La collana della Scuola di Alta Formazione Dottorale accoglie le migliori tesi di dottorato dell'Università degli Studi di Bergamo, insignite della dignità di stampa e sottoposte a procedura di *blind peer review*.

This research explores the evolving landscape of brand communication in social media, addressing unanswered questions and gaps at societal, brand-consumer relationship, and platform levels. The first essay analyzes how brands adapted rhetorical appeals on Twitter during crises like the COVID-19 pandemic, emphasizing emotive appeals and their positive reception by consumers. The second essay examines the impact of traditional versus woke communication cues on consumer engagement, revealing higher engagement with woke cues, especially from warm brands. The third essay introduces a taxonomy of affiliate fraud, offering strategies to preserve brands' integrity and proposing a two-stage affiliate listening protocol. Overall, this research contributes theoretically, managerially, and methodologically to the field of brand communication in social media.

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Federico Mangiò THE SOCIAL MEDIA IS THE MESSAGE
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Federico Mangiò

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Three Essays on Brand Communication

UNIVERSITÀ DEGLI STUDI DI BERGAMO

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“*Wherever there is persuasion, there is rhetoric.*
And wherever there is ‘meaning’,
there is ‘persuasion’”.

(Burke, 1950, p. 172)

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Introduction

Since the advent of Web 2.0, Kaplan and Haenlein foresaw in their seminal paper that social media platforms would serve as the "locomotive" driving the evolution of the World Wide Web in the subsequent years (2010: 61). More than a decade later, as we transition into the Web 3.0 era (Kim, 2021), it is undeniable that their assertion holds true. Indeed, the notion that social media platforms stand as one of the most emblematic technologies of our time has become almost self-evident (Alalwan, Rana, Dwivedi, and Algharabat, 2017; Appel, Grewal, Hadi, and Stephen, 2020; Li, Larimo, and Leonidu, 2021). Through such platforms, consumers can readily access vast amounts of information about brands, their competitors, and their products (Swaminathan, Schwartz, Menezes, and Hill, 2022); engage with like-minded individuals (McAlexander, Schouten, and Koenig, 2002; Muniz and O'Guinn, 2001); and voice their opinions and concerns (George and Leidner, 2019). Moreover, social media platforms provide consumers with the opportunity to forge personal, meaningful, and enduring connections with brands (Alawan, Rana, Dwivedi, and Algharabat, 2017). This represents just a short, incomplete list of all the activities that consumers can undertake on social media platforms. However, it clearly evidences the ubiquity and pervasiveness of the latter in the lives of consumers, who nowadays spend on average about twice as much time on such platforms as they did just a decade ago (Statista, 2022). Moreover, new market actors populating these digital ecosystem—like social media influencers (SMIs; Campbell and Farrell, 2020)—as well as new digital marketing strategies—like affiliate marketing programs (Edelman and Brandi, 2015)—have gained prominence and reshaped brand-consumer relationships in digital realms. Concurrently, a new generation of providers, like TikTok, Discord, and Twitch, entered the arena challenging the dominance of incumbents. Thus, it comes with little surprise to learn that social media platforms stably occupy a predominant share of digital marketing budgets of brands operating in multiple industries (Statista, 2021a), considering the platforms' ability to increase exposure and traffic, generate new leads, and develop loyal fan bases, among other positive outcomes (Statista, 2021b). On the academic side of the debate, the rise and success of social media platforms has naturally prompted a fertile literature, which covers manifold aspects and domains (for a comprehensive review on related topics, see Li, Larimo, and Leonidou, 2021; Voorveld, 2019).

The purpose of this work is precisely to contribute to the stream of literature focusing on "brand communication on social media" (Dahlen and Rosengren, 2016; Voorveld, 2019), conceived as "any piece of brand-related communication shared via social media enabling online users to access, share, engage with, add to, and co-create" (Voorveld, 2019: 15), and on its ability to elicit consumer engagement on social media (CESM), which signifies all brand-related online activities on the part of the consumer that vary in the degree to which the consumer interacts with, and engages in, the consumption, contribution, and creation of social media content (de Oliveira Santini, Ladeira, Pinto, *et al*., 2020; Schivinski, Christodoulides, and Dabrowski, 2016).

The richness of this literature stream does not imply, however, that research on brand communication on social media has lost priority and urgency. Several theoretical, conceptual, as well as methodological challenges—ranging, for example, from researching the role of new actors to using real social media data generated in unabridged settings—remain unsettled, thus offering proper avenues for carving out useful and original contributions (Li *et al*., 2021; Voorveld, 2019). In this vein, consumer engagement has consistently been one of the top research priorities listed by the Marketing Science Institute since the early 2000s (Brodie, Hollebeek, Jurić, and Ilić, 2011). Also for the biennium 2020-2022, the necessity of making sense of the evolving landscape of marketing communication and advertising by "defining brand value and the communication message" was overtly manifested by the same Institute, which urged marketing researchers to promptly answer questions like: "how do brands manage in times of crisis? [...] Should brands take a stand? [...] Can we find a better way to measure brand value and brand health using new data sources? [...] How do you measure the value of social influencer impact?" (MSI 2020, section 2, tier 1). The chapters contained in this work are precisely intended to help answer these open questions. Indeed, despite social media platform being around for a while now, we contend that further light upon brand communication on social media and its ability to trigger CESM must be shed. In particular, three macro trends concerning platforms, brands, and their audiences in can be articulated in support of this claim.

First, at the societal level, the intensification of unprecedented and unexpected types of crises and “paracrises” (Coombs and Holladay, 2012) substantially challenged the effectiveness of traditional communication models and strategies, putting at risk brand reputation, equity, as well as the relationship between brands and their audiences (Coombs, 2021; 2017). For example, mentioning two recent crises, the Covid-19 global pandemic has abruptly upset not only the economic and social paradigms but also the communicative paradigms on which brand activity had been based for decades, leaving brands with little to no guidance on how to best communicate with their audiences (Hesse, Niederle, Schön, and Stautz, 2021; Sobande, 2020; Taylor, 2020). Similarly, during the early phases of the Ukraine-Russia conflict, which escalated during the spring of 2022, brands that failed to promptly communicate their support to the Ukrainian side found themselves in the midst of boycotts and backlashes, initiated on social media platforms like Twitter (Sarkar, 2022).

