in 2008. Initially without a clear strategy, but now they employ sophisticated techniques for branding and use their posts for example to address important societal topics. As these media have become more and more important channels for brand communication, it is not surprising that brands are increasingly investing in the creation and distribution of content via social media.

Over the past few years, it has become common for brands to share content through their social media channels ("owned social media"; Colicev et al. 2018; Stephen and Galak 2012), expecting that their content stimulates social media engagement, earned social media, and sales (De Vries, Gensler, and Leeflang 2017; Hewett et al. 2016). Nevertheless, they may still question the overall return on their social media presence, as well as how they can design more effective owned social media campaigns along the purchase funnel (Appel et al. 2020). Assessing the strength of brands' social media marketing investment becomes especially important during strategic marketing decisions with managers wanting to understand the effect of their social media marketing investment on engagement or sales (Sprout Social 2023).

But not only does the shared content affect social media engagement, earned social media, and sales it can also affect consumers' brand associations. As marketers continue to invest in their social media efforts (Sprout Social 2021), they are in need of a solid understanding of *how their owned social media affect brands and consumers*. To answer this question, marketing scholars have conducted a large number of studies focusing on different sub questions. Their findings, however, are scattered across a wide range of academic outlets, and sometimes produce contradicting outcomes. One of the goals of this dissertation is to take stock of this research and use it to develop integrated insights into the impact and workings of brands' social media content. In addition to estimating the impact of social media content on consumers, work is needed to investigate the entire *chain of effects* that is triggered by owned social media: When a brand posts owned social media content, it generates *reach* via social media engagement, and through a more organic earned social media. It also activates and shapes consumers' *memory* for the brand, by creating and strengthening brand associations.

However, building and maintaining a strong positioning in the mind of the consumers requires continuous and active management, pushing brands to strike a balance between preserving their essence and core brand identity, and at the same time stay relevant in the eye of current trends and developments in society (e.g., Becker, Wiegand and Reinartz, 2019; Beverland, Wilnerm, and Mitchell 2015; Swaminathan et al. 2020). This tension is especially pertinent on social media platforms, which brands are increasingly leveraging to reach their customer base (Sprout Social 2021; Swaminathan et al. 2020) and as a strategic tool for brand building (CMO Survey 2023). On these platforms, brands can share content that reinforces their brand identity, or content related to societal issues that resonate with their target audience but may be unrelated to the brand's core, or even stay silent on topics that may be at their core. These adaptations may lead to misalignment between the positioning advocated by brands in their brand identity (conveyed in their mission statements) and their brand positioning (communicated via their social media content), creating a tension among the need of brands to stay relevant, avoid controversy, and the marketing communication mantra advocating for a consistent brand positioning.

1.1 Aim of This Dissertation

This dissertation aims to better understand the role of owned social media for strategic branding decisions. More specifically, to provide managers with clear guidelines on how to use their social media communication to affect important business outcomes along the purchase funnel from social media engagement, earned social media, brand associations, or sales. The aim is to develop generalizable insights into the use and impact of owned social media across different brands, industries, platforms, or countries in all three essays. The essays provide managers with recommendations on how they can best use owned social media content to communicate their brand identity. Special attention is given to content focusing on societal topics such as sustainability, community, and diversity. These topics gain more and more importance amongst consumers, so that brands need to decide how to address them. I propose that brands can approach this in different ways, including extending their communication to go beyond their core brand identity and highlighting the greater perils of hushing practices that have been largely overlooked in both literature and managerial guidelines.

1.2 Overview of Essays

The three essays of this dissertation are presented in Chapters 2 to 4. The first essay (Chapter 2) examines whether and when owned social media stimulate sales and not only social media engagement, highlighting which owned social media content is most effective and which other contextual factors moderate the effects. The second essay (Chapter 3) focuses on how owned social media affect consumers and presents the chain of effects that starts from consumers' exposure to a brand's social media through social media engagement, earned social media, and the creation and nurturing of brand associations, to ultimately influence consumer buying behavior. Chapter 4 examines how brands can use social media to extend their brand positioning to newer relevant topics and whether brands can stay silent about more polarizing topics without losing customer support. The three essays collectively address key questions concerning the effectiveness and strategic use of owned social media by brands, covering a broad range of topics. Through various methods, including meta-analyses and empirical research, they explore how owned social media impact both brands and consumers, contributing to a comprehensive understanding of social media marketing and branding strategies across diverse industries and countries. Chapter 5 summarizes the key contributions of this dissertation and presents directions for future research.

1.2.1 Essay 1

Essay 1 examines the impact of owned social media on social media engagement and sales, taking into account content, brand, industry, platform, and country characteristics. The chapter – which has been published in the *Journal of Marketing* – describes a meta-analysis of 1,641 elasticities obtained from 86 studies spanning from 2011 to 2021. Using elasticities allowed me to capture managerially more directly interpretable and useful effect sizes. Supporting some current beliefs (e.g., owned social media are more effective to boost sales for new [vs. mature] products), Chapter 2 also highlights several novel insights. Contrary to popular beliefs that owned social media mainly drive engagement and hardly affect sales, the results show the opposite. In addition, the results suggest ways to better adapt owned social media content to communication goals. To create engagement, content needs to focus on emotional needs and steer away from deals, which are the least effective content type. To stimulate sales, content should be more functional, rather than emotional, in nature and communicate product benefits.

Surprisingly, a large social media community is not essential for boosting sales, as owned social media are more effective for brands with fewer followers. Furthermore, while using one global social media strategy is tempting, owned social media are more effective in countries with high power distance.

1.2.2 Essay 2

Essay 2 addresses how owned social media affect consumers and explores the chain of effects set in motion by a brand's owned social media. It complements the meta-analysis of Chapter 2 by looking at the (much) larger set of studies that provides correlational data about the relationships between brands' own social media content and consumer behavior. Correlations are the preferred method for assessing a chain of effects as they provide a quantitative measure of the strength and direction of relationships between variables. This chapter proposes an "owned social media value chain" and analyzes the impact of owned social media on consumer buying behavior via social media engagement, earned social media, and brand associations. The framework reconciles conflicting results from previous research, drawing from 805 effect sizes based on correlations collected across 142 papers. The results suggest that the impact of owned social media on consumer buying behavior is established only through chain effects. Owned social media affect social media engagement and earned social media (reach), and together they influence brand associations (memory), which is the primary driver of consumer buying behavior. Moreover, these analyses confirm that owned social media can be an effective tool for managers seeking to stimulate earned social media and consequently consumer buying behavior. Finally, the meta-analysis shows how the effects vary across different types of social media platforms, including social networks, microblogs, blogs, forums, and brand communities.

1.2.3 Essay 3

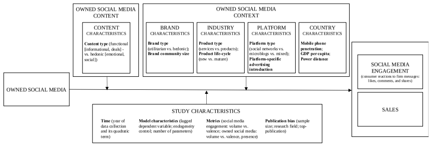
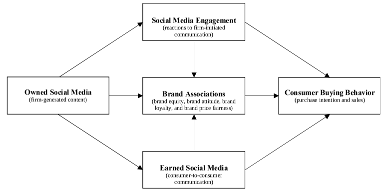
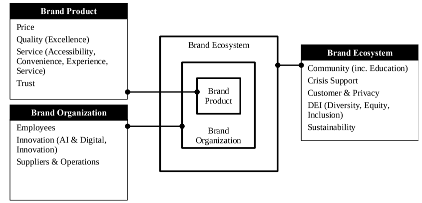
Essay 3 examines the relationships between brand positioning and social media content, whose investigation has been called for by the Marketing Science Institute’s Research Priorities (2022-2024). Social media has enabled and forced brands to take a more interactive approach to brand building, allowing brands to adapt to the evolution of consumers and the marketplace to stay relevant. These adaptations may result in a misalignment between the brand positioning articulated in their mission statements and the content shared on their social media. This can create tension among the brands' need to stay relevant, controversy avoidance, and the marketing communication mantra advocating for a consistent brand positioning. Such a misalignment may erode customer support. Exploring these issues, this essay establishes how brands can use social media to expand their brand positioning into newer, relevant topics without risking the loss of customer support, but also acknowledges that brands can maintain silent on more polarizing topics without facing a decline in customer support. Essay 3 studies the consequences of this misalignment on consumer engagement. The results emphasize that brand positioning misalignment does not hurt customer support when it allows the brand to stay relevant. Instead, when misalignment means positioning hushing it can substantially erode customer support.

1.3 Contributions

This dissertation contributes to the social media marketing and branding literature streams by highlighting the role of owned social media in brand strategy (see Table 1.1. for an overview of the main findings and contributions of each essay). The findings of this dissertation provide recommendations for both academics and managers. Using meta-analytical techniques, Essays 1 and 2 generalize across a large variety of settings, focusing on both elasticities and correlations to quantify the impact of owned social media on important marketing outcomes such as social media engagement, earned social media, brand associations and sales. Essay 1 provides implications for making an informed decision on how to leverage owned social media by revealing not only which owned social media content is more effective but also which brand, platform, and country characteristics have stronger effects. Essay 2 assists in gaining a clear understanding of the direct and indirect effects along the owned social media value chain. This enables them to better estimate the desired marketing outcomes.

Essay 3 offers an overview of various brand positioning dimensions, drawing from previous literature and current managerial practices. While the literature on brand communication has traditionally advocated the benefits of consistent marketing communication, this essay shows that misalignment may lead to higher customer support, quantifying the effects of extending and hushing as brand positioning strategies, and exploring when these alternative approaches may be more effective. In doing so, the chapter also provides relevant insights into the risks associated with brand positioning misalignment, such as green hushing or diversity hushing on social media.

Table 1.1. Focus and Summary of the Studies in the Dissertation

	Essay 1 (Chapter 2)	Essay 2 (Chapter 3)	Essay 3 (Chapter 4)
Title	*"A Meta-Analysis of the Effects of Brand Owned Social Media on Social Media Engagement and Sales"*	*"The Owned Social Media Value Chain: A Meta-Analysis on the Chain of Effects from Brand Owned Social Media to Consumer Buying Behavior"*	*"Brand Positioning Misalignment: Focus on the Ecosystem"*
Framework			
Research questions	• Are owned social media effective? • Which owned social media content is most effective? • Which other contextual factors moderate the effects?	• How do owned social media affect consumers? • What is the chain of effects which is set in motion?	• To what extent do brands' ecosystem positioning on social media misalign with their core brand identity? • Can brands use social media to extend their brand positioning without losing customer support? How do consumers respond when brands stay silent on ecosystem topics that are core to their brand identity? • Can brand actions offset the potential negative effect linked to the ecosystem positioning extending or hushing approaches?
Literature streams	• Social media marketing • Branding • Cross-country marketing	• Social media marketing • Branding	• Social media marketing • Branding
Research method	• Meta-analysis • Hierarchical linear model	• Meta-analysis • Structural equation model	• Regression • Control function approach
Data	1,641 meta-analytical effect sizes based on elasticities across 86 papers spanning from 2011 to 2021 and covering 31 industries, 14 platforms, and 17 countries	805 meta-analytical effects sizes based on correlations across 142 papers spanning from 2008-2019 and covering 21 platforms, 31 industries, and 34 countries	175,788 tweets from 136 global brands as well as mission statement from between 2021 and 2022 next to brand ESG scores from the Refinitiv database
Key dependent variables	• Social media engagement • Sales	• Consumer buying behavior • Brand associations	• Social media engagement
Key independent variables	• Owned social media	• Owned social media • Social media engagement • Earned social media	• Brand positioning dimensions • Brand positioning misalignment • Brand actions
Key results	• Owned social media create social media engagement, but the elasticity for sales is even larger. • For social media engagement, emotional content is more effective than other types of content, most likely	• Overall correlations between owned social media and the different behavioral outcomes are positive and significant. Total positive impact of owned social	• There is a substantial gap between the call to embrace the UN SDG goals and the dimensions that brands prioritize in their mission, as brands tend to focus more

	Essay 1 (Chapter 2)	Essay 2 (Chapter 3)	Essay 3 (Chapter 4)
	because it creates emotional arousal that fosters message liking and sharing. For sales, informational content is more effective than emotional and deals content, as it aids consumers in their purchase decisions. • The effect of owned social media on sales is stronger in smaller brand communities than in larger ones. The effect of owned social media on sales is stronger for new products than mature products. Owned social media are weaker on microblogs for social media engagement than on social networks given closer ties. Owned social media are more effective for sales in countries with higher mobile phone penetration and higher power distance.	media on consumer buying behavior is only established through the chain of effects. • At the start of this chain, owned social media influences social media engagement and earned social media (reach), and together they reinforce brand associations (memory). We empirically confirm that brand associations play an important mediating role at the center of the social media value chain.	on product and organization dimensions compared to ecosystem dimensions. • Brands do not lose customer support from extending their brand positioning on ecosystem dimensions to stay relevant on these topics. A silent brand positioning strategy on ecosystem dimensions leads to the lowest levels of social media engagement. • When community positioning is backed with actions, brands see higher levels of engagement. For brands that already score highly on the environmental ESG score, extending leads to lower levels of engagement. Consumers engage less with brands that invest more into diversity or environment initiatives but do not communicate sufficiently on their DEI or sustainability positioning on social media.
Theoretical contributions	• Consolidation of literature with systematic comparisons • Generalization across a large variety of settings reconciling conflicts in the literature • Overview of consequences of methodological choices and of important gaps in the literature	• Consolidation of literature with systematic comparisons • Proposing the owned social media value chain as framework • Confirming the role of brand associations at the center of the owned social media chain of effects	• Overview of brand positioning dimensions (including newer dimensions related to the UN SDG) • Development of brand positioning dictionaries • Conceptualization of brand positioning misalignment and showcasing instances when brands can and cannot misalign
Managerial implications	• Brands may underestimate the impact of their owned social media if they focus only on easy-to-measure metrics, such as those linked to social media engagement (e.g., likes, shares of owned social media posts). • Owned social media content needs to be adapted to the targeted outcome variable: whereas for social media engagement, managers need to focus on content expressing emotional needs (“the how”), for sales, objective information-based content (“the what”) has a stronger impact than emotional content. • It is more important to focus on the quality rather than quantity of followers. Managers need to address the platforms that are most appropriate by, for example, relying on social networks (Facebook) to stimulate social media engagement. Because many platforms are international, using one global social media strategy is tempting, but managers cannot count on the same type of response across countries.	• Managers should consider the entire ecosystem of effects set in motion by owned social media including social media engagement, earned social media, brand associations and consumer buying behavior. When comparing social media engagement with earned social media we observe similar correlations. Social media engagement can lead to similar results as earned social media. Given how simpler it may be to generate engagement compared to earned social media, managers can rely on levers they can more directly influence (social media engagement). • Our results provide strategic guidance to marketers concerned about the effectiveness of their social media efforts: a brand post on social media is able to affect consumer buying behavior if and only if it is able to reach consumers and make a memorable impression.	• Managers should recognize that customers nowadays seek more than just products and organization as they look for brands that align with their values and contribute positively to society. Managers can incorporate brand ecosystem positioning dimensions. by fostering conversations around these topics on social media. When they are part of the brand’s identity, staying silent on these dimensions can hurt consumer engagement. • Actively promoting ecosystem topics on social media allows brands to extend their brand positioning on these topics. Consumers do not appreciate any form of hushing (e.g., green, diversity, social), as they expect brands to talk about important societal issues if they are at the core of a brand’s identity. • For certain dimensions such as the community dimension managers should showcase the brands’ community efforts on social media if it aligns with the brands’ actions (“walk the talk”).

References

Appel, Gil, Lauren Grewal, Rhonda Hadi, and Andrew T. Stephen (2020), “The Future of Social Media in Marketing,” *Journal of the Academy of Marketing Science*, 48 (1), 79–95.

Becker, Maren, Nico Wiegand, and Werner J Reinartz (2019), "Does It Pay to Be Real? Understanding Authenticity in TV Advertising," *Journal of Marketing*, 83 (1), 24-50.

Beverland, Michael B (2005), "Crafting Brand Authenticity: The Case of Luxury Wines," *Journal of Management Studies*, 42 (5), 1003-29.

Colicev, Anatoli, Ashwin Malshe, Koen Pauwels, and Peter O’Connor (2018), “Improving Consumer Mindset Metrics and Shareholder Value Through Social Media: The Different Roles of Owned and Earned Media,” *Journal of Marketing*, 82 (1), 37–56.

De Vries, Lisette, Sonja Gensler, and Peter S.H. Leeflang (2017), “Effects of Traditional Advertising and Social Messages on Brand-Building Metrics and Customer Acquisition,” *Journal of Marketing*, 81 (5), 1–15.

Guttmann, Agnieszka (2020), “Leading Social Media Platforms Used by Marketers Worldwide as of January 2020,” *Statista* (July 15), https://www.statista.com/statistics/259379/social-media-platforms-used-by-marketers-worldwide/#:~:text=As%20of%20January%202020%2C%20Facebook,percent%20did%20so%20via%20Instagram.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), “Brand Buzz in the Echoverse,” *Journal of Marketing*, 80 (3), 1–24.

Marketing Science Insitute (2022), “Marketing Science Insitute Research Priorities 2022-2024,” https://www.msi.org/article/msi-announces-2022-24-research-priorities/

Sprout Social (2021), “The State of Social Media: After a Year of Transformation, Executives Are All-In on Social,” https://sproutsocial.com/insights/data/social-mediafuture-of-business-intelligence/.

Sprout Social (2023), “The Social Media Metrics to Track in 2023 (and Why),” (July 20), https://sproutsocial.com/insights/social-media-metrics/#engagement-metrics

Stephen, Andrew T. and Jeff Galak (2012), “The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace,” *Journal of Marketing Research*, 49 (5), 624–39.

Swaminathan, Vanitha, Alina Sorescu, Jan-Benedict EM Steenkamp, Thomas Clayton Gibson O’Guinn, and Bernd Schmitt (2020), "Branding in a Hyperconnected World: Refocusing Theories And Rethinking Boundaries," *Journal of Marketing*, 84 (2), 24-46.

Chapter II. A Meta-Analysis of the Effects of Brand Owned Social Media on Social Media Engagement and Sales[1]

Abstract

What are the effects of a brand's owned social media? This meta-analysis examines the impact of owned social media on social media engagement and sales. Whereas the findings support some current beliefs (e.g., owned social media are more effective to boost sales for new [vs. mature] products), it highlights several novel insights. Contrary to popular beliefs that owned social media mainly drive engagement and hardly affect sales, the results show the opposite, with an average elasticity of .137 for social media engagement and .353 for sales. In addition, the results suggest ways to better adapt owned social media content to communication goals. To create engagement, content needs to focus on emotional needs and steer away from deals, which are the least effective content type. To stimulate sales, content should be more functional, rather than emotional, in nature and communicate product benefits. Surprisingly, the authors find that growing a large social media community is not essential for boosting sales, as owned social media are more effective for brands with fewer followers. Furthermore, while using one global social media strategy is tempting, owned social media are more effective in countries with high power distance, calling for a less uniform approach.

Keywords: owned social media, social media engagement, sales, owned social media content, meta-analysis

[1] Published as Liadeli, Georgia, Francesca Sotgiu, and Peeter W. J. Verlegh (2023), "A Meta-Analysis of The Effects of Brands' Owned Social Media on Social Media Engagement and Sales," *Journal of Marketing*, 87 (3), 406-27.

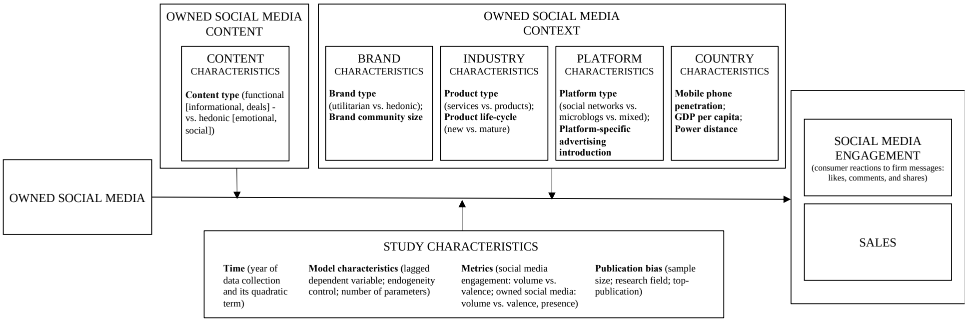
2.1 Introduction

With more than three billion social media users worldwide, brands have long recognized social media's ability to generate strong marketing outcomes, such as social media engagement and sales (Moorman 2018). Many brands have established an active social media presence that allows them to interact directly with their customers. This type of brand-controlled social media is commonly termed "owned social media" (Stephen and Galak 2012). Recent surveys indicate that social media marketing budgets will increase in the next three years (for 91% of firms) and that 62% of consumers believe that brands will succeed in the long run only if they have a strong social media presence (Sprout Social 2021). While brands are increasingly investing in owned social media, they may still question the overall return on their social media presence, as well as how they can design more effective owned social media campaigns along the purchase funnel (Appel et al. 2020).

In this article, we address three major questions that social media marketers are facing: First, brands that share their content through social media channels expect this content to stimulate social media engagement (likes, comments, or shares; De Vries, Gensler, and Leeflang 2017). Yet are owned social media also able to affect sales, or do they affect only social media engagement? Second, regardless of whether owned social media can significantly affect different brand metrics, such as engagement and sales, not all owned social media content is created equal: Content that generates social media engagement may not necessarily lead to additional sales. While social media marketing courses tend to highlight the importance of using "social" content (e.g., "End your posts with a question," "Make use of hashtags" "Involve your customers in online competitions") or relying on deals, generalizable knowledge on this topic is lacking. Can social content and deals engage customers more than other types of content? Are they also a more effective way to lift sales than other owned social media messages? Finally, different types of brands likely need different types of strategies: what works for hedonic brands may not work for more functional brands, and what works for products may not apply to services. Managers changing industries or searching across industries for inspiration may want to know whether owned social media are equally effective across different settings, enabling them to build on their or other brands' experience, or whether they must rethink the contribution of owned social media to their brand performance.

To address these questions, we conduct a meta-analysis on the large body of research on the effectiveness of owned social media to integrate studies' findings and explain their differences along three dimensions: variation along owned social media content, context (brand, industry, platform, and country), and study characteristics (see Figure 2.1). In addition, we contribute to the literature in three ways. First, research on the effectiveness of owned social media provides divergent results. For example, whereas some studies suggest that owned social media have a positive effect on sales (e.g., Hewett et al. 2016), others do not find a significant impact (e.g., Stephen and Galak 2012) or observe a negative relationship (e.g., Goh, Heng, and Lin 2013), further contributing to managers' uncertainty about the sales effectiveness of owned social media. Using meta-analytical techniques that enable us to generalize across a large variety of settings, we focus on elasticities to quantify the impact of owned social media volume (the number of posts) while also capturing the impact of different operationalizations of owned social media, such as valence (degree of positivity) and presence (vs. absence) of a brand social media post. We do so for two marketing outcomes: social media engagement and sales. Our findings are based on a meta-analysis on 1,641 elasticities across 86 studies spanning from 2011 to 2021 and covering 31 industries, 14 platforms, and 17 countries. Contrary to managerial beliefs that owned social media are primarily an engagement tool, we observe a stronger impact of owned social media on sales.

Figure 2.1 Conceptual Framework



Second, to consolidate the literature, we examine how owned social media content and context characteristics moderate the impact of brands' owned social media. Several studies have examined how owned social media content influences various performance measures (e.g., Akpinar and Berger 2017; De Vries, Gensler, and Leeflang 2012; Homburg, Ehm, and Artz 2015; Lee, Hosanagar, and Nair 2018; Meire et al. 2019), but systematic comparisons are lacking. Our results emphasize that different objectives (i.e., enhance social media engagement or lift sales) require different content (i.e., emotional content for social media engagement and informational content for sales). This study supports managers in making an informed decision on how to leverage owned social media by revealing not only which owned social media content is more effective but also which brand, platform, and country characteristics have stronger elasticities.

Third, our findings highlight study characteristics, such as the use of a lagged dependent variable in a model, that are linked to differential effectiveness of owned social media for social media engagement and for sales. This provides scholars with an overview of the consequences of their methodological choices. Finally, coding the available primary studies on the impact of owned social media on social media engagement and sales allow us to uncover important gaps in the literature.

2.1 Theoretical Background and Literature Review

Brands use owned social media to communicate with consumers. To better understand the effect of owned social media on marketing outcomes, we distinguish between the content used by brands (i.e., functional vs. hedonic content) and the context (i.e., brand characteristics, industry characteristics, platform characteristics, and country characteristics that may affect owned social media; see Figure 2.1). In this section, we conceptualize the effects of these dimensions on consumers' engagement with the brand's own social media, as well as its downstream impact on sales.

2.1.1 Owned Social Media Outcomes

Owned social media may elicit a different response among consumers along the purchase funnel, resulting in a different effectiveness of owned social media on social media engagement and sales (e.g., Akpinar and Berger 2017; Van Doorn et al. 2010). To account for this, we distinguish between these two outcomes.[2]

[2] While we could have explored more owned social media outcomes, our review of the literature uncovered work on these two marketing outcomes to grant a meta-analysis, whereas less research is available for other outcomes, such as brand knowledge (the results on brand knowledge are available on request).

2.1.1.1 Social media engagement

To gauge the extent to which consumers are receptive to the content that a brand shares on social media, managers tend to keep track of the level of engagement their posts attain. Consumers can interact with these posts by "liking" or "favoriting" them, by commenting on them, or by sharing them with others. These behaviors, referred to as social media engagement (Muntinga, Moorman, and Smit 2011; Srinivasan, Rutz, and Pauwels 2016), constitute a desirable response to brand content, as they help the content spread or "cascade" to other consumers.

2.1.1.2 Sales

Ultimately, brand communication is intended to increase sales. Indeed, a large body of research indicates that brands' social media has a positive impact on sales (e.g., Hewett et al. 2016; Mochon et al. 2017) by, for example, enhancing brand salience, creating awareness of relevant product offerings (Colicev et al. 2018), and building customer–firm relationships (Kumar et al. 2016).

2.1.2 Types of Owned Social Media Content

Marketing communication literature generally divides communication content into informational and emotional appeals. The first type of appeals focuses on the communication of a product's instrumental or functional benefits (i.e., the problems it solves), while the second type focuses on the emotional and experiential aspects of consumption, related to the excitement and pleasure the product provides (e.g., MacInnis, Rao, and Weiss 2002; Rossiter, Percy, and Bergkvist 2018). Research in the social media domain (see Appendix 2.1) has built on this distinction, dividing owned social media messages into functional and hedonic content (e.g., De Vries, Gensler, and Leeflang 2012; Lee, Hosanagar, and Nair 2018; Meire et al. 2019; Stephen, Sciandra, and Inman 2015; Tellis et al. 2019).

Within functional content, we distinguish between two types of product-related information: content that provides consumers with information about (1) the attributes of the product or service (e.g., Eigenraam, Eelen, and Verlegh 2021; Lee, Hosanagar, and Nair 2018; Meire et al. 2019) or (2) deals and other aspects of pricing (e.g., Tellis et al. 2019). Within hedonic content, we distinguish between emotional and social orientations. Some hedonic content is more emotion oriented, providing entertainment value or triggering emotional responses (e.g., Akpinar and Berger 2017; Eigenraam, Eelen, and Verlegh 2021; Stephen, Sciandra, and Inman 2015). Other hedonic content has a social orientation, focused on community building and dialogue. This latter type of hedonic content is also referred to as “social” or “social oriented” (e.g., De Vries, Gensler, and Leeflang 2012; Homburg, Ehm, and Artz 2015). Appendix 2.2 provides brand and industry examples of functional and hedonic types of content.