Second, and connected to the first trend, at the brand-consumer relationship level, brands increasingly have to consider and cater to new consumer demands and expectations, such as those related to responsible consumption, brand conscientiousness, and greater inclusion (Bajde and Rojas-Gaviria, 2021; Iglesias and Ind, 2020). In fact, consumer cohorts increasingly demand that brands take a stance on contentious socio-political issues, ranging from the support for civil rights of black people to gender equality and the protection of diversity (Sabate, 2020; Schmidt, Ind, and Guzman, 2021). However, how to best communicate in such circumstances, as well as who should do so to comply with the above-mentioned expectations, has still received scant attention (Mirzaei, Wilkie, and Siuki, 2022).

Third, at the technical-platform level, the social media ecosystem has witnessed the fast emergence and diffusion of new platforms, new actors, as well as new activities. These are characterized by idiosyncratic affordances and driven by logics different from the first generation of social media platforms, which can result in both advantages and opportunities, as well as disadvantages and threats. An example of the latter is affiliate marketing frauds, which are still poorly characterized by current literature (Mathur, Narayanan, and Chetty, 2018; Snyder and Kanich, 2016).

Research outline

This research aims to contribute to brand communication on social media scholarship by investigating overlooked aspects at each of the above-mentioned levels of the social media ecosystem. To situate this work in the relevant body of knowledge, we first take stock of the main concepts, models, and theoretical tenets that underpin brand communication on social media; we offer a review of previous empirical studies on the topic; lastly, we specify the epistemological and methodological foundations on which the subsequent chapters are grounded (Chapter 1). Then, following a “three essay” format, three original studies (essays) are separately presented in the following chapters (Chapter 3; Chapter 4; Chapter 5).

The first essay, “Branding Rhetoric in Times of a Global Pandemic: A Text-Mining Analysis” (Chapter 3), investigates how brand communication on social media evolved before, during, and in the aftermath of the first wave of the Covid-19 pandemic, and how consumers reacted to the rhetorical strategies that brands undertook during this period. Considering the “black-swan” nature of this specific crisis (Taleb, 2007), how to communicate to stay relevant and to keep consumers engaged during such an exogenous shock represented uncharted territory for academics and practitioners alike (Karpen and Conduit, 2020; Taylor, 2020). To fill this gap, in particular, this essay explores how the Covid-driven institutional change (Brown, Ainsworth, and Grant, 2012; Maguire and Hardy, 2009) was incorporated into the rhetorical cues adopted by brands on Twitter, and tests their effectiveness in triggering volume-based CESM. The results of a two-step text mining analytical protocol show that not only did brands in different industries abruptly and isomorphically change their brand communication on social media platforms by adopting novel and more socially sensitive rhetorical appeals (namely, “social pathos”) as the crisis unfolded, but also that such a choice was rewarded by their audiences through higher levels of CESM. This essay contributes both to the branding and crisis communication literature by shedding light on how brands adapt their communicative efforts during exogenous crises, and to neo-institutional theory by providing new explanations about the underexplored connection between institutional logics and persuasive appeals (Cornelissen, Durand, Fiss, Lammers, and Vaara, 2015).

This essay has been co-authored by Giuseppe Pedeliento (University of Bergamo), and Daniela Andreini (University of Bergamo) and has been published in the Journal of Advertising's pop-up special section "Advertising and Covid-19". We thank the Editor-in-Chief, the Guest Editors Laura Bright and Hope Jenses Schau, and two anonymous reviewers for their valuable comments during the review process, as well as Rossella Gambetti and Federica Ceccotti for their precious suggestions provided on an early version of this study during the 2020 Annual Conference of the Italian Marketing Association (SIM), and Marco Galvagno, who served as a discussant during the SIM workshop "Covid-19 and Marketing Research in Italy. Contributions to Theories, Methods, and Practices." This study, and in particular its design and methodological aspects, inspired a second original contribution, titled "Unpacking Brand Communication on Social Media through Top-down and Bottom-up Text-mining", which details the challenges encountered and strategies adopted during the design and implementation of the above-mentioned text-mining study. The case study is published in the case collection "SAGE Research Methods Business", and is included in Appendix to Chapter 2, for the sake of methodological clarity.

The second essay, "Woke Brand Communication and Consumers' Social Media Engagement: The Role of Brand Stereotypes and Language Expectancy" (Chapter 3), addresses the emergence and diffusion of so-called "woke" brand communication (Middleton and Turnbull, 2021; Mizrei, Wilkie, and Siuki, 2020), which represents a distinctive form of CSR communication where brands publicly support divisive socio-political issues (Mizraei *et al*., 2022). Since research shedding light on the outcomes of woke brand communication is limited, failing to compare the persuasive effects of this strategy with those prompted by traditional communication cues, and providing scant guidance on which brands should adopt this approach, we fill these gaps through a multi-industry field analysis. Drawing on Language Expectancy Theory (Burgoon, 1995), the Brands as Intelligent Agents framework (Kervyn *et al*., 2012), and previous CESM literature, our analysis compares the effects of traditional and woke brand communication on both the volume and semantic dimensions of CESM. Additionally, it identifies which type of brand (defined in terms of brand stereotypes) would be better suited to pursue woke communication on social media.

This essay has been co-authored by Giuseppe Pedeliento (University of Bergamo), Daniela Andreini (University of Bergamo), and Lia Zarantonello (University of Roehampton), and has been published on a regular issue of the Journal of Brand Management with the title "How persuasive is *woke* brand communication on social media? Evidence from a consumer engagement analysis on Facebook". We thank the Editor Mario Burghausen, and the anonymous reviewers for their valuable comments during the review process, as well as for the 2022 Global Brand Conference committee which awarded the conference paper version of this study with the Best Conference Paper Award.

The third essay, "All That Glitters Is Not Real Affiliation: How to Handle Affiliate Marketing Programs in the Era of Falsity" (Chapter 4), investigates affiliate marketing frauds, a contemporary threat for brands and their audiences that is growing concurrently with the expansion of influencer marketing. Given the direct and indirect cost losses caused to brands, affiliate frauds represent a significant danger. Acknowledging the lack of strategic and academic guidance on preventing and handling affiliate frauds, this article contributes conceptually to this overlooked area by providing an original classification that distinguishes between non-influencer and influencer falsity. Methodologically, it proposes and tests a two-stage affiliate listening protocol on real social media influencer affiliate data, which can be implemented by brands and practitioners alike.