Functional and hedonic content differ in the extent to which they are suitable for achieving engagement and sales goals. For social media engagement, we predict that hedonic content is more effective than functional content (both information and deal related). Compared with functional messages, hedonic content with an emotional message provides more of the emotional arousal that fosters message liking and sharing (Berger and Milkman 2012; Bernritter, Verlegh, and Smit 2016). While hedonic content that emphasizes a social motivation may provide less emotional arousal, it is still likely to be effective in creating social media engagement because it makes social connections more salient in the minds of consumers and thus provides a call to “engage” with others, which may foster commenting and sharing of content.

For sales, we predict that functional content is more effective than hedonic content. Akpinar and Berger (2017) explain that functional messages provide persuasive information about a product's attributes that aids consumers in their purchase decisions. Hedonic messages provide less decision-relevant information and therefore are a less potent driver of sales. Akpinar and Berger focus on functional messages providing information on product attributes rather than information about deals, but we expect their findings to hold for the latter type of functional messages: content about deals aligns more with a purchasing goal than an engagement goal (Van Doorn et al. 2010), and information on deals has a positive impact on sales (Ailawadi et al. 2009; Van Heerde, Leeflang, and Wittink 2004). We expect this effect also to occur for owned social media content.

2.1.3 Brand Characteristics

2.1.3.1 Brand type: utilitarian versus hedonic

Brands are typically classified into utilitarian vs. hedonic types (Chen, Lee, and Yap 2017; Kronrod and Danziger 2013). Utilitarian brands fulfill practical consumer needs or necessities (Mehta, Zhu, and Meyers-Levy 2014) and are often associated with traits such as efficiency, skill, confidence, and intelligence (Cuddy, Fiske, and Glick 2008). Hedonic brands address customer needs linked to pleasure, fun, enjoyment, or other attractive emotional states (Babin, Darden, and Griffin 1994). They are associated with traits such as friendliness and sociability (Cuddy, Fiske, and Glick 2008), and research has shown that consumers are more prone to interact with such brands on social media (Bernritter, Verlegh, and Smit 2016). Given this congruency or "fit" effect, we expect hedonic brands to be more effective for social media engagement than utilitarian brands.

2.1.3.2 Brand community size

The effectiveness of social media content is governed not only by the type of brand that publishes it but also by the size of the brand community. Brands often strive to grow their follower base, because larger social media communities can increase the reach of their message. For a brand with more followers, a one-unit increase in owned social media will have a greater unit effect on social media engagement and sales than for a brand with fewer followers. However, the percentage change in social media engagement and sales due to a percentage change in owned social media is not necessarily larger for a brand with more followers, as it may be relatively easier for the smaller brand to lift its lower base level (Bolton 1989). In this sense, message effectiveness is likely to decrease with size, suggesting a ceiling effect. Smaller brand communities are more tight-knit and more closely linked to the brand at the center, which causes consumers to identify and engage more with the brand (Algesheimer, Dholakia, and Herrmann 2005). As the size of a brand's community increases, it becomes more difficult for brands to maintain strong connections with their follower base and target messages to followers' needs. This is likely to reduce the engagement with the brand's social media messages and their effect on sales.

2.1.4 Industry Characteristics

2.1.4.1 Product type: products versus services

Because services are less tangible, less consistent, and more difficult to evaluate (Zeithaml, Parasuraman, and Berry 1985), owned social media are likely to be more critical to establish the relationship and trust that service brands require. Even if service and product brands' posts are similar in terms of content, consumers may respond differently to them because they have a greater need for information for services.

Therefore, we expect the impact of owned social media on engagement and sales to be greater for services than for products (De Oliveira Santini et al. 2020; Palmatier et al. 2006).

2.1.4.2 Product life cycle: new versus mature

Drawing from advertising literature that shows larger advertising elasticities for new versus mature products (Köhler et al. 2017; Sethuraman, Tellis, and Briesch 2011), we expect consumers to be more responsive to owned social media for new products. This is because consumers have not yet formed their preferences and have less knowledge about the brands' products (Sethuraman, Tellis, and Briesch 2011), making them both more malleable and motivated to process information for new than mature products (Moldovan, Goldenberg, and Chattopadhyay 2011) and leading to greater engagement. This also results in an increase in consumers' attention to and interest in buying the new product (Köhler et al. 2017).

2.1.5 Platform Characteristics

2.1.5.1 Type of platform: social networks versus microblogs

Social media channels differ from other digital channels in terms of their social community structure and ties among participants (see Appendix 2.3), though not all social media are created equal. Important distinctions between social networks (e.g., Instagram, Facebook) and microblogs (e.g., Twitter, Sina Weibo) are audience expectations and goals (e.g., Hennig-Thurau, Wiertz, and Feldhaus 2015; Marchand, Hennig-Thurau, and Wiertz 2017). Social networks revolve around users' social ties, which creates trust and personal connections and relates to the goal of building relationships (Buzeta, De Pelsmacker, and

Dens 2020). By contrast, microblogs are content-based and focused on broadcasting: they are more publicly visible and allow wider access than other types of social media (Kaplan and Haenlein 2011).

These differences between social media channels are likely to translate into differential effects of owned social media content on engagement and sales. It is difficult, however, to predict the direction of these effects. One prediction may be that content shared on social networks like Facebook and Instagram is more impactful than content shared on microblogs, because the former channels are characterized by stronger social ties and higher levels of trust. In contrast, microblogs are more suited to wider dissemination of content and generally reach larger numbers of consumers in a shorter time span. These characteristics have opposite and competing influences on channel-level elasticities, and we therefore refrain from a priori predictions about the resulting differences in these elasticities.

2.1.5.2 Advertising introduction (platform specific)

In addition to the type of platform, which influences how consumer process owned social media messages, platforms themselves have changed over time. Social media sites have evolved over the years, and this evolution may have altered their effectiveness (Voorveld 2019). After the novelty of the first years, the effectiveness of owned social media may have reached a plateau, as social media sites have become a crowded space for brands. The introduction of advertising on a given social media platform is a key event in these developments that may influence the effectiveness of social media content in different ways. Providing an a priori prediction of the direction of this effect is difficult. On the one hand, the introduction of advertising on a social media platform may reduce the audience's attention, as the "sponsored" ad is explicitly communicated to consumers, serving as an external cue and distracting consumers from the relationship-building nature of the social media posts (Kanuri, Chen, and Sridhar 2018). It may also reduce consumer trust in the medium because its commercial nature is incongruent with the context of social media (Buzeta, De Pelsmacker, and Dens 2020). The introduction of advertising on a platform may therefore activate persuasion knowledge and induce skepticism, making consumers less responsive to branded content (Tuk et al. 2009). On the other hand, the introduction of advertising entails a clearer distinction of "pure" advertising and a brand's owned social media content, which may help rather than hurt consumer trust in the latter (Boerman, Willemsen, and Van Der Aa 2017).

2.1.6 Country Characteristics

2.1.6.1 Social media accessibility and economic progress

Social media access can be facilitated through greater mobile phone penetration, linking this indicator to consumers' ability to access branded social media content (Kim, Moon, and Iacobucci 2019). Economic progress is another important factor that captures the average level of economic resources per person in a country, signaling consumers' possibility to take more risks, especially in their purchases (Datta et al. 2022). Marketing literature captures economic progress through the gross domestic product (GDP) per capita (Tellis, Stremersch, and Yin 2003). We expect both social media accessibility and economic progress to contribute to consumers' capability to access and act on owned social media, enhancing the impact of brand-related content across the two owned social media outcomes.

2.1.6.2 Cultural factors

In addition to socioeconomic variables, country-level differences may be due to cultural factors. In his pioneering work, Hofstede (1991) identified four major dimensions of national culture: power distance, uncertainty avoidance, masculinity, and individualism. Recently, Datta et al. (2022) find that power distance has a large and significant impact on elasticities across a range of marketing variables while other variables have no significant effect.[3] We therefore focus on power distance. Power distance, which describes the extent to which a culture is tolerant to inequality (Hofstede 1991), pertains to openness to sharing experience or knowledge (Hofstede and McCrae 2004). Thus, high-power-distance consumers may be more cautious about openly sharing their opinions online, signaling their identity (Eelen, Özturan, and Verlegh 2017), and expressing themselves freely during brand interactions (Hollebeek 2018). In addition, cultures high in power distance ascribe more importance to wealth and status and thus attach greater importance to the consumption of (national) brands, which enable consumers to signal their wealth to others (Wang, Torelli, and Lalwani 2020). We therefore expect owned social media content to have a weaker effect on social media engagement but a stronger effect on sales in high-power-distance than low-power-distance countries.

2.1.7 Control Variables: Study Characteristics

Several methodological characteristics could moderate the impact of owned social media on social media engagement and sales. Following previous meta-analyses (e.g., Edeling and Fischer 2016; You, Vadakkepatt, and Joshi 2015), we identify control

[3] We also estimated the other Hofstede dimensions (uncertainty avoidance, masculinity, and individualism). We found no significant effects across the outcome variables for masculinity and individualism. As we could only include one dimension at the time given high multicollinearity, in line with Datta et al. (2022), we focus on power distance instead of uncertainty avoidance.

variables that allow us to capture changes in consumers' responses to owned social media over time (the year of data collection) and to model choices signaling whether a study included a brand's previous standing (the inclusion of a lagged dependent variable in the model) or addressed causality (the inclusion of endogeneity controls). We also control for model differences, such as the number of variables used (the number of parameters) and the way they operationalize the dependent variable, social media engagement (valence vs. volume), and the independent variable, owned social media (valence, presence, and volume). Finally, we control for sample size by including the inverse of the number of observations, which is used in meta-analyses as a publication bias control (Stanley and Rosenberger 2009); the research field; and whether the paper was published in a top journal.

2.2 Data

2.2.1 Data Collection and Coding

For our meta-analysis, we collected studies that empirically investigate the impact of owned social media. In Appendix 2.4, we outline the detailed procedure of the database construction (preferred reporting items for systematic reviews and meta-analyses; Moher et al. 2009), and in Appendix 2.5, we report the final list of studies. First, we conducted a full literature search for published and unpublished work in academic databases, including EBSCOhost and Web of Science, and also searched SSRN, Marketing Science Institute, EconPapers, RePEc, and Google Scholar. Second, we performed a manual issue-by-issue review of Journal of Marketing, Journal of Marketing Research, Marketing Science, and Management Science (for a similar approach, see Babić-Rosario et al. [2016]). Third, we applied a snowballing procedure to identify additional studies from the reference lists.

Fourth, we posted a call on the ELMAR platform to identify unpublished work on the topic. We completed the search process in August 2021.

Of the initial articles identified, we included those that met the following criteria: (1) the primary study considered the impact of owned social media, (2) the context was social media platforms, and (3) the study reported statistical information that enabled us to compute the elasticities. When we could not calculate the elasticities, we contacted the authors of the studies to retrieve the missing information.

We identified two major owned social media outcomes: social media engagement and sales. We excluded outliers outside the interval of the mean elasticity plus or minus three standard deviations for each of the two dependent variables (43 for social media engagement, 8 for sales; Bijmolt, Van Heerde, and Pieters 2005; Edeling and Fischer 2016). This process resulted in a sample of 86 papers published between 2011 and 2021 and 1,641 elasticities based on 95,295,208 observations (M = 58,071, SD = 175,061). We used 2008 as the starting date for our literature search because it represents the milestone when large brands first joined social media (see Appendix 2.6), as well as the date of the first article published on owned social media (Porter and Donthu 2008). For the first three studies on the topic, we could not retrieve the information needed to calculate elasticities, moving the starting date of our data set to 2011. Approximately 81% of articles were published between 2016 to 2021, showing the growing importance of social media in recent years. Nearly all studies reported multiple effects (M = 19, min = 1, max = 150). Of the obtained elasticities, 46% derive from marketing literature, 23% from management and strategy, and 31% from information systems and computer science. Approximately 10% of the elasticities derive from working papers and conference proceedings papers.

To reduce error when collecting information from each study, we specified a coding protocol (Rubera and Kirca 2012) with agreed-on inclusion criteria, definitions, and guidelines on how to derive elasticities (see Appendix 2.7 for the elasticity calculation). Two coders validated the whole data set, and another independent coder validated 80% of the data set. The intercoder reliability reached 93%, with the disagreements resolved through discussion (Geyskens et al. 2009).

2.2.2 Variable Operationalization

Table 2.1 presents the operationalization of the variables. For the link between owned social media and social media engagement, we retrieved 1,349 elasticities (110 focus on owned social media volume, 227 on owned social media valence, and 1,012 on the presence of owned social media). A few papers focusing on social media engagement operationalize the dependent variable in terms of valence (e.g., positivity scales) rather than volume of social media engagement (e.g., number of comments). To account for this difference, we include a dummy variable to capture valence. (As a robustness check, we also excluded social media engagement operationalized as valence and obtained robust results.) We collected 292 elasticities between owned social media and sales (211 focus on owned social media volume, 19 on owned social media valence, and 62 on the presence of owned social media; for a similar number of elasticities, see You, Vadakkepatt, and Joshi [2015]). We coded actual sales and related proxies (e.g., number of categories sold, sales rank). For studies using sales rank (18 elasticities), we reverse-coded the effect size to account for the inverse relationship (Brynjolfsson, Hu, and Smith 2003). Appendix 2.8 lists the summary statistics, and Appendix 2.9 reports the correlation matrices for the moderating variables.

2.2.2.1 *Owned social media*

For 1,058 (of 1,641) elasticities, we code owned social media content into functional or hedonic categories. We further operationalize functional (27% of all effects) as content that is (1) informational (i.e., including information about the brand, the firm, the product, or events and other related topics) or (2) related to deals (i.e., price promotions or price information, labeled "deals" for brevity). We operationalize hedonic content (38% of all effects) as (1) emotional (i.e., contains emotions, evokes emotions, is high in arousal, or is entertaining) or (2) related to social content (i.e., focuses on community building, calls to action for engagement or contests, or interactivity and dialogue). We use dummy variables to define the content characteristics (with hedonic content as a reference), and we include one dummy to use whenever the content was not specified. Removing this unspecified content from the analysis does not alter the results.

2.2.2.2 *Brand characteristics*

To capture brand type, we include a dummy variable for utilitarian brands, leaving hedonic brands as reference. To classify brands, two marketing experts coded each elasticity in our sample as belonging to a hedonic brand (67% of the sample) or utilitarian brand (33% of the sample) following previous literature (e.g., Bart, Stephen, and Sarvary 2014; Khamitov, Wang, and Thomson 2019). Thus, they assigned a brand as utilitarian if it is predominantly purchased for practical reasons fulfilling functional needs and assigned a brand as hedonic if it is predominantly purchased for pleasure, fun, or enjoyment. For missing brand names, we inferred the brand type from the information provided in the primary studies about the category and type of purchase need (functional or hedonic). When an elasticity captured the average owned social media impact across multiple brands, we first classified each brand as hedonic or utilitarian and then assigned the brand type from the average score (e.g., if 30 of 50 brands could be classified as utilitarian, the average utilitarian score is .6, and the assigned brand type would be utilitarian). Whenever we needed more information, we contacted the authors. If we still had no information to classify the brands, we replaced the missing values by the mean of our sample.

To capture the brand community size, we include the number of followers (log-transformed) for every brand, platform, and year of data collection combination reported in the primary study. When the information was missing, we contacted the authors. If they did not have this information, we used the Wayback Machine (https://web.archive.org/) to retrieve the number of followers for the given brand and year, compiling a unique data set. This time-varying information can serve as a proxy for brand community power at the time of the original data collection. This is critical in meta-analytic work because retrieving time-specific information that matches the primary studies is often impossible.

2.2.2.3 Industry characteristics

The elasticities are linked to brands from 31 categories: airlines, alcohol and beverages, apparel, automotive, banking, beauty and personal care, consumer goods, candy, cooking services, do-it-yourself, durable goods, electronics, financial services (including microloans), garden center, health care, hotel services, luxury fashion, movies, museum, music, newspaper, restaurant services, retailing, sports, stationary, telecommunication services, transport, travel and tourism, TV shows, video games, and wellness provider. Most of the elasticities are coded for automotive (9%), apparel (9%), and retailing (6%). We divided the categories into three groups using two dummy variables for service (20%) and mixed (44%), leaving product (36%) as the reference.

We capture new product activity of brands (9%; i.e., a recent product introduction) with a dummy variable coded as 1 whenever the primary studies specified that the elasticity was related to a new product introduction/launch (this includes products that typically adhere to new product activity characteristics, such as movies, music, TV shows, or video games; Babić-Rosario et al. 2016). If the primary studies did not specify whether the product was recently introduced to the market, we classified the product as mature (91%; reference) (for a similar approach, see Köhler et al. [2017] and Sethuraman, Tellis, and Briesch [2011]).

2.2.2.4 Platform characteristics

The primary studies found elasticities on 14 social media sites: Facebook, Instagram, Kiva, Myspace, Reddit, Sina Weibo, Snapchat, Tumblr, Twitch, Twitter, WeChat, Weitao, YouTube, and unnamed forums, as well as social media in general, with the most frequent platforms being Facebook (60%), Twitter (17%), and YouTube (6%). To capture the platform type, we included two dummies, one for microblogs (22%) and one for mixed platform types (social networks; microblogs in any combination together; and blogs, forums, online communities, and social media in general; 8%), with social networks as the reference (70%). Prior research has mostly examined the impact of owned social media on social media engagement on the same platforms (for an exception, see Tellis et al. [2019]).

To further account for changes in social media platform policies that may have affected brands' social media content management on the one hand and consumers' reaction to owned social media content on the other hand, we include a dummy variable to account for the introduction of brand advertising on a given social media site. Eighty-seven percent of elasticities were retrieved from platforms at a time when social media advertising was already introduced.

2.2.2.5 *Country characteristics*

We harvest elasticities from 17 countries across North America (44%), Europe (17%), Asia (14%), and other regions (e.g., Africa, Australia/Oceania, Middle East, 3%; missing country information, 22%). We capture social media accessibility and economic progress by including mobile phone penetration and GDP per capita (log-transformed) per country at the time of data collection. Furthermore, to assess cultural differences across the 17 countries, we include the power distance dimension (Hofstede, Hofstede, and Minkov 2010). We replaced the missing values whenever the country was not specified by the mean of our sample (Khamitov, Wang, and Thomson 2019).

2.2.2.6 *Study characteristics*

The primary studies' data were collected between 2007 and 2019 (M = 2014, SD = 1.98). We used the year of data collection to explore whether effects vary over time; we also included a quadratic effect to capture possible nonlinear effects (Leeflang et al. 2000). In 21% of the cases, the primary studies included a lagged dependent variable in their response models, and in 31% of the cases, they controlled for endogeneity. The studies included 73 parameters on average (SD = 291.847) in their response models. In 7% of the cases, the dependent variable for social media engagement was operationalized as valence instead of volume (93%). Owned social media was operationalized as volume for 20% of the cases, as valence for 15%, and as presence for 65% (Hewett et al. 2016). We include two dummy variables to capture whether owned social media was operationalized as valence or presence instead of volume (reference). To control for differences in sample sizes across studies (often used as a proxy for publication selection bias; Stanley and Rosenberger 2009), we include the mean of the inverse of the square root of the sample size of the primary studies (M = .027, SD = .023). We include dummies for the research field, distinguishing among management (23%), information systems and computer science (31%), and marketing (46%, used as reference). Finally, for 32% of the cases, the data were published in a top journal outlet (based on the Financial Times Research rank list (Financial Times 2016).

Table 2.1 Operationalization of Variables

Variable	Description and Operationalization
Owned Social Media Outcomes	
Social media engagement	Outcome variable capturing social media engagement, including consumer reactions to firm-initiated communication such as likes, comments, shares, retweets, and posts on brand-controlled channels (Colicev et al. 2018; De Vries, Gensler, and Leeflang 2017).
Sales	Outcome variable capturing sales, the number of categories sold, sales rank, and show viewing (Kumar et al. 2016).
Owned social media content	Firm-initiated content shared on social media sites (Colicev et al. 2018; Stephen and Galak 2012).
Functional (27%)	Owned social media content capturing both functional and deals content. • Informational: Coded as 1 if the brand post contained information about (1) the brand or firm (Lee, Hosanagar, and Nair 2018), (2) the product (Tellis et al. 2019), or (3) events or other related topics (Meire et al. 2019) and 0 otherwise. • Deals: Coded as 1 if the brand post contained information about deals or price (Tellis et al. 2019) and 0 otherwise.
Hedonic (reference) (38%)	Owned social media content capturing both emotional and social content: • Emotional: Coded as 1 if the brand post (1) contained emotions (Lee, Hosanagar, and Nair 2018), (2) evoked emotions (Akpinar and Berger 2017), (3) was high in arousal (Stephen, Sciandra, and Inman 2015), or (4) was entertaining (De Vries, Gensler, and Leeflang 2012) and 0 otherwise. • Social: Coded as 1 if the brand post focused on (1) community building (Homburg, Ehm, and Artz 2015), (2) a call to action for engagement or contests (De Vries, Gensler, and Leeflang 2012), and (3) interactivity and dialogue (Homburg, Ehm, and Artz 2015) and 0 otherwise.
Unspecified (35%)	Dummy variable that equals 1 if the owned social media content was not specified in the primary study (e.g., only the volume of owned social media was captured) and 0 otherwise (Hewett et al. 2016).
Owned Social Media Context	
Brand Characteristics	
Brand type (33%)	Dummy variable that equals 1 if the brand is predominantly utilitarian and 0 if it is predominantly hedonic (Khamitov, Wang, and Thomson 2019).
Brand community size	Continuous variable for the number of followers for every brand, platform, and year of data collection combination retrieved from primary studies or via the Wayback Machine (log-transformed and mean-centered; Akpinar and Berger 2017).
Industry Characteristics	
Product (reference) (36%)	Dummy variable that equals 1 if the primary study focused on the product industry (e.g., consumer goods, consumer electronics, automotive, retailing) and 0 otherwise (Palmatier et al. 2006).

Variable	Description and Operationalization
Service (20%)	Dummy variable that equals 1 if the primary study focused on the service industry (e.g., banking, finance, tourism, hospitality, entertainment, business services) and 0 otherwise (Palmatier et al. 2006).
Mixed industries (44%)	Dummy variable that equals 1 if the primary study focused on various industries (service and product together) or no explicit clarification of the studied industry was provided and 0 otherwise (Palmatier et al. 2006).
New product (9%)	Dummy variable that equals 1 if the product was recently introduced to the market at time of data collection and 0 otherwise. New product activity is coded whenever it was directly specified in the primary studies or for products that typically adhere to new product activity characteristics (Köhler et al. 2017; Sethuraman, Tellis, and Briesch 2011).
Platform Characteristics	
Social networks (reference) (70%)	Dummy variable that equals 1 if the platform on which owned social and social media engagement was reported in the primary study is a social network (e.g., Facebook, Instagram, Myspace, WeChat, YouTube) and 0 otherwise (Colicev et al. 2018).
Microblogs (22%)	Dummy variable that equals 1 if the platform on which owned social media and social media engagement was reported in the primary study is a microblog (Sina Weibo, Twitter, Weitao) and 0 otherwise (Hennig-Thurau, Wiertz, and Feldhaus 2015).
Mixed platforms (8%)	Dummy variable that equals 1 if owned social media and social media engagement was reported on multiple types of platforms (e.g., social networks, microblogs and blogs, forum, online communities in any combination together, social media in general) and 0 otherwise (Colicev et al. 2018).
Platform-specific advertising (87%)	Dummy variable that equals 1 if the given social media site allowed for brand advertising in the year of data collection and 0 otherwise (timelines of Facebook, Twitter, LinkedIn, Instagram, and Myspace from Wikipedia in 2022 and Sina Weibo from The Next Web *Financial Times* 2013: https://en.wikipedia.org/wiki/History_of_Facebook#Timeline, https://en.wikipedia.org/wiki/Timeline_of_Twitter, https://en.wikipedia.org/wiki/Timeline_of_Instagram, https://en.wikipedia.org/wiki/Timeline_of_LinkedIn, https://en.wikipedia.org/wiki/Myspace, https://thenextweb.com/news/sina-weibo-activates-in-stream-advertising-in-quest-to-monetize-microblog).
Country Characteristics	
Mobile phone penetration	Continuous variable measuring the mobile phone penetration (%) per country at the time of data collection, operationalized as the number of mobile phones divided by country population (mean-centered; Kübler et al. 2018; extracted from https://data.worldbank.org/indicator/IT.CEL.SETS.P2).
GDP per capita	Continuous variable measuring the GDP per capita per country at the time of data collection, operationalized as the GDP (in USD) divided by country population (log-transformed and mean-centered; Kübler et al. 2018; extracted from https://data.worldbank.org/indicator/NY.GDP.PCAP.CD).
Power distance	Continuous variable for the level of power distance per country (mean-centered; Hofstede, Hofstede, and Minkov 2010; extracted from https://geerthofstede.com/research-and-vsm/dimension-data-matrix/).
Study Characteristics	
Year of data collection	Continuous variable for the year of data collection. If data collection was carried out over several years, we consider the mean of the data collection year (mean-centered; Leeflang et al. 2000).
Year of data collection^2	Continuous variable for the quadratic year of data collection (Leeflang et al. 2000).
Lagged dependent variable (21%)	Dummy variable that equals 1 if a lagged term of the dependent variable was included in the response model of the primary study and 0 otherwise (Sethuraman, Tellis, and Briesch 2011).
Endogeneity control (31%)	Dummy variable that equals 1 if the effect size was retrieved from a model that controlled for endogeneity, including control functions, Gaussian copula correction, generalized-method-of-moments approach, instrumental variables, simultaneous equations, treatment effects model, and experiments, and 0 otherwise (Köhler et al. 2017).
Number of parameters	Continuous variable for the number of variables including fixed effects that were used in the response model (mean-centered; Babić-Rosario et al. 2016).
Social media engagement valence (7%)	Dummy variable that equals 1 if the dependent variable social media engagement was a valence measure and 0 if it was a volume measure for social media engagement (e.g., Hewett et al. 2016).
Owned social media metric	
Volume (reference; 20%)	Dummy variable that equals 1 if owned social media were captured by the volume of firm-initiated posts (e.g., the number of tweets) and 0 otherwise (e.g., Hewett et al. 2016).

Variable	Description and Operationalization
Valence (15%)	Dummy variable that equals 1 if owned social media were captured by valence measure of firm-initiated posts on social media sites (e.g., degree of positivity) and 0 otherwise (e.g., Kanuri, Chen, and Sridhar 2018).
Presence (65%)	Dummy variable that equals 1 if owned social media were captured by the presence of firm-initiated posts on social media sites (e.g., the informativeness of social media posts, the presence of social media posts) and 0 otherwise (e.g., De Vries, Gensler, and Leeflang 2012).
Sample size	Continuous variable for the inverse of the square root of the sample size of the primary study (Stanley and Rosenberger 2009).
Research field	
Marketing (reference; 46%)	Dummy variable that equals 1 if the research field of the academic journal or unpublished work was marketing and 0 otherwise (Babić-Rosario et al. 2016).
Management (23%)	Dummy variable that equals 1 if the research field of the academic journal or unpublished work was management or strategy and 0 otherwise (Babić-Rosario et al. 2016).
Information systems and computer science (31%)	Dummy variable that equals 1 if the research field of the academic journal or unpublished work was information systems or computer science and 0 otherwise (Babić-Rosario et al. 2016).
Top-publication control (32%)	Dummy variable that equals 1 if the primary study has been published in a top academic journal based on the *Financial Times* 2016 list. The following journals in our sample are classified as top publications: *Journal of Marketing*, *Journal of Marketing Research*, *Journal of the Academy of Marketing Science*, *Journal of Consumer Research*, *Management Science*, *Information Systems Research*, *MIS Quarterly*, and *Journal of Management Information Systems*.