This essay has been co-authored by Giandomenico Di Domenico (Cardiff University) and has been published in Business Horizons' special issue "Managing in an Era of Falsity". We express our gratitude to the Editor-in-Chief, the Guest Editors Colin Campbell and Kirk Plangger, and three anonymous reviewers, as well as Annamaria Tuan and all the organizers of the Faculty Climber Community of the Italian Marketing Association (SIM), as this essay was initially conceived during its first edition.

Finally, in Chapter 5, we deliver our general conclusions.

Chapter 1. Literature Review and Epistemological Foundations

1.1 Literature Review

1.1.1. Social media and brand communication

Despite almost everyone could claim to know what social media platforms are, coming up with an exhaustive definition of social media is far from being straightforward. The social media arena is extremely dynamic, with new platforms sprouting daily (Phillips, Miller, and McQuarrie, 2014). Hence, overtime plural definitions have been proposed by the literature (Li *et al*., 2021). Indeed, especially at the dawn of Web 2.0 it was not easy to tell exactly which Internet-based technological applications belonged to this emerging domain (boyd and Ellison, 2007). Therefore, the first definitional attempts tried to describe social media primarily from a technological perspective, as the main urgency was to differentiate them from already existing online "places", like chats and e-mails, which already enabled different forms of Internet-based social interactions. For example, Berthon, Pitt, Plangger, and Shapiro (2012) defined social media as a series of hardware and software technological applications designed to foster inexpensive content creation, interaction, and interoperability among users. It was clear, then, that social media differed from existing forms of computer-mediated communication in that they redirected the locus of user activity from the desktop to the web, the locus of value production from the brand to the consumer and, consequently, the locus of power from the former to the latter (Berthon *et al*., 2012)

In this vein, drawing upon social presence (Short, Williams, and Christie, 1976), media richness (Daft and Lengel, 1986), and self-presentation (Goffman, 1959) theories, Kaplan and Haenlein defined social media not as a single digital environment, but rather as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and allow the creation and exchange of user-generated content [UGC[1], added]," (2010: 61). Thus, social media represents an umbrella term, comprising a plethora of

[1] UGC refers to all the various forms of media content that are publicly available and that are created by end-users outside of professional routines and practices (Kaplan and Haenlein, 2010: 61).

applications, ranging from blogging and microblogging sites (e.g., X and Sina Weibo), collaborative projects (e.g., Wikipedia), instant-messaging apps and platforms (e.g., WhatsApp and Messenger), social networking sites (SNS; e.g., Facebook and Instagram), content communities (e.g., YouTube and Pinterest), and virtual social and game worlds (e.g., Second Life and Decentraland).

Today, given the pervasiveness and cultural relevance of social media, appraising them from a technology-focused definitional perspective comes somehow to little use. Scholars prefer to define – and investigate- social media in terms of what users actually perform within such digital ecosystems (Appel *et al*., 2020; Katz and Foulkes, 1962). In this sense, Appel and colleagues suggest a purposefully broad definitional perspective, whereby social media can be conceived as:

> "a technology-centric—but not entirely technological—ecosystem in which a diverse and complex set of behaviors, interactions, and exchanges involving various kinds of interconnected actors (individuals and firms, organizations, and institutions) can occur."
>
> (Appel *et al*., 2020: 80)

In other words, social media do not simply represent a digital marketing tool for brands and marketers, nor merely the instantiation of electronic word-of-mouth (eWOM) for consumers, but rather a more pervasive media which "has essentially become almost anything—content, information, behaviors, people, organizations, institutions—that can exist in an interconnected, networked digital environment where interactivity is possible" (Appel *et al*., 2020: 80).

Since social media's first appearance in late Nineties (boyd and Ellison, 2007), brands have increasingly intensified their active presence in these ecosystems, particularly in the most prominent ones, represented by SNS like Facebook, Instagram, and X (Voorveld, 2019; Statista, 2021c). Brand presence in social media can take many forms, including brands' participation on the platforms as brand personae, publication of branded engagement opportunities for consumer participation through UGC, and the communication of branded content (Ashley and Tuten, 2015; Liu, Burns, and Hou, 2017; Voorveld, 2019).

The latter form of brand presence precisely comprises what is regarded as "brand communication on social media" (Voorveld, 2019), alternatively referred to as "firm-to-consumer social messages" (DeVries, Gensler, and Leeflang, 2017) or as "creative strategies for branded content", signifying all "executional factors and message strategies used to bridge the gap between what the marketer wants to say and what the consumer needs to hear" (Ashley and Tuten, 2015: 18). Brand communication on social media can be of two types: *organic* or *sponsored* (De Vries *et al*., 2017; Fulgoni, 2015; Quesenberry and Coolsen, 2019; Scheiner, Kol, and Levy, 2021). *Sponsored* brand posts differ from organic ones in that they are paid media, they are distributed through the social media advertising platform, and do not necessarily have to be displayed on the social media brand page. Moreover, they allow to make content more relevant to specific customer targets via personalized advertising (Maslowska, Smith, and van den Putte, 2016). Conversely, *organic* brand content is unpaid, and displayed to all the followers active on a given brand's social media page (Scheiner *et al*., 2021). Thus, we can say that sponsored brand communication on social media belongs, to a greater extent, to the advertising, whilst the organic ones to the broader marketing communication domain.

Determining the effectiveness of organic brand communication on social media platforms is a key priority – and a challenge – for brands and marketers, in particular in light of the recent drop in organic reach performances such platforms (Quesenberry and Coolsen, 2019). As a matter of fact, research noted that only about 1% of brand's followers on social media actively engage with branded content by liking, commenting, or sharing brand-generated posts (Lee, Hosanagar, and Nair, 2018). Despite this, academic research shedding light upon this topic is only emergent and, as we will detail further in this chapter, offer somehow inconclusive and conflictual results about how to strategically guide social media content engineering (Ashley and Tuten, 2015; Quesenberry and Coolsen, 2019; Deng *et al*., 2021; Li *et al*., 2021). In the following section, we review how communication effectiveness has traditionally been conceived and measured; then, we proceed to take stock of extant relevant empirical research.