Notes: The percentages in the first column represent the frequencies of the dummy variables in our data set.

2.3 Method

2.3.1 Computation of Elasticities

We retrieved elasticities (η) from the primary studies when reported. If elasticities were not available, we computed the elasticities from the parameter estimates and descriptive statistics as outlined in Appendix 2.7 (e.g., Edeling and Fischer 2016; Kremer et al. 2008). We corrected for measurement error elasticities based on constructs by dividing them by the square root of the product of the reliabilities pertaining to the two constructs (Hunter and Schmidt 2004).

2.3.2 Meta-Analytic Model and Estimation

Our analysis follows a two-step approach (Edeling and Fischer 2016; You, Vadakkepatt, and Joshi 2015). First, we compute the average owned social media elasticities for each dependent variable and analyze the distribution of the elasticities. Second, we identify significant moderators using a two-level hierarchical linear meta-analysis model (HiLMA; Bijmolt and Pieters 2001), with elasticities (Level 1) nested within papers (Level 2).[4] We estimate the following model for social media engagement and sales separately:

$$\begin{aligned}\text{Level1}\left(\text{elasticity}\right): Y_{ij} = a_{0j} + \sum_{m=1}^{4}\beta_m \text{ContentCharacteristics}_{mij} \\ + \sum_{b=5}^{6}\beta_b \text{BrandCharacteristics}_{bij} + \sum_{k=7}^{9}\beta_k \text{IndustryCharacteristics}_{kij} \\ + \sum_{p=10}^{12}\beta_p \text{PlatformCharacteristics}_{pij} + \sum_{c=13}^{15}\beta_c \text{CountryCharacteristics}_{cij} \\ + \sum_{s=16}^{27}\beta_s \text{StudyCharacteristics}_{sij} + e_{ij}, \text{ and}\end{aligned}$$

$$\text{Level 2}\left(\text{paper}\right): a_{0j} = g_0 + \mu_j,$$

where Y_{ij} is the *i*th owned social media elasticity from paper *j*; α_{0j} is the intercept for the *j*th paper; β_m, β_b, β_k, β_p, β_c, and β_s are the parameter estimates of different message characteristics *m*, brand characteristics *b*, industry characteristics *k*, platform characteristics *p*, country characteristics *c*, and study characteristics *s*, respectively; e_{ij} is a random error associated with the *i*th elasticity in paper *j* normally distributed with mean of 0 and variance of σ^2; g_0 is the overall intercept; and μ_j is the paper-level random-effect, normally distributed with mean of 0 and variance of τ. This multilevel random-effect structure accounts for within-paper correlation caused by multiple elasticities based on the same studies and samples (Lipsey and Wilson 2001). We estimate the models using the maximum likelihood estimation method because it produces robust, efficient, and consistent estimates (Singer and Willet 2003). These meta-analytic models enable us to

[4] We follow the meta-analytical practices (e.g., Bijmolt and Pieter 2001; Lipsey and Wilson 2001) and methodological standards, which indicate a strong preference for random effects over fixed effects in meta-analysis due to more realistic results, better fit of the data, and lower levels of type I error rate (Borenstein et al. 2010, p. 107; Geyskens et al. 2009, p. 6; Grewal, Puccinelli, Monroe 2018, p. 20).

account for cross-study differences of the included variables and their relationships, focusing on owned social media content (functional, hedonic, and unspecified) and four contextual moderators: (1) brand characteristics (utilitarian vs. hedonic brands, brand community size), (2) industry characteristics (service, product, and mixed; new products), (3) platform characteristics (social networks, microblogs, and multiple platforms; platform-specific advertising), and (4) country (mobile phone penetration, GDP per capita, and power distance). We also focus on the different methodological characteristics, such as the year of data collection (and its quadratic term), whether the model included a lagged dependent variable, whether the study controlled for endogeneity, how many parameters were used, whether the social media engagement dependent variable was captured by valence (vs. volume), whether owned social media itself was operationalized in a different way than volume (i.e., valence, or presence), the sample size, the research field (marketing, management, or information systems and computer science), and whether the paper was published in a top journal. We mean-centered all continuous variables by subtracting the mean for each variable to facilitate interpretation of the results (Echambadi and Hess 2007).

2.4 Results

2.4.1 Descriptive Analysis

In Figure 2.2, we present the distribution of the social media engagement and sales elasticities corrected for measurement error. Together with the overview reported in Table 2.2, these descriptive statistics provide first model-free evidence that owned social media have a positive impact across both outcomes. While, on average, the elasticities are positive, they are negative in 37% of the cases for social media engagement and 16% of the cases for sales. Appendix 2.10 illustrates the variation of the elasticities over time.

Figure 2.2 Frequency Distribution of the Observed Elasticities of Owned Social Media

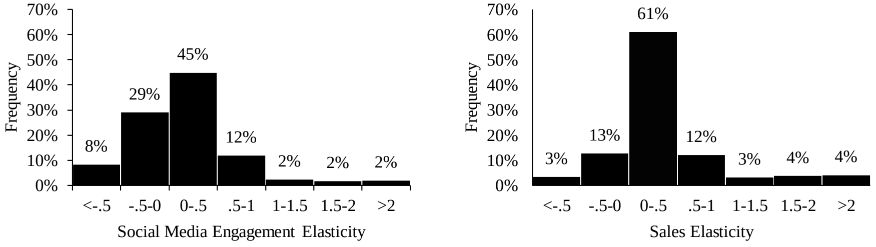


Table 2.2 Descriptive Statistics of Owned Social Media Elasticities on Social Media Engagement and Sales

	N (k)	No. of Papers	M	SD	t-Value (H_0: M = 0)	+ Sig.	– Sig.	+ n.s.	– n.s.	Mdn	Min	Max
Social media engagement	89,629,170 (1,349)	50	.137	.627	8.043***	594	303	252	200	.059	-2.54	2.923
Volume	3,885,760 (110)	13	.198	.431	4.814***	63	11	21	15	.038	-.303	2.125
Valence	2,421,547 (227)	20	.190	.548	5.232***	116	32	47	32	.066	-1.737	2.454
Presence	83,321,863 (1,012)	29	.119	.660	5.728***	415	260	184	153	.059	-2.54	2.923
Sales	5,666,038 (292)	37	.353	.835	7.224***	163	16	82	31	.107	-5.389	5.149
Volume	5,309,614 (211)	30	.345	.966	5.188***	101	16	72	22	.058	-5.389	5.149
Valence	157,104 (19)	4	.118	.373	1.378	8	0	2	9	.009	-.158	1.507
Presence	199,320 (62)	5	.452	.211	16.906***	54	0	8	0	.457	.010	.908

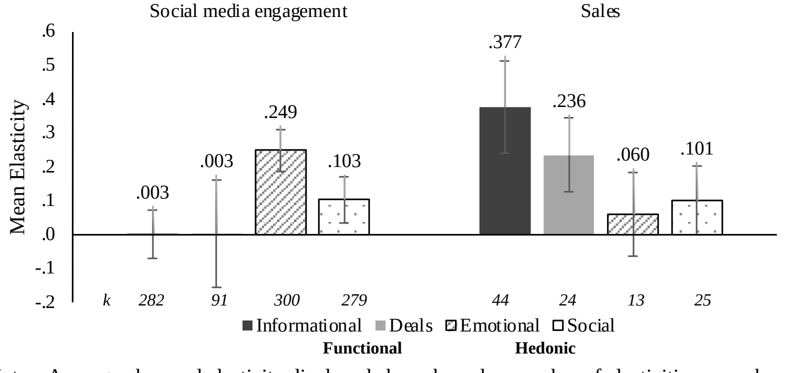
***$p < .01$ (two-tailed).
Notes: N = number of observations in primary studies; k = number of elasticities; t-value (H0: M = 0) = t-test against the null hypothesis that the mean is equal to zero; + (–) sig. = number of positive (negative) statistically significant elasticities; + (–) n.s. = number of positive (negative) nonsignificant elasticities. The imbalance in the number of effect sizes k across dependent variables is not uncommon in meta-analyses (see, e.g., Palmatier et al. 2006). These elasticities have been corrected for measurement error.

Overall, we find that increasing owned social media by 1% leads to an increase in social media engagement by .137% and in sales by .353% (the effects are significantly different from each other; $p < .001$). We find similar significant effects when we focus on owned social media volume ($p < .10$) and presence ($p < .001$), but the effect of valence does not significantly differ between engagement and sales. The stronger effect on sales may seem surprising because social media are often considered a tool to drive engagement rather than sales. It should be noted, however, that comparison across outcomes is not straightforward, as different outcomes refer to different levels of analysis. This stronger elasticity for sales may be the result of two effects: a "self-competition" effect and a "fan base versus customer base" effect. In the first case, if a brand increases the number of owned social media posts—for example, from one to five posts in a day—a given customer may react to one post but not to all five; these additional posts compete with each other for consumers' engagement ("self-competition"). In addition, social media allows everyone to engage with a brand, even if they do not consume the brand. This leads to the "fan base versus customer base" effect: the number of consumers engaging with a brand on social media tends to be higher than the number of consumers actually buying a brand, leading to a smaller impact of owned social media on social media engagement than sales.

Figure 2.3 shows considerable variation among the elasticities of owned social media across content types. We observe significantly larger social media engagement elasticities for hedonic content (M = .179, SD = .557) than for functional content (M = .003, SD = .650; $p < .001$). Within hedonic content, we observe higher elasticities for emotional content (M = .249, SD = .534) than for social content (M = .103, SD = .572; $p < .001$), while we observe no significant differences within functional content (informational content: M = .003, SD = .609; deals content: M = .003, SD = .767). For sales, we observe the opposite: significantly larger elasticities for functional (M = .327, SD = .396) than for hedonic (M = .087, SD = .232; $p < .001$) content. We find no significant differences within functional (informational content: M = .377, SD = .449; deals content: M = .236, SD = .259) and hedonic (emotional content: M = .060, SD = .205; social content: M = .101, SD = .248) content.

Overall, the descriptives indicate that owned social media have a positive effect on social media engagement and sales. They also reveal that the effect is not always positive, suggesting that the wrong social media post can decrease engagement and reduce sales, jeopardizing a firm's branding efforts. Moreover, the different impact of content type across owned social media outcomes underscores the importance of clearly defining the target outcome variable to create the most effective owned social media content. Finally, the large variation observed within each dependent variable calls for a moderation analysis. For example, we also observe that even within the same paper, owned social media is not always positive depending on the context (e.g., platform observed [Wang et al. 2021], modeling choices [Goh, Heng, and Lin 2013]; see also Appendix 2.11).

Figure 2.3 Average Observed Elasticities per Message Content (Model-Free Evidence)



Notes: Average observed elasticity displayed above bars; k = number of elasticities; error bars = 95% confidence intervals.

2.4.2 *The Moderating Role of Content and Context*

Table 2.3 reports the results of the multilevel random-effect model, together with the predicted elasticities (η) retrieved by setting all other variables at their sample means (see Bijmolt, Van Heerde, and Pieters 2005). Our models explain between 12% and 42%

of the Level 1 variance (Snijders and Bosker 1994), which is in line with other meta-analyses (e.g., 16% in Bijmolt, Van Heerde, and Pieters [2005], 26% in Babić-Rosario et al. [2016], 11% in You, Vadakkepatt, and Joshi [2015]). Overall, multicollinearity does not severely affect the model, with an average variance inflation factor between 3.32 and 4.34 (max = 9.57). To check the stability of the results, we conduct robustness checks, outlined at the end of this section.

For owned social media content, the results align closely with our expectations. For social media engagement, we find that informational content ($\beta = -.248$, $p < .01$; $\eta = .018$), deals ($\beta = -.254$, $p < .01$; $\eta = .012$), and social content ($\beta = -.154$, $p < .01$; $\eta = .112$) are less effective than emotional content. This finding is important because it contrasts conventional wisdom suggesting that managers focus on deals or social content to boost their social media engagement. We find that informational content ($\beta = .652$, $p < .05$; $\eta = .580$) and social content (.461, $p < .10$; $\eta = .338$) affect sales more than emotional content does. Yet the effects for informational and social content are not significantly different from each other ($p > .10$).

2.4.2.1 Brand characteristics

Surprisingly, we do not observe significant results for brand type across the dependent variables.[5] Instead, for the brand community size, we find larger sales elasticities for a smaller number of followers ($\beta = -.067$, $p < .01$; $\eta_{low} = .411$, $\eta_{high} = .268$). This may be

[5] While we observe no significant differences across brands, several studies have theorized and found a congruency or "fit" effect, in which hedonic messages work better for hedonic brands and functional messages work better for utilitarian brands (Eigenraam, Eelen, and Verlegh 2021; Rossiter, Percy, and Bergkvist 2018). The high multicollinearity prevents us from entering this "moderated-moderation" or three-way interaction directly into the main models in Table 2.3. We therefore explore these effects by running the models separately for hedonic and utilitarian brands. We report the results in Appendix 2.12. We examine differences between products and services in a similar manner in Appendix 2.13. For comparison, we include the average observed elasticities of the split samples in Appendix 2.14.

Table 2.3 The Moderating Role of Message Content and Context (HiLMA Results)

	Social Media Engagement				**Sales**			
	Expected Sign	*Estimate (β)*	*(SE)*	*Predicted Elasticity (η)*	*Expected Sign*	*Estimate (β)*	*(SE)*	*Predicted Elasticity (η)*
Intercept		.773	(.250)***			.595	(.275)**	
Owned Social Media Content								
Hedonic								
Emotional	Base			.266***	Base			-.073
Social	?	-.154	(.055)***	.112**	?	.461	(.279)*	.388**
Functional								
Informational	-	-.248	(.052)***	.018	+	.652	(.256)**	.580***
Deals	-	-.254	(.074)***	.012	+	-.027	(.296)	-.099
Unspecified		-.089	(.053)*	.177***		.455	(.233)*	.383***
Brand Characteristics								
Hedonic	Base			.135***	Base			.325***
Utilitarian	-	.010	(.062)	.146***	+	.172	(.178)	.497***
Brand community size (log)	-	-.028	(.017)	.180***.106***	-	-.067	(.024)***	.411***.268***
Industry Characteristics								
Product	Base			.274***	Base			.419***
Service	+	-.158	(.110)	.116	+	-.127	(.128)	.291***
Mixed industries		-.215	(.083)**	.060		a		
Mature product	Base							.104
New product	+	a			+	.545	(.184)***	.650***
Platform Characteristics								
Social networks	Base			.192***	Base			.276***
Microblogs	?	-.164	(.075)**	.028	?	-.149	(.162)	.127
Mixed platforms		-.279	(.142)*	-.087		1.326	(.255)***	1.601***
No platform-specific advertising	Base			.440**	Base			.811***
Platform-specific advertising	?	-.338	(.228)	.102**	?	-.600	(.206)***	.211***
Country								
Mobile phone penetration	+	-.014	(.005)***	.216***-.008	+	.054	(.008)***	-.241** .968***
GDP per capita (log)	+	.079	(.091)	.134***.166***	+	-.221	(.125)*	.612***.201**
Power distance	-	.000	(.002)	.135** .140***	+	.024	(.004)***	.127** .559***
Study Characteristics								
Year of data collection	+	.083	(.035)**		+	-.204	(.050)***	
Year of data collection squared	-	-.039	(.012)***	.174***.155***	-	-.034	(.010)***	.616***.046
No lagged DV	Base			.090**	Base			.424***
Lagged DV		.247	(.118)**	.337***		-.279	(.156)*	.145
No endogeneity control	Base			.113***	Base			.492***
Endogeneity control		.108	(.083)	.221***		-.235	(.150)	.256***
Number of parameters[c]		.002	(.040)	.139***.139***		-.022	(.008)**	.404***.368***
Social media engagement (DV) volume	Base			.106***	Base			
Social media engagement (DV) valence		.494	(.129)***	.600***		a		
Metric independent variable								
Volume	Base			.200**	Base			.552***
Valence		-.145	(.106)	.055		.088	(.238)	.640***
Presence		-.049	(.092)	.151		-.963	(.221)***	-.411**
Sample size		1.846	(1.583)	.104** .174***		-3.367	(2.684)	.420***.329***
Research field								
Marketing	Base			.121**	Base			.168
Management		.128	(.092)	.248***		a		
Information systems and computer science		-.063	(.092)	.057		.365	(.200)*	.533***
Non-top publication	Base			.142***	Base			.391***
Top publication		-.010	(.084)	.132*		-.109	(.135)	.282***
N (k)		89,629,170 (1,349)				5,666,038 (292)		
Wald χ^2 /		79.86				157.84		
Log-pseudolikelihood		-1,220.63				-297.96		
Snijders–Bosker pseudo-R^2 (Level 1 / Level 2)		.121 / .345				.419 / .719		
		Estimate	SE			Estimate	SE	
var (constant)		.135	.040			.000	.000	
var (residual)		.590	.012			.671	.028	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies (Edeling and Himme 2018). [b] The predicted elasticity is computed considering both year of data collection and year of data collection squared, and setting year of data collection at the 25th and 75th percentile and everything else at the mean. [c] The number of parameters is divided by 100. Notes: Expected sign: + = positive relationship (compared with base level); – = negative relationship; ? = ambiguous relationship; for empty cells we do not have expectations; β = beta coefficient; SE = standard error; η = predicted elasticity;

for continuous variables, the 25th and 75th percentile of the predicted elasticities are displayed; the significance level is computed using the delta method (see Bijmolt, Van Heerde, and Pieters 2005; Greene 2003). base = reference category; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities.

because our elasticities are relative effect sizes, indicating that a percentage change in sales due to a percentage change in owned social media is not necessarily larger for a brand with more followers, due to a ceiling effect for larger brands. While it may be easier for the smaller brand to lift its lower base level, larger brands are confronted with a ceiling effect, preventing them from exerting the same level of growth.

2.4.2.2 Industry characteristics

Although we find no significant differences across product versus service versus mixed industries, we observe that studies based on multiple industries tend to report smaller elasticities than studies focusing on only one industry ($\beta = -.215$, $p < .05$). For new products, we find larger sales elasticities ($\beta = .545$, $p < .01$; $\eta = .650$) than for mature products. This might be because social media may be more relevant for new products, as brands can provide more content to consumers who have not yet formed their preferences and have less knowledge about the products (Sethuraman, Tellis, and Briesch 2011).

2.4.2.3 Platform characteristics

In line with our predictions, owned social media on microblogs are less effective at stimulating social media engagement than that on social networks ($\beta = -.164$, $p < .05$; $\eta = .028$). Moreover, we find that the presence of advertising on a social media platform reduces the effect of owned social media on sales ($\beta = -.600$, $p < .01$; $\eta = .211$). This suggests that rather than reinforcing brand trust, the presence of advertising reduces consumer trust in the social media content, because it is incongruent with the social nature of the social media context, as we discussed in our conceptual framework.

2.4.2.4 Country characteristics

Some of the effects of economic progress may be due to the level of mobile penetration. For social media engagement, we find a negative effect of mobile phone penetration ($\beta = -.014$, $p < .01$; $\eta_{low} = .216$; $\eta_{high} = -.008$), which may indicate that in countries with a higher mobile phone penetration, consumers are more passively using social media on their mobile phones, rendering them less likely to like, share, and comment on content (Shankar et al. 2016). However, the level of mobile penetration positively affects the influence of owned social media on sales ($\beta = .054$, $p < .01$; $\eta_{low} = -.241$, $\eta_{high} = .968$). Contrary to our expectations, we find that owned social media exert a stronger effect on sales in countries with lower GDP per capita than in countries with higher GDP per capita ($\beta = -.221$, $p < .10$; $\eta_{low} = .612$, $\eta_{high} = .201$). A possible explanation is that social media use in countries with a higher GDP per capita is at a mature phase, which leaves little room for growth (Poushter, Bishop, and Chwe 2018). Moreover, the findings on the impact of power distance suggest that high-power-distance consumers rely more on branded social media content for sales to satisfy their materialistic needs ($\beta = .024$, $p < .01$; $\eta_{low} = .127$, $\eta_{high} = .559$).

2.4.2.5 Study characteristics

We test the moderating impact of study characteristics in the primary studies (Edeling and Fischer 2016). The impact of social media increases over time for social media engagement ($\beta = .083$, $p < .05$), suggesting that brands become more sophisticated with the use of owned social media. However, we also observe a diminishing effect, as indicated by the negative quadratic term ($\beta = -.039$, $p < .01$; $\eta_{low} = .174$, $\eta_{high} = .155$). For sales, we find a negative effect ($\beta = -.204$, $p < .01$), and this effect is further decreasing over time in a concave shape ($\beta = -.034$, $p < .01$; $\eta_{low} = .616$, $\eta_{high} = .046$).

Studies that include the lagged dependent variable for social media engagement find stronger effects than studies that do not include it ($\beta = .247$, $p < .05$; $\eta = .337$). For sales, for studies that include a lagged dependent variable to control for carryover effects, the effects tend to be smaller ($\beta = -.279$, $p < .10$; $\eta = .145$). For both outcomes, controlling for endogeneity does not significantly alter the impact of owned social media. For studies with a higher number of parameters, we observe smaller elasticities for sales ($\beta = -.022$, $p < .05$; $\eta_{low} = .404$, $\eta_{high} = .368$). When studies operationalize social media engagement as valence instead of volume, the elasticities tend to be larger ($\beta = .494$, $p < .01$; $\eta = .600$). Furthermore, when owned social media are operationalized as presence instead of volume, the sales elasticities tend to be smaller ($\beta = -.963$, $p < .01$; $\eta = -.411$). Finally, although we do not observe any significant difference across fields for social media engagement, we find that information systems and computer science studies tend to report larger effects than marketing studies for sales ($\beta = .365$, $p < .10$; $\eta = .533$).

2.4.2.6 Robustness checks

In Appendix 2.15, we report an intercept-only model. The intercepts can be interpreted as the average predicted elasticities and are aligned with the average observed elasticities reported in Table 2.2 ($\eta_{engagement} = .157$, $\eta_{sales} = .394$). To assess the stability of our results, we conducted several robustness checks. First, we ran the models using ordinary least squares (see Appendix 2.15). Second, we conducted sensitivity analyses by rerunning the models after removing one paper at a time; the results remained substantially the same (see Appendix 2.16). Third, two papers investigated the impact of owned social media on TV show viewing (12 elasticities). Although previous research has used TV show viewing as a proxy for sales (You, Vadakkepatt, and Joshi 2015), we exclude these elasticities and find robust results (see Appendix 2.17). Fourth, with regard to social media engagement, not all elasticities are based on engagement volume. Excluding social media engagement operationalized as valence leads to substantively similar results (see Appendix 2.18). Fifth, more variables could be used to capture brand, industry, platform, country, and study characteristics. We report the full list of variables coded but not included due to multicollinearity, lack of variation, and systematic nonsignificance in Appendix 2.19 and example results when including these variables in Appendix 2.20. Sixth, we used an alternative hierarchical structure by nesting elasticities within the data set (instead of within the paper). This led to the same results of the models displayed (see Appendix 2.21).

2.5 Discussion

Social media are an important marketing tool to sustain customer relationships and, consequently, to enhance firm performance. John Legere, former chief executive officer of T-Mobile USA, for example, turned the company's performance around through his social media strategy: "We've got a relationship on Twitter that's growing with customers, and that's something that many people are interested in" (Hanley Frank 2014). Other successful brands, such as Wendy's, Nike, Netflix, and National Geographic, have similar high-profile social media strategies. As such, in the last decade, marketing scholars have paid increased attention to social media, uncovering the effect of owned social media on different marketing outcomes. We offer new empirical generalizations on the impact of owned social media and also provide insights into when and how owned social media affect engagement and sales.

2.5.1 Key Takeaways and Their Managerial Implications

Overall, owned social media have a positive and significant impact on social media engagement and sales, and this effect is weaker for social media engagement ($\eta = .14$) than sales ($\eta = .35$; $p < .001$). Although managers are investing increasingly more in owned social media (Moorman and McCarthy 2021), they tend to monitor the effectiveness of their owned social media posts using metrics that are relatively easy to gather, such as those linked to social media engagement (e.g., likes, comments, shares; Sprout Social 2021). Not assessing the impact on sales may lead to misinterpretation of the effectiveness of owned social media and to the wrong use of content (as we conclude from our moderator analysis).

Table 2.4 summarizes the importance of different marketing instruments to managers, reporting the average sales elasticities for tools that can be directly controlled—such as price, advertising, and owned social media—and tools that cannot be directly controlled, such as electronic word of mouth (eWOM). Our results indicate that owned social media are a powerful tool to stimulate sales. While the effects are comparable to those of eWOM, marketers' control over brands' owned social media is considerably greater than their control over eWOM, which is in the hands of consumers. Moreover, our meta-analysis shows a large variation in effects, which suggests that managers need to be aware that not all owned social media campaigns are equally effective (see Table 2.5 for key findings).

Table 2.4 Comparison with Other Marketing Instrument Elasticities

Marketing Instrument	Dependent Variable	Average Elasticity	Source
Price	Sales	−2.62	Bijmolt, Van Heerde, and Pieters (2005, p. 145, predicted elasticity for brand-level aggregation = −2.50, p. 147)
Advertising (long term)	Sale	.12 (.24)	Sethuraman, Tellis, and Briesch (2011, p. 464)
eWOM volume (valence)	Sales	.24 (.42)	You, Vadakkepatt, and Joshi (2015, p. 29)
Owned social media volume (valence)	Sales	.35 (.12)	Current research
Owned social media volume (valence)	Social media engagement	.20 (.19)	Current research

2.5.2 Managerial Guidelines for Owned Social Media

Contrary to popular beliefs and managerial practices:

- *How can content types be leveraged more effectively on social media?* One of the most common mistakes of social media campaigns is the lack of an overall content strategy. Without content strategies, owned social media lose their effectiveness and may even lead to significant brand performance damage (Womack 2017). Our results can help managers develop such strategies by focusing on variables they can control directly. For example, they can balance “what they say” and “how they say it” depending on their goal: They can focus on the “how” to engage consumers with more emotional content and on the “what” to stimulate sales with more informational content (e.g., the hedonic brand Oreo recently boosted its sales using an informational post on Facebook [social network] about a recipe featuring its limited-edition red velvet flavor [new product]; Laroya 2020). Surprisingly, this guidance is not aligned with most social media content recommendations to “end posts with questions,” “ask customers to vote,” or “ask customers to send in pictures.” Although social content helps brands stand out online (Hall 2021), it is significantly less powerful than emotional content at stimulating social media engagement. We also find no evidence for a superior impact of deals, which marketers have named as one of their top three reasons for using social media (CMO Survey 2018).