1.1.2. Communication effectiveness

Historically, the effectiveness of speakers and communicators has been associated with the idea that what they communicate must be connotated by some traits able to ensure message popularity and diffusion among the target audiences (Holtzhausen and Zerfas, 2014). In the pre-digital era, a skilled orator or a great politician was defined precisely as one able to persuade and mobilize the largest crowds just through the power of his words. Along similar lines, religious books like the Bible, a "model of eloquence" capable of disseminating the religious dogma with little to no intermediation, became the most popular cultural artifact ever produced by humans, printed in billions of copies, and thus reaching billions of readers (Deetz, 1992). So, it is somehow unsurprising that in more recent times the capability of a message to become effective and popular has been labelled as, borrowing the medical jargon, communication virality, that is "a word-of-mouth-like cascade diffusion process wherein a message is actively forwarded from one person to another, within and between multiple weakly linked personal networks, resulting in a rapid increase in the number of people who are exposed to the message" (Hemsley and Mason, 2013: 144). Communication virality has indeed been the focus of interest and evaluation criterion of various domains interested in communication-related phenomena. Media and journalism studies, for example, tried to discover the enabling factors that allow a specific knowledge artifact to become "newsworthy" (Hansen, Arvidsson, Nielsen, Colleoni, and Etter, 2011; Trilling, Tolochko, and Burscher, 2017). Similarly, political scientists tried to model those traits and features that allow a political campaign to reach a wide body of voters (Kilinger and Svensson 2015). However, starting from the early Nineties, communication virality became particularly paradigmatic of the marketing discipline as well, precisely thanks to the spread of the Web technologies (Alahbash and McAlister, 2015; Berger and Milkman, 2012; Phelps, Lewis, Mobilio, Perry, and Raman, 2004; Seo, Li, Choi, and Yoon, 2018). As a matter of fact, drawing upon word-of-mouth studies and interpersonal communication theory (Lazarsfeld and Katz, 1955), the concept of "viral marketing" (Rayport, 1996) was introduced to signify those marketing communication strategies able to support easier, accelerated, and cost-reduced transmission of company and/or product information. Soon brands and practitioners discovered that viral marketing allowed brands to reach the same - if not higher - levels of product and brand recall and brand awareness with smaller budgets compared to traditional media, like high-frequency TV advertising (Kaplan and Haenlein, 2011; Welker, 2002). This made the exploration of the drivers capable of transforming marketing communication contents into real "viruses" a priority for both academicians and marketers, which overtime envisioned various virality models for marketing communication (Berger, 2016; Hinz, Skiera, Barrot, and Becker, 2011; Rosen, 2001; Van der Lans, Van Bruggen, Ekuashberg, and Wierenga, 2010). For instance, reviewing seminal studies on information diffusion, Shifman (2013) proposed a "6 Ps" framework that encompasses six key antecedents of communication virality. A message becomes a viral, independently from the context and media, when it expresses positivity, since individuals are more eager to share positive and/or humorous content to pander both self- presentation and social purposes; when it provokes high arousal emotions (both positive and negative), given that messages able to generate intense emotions like "wow effects" or anger mobilize individual active responses; when it conveys prestige, as more credible, famous, or celebrity-like communication sources are more easily trusted and shared; when it is structured according to a clear and comprehensible packaging, due to the fact that messages that are simpler and framed more straightforwardly are easier to process, and thus to share; similarly, when it holds a top positioning¸ given that the popularity of a cultural unit highly depends also on how it is displayed on the media, both physically (in terms of communicative design) and in networking terms (see e.g. "seeding strategies", Hinz *et al.*, 2011). Finally, for a message to become a viral, it should represent a participation tool to its recipients¸ since the virality of a message is enhanced not only if the audience is enabled to share the cultural unit, but also to personally interpret and modify it (see, relatedly, "personalized content sharing", Bennet and Segerberg, 2015). As mentioned, these six virality drivers showed to be effective across heterogenous communication domains and media. In particular, a stream of empirical literature at the intersection between branding, communication, and interactive marketing attempted to test their use also in the idiosyncratic online context of brand communication on social media (Alhabash and McAlister, 2015; Seo *et al.*, 2018; Voorveld, 2019). As a matter of facts, fostering a "networked" media logic capable of overthrowing traditional mass media logic by leveraging upon greater seed, the ability of bridging multiple networks, and person-to-person mode of diffusion (Kilinger and

Svensson, 2015), social media platforms brought integrated marketing communication and virality to unprecedent extents (Mangold and Faulds, 2009), to the point that "social media marketing" and "viral marketing" are often used as synonyms (Li *et al.*, 2021; Kaplan and Haenlein, 2011; Kozinets, de Valck, and Wojnicki, 2010). In fact, social media built-in metrics and functions, e.g., the famous "Like", "React", "Comment", "Share", and "Retweet" buttons, have been long used as proxies of content virality by analysts in the digital marketing industry (Alahbash and McAlister, 2015; Barger and Labrecque, 2013; Digital Marketing Statistics and Metrics, 2019). Such metrics represent also vessels of "social contagion" effects, given that seeing a friend engaging with a content on a social media platform actually increases the likelihood for users to engage with the same content in turn (Hodas and Lerman, 2014).

However, although useful, defining social media platforms merely as spreaders of communication virality would be extremely restrictive[2]. Communication on social media does not spread like a pathogen, completely indifferent to the will and agency of individuals. Rather, most of the times social media users "actively seek out information and consciously decide to propagate it" (Hodas and Lerman, 2014, italics added). Put it differently, social media are first and foremost a means through which consumers can satisfy their actual condition in contemporary society, where they find themselves divided between the necessity of satisfying social and communitarian needs and, at the same time, the needs for self-determination and uniqueness (a somewhat oxymoronic condition that Wellman and colleagues [2003] effectively label "networked individualism"). As a matter of fact, on such platforms users can easily signal their belonging to a community or their support to a cause - oftentimes also through low levels of commitment and activation ("clictivism"; George and Leidner, 2019) - but simultaneously they can express their creativity and reclaim their unique identity by influencing and reshaping at their will the consumer-brand relationship through the generation UGC (Holt, 2016). In other words, and with good reasons, social media platforms have been depicted as a key medium of the "participatory digital culture" (Jenkins,

[2] We do not suggest an absolute and dogmatic separation between the concepts of content virality and consumer engagement (introduced next). Virality and consumer engagement, especially in digital context, not only represent the two faces of the same phenomenon, but rather they appear to be interdependent and mutually reinforcing (Nikolinakou and King, 2018).