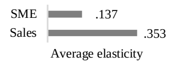
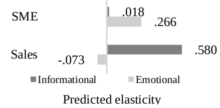
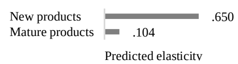
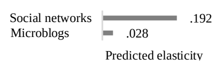
- Do brand characteristics affect social media effectiveness? Because the effectiveness of owned social media seems equally important across brand types, brand managers can build on the experience of other brands. Moreover, brands try to grow their brand communities to reach as many consumers as possible (Tubis 2018). This has even spawned an industry of agents selling followers to brands. However, to stimulate sales, these growth strategies are counterproductive, as we find that owned social media are more effective for small brand communities (consumers reward the intimacy of a small community with greater trust in the brand and its messages). This contradicts the popular belief of "the larger, the better," highlighting the need to focus more on the quality rather than quantity of followers.

In line with practice and previous research:

- How does social media effectiveness differ between platforms? Owned social media are more effective on social networks than on microblogs, suggesting that tie strength and trust provided by social networks are more important than the open access and wide dissemination facilitated by microblogs. This reflects current practice, as brands are mostly active on social networks such as Instagram and Facebook, with microblogs such as Twitter receiving less attention by marketers (Sprout Social 2021). Moreover, managers should be mindful that future changes in the platform environment can alter the way consumers interact with branded content. We observe that the introduction of advertising on the different social media platforms weakened the effect of owned social media on engagement. Although social media advertising may amplify the reach and engagement of owned social media content (Baradell 2021), it can distract the audience, reducing the contribution of owned social media.

- How does social media effectiveness vary by country? Because social media platforms are often international, managers may be tempted to use one global social media strategy. Instead, our results show that managers should adapt owned social media content strategies to account for differences in country characteristics to process branded content. The increasing use of social media on smartphones (Kübler et al. 2018) amplifies the impact of owned social media on sales. Not surprisingly, managers can expect stronger effects on sales in countries with a greater mobile phone penetration. Furthermore, for countries with high power distance, we find that owned social media exert stronger effects on sales. High power distance is indeed related to greater receptiveness of branded communication fulfilling materialistic and status needs (Datta et al. 2022). Together, these results urge marketers to consider cross-national differences when developing their social media strategies.
- Do study characteristics matter? Scholars and practitioners need to be careful when comparing the impact of owned social media across time—our results indicate that owned social media face a saturation effect, requiring a more sophisticated and integrated marketing strategy. Finally, our results show that several study characteristics may affect their conclusions, such as using a lagged dependent variable or controlling for endogeneity. This is important for both scholars and practitioners, because 85% of managers report that social media data will be a primary source of business intelligence moving forward (Sprout Social 2021).

Table 2.5 Summary of Key Findings and Managerial Implications

	Popular Beliefs and Managerial Practice	**Key Findings**	**Managerial Implications**
Are owned social media effective? For what?	Social media generate engagement but do not necessarily lift sales (Sprout Social 2021).	 The average elasticity of owned social media on sales is .35 (cf. .12 for advertising), while SME has the lowest average elasticity .14.	Surprisingly, while managers are investing more in owned social media (Moorman and McCarthy 2021), they need to be aware of its impact on SME and sales. Brands may underestimate the impact of their owned social media if they focus only on easy-to-measure metrics, such as those linked to SME (e.g., likes, shares of owned social media posts).
How can content types be leveraged more effectively on social media?	"End your posts with questions" and other social content advice can help secure SME (Hall 2021).	 Though effective, social content is not the most influential, especially for SME (Table 2.3): - SME: Emotional content has the strongest impact. - Sales: Informational content is as effective as social content.	Contradicting popular beliefs, owned social media content needs to be adapted to the targeted outcome variable: While for SME, managers need to focus on content expressing emotional needs ("the how"), for sales, objective information-based content has a stronger impact than emotional content.
	Communicating deals are one of the top three reasons for firms to use social media (CMO Survey 2018).	Deals have the lowest effect on SME and no significant effect on sales (Table 2.3 shows that the predicted elasticities are close to zero for both).	Investment in deals might not be the best choice for marketers on social media as it has no effect on SME and sales, contrary to traditional deal communication.
Do brand characteristics affect social media effectiveness?	Growing a large brand community is essential for a brand's social media strategy (Tubis 2018).	The effect of owned social media on sales is stronger in smaller than larger band communities.	Surprisingly, it is more important to focus on the quality rather than quantity of followers, to better understand and address consumer needs and expectations and create more authentic and intimate interactions.
Do industry characteristics affect social media effectiveness?	Creating content for new products will help to boost sales (*Forbes* Agency Council 2021).	 The effect of owned social media on sales is stronger for new products than mature products.	In line with popular beliefs, managers can benefit from creating content about new products on social media, boosting sales.
How does social media effectiveness differ between platforms?	Marketers can benefit the most from social networks such as Facebook and Instagram (Sprout Social 2021).	 Owned social media are weaker on microblogs for SME than on social networks given closer ties (Table 2.3).	Confirming managerial practices, the effect of owned social media is platform sensitive. Managers need to address the platforms that are most appropriate by, for example, relying on social networks (Facebook) to stimulate SME.
	Social media advertising helps amplify owned social media content (Baradell 2021).	The effect of owned social media is weaker when paid advertising was already introduced on social media sites (Table 2.3).	Surprisingly, platform advertising reduces the individual contribution of owned social media to affect marketing outcomes.
How does social media effectiveness vary by country?	Content campaigns work globally when broadcast on social media.	In countries with greater digital progressiveness (greater mobile phone penetration), owned social media are more effective for sales than for SME (Table 2.3). In countries with high power distance, the effect on sales is stronger.	Because many platforms are international, using one global social media strategy is tempting, but managers cannot count on the same type of response across countries.

Notes: The results are based on model-free evidence (Table 2.2) and the HiLMA results (Table 2.3). SME = social media engagement.

2.5.3 Limitations and Further Research

Our empirical generalization uncovers several promising avenues for further research (see Table 2.6). First, the nature of meta-analytical data forced us to focus on relatively broad constructs to explain heterogeneity in effects. For example, we separated owned social media into content types. Nevertheless, the effectiveness of new owned social media formats (e.g., brand live sessions, stories) or more content types than just traditional broad-stroke content dimensions (e.g., emotional vs. informational; Berger et al. 2020) remains unknown.

Second, examining the impact of owned social media on a broader range of marketing outcomes, such as brand health (e.g., Hanssens et al. 2014), would be highly relevant. Analyzing which brands obtain the largest share of social media engagement among a similar customer base, while accounting for the dynamic competitive setting, may improve understanding of owned social media.

Third, we found limited work that analyzed different brand types, such as luxury (e.g., Kim and Ko 2012) versus nonluxury brands or newer versus older brands. Yet these different types may differ in their use of owned social media to stimulate engagement and sales and may require very different content. Moreover, industry-specific differences deserve more research attention. We urge future studies to focus on the role of owned social media in a business-to-business (B2B) context, which is only partly covered in extant literature (e.g., Dholakia et al. 2009), as B2B firms heavily use social media to interact with their stakeholders, and insights based on business-to-consumer firms may not translate to their context.

Fourth, while we focused on brand characteristics, a more nuanced picture can be drawn by extracting information at the product level and analyzing its impact at the brand level. Social media are also home to behemoths such as Coca-Cola and Nike, which would benefit greatly from having a better understanding of how social media efforts at the product level translate into brand-level effects and how efforts at the brand level trickle down to the individual products in the brand portfolio.

Table 2.6 Future Research on Owned Social Media Effectiveness

Key Research Gaps	Open Questions
Content	
• New owned social media formats, content facets, and scheduling • Brand health measures and impact of competition on social media engagement	• What is the impact of new owned social media formats, the different content facets, and their interaction with scheduling? • How can social media engagement be used to measure brand health (e.g., share of voice)? What is the impact of competition on social media engagement?
Brand	
• Luxury brands, new brands, B2B • Brand versus product level (portfolio analysis and synergies) • Brand versus spokesperson versus influencers	• Is there a difference between luxury and nonluxury or new and old brands? • How does social media effectiveness differ in the B2B context? Do the same rules of the business-to-consumer context apply, or do managers need distinct B2B social media strategies? • How do social media efforts at the product level translate into brand-level effects, and how do efforts at the brand level trickle down to the individual products in the brand portfolio? • What is the difference in the impact of brand-related content distributed by the brand, spokesperson, or influencers?
Platform	
• Cross-platform research • Impact of new features and changing social media landscape • New versus mature channels	• How can spillover effects from different platforms be quantified? • Which content should be leveraged via temporary content display (Instagram stories) or outsourced to influencers? • When should brands use new versus mature platforms for their owned social media?
Country	
• Cross-country research • Country-of-origin effects • Emerging markets • Individual-level differences	• What is the effectiveness of a social media campaign launched from one country into another country? How can the cross-country effects of the same social media campaign be quantified? • Do country-of-origin effects play a role for owned social media effectiveness? Is the effect of owned social media on social media engagement and sales stronger for domestic than foreign brands? • Does social media effectiveness differ in emerging markets? Are separate owned social media strategies required for each country? • How does the impact of owned social media differ across individual consumer characteristics?
Chain of effects	Is there a chain of effects set in motion when brands post owned social media? Does owned social media directly affect sales, or does social media engagement or other marketing outcomes such as brand knowledge mediate this effect?

Fifth, it would be useful to establish how the impact of brand-related content on engagement and sales is affected when content is distributed by the brand itself rather than a spokesperson or (macro- and micro-) influencers (Leung et al. 2022; Leung, Gu, and

Palmatier 2022) to capture the different degree of official brand representation. With the role of influencers increasing, more work could focus on comparing the effectiveness (and interaction) between owned social media content and branded content posted by influencers. Influencers display brand-related content in different ways (from more functional to hedonic) and differ in terms of the number of followers (nano-, micro-, and macro-influencers) and personality type (some are followed for their knowledge and expertise [utilitarian characteristics] and some for their hedonic characteristics).

Sixth, the effect size distribution of the different platforms was not equal across variables, with most studies focusing on one platform at a time, mostly social networks. Further research could explore a more diversified set of platforms, enabling cross-platform comparisons and quantifying spillover effects from one platform to another. Moreover, studying the evolution of platforms (and their features) may shed new light on how the effectiveness of brands' social media posts changes over time. While we find, for example, that deals are the least effective owned social media content, the use of temporary content displays (e.g., Instagram stories) may provide brands with innovative tools that allow them to expose consumers to limited-time deals. The common practice of outsourcing deals to influencers may also limit brand equity erosion.

Seventh, limited work has examined cross-country differences. Given the global scenario that most brands operate in, research could focus on cross-country effects of owned social media to determine whether country-of-origin effects play a role, by comparing domestic versus foreign brands. Furthermore, social media research in less digitally and economically advanced countries would enrich current understanding of country differences. Studies could focus on the role of owned social media in emerging markets to emphasize which levers marketers should use in such settings. Moreover, it is relevant to understand how the impact of social media content varies across different types of consumers, leveraging and testing insights from experimental research on individual-level differences.

Eighth, to uncover the underlying mechanism at play, future research should focus on the chain of effects set in motion by owned social media, considering its ability to affect brand knowledge, as well as the mediating role of engagement.

Finally, we call for more complete reporting of studies. Meta-analyses rely on published and unpublished studies from a wide list of databases and journals. Although we made every effort to include all relevant research, some works may have eluded our search or could not be used because of the lack of information to compute elasticities. We therefore call attention to the importance of full reporting and disclosure of descriptive statistics in marketing research (Grewal, Puccinelli, and Monroe 2018).

References

Ailawadi, Kusum L., J.P. Beauchamp, Naveen Donthu, Dinesh K. Gauri, and Venkatesh Shankar (2009), "Communication and Promotion Decisions in Retailing: A Review and Directions for Future Research," *Journal of Retailing*, 85 (1), 42–55.

Akpinar, Ezgi and Jonah Berger (2017), "Valuable Virality," *Journal of Marketing Research*, 54 (2), 318–30.

Algesheimer, René, Utpal M. Dholakia, and Andreas Herrmann (2005), "The Social Influence of Brand Community: Evidence from European Car Clubs," *Journal of Marketing*, 69 (3), 19–34.

Appel, Gil, Lauren Grewal, Rhonda Hadi, and Andrew T. Stephen (2020), "The Future of Social Media in Marketing," *Journal of the Academy of Marketing Science*, 48 (1), 79–95.

Babić-Rosario, Ana, Francesca Sotgiu, Kristine de Valck, and Tammo H.A. Bijmolt (2016), "The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors," *Journal of Marketing Research*, 53(3), 297–318.

Babin, Barry J., William R. Darden, and Mitch Griffin (1994), "Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value," *Journal of Consumer Research*, 20 (4), 644–56.

Baradell, Scott (2021), "The Aspiring Thought Leader's Guide to Social Media," Forbes (August 24), https://www.forbes.com/sites/forbesagencycouncil/2021/08/24/the-aspiring-thought-leaders-guide-to-social-media/.

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

Berger, Jonah, Ashlee Humphreys, Stephan Ludwig, Wendy W. Moe, Oded Netzer, and David A. Schweidel (2020), "Uniting the Tribes: Using Text for Marketing Insight," *Journal of Marketing*, 84 (1), 1–25.

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

Bernritter, Stefan F., Peeter W.J. Verlegh, and Edith G. Smit (2016), "Why Nonprofits Are Easier to Endorse on Social Media: The Roles of Warmth and Brand Symbolism," *Journal of Interactive Marketing*, 33 (1), 27–42.

Bijmolt, Tammo H.A. and Rik G.M. Pieters (2001), "Meta-Analysis in Marketing When Studies Contain Multiple Measurements," *Marketing Letters*, 12 (2), 157–69.

Bijmolt, Tammo H.A., Harald J. Van Heerde, and Rik G.M. Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity," *Journal of Marketing Research*, 42 (2), 141–56.

Boerman, Sophie C., Lotte M. Willemsen, and Eva P. Van Der Aa (2017), "'This Post Is Sponsored': Effects of Sponsorship Disclosure on Persuasion Knowledge and Electronic Word of Mouth in the Context of Facebook," *Journal of Interactive Marketing*, 38 (2), 82–92.

Bolton, Ruth N. (1989), "The Relationship Between Market Characteristics and Promotional Price Elasticities," *Marketing Science*, 8 (2), 153–69.

Borenstein, Michael, Larry V. Hedges, Julian P. T. Higgins, and Hannah R. Rothstein (2010), "A Basic Introduction to Fixed-Effect and Random-Effects Models for Meta-Analysis," *Research Synthesis Methods*, 1 (2), 97–111.

Brynjolfsson, Erik, Yu Hu, and Michael D. Smith (2003), “Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers,” *Management Science*, 49 (11), 1580–96.

Buzeta, Cristian, Patrick De Pelsmacker, and Nathalie Dens (2020), “Motivations to Use Different Social Media Types and Their Impact on Consumers’ Online Brand-Related Activities (COBRAs*),” Journal of Interactive Marketing*, 52 (4), 79–98.

Chen, Charlene Y., Leonard Lee, and Andy J. Yap (2017), “Control Deprivation Motivates Acquisition of Utilitarian Products,” *Journal of Consumer Research*, 43 (6), 1031–47.

CMO Survey (2018), “CMO Survey Report: Highlights and Insights Report,” research report (February), https://cmosurvey.org/results/february-2018/.

Colicev, Anatoli, Ashwin Malshe, Koen Pauwels, and Peter O’Connor (2018), “Improving Consumer Mindset Metrics and Shareholder Value Through Social Media: The Different Roles of Owned and Earned Media,” *Journal of Marketing*, 82 (1), 37–56.

Cuddy, Amy J. C., Susan T. Fiske, and Peter Glick (2008), “Warmth and Competence as Universal Dimensions of Social Perception: The Stereotype Content Model and the BIAS Map,” *Advances in Experimental Social Psychology*, 40, 61–149.

Datta, Hannes, Harald J. van Heerde, Marnik G. Dekimpe, and Jan Benedict E.M. Steenkamp (2022), “Cross-National Differences in Market Response: Line-Length, Price, and Distribution Elasticities in 14 Indo-Pacific Rim Economies,” *Journal of Marketing Research*, 59 (2), 251–70.

De Oliveira Santini, Fernando, Wagner Junior Ladeira, Diego Costa Pinto, Márcia Maurer Herter, Claudio Hoffmann Sampaio, and Barry J. Babin (2020), “Customer Engagement in Social Media: A Framework and Meta-Analysis,” *Journal of the Academy of Marketing Science*, 48 (6), 1211–28.

De Vries, Lisette, Sonja Gensler, and Peter S.H. Leeflang (2012), “Popularity of Brand Posts on Brand Fan Pages: An Investigation of the Effects of Social Media Marketing,” *Journal of Interactive Marketing*, 26 (2), 83–91.

De Vries, Lisette, Sonja Gensler, and Peter S.H. Leeflang (2017), “Effects of Traditional Advertising and Social Messages on Brand-Building Metrics and Customer Acquisition,” *Journal of Marketing*, 81 (5), 1–15.

Dholakia, Utpal M., Vera Blazevic, Caroline Wiertz, and René Algesheimer (2009), “Communal Service Delivery: How Customers Benefit from Participation in Firm-Hosted Virtual P3 Communities,” *Journal of Service Research*, 12 (2), 208–26.

Echambadi, Raj and James D. Hess (2007), “Mean-Centering Does Not Alleviate Collinearity Problems in Moderated Multiple Regression Models,” *Marketing Science*, 26 (3), 438–45.

Edeling, Alexander and Marc Fischer (2016), “Marketing’s Impact on Firm Value: Generalizations from a Meta-Analysis,” *Journal of Marketing Research*, 53 (4), 515–34.

Edeling, Alexander and Alexander Himme (2018), “When Does Market Share Matter? New Empirical Generalizations from a Meta-Analysis of the Market Share–Performance Relationship,” *Journal of Marketing*, 82 (3), 1–24.

Eelen, Jiska, Peren Özturan, and Peeter W.J. Verlegh (2017), “The Differential Impact of Brand Loyalty on Traditional and Online Word of Mouth: The Moderating Roles of Self-Brand Connection and the Desire to Help the Brand,” *International Journal of Research in Marketing*, 34 (4), 872–91.

Eigenraam, Anniek W., Jiska Eelen, and Peeter W.J. Verlegh (2021), “Let Me Entertain You? The Importance of Authenticity in Online Customer Engagement,” *Journal of Interactive Marketing*, 54 (2), 53–68.

Financial Times (2016), “50 Journals used in FT Research Rank,” *Financial Times* (September 12),
https://www.ft.com/content/3405a512-5cbb-11e1-8f1f-00144feabdc0.

Forbes Agency Council (2021), “11 Creative Ways to Showcase a Newly Launched Product or Service,” Forbes (November 22), https://www.forbes.com/sites/forbesagencycouncil/2021/11/22/11-creative-ways-to-showcase-a-newly-launched-product-or-service/.

Geyskens, Inge, Rekha Krishnan, Jan-Benedict E.M. Steenkamp, and Paulo V. Cunha (2009), “A Review and Evaluation of Meta-Analysis Practices in Management Research,” *Journal of Management*, 35 (2), 393–419.

Goh, Khim-Yong, Cheng-Suang Heng, and Zhijie Lin (2013), “Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content,” *Information Systems Research*, 24 (1), 88–107.

Greene, William H. (2003), *Econometric Analysis*, 5th ed. Upper Saddle River, NJ: Prentice Hall.

Grewal, Dhruv, Nancy Puccinelli, and Kent B. Monroe (2018), “Meta-Analysis: Integrating Accumulated Knowledge*,” Journal of the Academy of Marketing Science*, 46 (1), 9–30.

Hall, Jason (2021), “Social Media Marketing Tips Every Business Should Be Using,” Forbes (October 29), https://www.forbes.com/sites/forbesagencycouncil/2021/10/29/social-media-marketing-tips-every-business-should-be-using/.

Hanley Frank, Blair (2014), “How T-Mobile Boss John Legere Uses Twitter to Stay Ahead of Rivals,” Geek Wire (October 5), https://www.geekwire.com/2014/john-legere-says-twitter-account-key-t-mobiles-business/.

Hanssens, Dominique M., Koen H. Pauwels, Shuba Srinivasan, Marc Vanhuele, and Gokhan Yildirim (2014), “Consumer Attitude Metrics for Guiding Marketing Mix Decisions,” *Marketing Science*, 33 (4), 534–50.

Hennig-Thurau, Thorsten, Caroline Wiertz, and Fabian Feldhaus (2015), “Does Twitter Matter? The Impact of Microblogging Word of Mouth on Consumers’ Adoption of New Movies,” *Journal of the Academy of Marketing Science*, 43 (3), 375–94.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), “Brand Buzz in the Echoverse,” *Journal of Marketing*, 80 (3), 1–24.

Hofstede, Geert (1991), *Cultures and Organizations: Software of the Mind*. London: McGraw-Hill.

Hofstede, Geert, Gert Jan Hofstede, and Michael Minkov (2010), *Cultures and Organizations: Software of the Mind*, 3rd ed. New York: McGraw-Hill.

Hofstede, Geert and Robert R. McCrae (2004), “Personality and Culture Revisited: Linking Traits and Dimensions of Culture,” *Cross-Cultural Research*, 38 (1), 52–88.

Hollebeek, Linda D. (2018), “Individual-Level Cultural Consumer Engagement Styles: Conceptualization, Propositions and Implications,” *International Marketing Review*, 35 (1), 42–71.

Homburg, Christian, Laura Ehm, and Martin Artz (2015), “Measuring and Managing Consumer Sentiment in an Online Community Environment,” *Journal of Marketing Research*, 52 (5), 629–41.

Hunter, John E. and Frank L. Schmidt (2004), *Methods of Meta-Analysis: Correcting Error and Bias in Research Findings*. 2d ed. Thousand Oaks, CA: SAGE Publications.

Kanuri, Vamsi K., Yixing Chen, and Shrihari Sridhar (2018), "Scheduling Content on Social Media: Theory, Evidence, and Application," *Journal of Marketing*, 82 (6), 89–108.

Kaplan, Andreas M. and Michael Haenlein (2011), "The Early Bird Catches the News: Nine Things You Should Know About Micro-Blogging," *Business Horizons*, 54 (2), 105–13.

Khamitov, Mansur, Xin Wang, and Matthew Thomson (2019), "How Well Do Consumer-Brand Relationships Drive Customer Brand Loyalty? Generalizations from a Meta-Analysis of Brand Relationship Elasticities," *Journal of Consumer Research*, 46 (3), 435–59.

Kim, Angella J. and Eunju Ko (2012), "Do Social Media Marketing Activities Enhance Customer Equity? An Empirical Study of Luxury Fashion Brand," *Journal of Business Research*, 65 (10), 1480–86.

Kim, Moon-Yong, Sangkil Moon, and Dawn Iacobucci (2019), "The Influence of Global Brand Distribution on Brand Popularity on Social Media," *Journal of International Marketing*, 27 (4), 22–38.

Köhler, Christine, Murali K. Mantrala, Sönke Albers, and Vamsi K. Kanuri (2017), "A Meta-Analysis of Marketing Communication Carryover Effects," *Journal of Marketing Research*, 54 (6), 990–1008.

Kremer, Sara T.M., Tammo H.A. Bijmolt, Peter S.H. Leeflang, and Jaap E. Wieringa (2008), "Generalizations on the Effectiveness of Pharmaceutical Promotional Expenditures," *International Journal of Research in Marketing*, 25 (4), 234–46.

Kronrod, Ann and Shai Danziger (2013), "'Wii Will Rock You!' The Use and Effect of Figurative Language in Consumer Reviews of Hedonic and Utilitarian Consumption," *Journal of Consumer Research*, 40 (4), 726–39.

Kübler, Raoul, Koen Pauwels, Gökhan Yildirim, and Thomas Fandrich (2018), "App Popularity: Where in the World Are Consumers Most Sensitive to Price and User Ratings?" *Journal of Marketing*, 82 (5), 20–44.

Kumar, Ashish, Ram Bezawada, Rishika Ritika, Ramkumar Janakiraman, and P.K. Kannan (2016), "From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior," *Journal of Marketing*, 80 (1), 7–25.

Laroya, Lianne (2020), "9 Best Social Media Marketing Examples Proven to Boost Sales," Smash Balloon (December), https://smashballoon.com/best-social-media-marketing-examples-proven-to-boost-sales/.

Lee, Dokyun, Kartik Hosanagar, and Harikesh S. Nair (2018), "Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook," *Management Science*, 64 (11), 5105–31.

Leeflang, Peter S.H., Dick R. Wittink, Michel Wedel, and Philippe A. Naert (2000), *Building Models for Marketing Decisions*. Boston: Kluwer Academic Publishers.

Leung, Fine F., Flora F. Gu, Yiwei Li, Jonathan Z. Zhang, and Robert W. Palmatier (2022), "Influencer Marketing Effectiveness," *Journal of Marketing*, 86 (6), 93–115.

Leung, Fine F., Flora F. Gu, and Robert W. Palmatier (2022), "Online Influencer Marketing," Journal of the Academy of Marketing Science, 50 (2), 226–51.

Lipsey, Mark W. and David B. Wilson (2001), *Practical Meta-Analysis*. Thousand Oaks, CA: SAGE Publications.