2009). Accordingly, thus, effective brand communication on social media should not merely aim to propagate a message minimizing its re-interpretation (Shifman, 2014). Rather, it should allow to nurture and maintain long-term relationships with consumers, who are not passive receivers of information but "productive publics" (Arvidsson, 2013; Arvidsson and Caliandro, 2016). Sharing this view, Alahbash and McAlister (2015) indeed argued that a more comprehensive view on communication virality on social media should emphasize not just users' behaviors in relation to the volume of network actors who shared a specific message (i.e., the so-called virality metrics), but also in terms of explicit emotional responses and attitudinal evaluations (i.e., affective evaluation) as well as in terms of active and public deliberation users instantiate as a reaction to social media messages.

Acknowledging this, hence a better prism to evaluate the effectiveness of brand communication on social media should be one which encompasses the above mentioned affective, social, and participatory dimensions (Hollebeek, Srivastava, and Chen, 2016). In line with recent contributions (Li *et al*., 2021), we contend that the concept of consumer engagement on social media (CESM from here on; de Oliveira-Santini *et al*., 2020[3]) is particularly well suited to do so, as we discuss in more details next.

1.1.3. Consumer engagement in social media

Drawing the conceptual boundaries of CESM is not an easy task, given its dynamic, multifaceted nature, and considering the lack of scholar consensus about this marketing construct (de Oliveira *et al*., 2020; Lamberton and Stephen, 2016). Even though CESM gained considerable academic traction recently, as shown by the high number of reviews aimed at taking a stock of its antecedents, effects, and measurements[4] (Barger, Peltier, and Schultz, 2016; de Oliveira *et al*., 2020; Lim and Rasul, 2022; Martinek, 2021; Maslowska, Malthouse, and Collinger, 2016), it drew upon an established scholar lineage that has been

[3] "Consumer engagement", "digital engagement", or "customer engagement" are often used alternatively in this literature (de Oliveira-Santini *et al*., 2021; Chen *et al*., 2022; Schiwinski *et al*., 2016). Recent systematizations of this research stream (e.g. de Oliveria *et al*., 2021; Lim and Rasul, 2022) use as keywords for their PRISMA protocols both these versions, corroborating the fact that these terms can be used as synonyms. Still, for the sake of consistency, from here on in this work we will always refer to "consumer engagement".
[4] See also Figure 1, which clearly depicts a peak in CESM-related publications in the recent period.

carried on since the beginning of the Web 2.0 era (Gambetti and Graffigna, 2010). Indeed, as it is self-evident from the acronym, CESM spun-off from the older and well-established concept of consumer-brand engagement (CBE from here on; Brodie *et al*., 2011; 2013; Gambetti and Graffigna, 2010; Gambetti, Graffigna, and Biraghi, 2015; Hollebeek , Glynn, and Brodie, 2014) and indeed shares much of the tenets of this lineage and translates them into the digital realms of social media platforms (Eigenraam , Eelen, Van Lin, and Verlegh, 2018). During the turn towards the experience economy and the diffusion of service-dominant logic (SDL; Lusch and Vargo 2006; 2008), CBE was first introduced by marketing and branding practitioners to signify all brand efforts aimed at establishing a personal, strong, and enduring connection between brands and consumers based on interaction, shared values, experiential contents, and rewards (Gambetti and Graffigna, 2010). Since then, it populated both academics' research projects and practitioners' agendas as it turned out to have strong predictive power for pivotal consumer, brand, and market outcomes, including loyalty (e.g., Leckie, Nyadzayo, and Johnson, 2016; Schau, Muñiz, and Arnould, 2009), purchase intention (e.g., Baker, Donthu, and Kumar, 2016), sales (e.g., Borah and Tellis, 2016), financial and reputational advantages (e.g., Kumar and Pansari, 2016), among many others (Barger *et al*., 2016). Providing a unique and unequivocal definition of CBE thus turned out to be difficult, as it is intrinsically a complex concept. In this vein, Gambetti *et al*. (2015) define CBE both as a "meta-organizer" of the brand-consumer relationship instantiated by consumers and brands along different levels of increasing interactivity and activation via multiple dimensions or resources, as well as a "semantic container" of other key marketing (but also non-marketing-related; Brodie *et al*., 2011) constructs, like brand involvement, brand attachment, and brand experience[5] (Gambetti *et al*., 2015:1).

Overall, the CBE field can be split according two main conceptualizations backed by two different epistemological and methodological stances embraced by marketing scholars who investigated this concept[6] (de Oliveira *et al*., 2020; Eigenraam *et al*., 2018; Sheiner *et al*.,

[5] For a conceptual distinction between CBE and the mentioned concepts, please refer to Gambetti *et al*. (2015).
[6] Please notice that such conceptualizations are not necessarily independent. Engagement processes are re-iterative, in that CBE is fueled by motivational states, which are expressed through practices in behaviors that go beyond purchase, and which can then refuel actors' motivational states in turn (Brodie *et al*., 2013; Van Doorn *et al*., 2010)

2021). According to the psychological perspective (e.g. Bowden, 2009; Calder and Malthouse, 2008; Hollebeek *et al*., 2014), CBE is conceived as psychological mind state of the consumer comprising *cognitive processing* (that is, a consumer's level of thought and elaboration about a specific brand, or "immersion"), *affection* (that is, a consumer's degree of brand-related emotions, or "passion"), and *activation* (that is, the actual amount of time, energy, an effort a consumer spends with a specific brand) components (Hollebeek, 2011), occurring by virtue of "dynamic, iterative process within service relationships that cocreate value" (Brodie *et al*., 2011: 260). CBE conceived as a psychological mind state reflects consumers' self-brand connections, inner emotions, and attachment towards the brands. Method-wise, consistently with such conceptualization, studies investigating CBE as a psychological state tended to privilege qualitative (e.g., Hodis, Sriramachandramurthy, and Sashittal, 2015), survey-based (e.g., Cao, Meadows, and Wong., 2021), or experimental (e.g., Giakoumaki and Krepapa, 2020) designs. Conversely, according to the behavioral perspective (e.g., Gummerus, Liljander, Weman, and Pihlström, 2012; Kitirattarkarn, Araujo, and Neijens, 2019; Van Doorn, Lemon, Mittal, Nass, Pick, Pirner, and Verhoef, 2010; Shaefer, Falk, Kumar, and Schamari, 2021), CBE is conceived as a set of consumer behaviors enacted towards a brand which go beyond purchase or purchase-related activities (Van Doorn *et al*., 2010). In this vein, CBE is intended as consumers' motivation to actively invest in cognitive, emotional, conative, but also social (Gambetti *et al*., 2015; Hollebeek *et al*., 2016) resources during brand interactions triggered by behavioral actions. Such behavioral actions have been named "practices" (Eigenraam *et al*., 2018) or "initiatives" (Gill, Sridhar, and Grewal, 2017; Kumar and Pansari, 2016) and, when they take place online, like in the domain of social media platforms, they are referred to as digital initiatives (Dhaoui and Webster, 2020; Eigenraam *et al*., 2018; Harrigan Evers, Miles, and Daly, 2018; Li *et al*., 2021; Muntinga, Moorman, and Smit, 2011). Both brands and consumers can initiate digital engagement initiatives. Collecting more than 260 digital practices performed on social media, Eigenraam *et al*. (2018) identified two macro groups of digital engagement initiatives sparked by brands – namely, "for fun" initiatives (e.g., playing a game or participating to a brand contest), and "for learning" initiatives (e.g., viewing a video and signing up for updates) -, and two initiated by consumers – namely, "working for the brand" initiatives (e.g. provide suggestions for improvements, creating and ad for the brand) and "talking about the brand" initiatives (e.g., brand referral and product recommendation activities). Brand communication on social media clearly falls into the brand-generated initiatives category, as brand communication is a pivotal corporate tool brands can dispose of to trigger and intensify CBE (Gambetti *et al*., 2015). Indeed, whenever consumers react to such brand initiatives, they generate CESM, which can occur in a variety of "tangible and actionable" ways (Schaefer, Falk, Kumar, and Schamari, 2021).

Though, to date little agreement exist regarding which the best message strategies and executional factors are to engage online audiences (Deng, Wang, Rod, and Ji, 2021; Ibrahim, Wang, and Bourne, 2017; Quesenberry and Coolsen, 2020; Li *et al.*, 2021). Moreover, a limitation of this knowledge domain is that extant studies rarely investigated real social media data, relying mainly on self-reported data collected through surveys or experimental designs (de Oliveira *et al*., 2020; Dimitrova and Matthes, 2018; Martinek, 2021; Voorveld, 2019). As outlined by Voorveld, "compared to other media, social media are, however, unique with regard to the massive amounts of data they provide. The data and metrics supplied by social media companies and the scraping of log data of social media platforms have great potential to examine and explain consumers' interactions and responses to brand communication in social media in a natural setting" (2019: 23). Using them can greatly help enhancing ecological validity of the enquiries, minimizing well-known biases like social-desirability bias (Fisher, 1993), and finally testing the validity of theory to naturally occurring phenomena (Areni, 2021; Grant and Wall, 2009)

To mitigate such concerns, we thus proceeded to take stock of the CESM body of literature which explored the effectiveness of brand-generated CESM initiatives adopting quasi-experimental research designs, that is monitoring and assessing brand communication on social media using real social media data.

1.1.4. CESM field studies: a systematic perspective

Review protocol- Following the precepts of systematic literature review (Tranfield, Denyer, and Smart, 2003), we searched the Scopus (Elsevier) database for academic articles written in English only and published in the period 2005-2021 using the keywords "consumer engagement”, “customer engagement”, “consumer-brand engagement”, and “digital engagement” everywhere in the article’s title, abstract, and keywords. As we are interested in brand-initiated digital engagement practices in social media only, we restricted the focus of our search by applying two additional set of keywords, the first focusing on relevant social media platform (namely, “social media”, “Facebook”, “Twitter”, “YouTube”, “Instagram”), the second denoting relevant brand-initiated CESM practices (namely, post*, messag*, content). This led to identify 312 articles in multiple subject areas. We then screened for research quality and impact by focusing only on articles published in ABS-ranked international journals, narrowing down the sample to 83 articles. Their suitability was inspected by the author who carefully inspected their title, abstract, and full text. Criteria for inclusion comprised: field study, and behavioral manifestation of CESM as key dependent variable. Review, conceptual, purely methodological, and articles that lacked any factual connection with the scope of the review were discarded, thus leading to 33 articles. In the third step, for further exhaustiveness of the review process, a snowballing approach was undertaken starting from the literature cited by the articles identified in the previous steps. This led to identify 5 original articles, obtaining a final dataset of 38 articles. In the data analysis stage, all 38 articles were analyzed though a four-step protocol involving i) documenting, ii) attaining basic understanding, iii) coding and iv) categorization (Kaartemo and Helkkula, 2019). In the documentation stage, we enlisted the details of the articles including the year of publication, journal name, title, abstract and original keywords. Subsequently, the selected articles were read to familiarize with the research field and its evolution. During the third stage, each retained publication was coded according to the following criteria: research question and literature gap addressed, data, methodology, theoretical lens adopted, antecedents, outcomes, and other constructs used as controls or robustness checks as well as their operationalization strategies in the empirical studies, key findings, and contributions. Finally, the reviewed studies were grouped based on which category of brand-generated CESM initiative they focused on. To this aim, we employed Sabate, Berbegal-Mirabent, Cañabate, and Lebherz (2014)’s classification which distinguishes brand social media posts’ content attributes via the hard versus soft criterion. Hard attributes are those content attributes that can be evaluated without the need of any subjective interpretation, like in the case of the media richness or vividness of a branded posts or the time and frequency of posting, and that in social media environments are oftentimes encapsulated in the metadata of the platforms themselves. Conversely, soft attributes are semantic, rhetorical, or pragmatic in nature, and thus include all those content attributes that require a qualitative interpretation to be fully grasped by the recipient (Sabate *et al*., 2014). Moreover, given that, compared to traditional media, written verbal cues represent the key medium through which a message is conveyed in social media (Humphreys, 2021; Jakic, Wagner, and Meyer, 2017), we also adopted a linguistic lens to further categorize the soft content attributes. Soft attributes can indeed be classified according to two semantic dimensions: whether they regard language content or language style (Kronrod, 2022; Tausczik and Pennebaker, 2010). The former ones are used to convey the explicit content of a message, which can be highly context specific, and in brand communication on social media is usually referred to in terms of "content orientations" of a specific brand-generated post (e.g., "informational", "entertaining", "relational", or "remunerative" orientations; Dolan , Conduit, Frethey-Bentham, Fahy, and Goodman, 2019; Lee *et al*., 2018; Tellis , MacInnis, Tirunillai, and Zhang, 2019; Vlacvei , Notta, and Koronaki, 2021). The latter ones are used instead to convey more implicit language dimensions, such as message complexity, readability, emotionality, subjectivity, certainty, or informality (Cruz, Leonhardt, and Pezzuti; 2017; Deng, Hine, Ji, and Wang, 2021; Jakic *et al*., 2017; Pacer, Chandler, Poole, and Noseworthy, 2018; Pezzutti, Leonhardt, and Warren, 2021), and in that pertain the style through which a message content is conveyed. Soft content attributes could also reflect the pragmatic aspects of language, that is the influences of contextual elements on meaning (Humphreys and Wang, 2018). Lastly, soft content attributes are not solely comprising textual language instantiations, but also paralinguistic ones, ranging from pictographs like emojics and emoticons (McShane, Pancer, Pool, and Deng, 2022) and textual instantiations of nonverbal audible, tactile, and visual elements (Luangrath, Peck, and Barger, 2017). Additionally, following previous customer engagement theory (de Oliveira *et al*. 2020; Pansari and Kumar, 2017), we also categorized a set of contextual factors that can influence the effect of CESM antecedents.