MacInnis, Deborah J., Ambar G. Rao, and Allen M. Weiss (2002), “Assessing When Increased Media Weight of Real-World Advertisements Helps Sales,” *Journal of Marketing Research*, 39 (4), 391–407.
Marchand, André, Thorsten Hennig-Thurau, and Caroline Wiertz (2017), “Not All Digital Word of Mouth Is Created Equal: Understanding the Respective Impact of Consumer Reviews and Microblogs on New Product Success,” *International Journal of Research in Marketing*, 34 (2), 336–54.
Mehta, Ravi, Rui Zhu, and Joan Meyers-Levy (2014), “When Does a Higher Construal Level Increase or Decrease Indulgence? Resolving the Myopia Versus Hyperopia Puzzle,” *Journal of Consumer Research*, 41 (2), 475–88.
Meire, Matthijs, Kelly Hewett, Michel Ballings, V. Kumar, and Dirk Van den Poel (2019), “The Role of Marketer-Generated Content in Customer Engagement Marketing,” *Journal of Marketing*, 83 (6), 21–42.
Mochon, Daniel, Karen Johnson, Janet Schwartz, and Dan Ariely (2017), “What Are Likes Worth? A Facebook Page Field Experiment,” *Journal of Marketing Research*, 54 (2), 306–17.
Moher, David, Alessandro Liberati, Jennifer Tetzlaff, and Douglas G. Altman (2009), “Statement,” *Physical Therapy*, 89 (9), 873–80.
Moldovan, Sarit, Jacob Goldenberg, and Amitava Chattopadhyay (2011), “The Different Roles of Product Originality and Usefulness in Generating Word-of-Mouth,” *International Journal of Research in Marketing*, 28 (2), 109–19.
Moorman, Christine (2018), “Social Media Spending, Use and Distraction,” Forbes (March 21), https://www.forbes.com/sites/christinemoorman/2018/03/21/social-media-spending-use-and-distraction/.
Moorman, Christine and Torren McCarthy (2021), “CMOs: Adapt Your Social Media Strategy for a Post-Pandemic World,” *Harvard Business Review* (January 19), https://hbr.org/2021/01/cmos-adapt-your-social-media-strategy-for-a-post-pandemic-world.
Muntinga, Daniël G., Marjolein Moorman, and Edith G. Smit (2011), “Introducing COBRAs: Exploring Motivations for Brand-Related Social Media Use,” *International Journal of Advertising*, 30 (1), 13–46.
Palmatier, Robert W., Rajiv P. Dant, Dhruv Grewal, and Kenneth R. Evans (2006), “Factors Influencing the Effectiveness of Relationship Marketing: A Meta-Analysis,” *Journal of Marketing*, 70 (4), 136–53.
Porter, Constance Elise and Naveen Donthu (2008), “Cultivating Trust and Harvesting Value in Virtual Communities,” *Management Science*, 54 (1), 113–28.
Poushter, Jacob, Caldwell Bishop, and Hanyu Chwe (2018), “Social Media Use Continues to Rise in Developing Countries but Plateaus Across Developed Ones Digital Divides Remain, Both Within and Across Countries,” Pew Research Center (June 19), https://pewrsr.ch/3iycrBS.
Rossiter, John R., Larry Percy, and Lars Bergkvist (2018), *Marketing Communications: Objectives, Strategy, Tactics*. London: SAGE Publications.
Rubera, Gaia and Ahmet H. Kirca (2012), “Firm Innovativeness and Its Performance Outcomes: A Meta-Analytic Review and Theoretical Integration,” *Journal of Marketing*, 76 (3), 130–47.
Sethuraman, Raj, Gerard J. Tellis, and Richard A. Briesch (2011), “How Well Does Advertising Work? Generalizations from Meta-Analysis of Brand Advertising Elasticities,” *Journal of Marketing Research*, 48 (3), 457–71.
Shankar, Venkatesh, Mirella Kleijnen, Suresh Ramanathan, Ross Rizley, Steve Holland, and Shawn Morrissey (2016), “Mobile Shopper Marketing: Key Issues, Current

Insights, and Future Research Avenues," *Journal of Interactive Marketing*, 34 (2), 37–48.
Singer, Judith D. and John B. Willet (2003), *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. New York: Oxford University Press.
Snijders, Tom A.B. and Roel Bosker (1994), "Modeled Variance in Two-Level Models," *Sociological Methods and Research*, 22 (3), 342–63.
Sprout Social (2021), "The State of Social Media: After a Year of Transformation, Executives Are All-In on Social," (accessed March 2021), https://sproutsocial.com/insights/data/social-media-future-of-business-intelligence/.
Srinivasan, Shuba, Oliver J. Rutz, and Koen Pauwels (2016), "Paths To and Off Purchase: Quantifying the Impact of Traditional Marketing and Online Consumer Activity," *Journal of the Academy of Marketing Science*, 44 (4), 440–53.
Stanley, T.D. and Randall S. Rosenberger (2009), "Are Recreation Values Systematically Underestimated? Reducing Publication Selection Bias for Benefit Transfer," working paper, Department of Economics, Hendrix College.
Stephen, Andrew T. and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (5), 624–39.
Stephen, Andrew T., Michael Sciandra, and Jeffrey Inman (2015), "Is It What You Say or How You Say It? How Content Characteristics Affect Consumer Engagement with Brands on Facebook," working paper, Saïd Business School, University of Oxford.
Tellis, Gerard J., Deborah J. MacInnis, Seshadri Tirunillai, and Yanwei Zhang (2019), "What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence," Journal of Marketing, 83 (4), 1–20.
Tellis, Gerard J., Stefan Stremersch, and Eden Yin (2003), "The International Takeoff of New Products: The Role of Economics, Culture, and Country Innovativeness," *Marketing Science*, 22 (2), 188–208.
Tubis, Nick (2018), "Starting from Scratch: The Simple Guide to Social Media and SEO Success," Forbes (March 27), https://www.forbes.com/sites/forbescommunicationscouncil/2018/03/27/starting-from-scratch-the-simple-guide-to-social-media-and-seo-success/.
Tuk, Mirjam A., Peeter W.J. Verlegh, Ale Smidts, and Daniel H.J. Wigboldus (2009), "Sales and Sincerity: The Role of Relational Framing in Word-of-Mouth Marketing," *Journal of Consumer Psychology*, 19 (1), 38–47.
Van Doorn, Jenny, Katherine N. Lemon, Vikas Mittal, Stephan Nass, Doreén Pick, Peter Pirner, et al. (2010), "Customer Engagement Behavior: Theoretical Foundations and Research Directions," *Journal of Service Research*, 13 (3), 253–66.
Van Heerde, Harald J., Peter S.H. Leeflang, and Dick R. Wittink (2004), "Decomposing the Sales Promotion Bump with Store Data," Marketing Science, 23 (3), 317–34.
Voorveld, Hilde A.M. (2019), "Brand Communication in Social Media: A Research Agenda," *Journal of Advertising*, 48 (1), 14–26.
Wang, Yen-Yao, Chenhui Guo, Anjana Susarla, and Vallabh Sambamurthy (2021), "Online to Offline: The Impact of Social Media on Offline Sales in the Automobile Industry," *Information Systems Research*, 32 (29), 582–604.
Wang, Jessie J., Carlos J. Torelli, and Ashok K. Lalwani (2020), "The Interactive Effect of Power Distance Belief and Consumers' Status on Preference for National (vs. Private-Label) Brands," *Journal of Business Research*, 107, 1–12.
Womack, LaKesha (2017), "Is Your (Lack of) Social Media Strategy Killing Your Business?" Forbes (October 6),

https://www.forbes.com/sites/forbescoachescouncil/%202017/10/06/is-your-lack-of-social-media-strategy-killing-your-business/.
You, Ya, Gautham G. Vadakkepatt, and Amit M. Joshi (2015), "A Meta-Analysis of Electronic Word-of-Mouth Elasticity," *Journal of Marketing*, 79 (2), 19–39.
Zeithaml, Valarie A., Ananthanarayanan Parasuraman, and Leonard L. Berry (1985), "Problems and Strategies in Services Marketing," *Journal of Marketing*, 49 (2), 33–46.

Appendix 2.1 Owned Social Media in Selected Literature[a]

Study	*Owned Social Media Concept*	*Outcome Variables*	*Social Media Engagement*	*Sales*	*Owned Social Media Content*				*Platform*	*Industry*	*Country*
					Informational	*Deals*	*Emotional*	*Social*			
Dhaoui and Webster (2021)	Brand posts	Number of likes Number of shares	✓						Facebook	Mixed industries	U.S.
Unnava and Aravindakshan (2021)	Social media posts	Number of likes, comments, and shares	✓						Facebook Instagram Twitter	Mixed industries	*Not reported*
Ordenes et al. (2019)	Brand messages	Number of shares Number of retweets Number of likes	✓		✓		✓	✓	Facebook Twitter	Mixed industries	*Not reported*
Meire et al. (2019)	Marketer-generated content	Customer sentiment	✓		✓		✓	✓	Facebook	Sport	Belgium
Tellis et al. (2019)	Online brand content	Number of shares	✓		✓	✓	✓		YouTube Facebook Twitter LinkedIn Google+	Mixed industries	U.S.
Kanuri, Chen, and Sridhar (2018)	Social media posts	Link clicking		✓	✓		✓		Facebook	Media	U.S.
Lee, Hosanagar, and Nair (2018)	Online brand content	Number of likes Number of comments	✓		✓	✓	✓	✓	Facebook	Mixed industries	U.S.
Akpinar and Berger (2017)	Online brand campaigns	Number of shares Brand evaluation Purchase intention	✓		✓		✓		Social media	Mixed industries	U.S.
Gao and Feng (2016)	Brand message content	Participation intention Brand awareness Brand knowledge Brand personality Brand attitude	✓		✓		✓	✓	Renren Sina Weibo	Consumer & retail; Technology	China
Hewett et al. (2016)	Firm communication	Twitter posts Customer deposits		✓					Twitter	Financial services	U.S.
Koch and Benlian (2015)	Online viral marketing	Number of shares	✓				✓	✓	Facebook	Consumer & retail	Germany
Kumar et al. (2016)	Firm-generated content	Customer spending Cross-buying behavior		✓			✓		Social media	Consumer & retail	U.S.
Lovett and Staelin (2016)	Owned media	TV show viewing		✓					Online	Media	U.S.
Homburg, Ehm, and Artz (2015)	Firm engagement	Consumer sentiment	✓		✓			✓	Online community	Tourism; Do-it-yourself	*Not reported*
Goh, Heng, and Lin (2013)	Marketer-generated content	Purchase expenditure		✓	✓				Facebook	Consumer & retail	Asia
De Vries, Gensler, and Leeflang (2012)	Brand posts	Number of likes Number of comments	✓		✓		✓	✓	Facebook	Consumer & retail	U.S.
Stephen and Galak (2012)	Owned social media	Sales		✓					Blog	Financial services	U.S.

[a] See Appendix 2.5 for the full list.

Appendix 2.2 Examples of Owned Social Media Content Types Per Industry

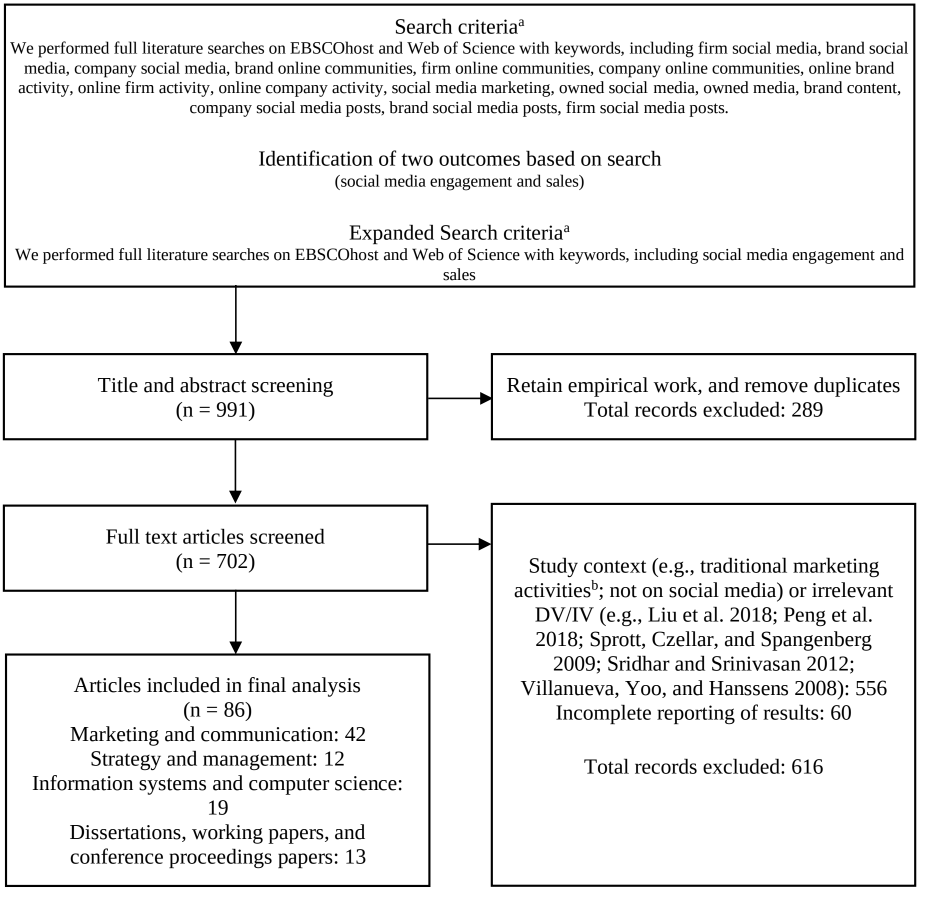
		Service	Automotive	Consumer & Retail	Electronics & Technology	Example from Literature
Functional	Informational	**starbucks** We're committed to a more sustainable way to sip. 💚 This month, we will complete our rollout of lightweight, strawless lids to stores in the US and Canada, eliminating an estimated 1 billion single-use plastic straws a year.	**teslamotors** Software Version 10.0 is here, and it's big. It's rolling out to cars starting this week.	**walmart** 👋hello to @hairitagebymindy and 👋goodbye to bad hair days. Mindy McKnight's new line of plant-based products are expertly crafted for you and your family's diverse hair care needs. Available exclusively at Walmart now!	**microsoft** Clean. The new Xbox Wireless Controller is available in black, white, and ... blue. 🔵⚫⚪	"Informing customer about products, events, or the company" (e.g., Meire et al. 2019)
	Deals	**starbucks** Calling all Starbucks® Rewards members. 📣 The most rewarding week of the year starts today. Check the app daily for exclusive offers, games and more. ⭐ Click the link in bio to join in on the fun.	**Tesla** @Tesla · 10. Sep. 2019 You can now get 2k miles of free Supercharging for you *and* a friend via our referral program. ...great news for those of you who love posting your referral code in our Twitter replies (RIP my mentions)	**walmart** Say "YAY!" for online savings during best of baby month! 🤗 Shop top baby brands now. #WalmartBaby	**Microsoft** @Microsoft · 22. Nov. 2017 Our #BlackFriday deals are 🔥🔥🔥. Preview them here: microsoft.com/en-us/devices/...	"Contains deals, product prices or compares prices" (e.g., Lee, Hosanagar, and Nair 2018)
Hedonic	Emotional	**starbucks** Trading in winter blues for springtime blooms. 🌼 Regram: @thecountrychicboutiquewi	**teslamotors** "I really miss gas stations" said nobody ever.	**walmart** This #LoveYourPetDay, give your lifelong friend the lounging lifestyle they deserve. #WalmartPets	**microsoft** ❤️💚 Feel-good carousel alert 💛💙 . Many of us are still working from home, so we asked our coworkers to share pictures of their pets! The companions who keep us company and make the best guest appearances during our Microsoft Teams meetings. 🐶🐱🐰	"Contains emotions, evokes emotions, or high in arousal" (e.g., Meire et al. 2019)
	Social	**starbucks** Happy #NationalCoffeeDay! What does coffee mean to you? ☕ 💚	**teslamotors** New Sketchpad features are rolling out in our next software update. What will you draw? 🎨 (@goro.fujita)	**walmart** From frontlines to homeschools to comforting video calls, tell us how your mom is making a difference. Tag your photos with #MomsAreEssential and @walmart for a chance to be featured in our Mother's Day story.	**microsoft** Tap the ❤️ if you've ever used #MicrosoftWord.	"Contains calls to action or enables interaction" (e.g., Homburg, Ehm, and Artz 2015; Stephen, Sciandra, and Inman 2015)

Notes: The messages come from the Instagram and Twitter pages of the respective brands. We rely on the primary studies for the actual classification and coding of the owned social media content. This table only provides examples of the actual variation of owned social media across industries.

Appendix 2.3 Differences Across Digital Platforms

	Social Community	*Ties*	*Involvement*	*Interactivity*	*Private vs. Public*	*Persuasiveness*	*This Paper*
Social networks (e.g., Facebook)	x	Strong	Low	High	Private	Medium	x
Microblogs (e.g., Twitter)	x	Weak	Low	Medium	Public	Low	x
Blogs, forums, & online communities	x	Strong	High	High	Private	High	x
Review platforms	Not social media	No ties	Low	Low	Public	High	
e-commerce platforms	Not social media	No ties	Low	Low	Public	High	

Appendix 2.4 Article Search and Inclusion Process (Prisma Approach)



[a]PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Moher et al. 2009). [b] These studies were retrieved after using keywords such as sales. Notes: DV = dependent variable; IV = independent variable.

Appendix 2.5 Primary Studies on Owned Social Media

Authors	*Year*	*Publication Outlet*	*Volume (Issue), Pages*	*Research Context*	*Dependent Variables*	*Number Elasticities*
Ansari et al.	2018	Journal of Marketing Research	55 (3), 321–338	Music industry in Europe	Song plays	8
Antoniadis, Paltsoglou, and Patoulidis	2019	International Journal of Retail & Distribution Management	47 (9), 957–973	18 retail brands in Greece	likes, reactions, comments, shares	15
Bai and Yan	2020	Journal of Electronic Commerce Research	21 (1), 56-74	38 brands from mixed industries in China	Comments, Posts	4
Banerjee and Chua	2019	Journal of Brand Management	26 (6), 621–633	50 brands from mixed industries and several countries	Likes, comments, shares	24
Bapna, Benner, and Qiu	2019	MIS Quarterly	43 (2), 425-452	Retail industry in the U.S.	Likes	72
Bourreau, Maillard, and Moreau	2014	Working Paper		Music industry in the U.S.	Song plays	4
Buzeta, De Pelsmacker, and Dens	2020	Journal of Interactive Marketing	52, 79-98	Survey in the U.S.	Consumption, contribution of brand-related posts	32
Camarero, Garrido, and San Jose	2018	International Journal of Human–Computer Interaction	34 (12), 1119–1134	Multicountry survey about museums	Likes, comments, shares	28
Casaló, Flavián, and Ibáñez-Sánchez	2021	Journal of Business Research	130 (1), 416–425	Survey about 1 fashion brand	Engagement	1
Chae	2020	The Journal of Asian Finance, Economics and Business	7 (10), 501–511	11 global brands from mixed industries	Likes, shares	26
Chae	2021	Sustainability	13 (7), 3812	8 brands from mixed industries in the U.S.	Likes, shares	60
Chang et al.	2018	Decision Support Systems	107, 13-25	Experiment about travel brand in Taiwan	Number of customers	36
Chang, Yu, and Lu	2015	Journal of Business Research	68 (4), 777–782	Cooking community in Taiwan	Like and share intention	4
Chen et al.	2020	Internet Research	30 (5), 1565–1581	Movie industry in the U.S.	Box office sales	5
Chen, De, and Hu	2013	Working Paper		Music industry in the U.S.	Sales rank	2
Chen, De, and Hu[a]	2015	Information Systems Research	26 (3), 513–531	Music industry in the U.S.	Sales rank	16
Chu et al.	2020	Electronic Commerce Research	39 (3), 12055	Automotive industry in China	Likes, comments, shares	36
Chu et al.	2020	Journal of Electronic Commerce Research	21 (4), 252-276	Automotive industry in China	Likes	28
Dabbous and Barakat	2020	Journal of Retailing and Consumer Services	53 (3), 101966	Survey about 4 fashion brands in Lebanon	Engagement	2
Danaher and Dagger	2013	Journal of Marketing Research	50 (4), 517-534	Survey about retail brand in Australia	Sales	1
Davis et al.	2019	Journal of Business Research	100, 150–164	Multicountry mixed industry survey	Likes, shares	42
de Vries and Carlson	2014	Journal of Brand Management	21 (6), 495–515	Service and product brands in Australia	Consumer engagement	2
de Vries, Gensler, and Leeflang	2012	Journal of Interactive Marketing	26 (2), 83–91	11 global brands from mixed industries	Likes, comments	18

Authors	*Year*	*Publication Outlet*	*Volume (Issue), Pages*	*Research Context*	*Dependent Variables*	*Number Elasticities*
Dhaoui and Webster	2021	International Journal of Research in Marketing	38 (1), 155–175	2740 brands from mixed industries in the U.S.	Likes, shares	2
Edney et al.	2018	Journal of Medical Internet Research	20 (12),	Fitness tracker brands in the U.S.	Likes, comments, shares	6
Fernandes and Castro	2020	Journal of Marketing Management	36 (7-8), 660–681	Survey in Portugal	Lurking, posting	8
Frick, Tsekouras and Li	2014	Conference proceedings		Music industry in the U.S.	Sales	2
Goh, Heng, and Lin	2013	Information Systems Research	24 (1), 88–107	Apparel industry in Asia	Sales	4
Gong et al.	2017	Journal of Marketing Research	54 (6), 833–850	Broadcasting industry in China	Show viewing	10
Gruner et al.	2019	Journal of Product Innovation Management	36 (2), 172–195	Survey about new product launches	Sales	4
Hayes et al.	2019	International Journal of Advertising	39 (1), 131–165	Experiment about flue medicine in the U.S.	Brand attitude, retweets, purchase intention	2
Hernández-Ortega et al.	2020	Journal of Destination Marketing & Management	18 (3), 100504	Tourism industry in Spain	Organic reach	4
Hewett et al.	2016	Journal of Marketing	80 (3), 1–24	Financial service industry in the U.S.	Customer deposits	10
Homburg, Ehm, and Artz	2015	Journal of Marketing Research	52 (5), 629–641	DIY, hotel and airline industry	Consumer sentiment	12
Islam and Rahman	2017	Telematics and Informatics	34 (4), 96–109	Survey about mixed industries in India	Customer engagement	6
Jayson, Block, and Chen	2018	Journal of Advertising Research	58 (1), 77–89	839 brands from mixed industries in the U.S.	Sales	15
Johnen and Schnittka	2019	Journal of the Academy of Marketing Science	47 (5), 858–878	Mixed industries in Germany	Virality	14
Kanuri, Chen, and Sridhar	2018	Journal of Marketing	82 (6), 89–108	Newspaper brand in the U.S.	Link clicking	3
Klassen et al.	2018	Journal of Medical Internet Research	20 (6),	Food, health and lifestyle brands in Australia	Likes, comments, shares	23
Kumar et al.	2016	Journal of Marketing	80 (1), 7–25	Wine and spirits retailer in the U.S.	Customer spending, cross-buying	2
Labrecque, Swani, and Stephen	2020	Psychology and Marketing	37 (6), 796–814	90 global brands from mixed industries	Likes, comments, shares	54
Lee et al.	2021	Journal of Travel Research	60 (3), 670–686	Tourism industry in South Korea	Comments, posts	10
Lee, Hosanagar, and Nair	2018	Management Science	64 (11), 5105–5131	782 brands from mixed industries in the U.S.	Likes, comments	100
Lei, Pratt, and Wang	2017	Asia Pacific Journal of Tourism Research	22 (3), 316–328	7 resorts brands in China	Likes, comments, shares	36
Lin and Goh	2011	Conference proceedings		Apparel industry in Asia	Sales	6
Liu, Shin, and Burns	2021	Journal of Business Research	125 (3), 815–826	15 luxury fashion brands	Engagement	3
Lu and Miller	2019	Journal of Interactive Marketing	46, 87–100	Green food product retailer in Australia	Sales	7
Lu, Dinner, and Grewal	2019	Working Paper		Movie industry in the U.S.	Box office sales	17
Lu, Dinner, and Grewal[b]	2021	Working Paper		Movie industry in the U.S.	Box office sales	46

Authors	*Year*	*Publication Outlet*	*Volume (Issue), Pages*	*Research Context*	*Dependent Variables*	*Number Elasticities*
Mandler, Johnen, and Gräve	2020	Journal of Business Research	120 (2), 330–342	18 luxury brands from mixed industries	Love reactions	5
McClure and Seock	2020	Journal of Retailing and Consumer Services	53 (3), 101975	Survey in the U.S.	Involvement	1
Meire et al.	2019	Journal of Marketing	83 (6), 21–42	Soccer in Europe	Consumer sentiment	4
Menon et al.	2019	Journal of Air Transport Management	79, 101678	Airline brand in Iceland	Likes, comments, shares	46
Mochon et al.	2017	Journal of Marketing Research	54 (2), 306–317	Experiment with wellness program in South Africa	Health care and lifestyle points	14
Molina et al.	2020	Journal of Destination Marketing & Management	18 (3), 100498	Tourism industry in the U.K. and Spain	Likes, shares	22
Naqvi, Jiang, and Naqvi	2021	Asia Pacific Journal of Marketing and Logistics	33 (7), 1535–1555	Survey about 7 brands in Pakistan	Engagement	1
Nepomuceno, Visconti, and Cenesizoglu	2020	Journal of Marketing Management	36 (17-18), 1762–1804	Music industry and gaming industry in the U.S.	Sales of music songs and games	6
Nisar and Prabhakar	2018	Transportation Research Part A: Policy and Practice	113, 318–334	Train journeys in the U.K.	Sales	4
Park and Jiang	2021	Corporate Communications: An International Journal	26 (3), 501–520	Survey in the U.S.	Consumption, contribution of brand posts	8
Ren et al.	2016	Conference proceedings		Electronics industry in China	Sales	4
Ren, Tan, and Wan	2020	Working Paper		Retail industry in China	Sales	9
Rietveld et al.	2020	Journal of Interactive Marketing	49 (2), 20–53	59 global brands from mixed industries	Likes, comments	24
Schultz	2017	Electronic Commerce Research and Applications	26, 23–34	Survey about food brands in Germany	Likes, comments, shares	150
Soboleva et al.	2017	Journal of Marketing Management	33 (13-14), 1120–1148	32 global brands from mixed industries	Retweet	21
Song et al.	2019	Information Systems Research	30 (1), 191-203	Movie industry in China	Box office sales	1
Song, Goh, and Phan	2020	Conference proceedings		Apparel industry in Asia	Sales	3
Stephen and Galak	2012	Journal of Marketing Research	49 (5), 624-639	Microloans in the U.S.	Sales	2
Stephen, Sciandra, and Inman	2015	Working Paper		8 brands in the U.S.	Likes, clicks, negatives, comments, shares	34
Swani et al.	2017	Industrial Marketing Management	62, 77–87	B2B and B2C industry context	Likes, comments	24
Swani, Milne, and Miller	2021	Journal of Business Research	125 (3), 785–797	213 global brands from mixed industries	Likes	8
Tellis et al.	2019	Journal of Marketing	83 (4), 1–20	79 brands from mixed industries in the U.S.	Shares	84
Thornhill, Xie, and Lee	2017	Journal of Hospitality and Tourism Technology	8 (1), 87–100	6 service provider brands in Europe	Sales	1
Unnava and Aravindakshan	2021	Journal of the Academy of Marketing Science	49 (5), 864–881	20 global brands from mixed industries	Likes, comments, shares	12

Authors	*Year*	*Publication Outlet*	*Volume (Issue), Pages*	*Research Context*	*Dependent Variables*	*Number Elasticities*
Villarroel Ordens et al.	2019	Journal of Consumer Research	45 (5), 988–1012	Mixed industries	Likes, shares, retweets	127
Viswanathan et al.	2018	Journal of Service Management	29 (3), 378–398	TV shows in the U.S.	Tweets, show viewing	2
Wagner, Baccarella, and Voigt	2017	European Management Journal	35 (5), 606–616	10 automotive brands in the U.S.	Likes, comments, shares	78
Wang et al.	2021	Information Systems Research	32 (2), 582-604	Automotive industry in the U.S.	Sales	5
Wang, Greenwood, and Pavlou	2020	MIS Quarterly	44 (4), 1521–1571	Luxury shoe brands in China	Number of purchases	22
Weiger, Wetzel, and Hammerschmidt	2019	European Journal of Marketing	53 (9), 1808–1832	Survey in Germany	User-generated content	6
Xie and Lee	2015	Journal of Management Information Systems	32 (2), 204–238	Six FMCG brands	Sales, purchase intention	5
Yang et al.	2019	Electronic Commerce Research and Applications	35, 100844	Electrical goods retailer in China	Spending	6
Yao, Shanoyan, and Boyer	2018	Agribusiness	35 (2), 1-17	Survey in the U.S.	Sales	1
Yoshida et al.	2018	Electronic Commerce Research and Applications	28, 208–218	Survey about football and baseball clubs in Japan	Engagement, brand loyalty	2
Yu and Chen	2015	Conference proceedings		Movie industry in the U.S.	Box office sales	8
Yu et al.	2020	Working Paper		Movie industry in the U.S.	Box office sales	17
Zhou et al.	2015	Conference proceedings		259 brands from mixed industries in the U.S.	Sales	2

[a] We include two versions of this study—the published article from 2015 and a working paper from 2013—because additional results are reported in the more recent version. [b] We include two versions of this study (2019 and 2021) because additional results are reported in the more recent version. Notes: FMCG = fast-moving consumer goods; DIY = do it yourself; B2B = business-to-business; B2C = business-to-consumer.