Results: Research stream evolution. The academic production of CESM field studies increased considerably in the last decade, showing a particular peak especially in 2021, concurrently with the wide penetration of social media platforms into consumer's routines (Figure 1). Not surprisingly, the most prolific outlets are those traditionally focused on interactive marketing topics (Journal of Interactive Marketing, 4; Journal of Research in Interactive Marketing, 3) but also journals publishing branding and brand management studies (Journal of Product and Brand Management, 3). Despite the predominance of marketing outlets (17 out of 21 journals), we identified also relevant studies published on a variety of journals not specifically focused on marketing (e.g., European Management Journal, 2; Management Science, 1; Online Information Review, 3) signaling that the topic generated academic discussion in multiple fields.

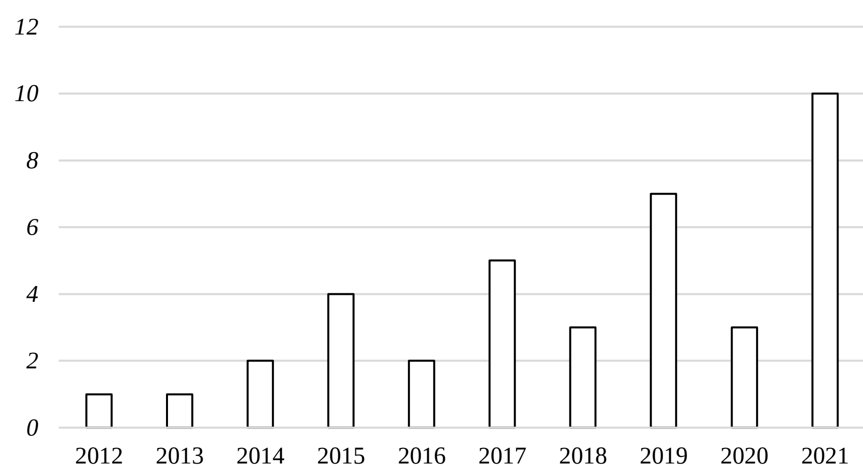

Figure 1: CESM field studies academic production, by year.

Data and methods. Despite being quite variegated, method-wise this subfield is overall connotated by the adoption of convergent research designs. The great majority (33) of studies investigated focused on Facebook data, whereas multi-platform investigations are limited (6). Early studies turn out to be somehow debatable for what concerns data collection, as they relied on non-structured, hardly replicable social media data collection strategies involving for example manual collection or snapshotting of brand-generated or brand-related social media content (e.g., Ashley and Tuten, 2015; Sabate *et al*., 2014). However, leveraging upon platform-specific Application Programming Interfaces (APIs), which allowed not only to retrieve bigger samples, but also to enhance research transparency (Boegershausen, Datta, Borah, and Stephen, 2022), became the standard among more recent contributions. Also, early publications (e.g., Ashley and Tuten, 2015; Luarn, Lin, and Chiu, 2015) investigated relatively narrow datasets, both in terms of absolute data units (e.g., brand-generated posts) or period covered, processed with rather simple analytical frameworks (e.g., manual content analysis paired with ANOVA or correlation analysis); differently, more recent contributions started to embrace more reliable, big-data friendly approaches, combining top-down (e.g., Deng *et al*., 2021a; 2021b) or machine learning-driven automated content analysis with predictive analysis (e.g., Lee *et al*., 2018; Shahabaznezahd, Dolan, Rashidirad, 2021; Tellis *et al*., 2019).