Appendix 2.6 Research Evolution and Major Milestones of Owned Social Media

2000–2004: Early Stage

Emerging online platforms for individual expression augmenting offline life for consumers (Lamberton and Stephen 2016)

Focus on consumer-to-consumer conversation

2005–2007: Mainstream Stage

Mainstream use of online platforms by consumers to share opinions and gain information (Lamberton and Stephen 2016)

Focus on consumer-to-consumer conversation

2008: Brands on Social Media

Large brands join social media such as Twitter and Facebook (TweetReports 2011)

2009–2012: Early Stage of Owned Social Media

Emerging use of social media for content creation by brands (Allebach 2019)

Focus on social media engagement

2013–2017: Maturity Stage of Owned Social Media

Sophisticated use of social media for content creation and consumer interaction by brands (Allebach 2019)

Focus on stimulating social media engagement and sales

2018–Now: Owned Social Media 2.0

Evolution of content creation to also cover more polarizing topics with social impact (e.g., Black Lives Matter, sustainability) next to heightened humanization of brand content (e.g., memes) (Allebach 2019)

Focus on stimulating social media engagement and sales

Appendix 2.7 Elasticity Transformation Equations

Regression Specification	Statistical Model	Expression for Elasticity
Linear	$y = \alpha + \beta x + \varepsilon$	$\beta(\bar{x} / \bar{y})$
Linear-log	$y = \alpha + \beta \ln(x) + \varepsilon$	$\beta(1/ \bar{y})$
Log-linear	$\ln(y) = \alpha + \beta x + \varepsilon$	$\beta\bar{x}$
Log-log	$\ln(y) = \alpha + \beta \ln(x) + \varepsilon$	β

Notes: These regression specifications are the most used in owned social media research; y = dependent variable (social media engagement or sales); x = independent variable (owned social media); β = beta coefficient; $\bar{y}$ = mean of the dependent variable; $\bar{x}$ = mean of the independent variable. For owned social media presence vs. absence, the elasticity calculation boils down to an arc elasticity: (delta y / delta x) * ($\bar{x}$ / $\bar{y}$) = $\beta(\bar{x} / \bar{y})$.

Appendix 2.8 Summary Statistics for Variables in The HiLMA

	Social Media Engagement		**Sales**	
	k	*M (SD)*	*k*	*M (SD)*
Owned Social Media	1,349		292	
Hedonic	579	.429 (.495)	38	.130 (.337)
Emotional	300	.222 (.416)	13	.045 (.207)
Social	279	.207 (.405)	25	.086 (.280)
Functional	373	.277 (.447)	68	.233 (.423)
Informational	282	.209 (.407)	44	.151 (.358)
Deals	91	.067 (.251)	24	.082 (.275)
Unspecified	397	.294 (.456)	186	.637 (.482)
Brand Characteristics				
Brand type (utilitarian vs. hedonic)	498	.369 (.483)	47	.161 (.368)
Brand community size (number of followers [log])	1,349	14.282 (2.007)	292	13.305 (2.434)
Industry Characteristics	1,349		292	
Product	455	.337 (.473)	140	.479 (.500)
Service	174	.129 (.335)	151	.517 (.501)
Mixed industries	720	.534 (.499)	1	.003 (.059)
New product	18	.013 (.115)	133	.455 (.499)
Platform Characteristics				
Social networks	988	.732 (.443)	166	.568 (.496)
Microblogs	254	.188 (.391)	98	.336 (.473)
Mixed platforms	107	.079 (.270)	28	.096 (.295)
Platform-specific advertising	1,199	.889 (.314)	223	.764 (.426)
Country Characteristics				
Mobile phone penetration (%)	1,349	108.836 (10.679)	292	102.929 (15.477)
GDP per capita (log)	1,349	10.576 (.576)	292	10.166 (.848)
Power distance	1,349	32.864 (22.621)	292	49.400 (18.489)
Study Characteristics				
Year of data collection	1,349	2014 (1.871)	292	2013 (2.009)
Lagged DV	267	.198 (.399)	74	.253 (.436)
Endogeneity control	332	.246 (.431)	172	.589 (.493)
Number of parameters[a]	1,349	36.155 (66.441)	292	244.209 (651.050)
Social media engagement valence (DV)	91	.067 (.251)		
Metric independent variable	1,349		292	
Volume	110	.082 (.274)	211	.723 (.448)
Valence	227	.168 (.374)	19	.065 (.247)
Presence	1,012	.750 (.433)	62	.212 (.410)
Sample size	1,349	.027 (.023)	292	.029 (.023)
Research field control	1,349		292	
Marketing	621	.460 (.499)	134	.459 (.499)
Management	373	.277 (.447)	10	.034 (.182)
Information systems & computer science	355	.263 (.441)	148	.507 (.501)
Top-publication control	425	.315 (.465)	103	.353 (.479)

[a] Number of parameters includes fixed effect parameters. Notes: Empty cells are not estimated for the link of owned social media to the respective outcome variable; k = number of effect sizes; M = mean for continuous variables and frequency for dummy variables; SD = standard deviation; DV = dependent variable.

Appendix 2.9 Correlation Matrix of Variables Included in the HiLMA

Social Media Engagement

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(1) Social																										
(2) Informational	-.263																									
(3) Deals	-.137	-.138																								
(4) Unspecified	-.330	-.332	-.174																							
(5) Utilitarian	.011	-.061	-.053	-.005																						
(6) Brand community size (log)	.113	-.086	-.018	.001	-.062																					
(7) Service	.022	-.040	.038	.072	-.084	-.374																				
(8) Mixed industries	-.033	-.006	.044	-.091	-.042	.407	-.412																			
(9) Microblogs	.058	-.150	-.099	.209	.107	-.137	.047	-.048																		
(10) Mixed platforms	.033	-.043	-.002	.027	-.156	.258	-.097	.164	-.141																	
(11) Platform-specific advertising	.082	-.149	.011	-.030	.212	.388	.038	.218	.170	-.001																
(12) Mobile phone penetration	.059	-.050	.059	-.137	.047	.183	-.082	.030	-.110	.198	.310															
(13) GDP per capita (log)	.001	-.003	.066	-.178	.042	.172	-.199	.235	-.284	.159	-.048	.534														
(14) Power distance	-.018	.053	.035	-.085	.004	-.272	.154	-.350	.022	.038	.044	-.157	-.435													
(15) Year of data collection	.027	-.065	.017	.024	-.009	.232	-.027	.240	.208	.031	.629	.483	-.109	-.067												
(16) Year of data collection^2	-.067	.121	.061	.015	-.334	-.195	-.089	.040	-.138	-.101	-.632	-.207	.011	.043	-.112											
(17) Lagged DV	.063	-.068	-.045	.112	-.249	.398	-.158	.442	.127	.446	.176	-.004	.102	-.291	.238	-.088										
(18) Endogeneity control	.023	-.086	-.064	.201	-.159	.208	-.076	.179	.451	-.129	.158	-.353	-.270	-.049	.090	.053	.498									
(19) Number of parameters	-.030	-.057	-.038	.145	-.007	.018	.042	-.049	.031	.276	-.292	-.095	.056	-.053	-.264	.125	-.006	.092								
(20) Social media engagement valence (DV)	.009	.058	.093	-.096	-.065	.129	-.015	.056	-.114	.085	-.074	.151	-.071	.090	.183	.392	-.119	-.051	.183							
(21) Owned social media valence	-.132	.110	.021	-.204	-.069	.036	-.126	.345	-.024	-.110	.121	.121	-.001	-.136	.292	.084	.055	.024	-.105	.472						
(22) Owned social media presence	.104	-.032	.032	.091	.044	-.017	.018	-.268	-.204	.062	-.052	-.132	.027	.094	-.264	-.090	-.031	-.135	-.206	-.452	-.779					
(23) Sample size	.046	.051	.077	-.166	.186	-.190	.332	-.226	-.258	-.071	.075	.372	.115	.121	.132	-.027	-.270	-.424	-.215	.237	.108	.021				
(24) Management	-.009	.000	.025	-.094	.097	.244	.009	.123	-.009	.346	.155	.037	.317	.119	-.187	-.212	.051	-.161	.033	-.133	-.229	.181	-.151			
(25) Information systems & computer science	.052	.003	-.053	.043	-.053	-.222	-.079	-.528	.005	-.126	-.174	-.010	-.216	.267	-.163	.020	-.297	-.076	-.078	-.107	-.233	.252	.196	-.369		
(26) Top publication control	-.086	.048	-.030	-.004	-.251	-.006	-.242	.352	-.012	-.128	-.187	-.261	.186	-.219	-.152	.184	.228	.350	.172	-.081	.121	-.073	-.268	-.062	-.144	

Notes: DV = dependent variable; we mean-centered all continuous variables.

Sales

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1) Social																								
(2) Informational	-.129																							
(3) Deals	-.092	-.126																						
(4) Unspecified	-.405	-.558	-.396																					
(5) Utilitarian	-.134	-.002	.005	.040																				
(6) Brand community size (log)	.207	.060	-.168	-.056	-.231																			
(7) Service	.247	-.187	.040	-.003	-.099	.021																		
(8) New product	.335	.172	-.224	-.182	-.326	.175	.141																	
(9) Microblogs	.301	.187	-.133	-.218	.143	.081	.208	.355																
(10) Mixed platforms	-.058	-.105	-.055	.125	.332	.133	-.174	-.134	-.231															
(11) Platform-specific advertising	.170	-.126	.108	-.085	-.195	-.003	.269	.331	.037	-.366														
(12) Mobile phone penetration	.119	-.192	.438	-.150	-.154	-.219	.553	-.005	-.005	-.103	.455													
(13) GDP per capita (log)	.261	-.144	-.351	.175	.057	.208	.274	.449	.112	.220	.021	.092												
(14) Power distance	-.182	.175	.065	-.107	-.051	-.203	-.154	-.304	.086	-.344	.128	-.166	-.732											
(15) Year of data collection	.167	-.004	.212	-.254	.009	-.070	.096	.084	.250	-.050	.484	.431	-.285	.317										
(16) Year of data collection²	-.122	.235	-.053	-.089	.136	-.007	-.214	.086	-.021	.086	-.037	-.268	-.113	.077	-.094									
(17) Lagged DV	-.094	.085	-.060	.063	.109	-.247	-.225	.258	-.097	-.056	-.047	-.197	.406	-.305	-.435	.251								
(18) Endogeneity control	.156	-.057	.149	-.182	-.183	-.115	.265	.261	.196	-.224	.404	.351	.025	.068	-.034	-.104	.007							
(19) Number of parameters	-.043	-.148	.368	-.048	-.142	-.082	-.026	-.232	-.163	-.115	.150	.250	-.402	.209	.281	-.035	-.198	-.068						
(20) Owned social media valence	-.081	.044	.073	-.205	.187	-.076	-.051	-.158	.224	.008	-.082	-.113	-.071	.136	-.002	.014	.006	.079	-.093					
(21) Owned social media presence	-.159	.015	.271	-.026	-.227	-.240	.301	-.307	-.192	-.141	.052	.416	-.391	.267	-.082	-.288	-.302	.417	.130	-.137				
(22) Sample size	-.181	.213	-.128	.003	.308	-.057	.064	.015	.120	.171	-.080	-.143	.019	-.003	-.040	.065	-.054	-.239	-.311	.166	.044			
(23) Information systems & computer science	-.237	-.044	-.229	.309	-.164	.092	-.131	-.171	-.459	-.330	.225	-.333	-.236	.259	-.228	.225	.055	-.142	.005	-.267	.093	.080		
(24) Top publication control	-.226	.050	.144	.021	.008	-.364	-.334	-.128	-.176	-.119	-.180	-.103	-.317	.151	-.180	.242	.262	.005	.383	.096	.055	-.329	.011	

Notes: DV = dependent variable; we mean-centered all continuous variables.

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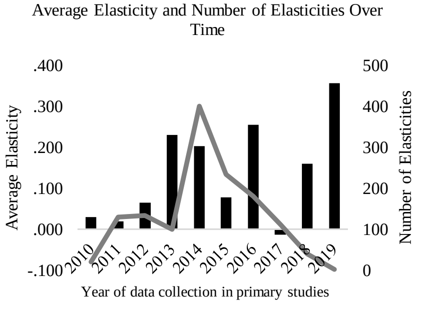
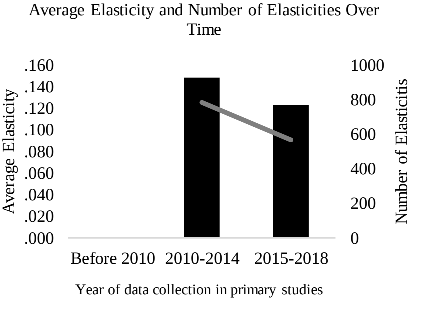
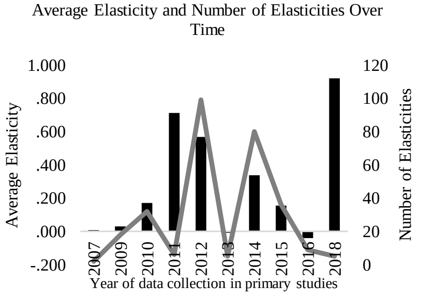
Appendix 2.10 Average Owned Social Media Elasticity and Number of Elasticities Over Time

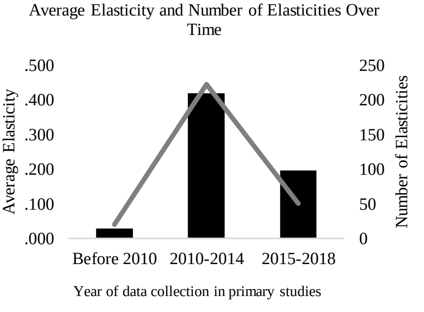
A. Social media engagement





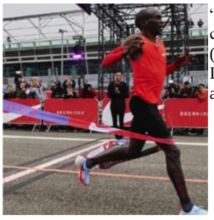
B. Sales





Notes: The bars illustrate the average owned social media elasticity, and the lines indicate the number of elasticities.

Appendix 2.11 Examples of Owned Social Media Posts from Primary Studies

	Positive		**Not always positive**	
SME		"The barrier just got that much closer. #Breaking2 #JustDoIt" (Brand: Nike; Platform: Instagram; Source: Rietveld et al. 2020, p. 21)		"Our grocery aisles across the country are now stocked with more local, fresh fruit and vegetables" (Brand: Walmart; Platform: Facebook; Source: Lee, Hosanagar, and Nair 2018, p. 5109)
	No visual example	"Everything stays possible! Come in great numbers to the stadium on Thursday and push the team to the next round in the cup!" (Brand: Belgian soccer club; Platform: Facebook; Source: Meire et al. 2019, p. 29)	*No visual example*	"It's time for the newest round of team member introductions… meet our new Social Media Manager <name deleted for privacy>! We're so happy to have her as part of our team." (Brand: retail brand; Platform: Facebook; Source: Bapna, Benner, and Qui 2019, Web Appendix A)
Sales		"Who would like to earn an extra 2500 Vitality points? Let us know and we'll tell you how." (Brand: Discovery Vitality; Platform: Facebook; Source: Mochon et al. 2017, Web Appendix B.)		"Welcome to our kid model show in XXX mall 7 pm next Monday! Plenty of gifts for you!!!" (Brand: FFS Retailer; Platform: Facebook; Source: Goh et al. 2013, p. 94)
		"A revolution in performance and design - the #BMWi8. #HelloFuture" (Brand: BMW; Platform: Facebook; Source: Wang et al. 2021, p. 589)		"How the #BMW 4 Series Gran Coupe evolved from a 1970's classic bit.ly/1xq7i33 via @Medium" (Brand: BMW; Platform: Twitter; Source: Wang et al. 2021, p. 589)

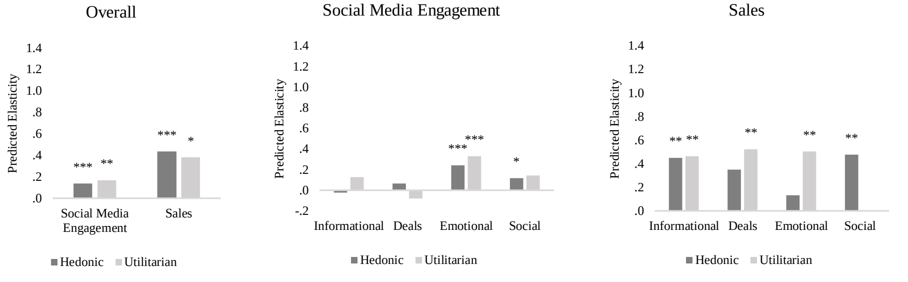
Notes: SME = social media engagement.

Appendix 2.12 Predicted Owned Social Media Elasticities Across Brand Characteristics (Full HiLMA Model)

While we observe no significant differences across brands, several studies have theorized and found a congruency or "fit" effect, in which hedonic messages work better for hedonic brands and functional messages work better for utilitarian brands (Eigenraam, Eelen, and Verlegh 2021; Rossiter, Percy, and Bergkvist 2018; Voss, Spangenberg, and Grohmann 2003). For example, for hedonic products, functional content could prompt consumers to evaluate the product more carefully and hence harm sales. The high multicollinearity prevents us from entering this "moderated-moderation" or three-way interaction directly into the main models. We therefore explore these effects by running the models separately for hedonic and utilitarian brands. In Panel A we report the predicted elasticities based on a subset of variables due to high multicollinearity, while we show in Panel B the figure based on the full set of variables. For comparison, we include the average observed elasticities of the split samples in Appendix 2.14 (for a similar approach, see Bijmolt, Van Heerde, and Pieters 2005). The split-sample analyses confirm that owned social media have a positive effect across both outcomes, with the strongest effect on sales linked to hedonic brands (though this effect is not significantly stronger than that for utilitarian brands, $p > .10$) (Panel A, Overall).

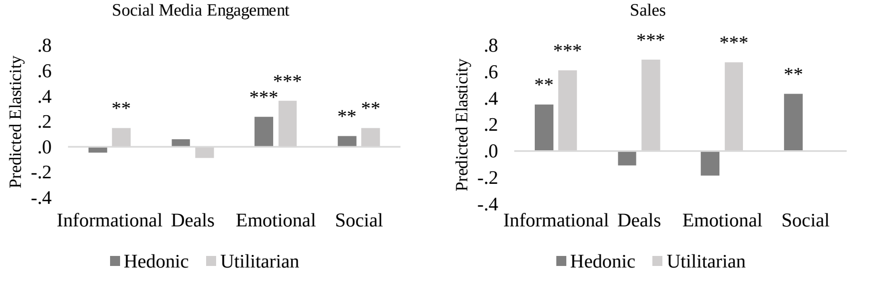
We observe some differences between types of brands, which are largely consistent with the notion of brand–message congruency effects, though the pattern is not uniform across outcomes. As shown in Panel A, for social media engagement and sales, we find rather similar effects across types of content. For hedonic brands, in line with the congruency hypothesis, we find that emotional content ($p < .01$) mostly influences social media engagement while informational content has no effect. For sales, however, a different pattern occurs, with informational and social content having the strongest effects ($p < .05$) and deals content having nonsignificant effects. However, informational and social content are not significantly different from each other ($p > .10$). Taken together, these results provide support for the brand–message congruency hypotheses, but the pattern is not unequivocal. Especially for sales, additional research is necessary to better understand the effects of different content.

A. Owned social media elasticities across brand characteristics (reduced model).



* $p < .10$, ** $p < .05$, *** $p < .01$. Notes: We compute the predicted elasticities from the coefficients of the random-effect hierarchical linear models. For the “Overall” graph, we compute the predicted elasticity from intercept-only models; for the other two graphs, due to high multicollinearity and a smaller sample size, we include the independent variables owned social media content types, platform variables sample size, and the owned social media metrics valence and presence. We use the delta method to retrieve the significance levels for the predicted elasticities reported in the graphs (see Bijmolt, Van Heerde, and Pieters 2005; Greene 2003). Content with fewer than three observations was not included (Palmatier et al. 2006).

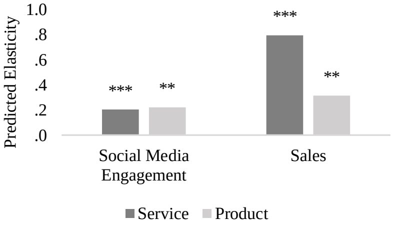
B. Owned social media elasticities across brand characteristics (full model).



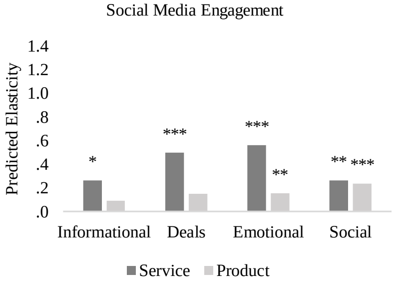
* $p < .10$, ** $p < .05$, *** $p < .01$. Notes: We compute the predicted elasticities from the coefficients of the random-effect hierarchical linear models. We use the delta method to retreive the significance levels for the predicted elasticities reported in the graphs (see Bijmolt, Van Heerde, and Pieters 2005; Greene 2003). Variables with fewer than three observations were not included (Palmatier et al. 2006). For the hedonic split social media engagement model and sales we included the following variables: owned social media content types (informational, deals, social, unspecified), the number of followers (log), service, mixed industries (only in the social media engagement model), new product (only in the sales model), platform dummies (microblogs, mixed), platform-specific advertising, mobile phone penetration, GDP per capita (log), power distance, year of data collection, quadratic term of year of data collection, lagged dependent variable, endogeneity control, number of parameters, social media engagement valence (only in the social media engagement model), owned social media metrics (valence, presence), sample size, research field (management [only in the social media engagement model], information systems and computer science), and top-publication. For the utilitarian split social media engagement model we included the very same variable used for the hedonic split, with the exception of platform-specific advertising, which we could not include due to high multicollinearity, while in the sales model, we dropped research field (information systems and computer science), and top-publication for the same reason.

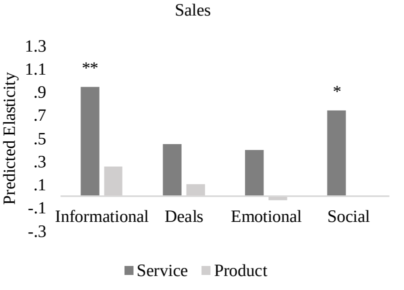
Appendix 2.13 Owned Social Media Elasticities Across Industry Characteristics

A. Predicted elasticity of owned social media across industry characteristics



B. Predicted elasticity of owned social media message content across industry characteristics

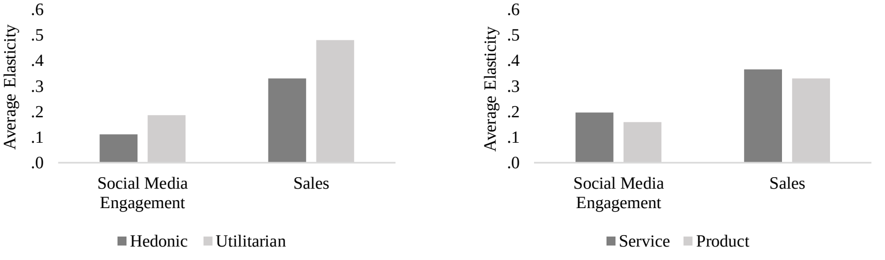




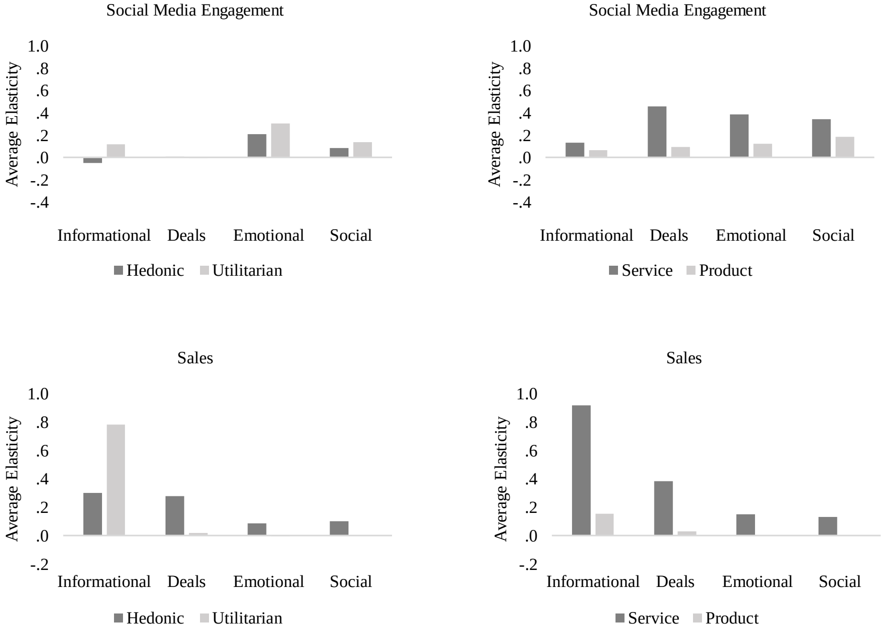
* $p < .10$, ** $p < .05$, *** $p < .01$. Notes: We compute the predicted elasticities from the coefficients of the random-effect hierarchical linear models. For Panel A, we run an intercept-only model, restricting the sample to either service or products. For Panel B, these models only include the following independent variables: owned social media content types (informational, deals, social, unspecified), platform variables (microblogs, mixed), valence and presence of owned social media, and sample size. We use the delta method to retreive the significance levels for the predicted elasticities reported in the graphs (see Bijmolt, Van Heerde, and Pieters 2005; Greene 2003). Variables with fewer than three observations were not included (Palmatier et al. 2006).

Appendix 2.14 Average Owned Social Media Elasticities for Different Brands and Industries

A. Average elasticity of owned social media across brand and industry characteristics on social media engagement and sales



B. Average elasticity of owned social media message content across brand and industry and platforms characteristics on social media engagement and sales



Notes: Content with fewer than three observations was not included (Palmatier et al. 2006).

Appendix 2.15 Comparison of Intercept-Only Model, OLS Model, and HiLMA Model

	Social Media Engagement			**Sales**		
	OLS Model	HiLMA Intercept-Only Model	HiLMA Main Model	OLS Model	HiLMA Intercept-Only Model	HiLMA Main Model
	Estimate (SE) (β)	*Estimate (SE) (β)*	*Estimate (SE) (β)*	*Estimate(SE) (β)*		*Estimate (SE) (β)*
Intercept	.583 (.161)***	.157 (.043)***	.773 (.250)***	.595 (.287)**	.394. (.115)***	.595 (.275)**
Owned Social Media Content						
Hedonic						
Emotional (ref)						
Social	-.149 (.055)***		-.154 (.055)***	.461 (.292)		.461 (.279)*
Functional						
Informational	-.266 (.052)***		-.248 (.052)***	.652 (.267)**		.652 (.256)**
Deals	-.239 (.075)***		-.254 (.074)***	-.027 (.310)		-.027 (.296)
Unspecified	-.057 (.053)		-.089 (.053)*	.455 (.243)*		.455 (.233)*
Brand Characteristics						
Hedonic (ref)						
Utilitarian	.002 (.047)		.010 (.062)	.172 (.186)		.172 (.178)
Brand community size (log)	-.033 (.014)**		-.028 (.017)	-.067 (.025)***		-.067 (.024)***
Industry Characteristics						
Product (ref)						
Service	-.191 (.080)**		-.158 (.110)	-.127 (.134)		-.127 (.128)
Mixed industries	-.211 (.057)***		-.215 (.083)**	[a]		[a]
Mature product (ref)						
New product	[a]		[a]	.545 (.193)***		.545 (.184)***
Platform Characteristics						
Social network (ref)						
Microblogs	-.108 (.062)*		-.164 (.075)**	-.149 (.169)		-.149 (.162)
Mixed platforms	-.155 (.104)		-.279 (.142)*	1.326 (.267)***		1.326 (.255)***
No platform-specific advertising (ref)						
Platform-specific advertising	-.137 (.144)		-.338 (.228)	-.600 (.215)***		-.600 (.206)***
Country						
Mobile phone penetration	-.012 (.004)***		-.014 (.005)***	.054 (.008)***		.054 (.008)***
GDP per capita (log)	.050 (.065)		.079 (.091)	-.221 (.130)*		-.221 (.125)*
Power distance	.000 (.001)		.000 (.002)	.024 (.004)***		.024 (.004)***
Study Characteristics						
Year of data collection	.053 (.022)**		.083 (.035)**	-.204 (.052)***		-.204 (.050)***
Year of data collection^2	-.031 (.009)***		-.039 (.012)***	-.034 (.011)***		-.034 (.010)***
No lagged DV (ref)						
Lagged DV	.181 (.080)**		.247 (.118)**	-.279 (.163)*		-.279 (.156)*
No endogeneity control (ref)						
Endogeneity control	.097 (.075)		.108 (.083)	-.235 (.157)		-.235 (.150)
Number of parameters[b]	-.027 (.036)		.002 (.040)	-.022 (.009)**		-.022 (.008)**
Social media engagement volume (DV) (ref)						
Social media engagement valence (DV)	.467 (.108)***		.494 (.129)***	[a]		[a]
Metric independent variable						
Volume (ref)						
Valence	-.150 (.097)		-.145 (.106)	.088 (.249)		.088 (.238)
Presence	-.114 (.082)		-.049 (.092)	-.963 (.231)***		-.963 (.221)***
Sample size	2.524(1.127)**		1.846(1.583)	-3.367(2.807)		-3.367(2.684)
Research field						
Marketing (ref)						
Management	.117 (.061)*		.128 (.092)	[a]		[a]

Information systems & computer science	-.102 (.059)*		-.063 (.092)	.365 (.209)*		.365 (.200)*
Non-top publication (ref)						
Top publication	.063 (.054)		-.010 (.084)	-.109 (.141)		-.109 (.135)
N (k)	89,629,170 (1,349)	89,629,170 (1,349)	89,629,170 (1,349)	5,666,038 (292)	5,666,038 (292)	5,666,038 (292)
Snijders–Bosker pseudo-R^2 (Level 1/Level 2)			.121 / .345			.419 /.719
Adjusted R^2	.069			.293		

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018). [b] The number of parameters is divided by 100.
Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

Appendix 2.16 Sensitivity Analysis Removing One Paper at a Time Rerunning the Main HiLMA Model

	Social Media Engagement					Sales				
	Direction and significance of estimate (β) from main HiLMA results	*Percent of cases (%) for the direction and significance of estimate (β) when removing one paper at a time rerunning the main HiLMA Model*				*Direction and significance of estimate (β) from main HiLMA results*	*Percent of cases (%) for the direction and significance of estimate (β) when removing one paper at a time rerunning the main HiLMA Model*			
		+ sig.	*– sig.*	*+ n.s.*	*– n.s.*		*+ sig.*	*– sig.*	*+ n.s.*	*– n.s.*
Owned social media content										
Social	– sig.	0%	96%	0%	4%	+ sig.	43%	0%	57%	0%
Informational	– sig.	0%	100%	0%	0%	+ sig.	100%	0%	0%	0%
Deals	– sig.	0%	100%	0%	0%	– n.s.	0%	0%	31%	69%
Unspecified	– sig.	0%	68%	0%	32%	+ sig.	74%	0%	26%	0%
Brand Characteristics										
Utilitarian	. + n.s.	2%	0%	86%	12%	+ n.s.	3%	0%	97%	0%
Brand community size (log)	– n.s.	0%	24%	0%	76%	– sig.	0%	91%	0%	9%
Industry Characteristics										
Service	– n.s.	0%	12%	0%	88%	– n.s.	0%	0%	14%	86%
Mixed industries	– sig.	0%	98%	0%	2%	[a]				
New product	[a]					+ sig.	91%	0%	9%	0%
Platform Characteristics										
Microblogs	– sig.	0%	96%	0%	4%	– n.s.	0%	3%	6%	91%
Mixed platforms	– sig.	0%	94%	0%	6%	+ sig.	97%	0%	3%	0%
Platform-specific advertising	– n.s.	0%	18%	2%	80%	– sig.	0%	91%	0%	9%
Country										
Mobile phone penetration	– sig.	0%	98%	0%	2%	+ sig.	100%	0%	0%	0%
GDP per capita (log)	+ n.s.	0%	2%	98%	0%	– sig.	0%	60%	0%	40%
Power distance	+ n.s.	0%	0%	72%	28%	+ sig.	100%	0%	0%	0%
Study Characteristics										
Year of data collection	+ sig.	94%	0%	6%	0%	– sig.	0%	100%	0%	0%
Year of data collection^2	– sig.	0%	98%	0%	2%	– sig.	0%	97%	0%	3%
Lagged DV	+ sig	98%	0%	2%	0%	– sig.	0%	74%	3%	23%
Endogeneity control	+ n.s.	2%	0%	98%	0%	– n.s.	0%	40%	0%	60%
Number of parameters	+ n.s.	0%	0%	76%	24%	– sig.	0%	97%	0%	3%
Social media engagement valence (DV)	+ sig	100%	0%	0%	0%	[a]				
Metric independent variable										
Valence	– n.s.	0%	4%	0%	96%	+ n.s.	3%	0%	71%	26%
Presence	– n.s.	0%	0%	4%	96%	– sig.	0%	100%	0%	0%
Sample size	+ n.s.	6%	0%	92%	2%	– n.s.	0%	20%	0%	80%
Research field										
Management	+ n.s.	8%	0%	92%	0%	[a]				
Information systems & computer science	– n.s.	0%	4%	4%	92%	+ sig	63%	0%	37%	0%
Top publication	– n.s.	0%	2%	12%	86%	– n.s.	3%	0%	3%	94%

[a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018). Notes: +(–) sig. = number of positive (negative) statistically significant elasticities; +(–) n.s. = number of positive (negative) nonsignificant elasticities; β = beta coefficient;

Appendix 2.17 HiLMA Results Without TV Show Viewing for Sales

	Sales			
	HiLMA without TV Show Viewing		HiLMA Main Model	
	Estimate (β)	*(SE)*	*Estimate (β)*	*(SE)*
Intercept	.587	(.283)**	.595	(.275)**
Owned social media content				
Hedonic				
Emotional (ref)				
Social	.495	(.287)*	.461	(.279)*
Functional				
Informational	.585	(.262)**	.652	(.256)**
Deals	-.036	(.301)	-.027	(.296)
Unspecified	.502	(.239)**	.455	(.233)*
Brand Characteristics				
Hedonic (ref)				
Utilitarian	.125	(.184)	.172	(.178)
Brand community size (log)	-.064	(.025)**	-.067	(.024)***
Industry Characteristics				
Product (ref)				
Service	-.138	(.141)	-.127	(.128)
Mixed industries	[a]		[a]	
Mature product (ref)				
New product	.386	(.234)*	.545	(.184)***
Platform Characteristics				
Social network (ref)				
Microblogs	-.157	(.165)	-.149	(.162)
Mixed platforms	1.336	(.265)***	1.326	(.255)***
No platform-specific advertising (ref)				
Platform-specific advertising	-.442	(.240)*	-.600	(.206)***
Country				
Mobile phone penetration	.061	(.009)***	.054	(.008)***
GDP per capita (log)	-.233	(.129)*	-.221	(.125)*
Power distance	.023	(.004)***	.024	(.004)***
Study Characteristics				
Year of data collection	-.232	(.055)***	-.204	(.050)***
Year of data collection^2	-.027	(.011)**	-.034	(.010)***
No lagged DV (ref)				
Lagged DV	-.263	(.162)	-.279	(.156)*
No endogeneity control (ref)				
Endogeneity control	-.288	(.155)*	-.235	(.150)
Number of parameters[b]	-.022	(.009)***	-.022	(.008)**
Social media engagement volume (DV) (ref)				
Social media engagement valence (DV)	[a]		[a]	
Metric independent variable				
Volume (ref)				
Valence	.179	(.254)	.088	(.238)
Presence	-1.238	(.332)***	-.963	(.221)***
Sample size	-3.592	(2.808)	-3.367	(2.684)
Research field				
Marketing (ref)				
Management	[a]		[a]	
Information systems & computer science	.406	(.211)*	.365	(.200)*
Non-top publication (ref)				
Top publication	-.206	(.157)	-.109	(.135)
N (k)	5,660,726 (280)		5,666,038 (292)	
Snijders–Bosker pseudo-R^2 (Level 1 /Level 2)	.428 /.725		.419 /.719	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018); [b] The number of parameters is divided by 100. Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

Appendix 2.18 HilMA Results Without Social Media Engagement Valence (Dependent Variable)

	Social Media Engagement			
	HilMA Model Without Social Media Engagement Valence		HiLMA Main Model	
	Estimate (β)	*(SE)*	*Estimate (β)*	*(SE)*
Intercept	.971	(.248)***	.773	(.250)***
Owned social media content				
Hedonic				
Emotional (ref)				
Social	-.171	(.059)***	-.154	(.055)***
Functional				
Informational	-.286	(.055)***	-.248	(.052)***
Deals	-.286	(.081)***	-.254	(.074)***
Unspecified	-.096	(.055)*	-.089	(.053)*
Brand Characteristics				
Hedonic (ref)				
Utilitarian	.019	(.065)	.010	(.062)
Brand community size (log)	-.036	(.017)**	-.028	(.017)
Industry Characteristics				
Product (ref)				
Service	-.322	(.118)***	-.158	(.110)
Mixed industries	-.351	(.087)***	-.215	(.083)**
Mature product (ref)				
New product	[a]		[a]	
Platform Characteristics				
Social network (ref)				
Microblogs	-.215	(.074)***	-.164	(.075)**
Mixed platforms	-.096	(.169)	-.279	(.142)*
No platform-specific advertising (ref)				
Platform-specific advertising	-.406	(.216)*	-.338	(.228)
Country				
Mobile phone penetration	-.017	(.005)***	-.014	(.005)***
GDP per capita (log)	.002	(.104)	.079	(.091)
Power distance	-.002	(.002)	.000	(.002)
Study Characteristics				
Year of data collection	.087	(.032)***	.083	(.035)**
Year of data collection^2	-.053	(.013)***	-.039	(.012)***
No lagged DV (ref)				
Lagged DV	.202	(.121)*	.247	(.118)**
No endogeneity control (ref)				
Endogeneity control	.182	(.099)*	.108	(.083)
Number of parameters[b]	.103	(.108)	.002	(.040)
Social media engagement volume (DV) (ref)				
Social media engagement valence (DV)			.494	(.129)***
Metric independent variable				
Volume (ref)				
Valence	-.219	(.116)*	-.145	(.106)
Presence	-.114	(.101)	-.049	(.092)
Sample size	4.053	(1.695)**	1.846	(1.583)
Research field				
Marketing (ref)				
Management	.143	(.088)	.128	(.092)
Information systems & computer science	-.153	(.087)	-.063	(.092)
Non-top publication (ref)				
Top publication	.082	(.083)	-.010	(.084)
N (k)	89,445,329 (1,258)		89,629,170 (1,349)	
Snijders–Bosker pseudo-R^2 (Level 1 /Level 2)	.148 / .587		.121 / .345	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018); [b] The number of parameters is divided by 100.
Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

Appendix 2.19 Full List of Moderating Variables Collected But Not Included in the Analyses Because of Multicollinearity, Lack of Variation, and Systematic Non-Significance

	Moderator
Brand characteristics	Luxury brand
	Durable vs. non-durable brand
	Search vs. experience vs. credence brand
	Premium vs. middle vs. value brand
	Perceived risk of brand
	Category involvement
	Local vs. global brand
	Single vs. multiple brands
Industry characteristics	Number of firms
	Advertising expenditure
	Research and development expenditure
	Sales growth
	Herfindahl index
Platform characteristics	Visibility of content (privacy regulations over time)
	Dummy variables for key social media platforms (Facebook, Instagram, Myspace, Sina Weibo, Twitter, WeChat, Weitao, YouTube)
Country characteristics	Number of patents
	Internet penetration
	Fixed broadband subscriptions
	English ability index
	Uncertainty avoidance
	Individualism vs. collectivism
	Masculinity vs. femininity
	Long-term orientation vs. short-term orientation
	Indulgence vs. restraint
	Country dummies: Asia, U.S., Europe
Control variables	Time fixed effects
	Temporal aggregation
	Cross-sectional vs. time-series vs. panel data
	Marketing-mix control
	Primary data vs. secondary data
	Unpublished vs. published data
	Product vs. brand-level data
	Brand- vs. consumer- vs. post-level data
	Content operationalized with a scale
	Content classified using machine learning
	Multiple content types studied vs. one content type only

Notes: The results including the different moderating variables are available upon request.

Appendix 2.20 Robustness Checks Example Results for Variables with High Multicollinearity or Nonsignificance

A. Comparison of Main HiLMA results with HiLMA results including a dummy for primary data

	Social Media Engagement				Sales			
	HiLMA With Primary Data Dummy[c]		HiLMA Main Model		HiLMA With Primary Data Dummy[c]		HiLMA Main Model	
	Estimate (β)	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*
Intercept	.738	(.254)***	.773	(.250)***	.648	(.274)**	.595	(.275)**
Owned social media content								
Hedonic								
Emotional (ref)								
Social	-.161	(.055)***	-.154	(.055)***	.401	(.278)	.461	(.279)*
Functional								
Informational	-.248	(.052)***	-.248	(.052)***	.585	(.256)**	.652	(.256)**
Deals	-.258	(.074)***	-.254	(.074)***	-.022	(.294)	-.027	(.296)
Unspecified	-.096	(.053)*	-.089	(.053)*	.408	(.232)*	.455	(.233)*
Brand Characteristics								
Hedonic (ref)								
Utilitarian	.012	(.062)	.010	(.062)	.351	(.195)*	.172	(.178)
Brand community size (log)	-.031	(.018)*	-.028	(.017)	-.078	(.025)***	-.067	(.024)***
Industry Characteristics								
Product (ref)								
Service	-.171	(.111)	-.158	(.110)	-.160	(.128)	-.127	(.128)
Mixed industries	-.238	(.085)***	-.215	(.083)**	[a]		[a]	
Mature product (ref)								
New product	[a]		[a]		.581	(.184)***	.545	(.184)***
Platform Characteristics								
Social network (ref)								
Microblogs	-.174	(.076)**	-.164	(.075)**	-.281	(.172)	-.149	(.162)
Mixed platforms	-.335	(.146)**	-.279	(.142)*	1.260	(.255)***	1.326	(.255)***
No platform-specific advertising (ref)								
Platform-specific advertising	-.294	(.231)	-.338	(.228)	-.627	(.205)***	-.600	(.206)***
Country								
Mobile phone penetration	-.014	(.005)***	-.014	(.005)***	.050	(.008)***	.054	(.008)***
GDP per capita (log)	.068	(.092)	.079	(.091)	-.240	(.124)*	-.221	(.125)*
Power distance	.000	(.002)	.000	(.002)	.021	(.004)***	.024	(.004)***
Study Characteristics								
Year of data collection	.080	(.035)**	.083	(.035)**	-.169	(.052)***	-.204	(.050)***
Year of data collection^2	-.038	(.013)***	-.039	(.012)***	-.031	(.010)***	-.034	(.010)***
No lagged DV (ref)								
Lagged DV	.315	(.126)**	.247	(.118)**	-.348	(.158)**	-.279	(.156)*
No endogeneity control (ref)								
Endogeneity control	.078	(.085)	.108	(.083)	-.099	(.162)	-.235	(.150)
Number of parameters[b]	.072	(.058)	.002	(.040)	-.022	(.008)**	-.022	(.008)**
Social media engagement volume (DV) (ref)								
Social media engagement valence (DV)	-.101	(.383)	.494	(.129)***	[a]		[a]	
Metric independent variable								
Volume (ref)								
Valence	-.145	(.106)	-.145	(.106)	.003	(.240)	.088	(.238)
Presence	-.034	(.092)	-.049	(.092)	-.315	(.374)	-.963	(.221)***
Sample size	1.708	(1.594)	1.846	(1.583)	-2.508	(2.693)	-3.367	(2.684)
Research field								
Marketing (ref)								
Management	.131	(.093)	.128	(.092)	[a]		[a]	
Information systems & computer science	-.053	(.093)	-.063	(.092)	.351	(.199)*	.365	(.200)*
Non-top publication (ref)								
Top publication	.003	(.085)	-.010	(.084)	-.168	(.137)	-.109	(.135)
Primary data dummy[c]	.658	(.399)*			-.689	(.322)**		
N (k)	89,629,170 (1,349)		89,629,170 (1,349)		5,666,038 (292)		5,666,038 (292)	
Snijders–Bosker pseudo-R^2 (Level 1 /Level 2)	.122 / .342		.121 / .345		.428 / .723		.419 /.719	
Maximum variance inflation factor (VIF)	29.33		7.55		15.41		9.57	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018); [b] The number of parameters is divided by 100; [c] Primary data dummy = dummy variable that equals 1 for survey or experimental data and 0 for longitudinal data. Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

B. Comparison of Main HiLMA Results with HiLMA Results Including a Dummy for Papers Studying More Than One Content Type

	Social Media Engagement				**Sales**			
	HiLMA with Additional Content Dummies		HiLMA Main Model		HiLMA with Additional Content Dummies		HiLMA Main Model	
	Estimate (β)	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*
Intercept	.776	(.251)***	.773	(.250)***	.554	(.275)**	.595	(.275)**
Owned social media content								
Hedonic								
Emotional (ref)								
Social	-.154	(.055)***	-.154	(.055)***	.523	(.281)*	.461	(.279)*
Functional								
Informational	-.247	(.052)***	-.248	(.052)***	.698	(.256)***	.652	(.256)**
Deals	-.253	(.074)***	-.254	(.074)***	-.016	(.295)	-.027	(.296)
Unspecified	-.089	(.053)*	-.089	(.053)*	.549	(.240)**	.455	(.233)*
Brand Characteristics								
Hedonic (ref)								
Utilitarian	.010	(.062)	.010	(.062)	.221	(.180)	.172	(.178)
Brand community size (log)	-.027	(.018)	-.028	(.017)	-.072	(.025)***	-.067	(.024)***
Industry Characteristics								
Product (ref)								
Service	-.162	(.113)	-.158	(.110)	-.196	(.136)	-.127	(.128)
Mixed industries	-.214	(.083)**	-.215	(.083)**	[a]		[a]	
Mature product (ref)								
New product	[a]		[a]		.544	(.184)***	.545	(.184)***
Platform Characteristics								
Social network (ref)								
Microblogs	-.166	(.077)**	-.164	(.075)**	-.056	(.173)	-.149	(.162)
Mixed platforms	-.280	(.142)**	-.279	(.142)*	1.349	(.255)***	1.326	(.255)***
No platform-specific advertising (ref)								
Platform-specific advertising	-.346	(.232)	-.338	(.228)	-.681	(.212)***	-.600	(.206)***
Country								
Mobile phone penetration	-.014	(.005)***	-.014	(.005)***	.058	(.008)***	.054	(.008)***
GDP per capita (log)	.079	(.092)	.079	(.091)	-.206	(.125)*	-.221	(.125)*
Power distance	.000	(.002)	.000	(.002)	.025	(.004)***	.024	(.004)***
Study Characteristics								
Year of data collection	.083	(.035)**	.083	(.035)**	-.219	(.051)***	-.204	(.050)***
Year of data collection^2	-.039	(.013)***	-.039	(.012)***	-.029	(.010)***	-.034	(.010)***
No lagged DV (ref)								
Lagged DV	.248	(.119)**	.247	(.118)**	-.346	(.162)**	-.279	(.156)*
No endogeneity control (ref)								
Endogeneity control	.111	(.085)	.108	(.083)	-.232	(.149)	-.235	(.150)
Number of parameters[b]	.003	(.040)	.002	(.040)	-.021	(.008)**	-.022	(.008)**
Social media engagement volume (DV) (ref)								
Social media engagement valence (DV)	.492	(.130)***	.494	(.129)***	[a]		[a]	
Metric independent variable								
Volume (ref)								
Valence	-.142	(.107)	-.145	(.106)	-.047	(.254)	.088	(.238)
Presence	-.046	(.093)	-.049	(.092)	-.951	(.221)***	-.963	(.221)***
Sample size	1.877	(1.601)	1.846	(1.583)	-4.622	(2.804)*	-3.367	(2.684)
Research field								
Marketing (ref)								
Management	.127	(.092)	.128	(.092)	[a]		[a]	
Information systems & computer science	-.065	(.093)	-.063	(.092)	.416	(.202)**	.365	(.200)*
Non-top publication (ref)								
Top publication	-.010	(.085)	-.010	(.084)	-.102	(.135)	-.109	(.135)
Only 1 owned social media content type[c]	.017	(.106)						
Multiple owned social media content types[d]					.309	(.208)		
N (k)	89,629,170 (1,349)		89,629,170 (1,349)		5,666,038 (292)		5,666,038 (292)	
Snijders–Bosker pseudo-R^2 (Level 1 /Level 2)	.121 / .343		.121 / .345		.424 / .721		.419 /.719	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018); [b] The number of parameters is divided by 100. [c] Only 1 owned social media content type = dummy variable that equals 1 if the primary study studied only one content type (in 24% of the papers we observe that authors focus on one type of content only); [d] Multiple owned social media content types = dummy variable that equals 1 if the primary study studied multiple types of content (in 29% of the papers we observe that authors focus on multiple types of content). Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

C. Comparison of Main HiLMA Results with HiLMA Results Including Alternative Platform Dummies

	Social Media Engagement				**Sales**			
	HiLMA with Alternative Platform Dummies		HiLMA Main Model		HiLMA with Alternative Platform Dummies		HiLMA Main Model	
	Estimate (β)	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*
Intercept	.744	(.250)***	.773	(.250)***	.557	(.285)*	.595	(.275)**
Owned social media content								
Hedonic								
Emotional (ref)								
Social	-.148	(.055)***	-.154	(.055)***	.356	(.280)	.461	(.279)*
Functional								
Informational	-.243	(.052)***	-.248	(.052)***	.539	(.258)**	.652	(.256)**
Deals	-.246	(.074)***	-.254	(.074)***	.056	(.300)	-.027	(.296)
Unspecified	-.085	(.053)	-.089	(.053)*	.348	(.236)	.455	(.233)*
Brand Characteristics								
Hedonic (ref)								
Utilitarian	.000	(.066)	.010	(.062)	.200	(.201)	.172	(.178)
Brand community size (log)	-.031	(.020)	-.028	(.017)	-.029	(.031)	-.067	(.024)***
Industry Characteristics								
Product (ref)								
Service	-.117	(.115)	-.158	(.110)	.04	(.145)	-.127	(.128)
Mixed industries	-.204	(.085)**	-.215	(.083)**	[a]		[a]	
Mature product (ref)								
New product	[a]		[a]		.324	(.249)	.545	(.184)***
Platform Characteristics								
Social network (ref)								
Microblogs			-.164	(.075)**			-.149	(.162)
Mixed platforms			-.279	(.142)*			1.326	(.255)***
Facebook[b] (ref)								
Instagram[b]	-.109	(.166)			[a]			
Twitter[b]	-.191	(.083)**			-.171	(.216)		
Sina Weibo[b]	.158	(.229)			.065	(.441)		
Other platforms[b]	[a]				.111	(.248)		
Mixed platforms[b]	.020	(.109)			1.090	(.252)***		
No platform-specific advertising (ref)								
Platform-specific advertising	-.297	(.229)	-.338	(.228)	-.537	(.304)*	-.600	(.206)***
Country								
Mobile phone penetration	-.017	(.005)***	-.014	(.005)***	.041	(.008)***	.054	(.008)***
GDP per capita (log)	.133	(.104)	.079	(.091)	-.098	(.135)	-.221	(.125)*
Power distance	-.001	(.002)	.000	(.002)	.018	(.006)***	.024	(.004)***
Study Characteristics								
Year of data collection	.082	(.035)**	.083	(.035)**	-.162	(.052)***	-.204	(.050)***
Year of data collection^2	-.039	(.013)***	-.039	(.012)***	-.025	(.011)**	-.034	(.010)***
No lagged DV (ref)								
Lagged DV	.142	(.108)	.247	(.118)**	-.317	(.174)*	-.279	(.156)*
No endogeneity control (ref)								
Endogeneity control	.091	(.093)	.108	(.083)	-.246	(.148)*	-.235	(.150)
Number of parameters[c]	-.029	(.038)	.002	(.040)	-.017	(.009)*	-.022	(.008)**
Social media engagement volume (DV) (ref)								
Social media engagement valence (DV)	.459	(.135)***	.494	(.129)***	[a]		[a]	
Metric independent variable								
Volume (ref)								
Valence	-.156	(.106)	-.145	(.106)	-.008	(.241)	.088	(.238)
Presence	-.080	(.093)	-.049	(.092)	-.656	(.244)***	-.963	(.221)***
Sample size	2.748	(1.668)*	1.846	(1.583)	-3.115	(2.656)	-3.367	(2.684)
Research field								
Marketing (ref)								
Management	.063	(.089)	.128	(.092)	[a]		[a]	
Information systems & computer science	-.164	(.100)*	-.063	(.092)	.289	(.226)	.365	(.200)*
Non-top publication (ref)								
Top publication	.021	(.086)	-.010	(.084)	-.11	(.144)	-.109	(.135)
N (k)	89,629,170 (1,349)		89,629,170 (1,349)		5,666,038 (292)		5,666,038 (292)	
Snijders–Bosker pseudo-R^2 (Level 1 / Level 2)	.121 / .346		.121 / .345		.421 / .720		.419 /.719	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018); [b] We included alternative platform dummies: (1) Facebook (reference) = dummy variable that equals 1 if the platform on which owned social media and social media engagement was reported in the primary study is Facebook, and 0 otherwise; (2) Instagram = dummy variable that equals 1 if the platform on which owned social media and social media engagement was reported in the primary study is Instagram, and 0 otherwise; (3) Twitter = dummy variable that equals 1 if the

platform on which owned social media and social media engagement was reported in the primary study is Twitter, and 0 otherwise; (4) Sina Weibo = dummy variable that equals 1 if the platform on which owned social media and social media engagement was reported in the primary study is Sina Weibo, and 0 otherwise; (5) Other platforms = dummy variable that equals 1 if the platform on which owned social media and social media engagement was reported in the primary study is WeChat, Myspace, or Weitao, and 0 otherwise; (6) Mixed platforms = dummy variable that equals 1 if owned social media and social media engagement was reported on multiple types of platforms (e.g., social networks, microblogs and blogs, forum, and online communities in any combination together) or blogs, forums, and social media in general and 0 otherwise. [c] The number of parameters is divided by 100. Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

Appendix 2.21 HiLMA Results with Alternative Nested Structure Using Datasets Instead of Papers As Level 2

	Social Media Engagement				**Sales**			
	HiLMA Alternative Nested Structure		HiLMA Main Model		HiLMA Alternative Nested Structure		HiLMA Main Model	
	Estimate (β)	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*	*Estimate (β)*	*(SE)*
Intercept	.585	(.285)**	.773	(.250)***	.595	(.275)**	.595	(.275)**
Owned social media content								
Hedonic								
Emotional (ref)								
Social	-.161	(.055)***	-.154	(.055)***	.461	(.279)*	.461	(.279)*
Functional								
Informational	-.244	(.051)***	-.248	(.052)***	.652	(.256)**	.652	(.256)**
Deals	-.250	(.073)***	-.254	(.074)***	-.027	(.296)	-.027	(.296)
Unspecified	-.101	(.052)*	-.089	(.053)*	.455	(.233)*	.455	(.233)*
Brand Characteristics								
Hedonic (ref)								
Utilitarian	-.011	(.068)	.010	(.062)	.172	(.178)	.172	(.178)
Brand community size (log)	-.026	(.020)	-.028	(.017)	-.067	(.024)***	-.067	(.024)***
Industry Characteristics								
Product (ref)								
Service	-.107	(.119)	-.158	(.110)	-.127	(.128)	-.127	(.128)
Mixed industries	-.179	(.091)**	-.215	(.083)**	[a]		[a]	
Mature product (ref)								
New product	[a]		[a]		.545	(.184)***	.545	(.184)***
Platform Characteristics								
Social network (ref)								
Microblogs	-.031	(.101)	-.164	(.075)**	-.149	(.162)	-.149	(.162)
Mixed platforms	-.264	(.155)*	-.279	(.142)*	1.326	(.255)***	1.326	(.255)***
No platform-specific advertising (ref)								
Platform-specific advertising	-.205	(.258)	-.338	(.228)	-.600	(.206)***	-.600	(.206)***
Country								
Mobile phone penetration	-.011	(.006)**	-.014	(.005)***	.054	(.008)***	.054	(.008)***
GDP per capita (log)	.062	(.101)	.079	(.091)	-.221	(.125)*	-.221	(.125)*
Power distance	.000	(.002)	.000	(.002)	.024	(.004)***	.024	(.004)***
Study Characteristics								
Year of data collection	.056	(.039)	.083	(.035)**	-.204	(.050)***	-.204	(.050)***
Year of data collection^2	-.030	(.014)**	-.039	(.012)***	-.034	(.010)***	-.034	(.010)***
No lagged DV (ref)								
Lagged DV	.257	(.127)**	.247	(.118)**	-.279	(.156)*	-.279	(.156)*
No endogeneity control (ref)								
Endogeneity control	.053	(.086)	.108	(.083)	-.235	(.150)	-.235	(.150)
Number of parameters[b]	-.006	(.045)	.002	(.040)	-.022	(.008)**	-.022	(.008)**
Social media engagement volume (DV) (ref)								
Social media engagement valence (DV)	.518	(.133)***	.494	(.129)***	[a]		[a]	
Metric independent variable								
Volume (ref)								
Valence	-.097	(.108)	-.145	(.106)	.088	(.238)	.088	(.238)
Presence	.005	(.956)	-.049	(.092)	-.963	(.221)***	-.963	(.221)***
Sample size	.779	(1.673)	1.846	(1.583)	-3.367	(2.684)	-3.367	(2.684)
Research field								
Marketing (ref)								
Management	.093	(.099)	.128	(.092)	[a]		[a]	
Information systems & computer science	-.068	(.101)	-.063	(.092)	.365	(.200)*	.365	(.200)*
Non-top publication (ref)								
Top publication	.010	(.089)	-.010	(.084)	-.109	(.135)	-.109	(.135)
N (k)	89,629,170 (1,349)		89,629,170 (1,349)		5,666,038 (292)		5,666,038 (292)	
Snijders–Bosker pseudo-R^2 (Level 1 /Level 2)	.105 / .273		.121 / .345		.393 / .684		.419 /.719	

* $p < .10$, ** $p < .05$, *** $p < .01$. [a] We removed variables with fewer than seven observations and fewer than three studies from the analysis (Edeling and Himme 2018); [b] The number of parameters is divided by 100. Notes: β = beta coefficient; SE = standard error; DV = dependent variable; N = number of observations in primary studies; k = number of elasticities; ref = reference category.

References of the Appendix

Akpinar, Ezgi and Jonah Berger (2017), "Valuable Virality," *Journal of Marketing Research*, 54 (2), 318–30.

Allebach, Nathan (2019), "Brand Twitter Grows Up How Corporate Social Media (Mostly) Moved Past Its Awkward Phase and Connected with Audiences," *Vulture*, (June 24), https://www.vulture.com/2019/06/brand-twitter-jokes-history.html

Bapna, Sofia, Mary J. Benner, and Liangfei Qiu (2019), "Nurturing Online Communities: An Empirical Investigation1," *MIS Quarterly: Management Information Systems*, 43 (2), 425–52.

Bijmolt, Tammo H.A., Harald J. Van Heerde, and Rik GM Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity," *Journal of Marketing Research*, 42 (2), 141-56.

De Vries, Lisette, Sonja Gensler, and Peter S.H. Leeflang (2012), "Popularity of Brand Posts on Brand Fan Pages: An Investigation of the Effects of Social Media Marketing," *Journal of Interactive Marketing*, 26 (2), 83–91.

Dhaoui, Chedia, and Cynthia M. Webster, (2021) "Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Let's Have a (Positive) Conversation," *International Journal of Research in Marketing*, 38 (1), 155–75.

Edeling, Alexander and Marc Fischer (2016), "Marketing's Impact on Firm Value: Generalizations from a Meta-Analysis," *Journal of Marketing Research*, 53 (4), 515–34.

Edeling, Alexander and Alexander Himme (2018), "When Does Market Share Matter? New Empirical Generalizations from a Meta-Analysis of the Market Share-Performance Relationship," *Journal of Marketing*, 82 (3), 1–24.

Eigenraam, Anniek W., Jiska Eelen, and Peeter W.J. Verlegh (2021), "Let Me Entertain You? The Importance of Authenticity in Online Customer Engagement," *Journal of Interactive Marketing*, 54, 53-68.

Gao, Qin and Chenyue Feng (2016), "Branding with Social Media: User Gratifications, Usage Patterns, and Brand Message Content Strategies," *Computers in Human Behavior*, 63, 868–90.

Goh, Khim-Yong, Cheng-Suang Heng, and Zhijie Lin (2013), "Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content," *Information Systems Research*, 24 (1), 88–107.

Greene, William H. (2003), Econometric Analysis. 5th ed. Upper Saddle River, NJ: Prentice Hall.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing*, 80 (3), 1–24.

Homburg, Christian, Laura Ehm, and Martin Artz (2015), "Measuring and Managing Consumer Sentiment in an Online Community Environment," *Journal of Marketing Research*, 52 (5), 629–41.

Kanuri, Vamsi K., Yixing Chen, and Shrihari Sridhar (2018), "Scheduling Content on Social Media: Theory, Evidence, and Application," *Journal of Marketing*, 82 (6), 89–108.

Koch, Oliver Francis and Alexander Benlian (2015), "Promotional Tactics for Online Viral Marketing Campaigns: How Scarcity and Personalization Affect Seed Stage Referrals," *Journal of Interactive Marketing*, 32, 37–52.

Kumar, Ashish, Ram Bezawada, Rishika Rishika, Ramkumar Janakiraman, and P.K. Kannan (2016), "From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior," *Journal of Marketing*, 80 (1), 7–25.

Lamberton, Cait and Andrew T. Stephen (2016), "A Thematic Exploration of Digital, Social Media, and Mobile Marketing: Research Evolution From 2000 to 2015 and An Agenda for Future Inquiry," *Journal of Marketing,* 80 (6), 146-172.
Lee, Dokyun, Kartik Hosanagar, and Harikesh S. Nair (2018), "Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook," *Management Science*, 64 (11), 5105–31.
Liu, Xuan., Savannah Wei Shi, Thales Teixeira, and Michel Wedel (2018), "Video Content Marketing: The Making of Clips," *Journal of Marketing*, 82(4), 86–101.
Lovett, Mitchell J. and Richard Staelin (2016), "The Role of Paid, Earned, and Owned Media in Building Entertainment Brands: Reminding, Informing, and Enhancing Enjoyment," *Marketing Science*, 35 (1), 142–57.
Meire, Matthijs, Kelly Hewett, Michel Ballings, V. Kumar, and Dirk Van den Poel (2019), "The Role of Marketer-Generated Content in Customer Engagement Marketing," *Journal of Marketing*, 83 (6), 21–42.
Mochon, Daniel, Karen Johnson, Janet Schwartz, and Dan Ariely (2017), "What Are Likes Worth? A Facebook Page Field Experiment," *Journal of Marketing Research*, 54 (2), 306–17.
Moher, David, Alessandro Liberati, Jennifer Tetzlaff, and Douglas G. Altman (2009), "Statement," *Physical Therapy*, 89 (9), 873–80.
Ordenes, Francisco Villarroel, Dhruv Grewal, Stephan Ludwig, Ko De Ruyter, Dominik Mahr, and Martin Wetzels (2019), "Cutting Through Content Clutter: How Speech and Image Acts Drive Consumer Sharing of Social Media Brand Messages," *Journal of Consumer Research*, 45 (5), 988–1012.
Palmatier, Robert W., Rajiv P. Dant, Dhruv Grewal, and Kenneth R. Evans (2006), "Factors Influencing the Effectiveness of Relationship Marketing: A Meta-Analysis," *Journal of Marketing*, 70 (4), 136–53.
Peng, Jing, Agarwal, Ashish, Hosanagar, Kartik, and Iyengar, Raghuram (2018), "Network Overlap and Content Sharing on Social Media Platforms," *Journal of Marketing Research*, 55 (4), 571-85.
Rietveld, Robert, Willemijn van Dolen, Masoud Mazloom, and Marcel Worring (2020), "What You Feel, Is What You Like Influence of Message Appeals on Customer Engagement on Instagram," *Journal of Interactive Marketing*, 49, 20–53.
Rossiter, John R., Larry Percy, and Lars Bergkvist (2018), *Marketing Communications: Objectives*, Strategy, Tactics. London: SAGE Publications.
Sprott, David, Sandor Czellar, and Eric Spangenberg (2009), "The Importance of a General Measure of Brand Engagement on Market Behavior: Development and Validation of a Scale," *Journal of Marketing Research*, 46 (1), 92–104.
Sridhar, Shrihari and Raji Srinivasan (2012), "Social Influence Effects in Online Product Ratings," *Journal of Marketing*, 76 (5), 70-88.
Stephen, Andrew T. and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (5), 624–39.
Tellis, Gerard J., Deborah J. MacInnis, Seshadri Tirunillai, and Yanwei Zhang (2019), "What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence," *Journal of Marketing*, 83 (4), 1–20
TweetReports (2011), "First Tweets By 53 of the World's Most Recognized Brands," https://www.tweetreports.com/twitter/first-tweets-worlds-most-recognized-brands/
Unnava, Vasu, and Ashwin Aravindakshan (2021), "How Does Consumer Engagement Evolve When Brands Post Across Multiple Social Media?" *Journal of the Academy of Marketing Science*, 49 (5), 864–881.

Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2008), “The Impact of Marketing-Induced versus Word-of-Mouth Customer Acquisition on Customer Equity Growth,” *Journal of Marketing Research*, 45 (1), 48-59.

Voss, Kevin E., Eric R. Spangenberg, and Bianca Grohmann (2003), "Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude,” *Journal of Marketing Research*, 40 (3), 310-20.

Wang, Yen-Yao, Chenhui Guo, Anjana Susarla, Vallabh Sambamurthy (2021), “Online to Offline: The Impact of Social Media on Offline Sales in the Automobile Industry,” *Information Systems Research*, 32 (29), 582-604.

Chapter V. Discussion and Conclusion

Motivated by the shift towards social media as a strategic tool, this dissertation sets out to explore *how brand's owned social media affect both brands and consumers*. To this end, the three studies of this dissertation aim to explain how managers can use different types of owned social media to stimulate social media engagement and sales, identify the chain of effects which is set in motions, and explore how brands can leverage their owned social media to engage in conversations about important societal topics that may or may not align with their brand identity. Each chapter adds to the social media and branding literature by consolidating existing literature through systematic comparisons and providing generalizations across a large variety of settings (Chapter 2), proposing, and validating the owned social media value chain as framework (Chapter 3), and conceptualizing two types of brand positioning misalignment on social media (extending vs. silent brand positioning) (Chapter 4). This closing chapter will discuss the theoretical implications as well as implications for social media and brand managers, concluding with directions for future research questions that are not addressed in this dissertation, as well as limitations.

5.1 Theoretical Implications

This dissertation contributes to the literature in three ways. First, it enhances the understanding of owned social media's impact on strategic marketing outcomes. Research on the effectiveness of owned social media provides divergent results. For example, whereas some studies suggest that owned social media have a positive effect on sales (e.g., Hewett et al. 2016), others do not find a significant impact (e.g., Stephen and Galak 2012) or observe a negative relationship (e.g., Goh, Heng, and Lin 2013), highlighting the need for a better understanding of the impact of owned social media. Chapter 2 aims to bridge this gap in the literature by using meta-analytical techniques to generalize findings across various settings for two marketing outcomes: social media engagement and sales. Chapter 3 goes beyond tallying and comparing the effects of owned social media and proposes a chain of effects framework that highlights the cascade of effects triggered by brands' owned social media, acting through two key constructs: reach and memory. This framework provides a clearer understanding of the direct and indirect effects along this chain, enabling academics (and practitioners) to better estimate the impact of owned social media on desired marketing outcomes. Chapter 4 argues and illustrates that brands do not need to restrict themselves to communicating their core identity in their social media to impact social media engagement; instead, they can often stretch their brand along new dimensions using social media. While this may create a perception of misalignment between the core brand identity and its portrayal on social media, the chapter shows instances where such misalignment may lead to higher customer support (e.g., for specific brand actions or positioning dimensions).

Second, the three studies contribute to the branding literature by looking at the strategic role of owned social media for brand building in the digital era. Chapter 2 examines the importance of owned social media and the consequences of employing the wrong owned social media content on branding efforts. It also examines differences of owned social media along different brand characteristics. Surprisingly, it is more important to focus on the quality rather than quantity of a brand community size (brand strength on social media), to better understand and address consumer needs and expectations and create more authentic and intimate interactions. Chapter 3 confirms the central role of brand associations at the core of the chain of effects, which highlights the role of social media as a branding instrument. While traditional marketing literature has emphasized the central role of brand associations (e.g., Keller and Brexendorf 2019; Keller and Lehmann 2003; Rust et al. 2004; Srivastava, Shervani, and Fahey 1998; Swaminathan et al. 2022), work in social media marketing has paid little attention to the activation of brand associations. To the best of my knowledge, no empirical work has directly tested or quantified a chain of effects with brand associations at the core. Chapter 4 examines brand positioning, an important branding tool, in the social media context. It provides an overview of the different dimensions brands use to position themselves, based on previous literature and current managerial practice. An overview of these brand positioning dimensions may help future scholars better understand the competitive landscape, as well as differences across brands and industries.

Third, the dissertation's findings extend the current understanding of methodological choices in social media research. The findings of Chapter 2 highlight study characteristics, such as the use of a lagged dependent variable in a model, that are linked to differential effectiveness of owned social media for social media engagement and for sales. This provides scholars with an overview of the consequences of their methodological choices. Chapter 3, which codes the available primary studies on the impact of owned social media on social media engagement, earned social media, brand associations, and consumer buying behavior, allows us to uncover important gaps in the literature. This comprehensive framework contributes to advancing the field of social media research. Chapter 4 develops a procedure and tools for assessing the misalignment between the brand positioning as documented in their mission and the brand’s social media content. Such an overview can provide valuable information when planning strategic alliances and mergers, or in cases where marketing information is not available to investors. Our procedure and the dictionary that I developed to conduct these analyses can assist academics studying brand positioning and (social media) communications, and thus contribute to the development of this budding research area.

5.2 Managerial Implications

The findings of the three studies are useful for marketing managers, making decisions regarding social media and branding, contributing to practice in three ways. First, managers can learn from this dissertation about the holistic impact of owned social media on strategic marketing outcomes. Chapter 2 shows that brands may underestimate the impact of their owned social media if they focus only on easy-to-measure metrics, as the average elasticity is significantly larger for sales than for social media engagement. Moreover, Chapter 3 highlights the positive impact of owned social media beyond social media engagement. Interestingly, managers tend to monitor the effectiveness of their owned social media campaigns in terms of social media engagement (likes, comments, and shares), but less often in terms of earned social media, brand associations, and actual sales (Sprout Social 2021), even though the overall correlations between owned social media and the different behavioral outcomes are positive and significant. By not capturing these effects, they may underestimate the impact of their owned social media, as they may fail to understand how their content on social media affects consumers along the owned social media value chain. Chapter 4 explores the impact of owned social media on customer support and shows that misalignment between owned social media content and a brand's identity does not always hurt customer support. However, consumers do not appreciate green hushing or diversity hushing as they expect brands to talk about important societal issues. When managers fail to deliver on their promises outlined in their brand identity, it can harm customer support.

Second, managers can use the learning of this dissertation for the strategic adaption of their owned social media content. Chapter 2 shows that owned social media content needs to be adapted to the targeted outcome variable: whereas for social media engagement, managers need to focus on content expressing emotional needs ("the how"), for sales, objective information-based content ("the what") has a stronger impact than emotional content. From Chapter 3, managers can see that owned social media content also influences earned social media. Marketers have long recognized the power of earned social media and its significant contribution to a firm's performance. However, they may question how to initiate organic and spontaneous conversations about their brands. By building on existing work, our findings can reassure marketers that owned social media content can serve as a simple yet effective way to stimulate earned social media. Chapter 4 shows that managers can explore newer topics related to the brand ecosystem to be more flexible. By avoiding taking a stance, they can still communicate on themes including DEI, sustainability, or community engagement, resonating with a wider audience. In particular, for certain dimensions such as the community dimension managers can showcase the brands' community positioning on social media if it aligns with their brands' actions ("walking the talk").

Third, this dissertation highlights the importance of context when managers are using owned social media. Chapter 2 highlights how in terms of brand community size, it is more important to focus on the quality rather than the quantity of followers, to better understand and address consumer needs and expectations, and to create more authentic and intimate interactions. Moreover, because many platforms are international, using one global social media strategy is tempting, but managers cannot expect the same type of response across countries. Both Chapter 2 and Chapter 3 emphasize that the effect of owned social media is platform sensitive. Managers need to address the platforms that are most appropriate. For example, Chapter 2 explains the importance of relying on social networks (such as Facebook) to stimulate social media engagement, while Chapter 3 analyzes whether the effects of the owned social media value chain vary across social networks, microblogs, blogs, forums, and brand communities. The findings of Chapter 3 reveal that while owned social media has a similar impact on earned social media across all platforms, the impact of owned social media, earned social media, and brand associations on consumer buying behavior varies substantially from one platform to another.

5.3 Limitations and Future Research

This dissertation has overarching limitations and uncovers areas of future research. First, while this dissertation established the important impact of owned social media content on strategic marketing outcomes, it neglected the effectiveness of other owned social media formats (e.g., brand live sessions, stories, videos, images). Future research could explore how brands communicate through images, visual cues, and design elements. Incorporating image analysis into the research methodology would help capture the multifaceted nature of owned social media.

Second, it remains unclear to what extent the findings of this dissertation are applicable to contexts where the brand does not own its social media communication. It would be useful to establish how the impact of brand-related content is affected when distributed by influencers (Leung et al. 2022; Leung, Gu, and Palmatier 2022). With the increasing role of influencers, further research could focus on comparing the effectiveness and interaction between owned social media content and branded content posted by influencers. For example, influencers present brand-related content in various formats, from "unboxing" to "get ready with me" videos and differ in terms of follower count (nano-, micro-, and macro-influencers). Moreover, influencers promoting a brand on social media may foster brand associations or stimulate engagement and earned social media for the promoted brand. However, brands cannot measure whether consumers form brand associations truly for their brand, or if they primarily serve to build rapport for the influencer. Hence, more research is needed on the role of intermediaries such as influencers.

Third, integrating the consumer perspective through behavioral research into the analysis of the owned social media value chain (Chapter 3) and the brand positioning misalignment (Chapter 4) can offer a more comprehensive understanding for academics and managers. Gaining further insights into how the owned social media value chain varies across various contexts, and understanding how consumers react to the misalignment between a brand's identity and positioning, would be valuable and provide marketers with new insights to refine their positioning strategies and create stronger connections with desired consumer segments, not only in terms of social media engagement but also in other branding outcomes such as brand evaluations or purchase intentions.

Fourth, the three studies found limited work that analyzed different brand types, such as luxury versus nonluxury brands. Yet, these different types may differ in their use of owned social media to stimulate the different marketing outcome variables or to position the brand along the ecosystem dimensions. Moreover, industry-specific differences deserve more research attention. We urge future studies to focus on the role of owned social media in a business-to-business (B2B) context, which is only partly covered in extant literature, as B2B firms heavily use social media to interact with their stakeholders, and insights based on business-to-consumer firms may not translate to their context.

Last, it is important to recognize that the social media landscape is in constant flux. Relatively new channels like TikTok, and even older players like Snapchat, have received much less attention compared to Facebook, Twitter, and Instagram. Exploring and comparing the workings of owned social media content and brand positioning across these different platforms is important. While our analyses of platform effects (Chapter 2 and Chapter 3) provide some insights into differences between well-established platforms, systematically tracking these developments as new channels emerge can be valuable. Further research could explore a more diversified set of platforms, enabling cross-platform comparisons and quantifying spillover effects from one platform to another, while also studying the evolution of platforms and their features to shed new light on how the effectiveness of owned social media changes over time.

References

Goh, Khim-Yong, Cheng-Suang Heng, and Zhijie Lin (2013), "Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content," *Information Systems Research*, 24 (1), 88–107.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing*, 80 (3), 1–24.

Keller, Kevin Lane and Timo Oliver Brexendorf (2019), "Measuring Brand Equity," in *Handbuch Markenführung*. Wiesbaden: Springer Gabler, 1409-39.

Keller, Kevin Lane and Donald R. Lehmann (2003), "How Do Brands Create Value? Value Emerges Through a Unique Chain of Events," *Marketing Management*, 12 (3), 26–31.

Leung, Fine F., Flora F. Gu, and Robert W. Palmatier (2022), "Online Influencer Marketing," Journal of the Academy of Marketing Science, 50 (2), 226–51.

Leung, Fine F., Flora F. Gu, Yiwei Li, Jonathan Z. Zhang, and Robert W. Palmatier (2022), "Influencer Marketing Effectiveness," *Journal of Marketing*, 86 (6), 93–115.

Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions," *Journal of Marketing*, 68 (4), 76-89.

Sprout Social (2021), "The State of Social Media: After a Year of Transformation, Executives Are All-In on Social," https://sproutsocial.com/insights/data/social-mediafuture-of-business-intelligence/.

Stephen, Andrew T. and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (5), 624–39.

Swaminathan, Vanitha, Sayan Gupta, Kevin Lane Keller, and Donald Lehmann (2022), "Brand Actions and Financial Consequences: A Review of Key Findings and Directions for Future Research," *Journal of the Academy of Marketing Science*, 50 (4), 639-664.

Summary

Many brands have established an active social media presence that allows them to interact directly with their customers. Initially without a clear strategy, brands now employ sophisticated techniques for branding and use their posts for example to address important societal topics. This dissertation seeks to better understand the role of owned social media for branding strategy. More specifically, to provide managers with clear guidelines on how to use their social media communication to affect important business outcomes along the purchase funnel from social media engagement, earned social media, brand associations, and sales. The goal is to develop generalizable insights into the use and impact of owned social media across different brands, industries, platforms, or countries in all three essays. The research highlights which content proves more effective in driving results, with special attention given to content focusing on societal topics such as sustainability, community, and diversity. This dissertation also explores the challenges of social media content effectiveness, highlighting not only the dangers of washing practices (e.g., greenwashing, diversity washing), but also the even higher risks associated with hushing approaches.

This dissertation addresses these questions in three essays. *Chapter 2* examines whether and when owned social media stimulate sales and not only social media engagement, highlighting which owned social media content is most effective and which other contextual factors moderate the effects. *Chapter 3* focuses on how owned social media affect consumers and presents the chain of effects that starts from consumers' exposure to a brand's social media through social media engagement, earned social media, and the creation and nurturing of brand associations, to ultimately influence consumer buying behavior. *Chapter 4* examines how brands can use social media to extend their brand positioning to newer relevant topics and whether brands can stay silent about more polarizing topics without losing customer support. The three essays collectively address

key questions concerning the effectiveness and strategic use of owned social media by brands, covering a broad range of topics. Through various methods, including meta-analyses and empirical research, they explore how owned social media impact both brands and consumers, contributing to a comprehensive understanding of social media marketing and branding strategies across diverse industries and countries.

Overall, this dissertation contributes to the social media marketing and branding literature streams by highlighting the role of owned social media in brand strategy. The findings of this dissertation provide recommendations for both academics and managers. While *Chapter 2* provides implications for making an informed decision on how to leverage owned social media by revealing not only which owned social media content is more effective but also which brand, platform, and country characteristics have stronger effects, *Chapter 3* helps gaining a clear understanding of the direct and indirect effects along the owned social media value chain. Using meta-analytical techniques, Chapters 2 and 3 generalize across a large variety of settings, focusing on both elasticities and correlations to quantify the impact of owned social media on important marketing outcomes such as social media engagement, earned social media, brand associations and sales. This enables managers to better estimate the desired marketing outcomes.

Chapter 4 offers an overview of various brand positioning dimensions, drawing from previous literature and current managerial practices. While the literature on brand communication has traditionally advocated the benefits of consistent marketing communication, this essay shows that misalignment may lead to higher customer support, quantifying the effects of extending and hushing as brand positioning strategies, and exploring when these alternative approaches may be more effective. In doing so, the chapter also provides relevant insights into the risks associated with brand positioning misalignment, such as green hushing or diversity hushing on social media.

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THE ROLE OF OWNED SOCIAL MEDIA IN BRAND STRATEGY

Many brands have established an active social media presence that allows them to interact directly with consumers. Initially without a clear strategy, brands now employ sophisticated techniques for branding and use their posts for example to address important societal topics. This dissertation aims to better understand the role of owned social media for strategic branding decisions. More specifically, to provide managers with clear guidelines on how to use their social media communication to affect important business outcomes along the purchase funnel from social media engagement, earned social media, brand associations, and sales. The aim is to develop generalizable insights into the use and impact of owned social media across different brands, industries, platforms, or countries in all three essays. The research highlights which content proves more effective in driving results, with special attention given to content focusing on societal topics such as sustainability, community, and diversity. This dissertation also explores social media positioning challenges, highlighting not only the dangers of washing practices (e.g., greenwashing, diversity washing), but also the even higher risks associated with hushing communication approaches.

ABOUT THE AUTHOR

Georgia Liadeli conducted her PhD studies at the Vrije Universiteit Amsterdam. She holds a MSc in Marketing (cum laude) from the Vrije Universiteit Amsterdam and a BSc in International Business Administration from the University of Tübingen. Her main research interests focus on marketing strategy, branding, marketing with purpose, and social media.

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