Theoretical approaches. Theory-wise, most studies (22) are rooted in traditional advertising and communication models, including among others the advertising message typology (Puto and Wells, 1984), the encoding-decoding model of communication (Hall, 2003), the uses and gratification theory (Katz and Foulkes, 1962), the persuasion knowledge model (Friedstad and Wright, 1994). Yet, also psychological models (e.g., dual processing theory, Kahneman, 2011; elaboration likelihood model, Petty and Cacioppo, 1986; psychological motivation framework, Berger, 2014; message framing theory, Smith and Petty, 1996), and linguistic (Halliday, 1976; Giles, Coupland, and Coupland, 1991) as well as psycholinguistic (Adkins and Brashers, 1995) theories are applied, given the textual nature of the brand-generated CESM initiatives investigated. Beyond formal theoretical lenses and models, some CESM field studies also developed their conceptual models without mobilizing a specific theoretical framework, but building upon previous bodies of related conceptual and empirical literature, such as the (e)WOM (e.g. de Vries, Gensler, and Leeflang, 2012), brand communities (Pletikosa Cvijikj and Michahelles, 2014), and brand experience literatures (Tafesse, 2016), or the CBE literature itself (Devereux, Grimmer, and Grimmer, 2020; Shultz, 2017; Vlacvei *et al*., 2021).

Independent variables. As for the independent variables, as depicted in Figure 2, the main drivers of CESM embedded in brand communication in social media can be gathered in two main groups, that we label as *content-level* and *contextual* factors. *Content-level* factors comprise all those content engineering elements (Lee *et al*., 2018) that compose the actual content of a brand-generated social media post, and which can regard both the soft and hard content factors (Sabate *et al*., 2014). Since social media campaigns are designed and implemented according to a top-down logic by brands and social media managers, content-level factors are under the direct control of the latter ones. As for soft content factors, the literature tested three main content orientations or message strategies that brands can implement in their posts: *rational*, *transformational*, *interactional*. Rational (also referred to as "informative", "utilitarian", "instrumental", or "functional") content orientations target the receiver's rationality, intellectual processing, and informational needs by providing information which is perceived as factual and resourceful, or by providing any extent of transactional or remunerative incentive to the receiver (e.g., Dolan *et al*., 2019; Kim *et al*., 2019; Tellis *et al*., 2019). Transformational (also referred to as "emotional", "socioemotional", "experiential", or "hedonic") content orientations target the psychological and emotive characteristics of the audience, both via content which is perceived as entertaining, humorous, and fun and which addresses the target audience's social needs of group belonging, social integration and interaction, as in the case of philanthropic content (e.g., Ashley and Tuten, 2015; Dolan *et al*., 2019, Lee *et al*., 2018). Lastly, interactional (also referred to as "interactive", "direct call") content orientations characterize many-to-many communication media (Hoffman and Novak, 1996), and on social media platforms include all those content strategies that brands perform to instantiate a two-way communication with their consumers, for instance through questions, surveys, quizzes, and call-to-actions (e.g., de Vries *et al*., 2012; Quesenberry and Coolsen, 2019).

Among the soft content factors, beyond the actual content of a post, the reviewed literature investigated also the effect that its linguistic style or framing can exert on various CESM behaviors. For example, studies empirically validate that posts that are easier to read (Pacer *et al*., 2019) or that are framed by less complex language or visual content (Deng *et al*., 2021b) are less likely to inhibit CESM behaviors. Pezzutti and colleagues (2021) found that brand-generated posts that express certainty in their messages increase CESM, because using certain language makes brands seem more powerful. Munaro and colleagues (2021) find evidence that subjective linguistic style tend to be more effective that emotional and analytical ones in creating active CESM on YouTube contents, because they are perceived as more informal and thus enhance a greater sense of closeness and identification with the speaker.

Regarding the hard content factors, CESM field studies elaborate on four main drivers. Media richness (also referred to as “vividness”) signifies the extent to which a social media post is able to elicit sensorial stimulation in the receiver thanks to its formal features, for example the inclusion of multimedia content. Rich media include sounds, animations, and videos, whilst pictorial posts are regarded as low-vividness social media content (Cvijikj and Michahelles, 2014; de Vries *et al*., 2012; Shahabaznezahd *et al*., 2021). Posting time regards the post scheduling strategies, including the time of the day (e.g. working vs non-working hours), day of the week (e.g., weekend or not), and time of the year (e.g. month, quarter), and are used to account for attention cycles as well as seasonality effects (Cvijikj and Michahelles, 2014; Dhaoui and Webster, 2021; Moran *et al*., 2019). Posting frequency (also referred to as “post freshness” or “post age”) instead refers to how many posts each brand publishes on its social media page and is given by the lag dividing one post from its immediately preceding posts (Khobzi *et al*., 2021; Shahabaznezahd *et al*., 2021). As fresher posts are more likely to show up on a consumer’s feed, whereas visiting and scrolling down a page is required to engage with older posts, engaging with the former ones is more convenient for consumers. Relatedly, also the post positioning represents a relevant hard factor, as social media managers can opt for fixing at the top a brand’s page specific post for longer periods, granting them greater visibility (de Vries *et al*., 2012; Schultz, 2017).

Contextual factors. Conversely to the case of content factors, contextual factors refer to all those elements that, to different extents, escape the direct control of brands while planning the social media communication. Contextual factors are usually integrated as moderators, mediators or control variables in the reviewed studies, and spam across various dimensions of the brand social media communication ecosystem, including the post-level (e.g., the feedback effect exerted by volume and valence of UGC posted below a specific post; Shahabaznezahd *et al*., 2021), the platform-level (e.g., type of platform; Shahabaznezahd *et al*., 2021), the consumer-level (e.g., collectivism; Pezzutti *et al*., 2021), the brand-level (e.g., size of follower base, brand equity; Araujo *et al*., 2015; Lee *et al*., 2018), and the industry or product-level (e.g., sector or product category, B2C vs B2B, mass vs luxury; de Vries *et al*., 2012; Tafesse, 2016; Swani *et al*., 2013).

Regarding the effects that content-level and contextual factors exert on various CESM behaviors, the review of the findings revealed that, if at the single contribution-level the results reviewed are meaningful, they provide instead a somewhat inconclusive picture at the aggregate level. For example, this empirical literature provides conflictual results regarding the effect that the same content orientations or message strategies (e.g. transformational vs informational ones) exert on CESM (e.g. Vlacvei *et al*., 2021; Tellis *et al*., 2019). Likewise, mixed effects connotate not only soft content factors, but also hard ones. In this vein, it is not definitive whether a moderate (e.g. Luarn *et al*., 2015; Moran *et al*., 2019) or high level of media richness or vividness (e.g. Sabate *et al*., 2014) should be included in brand-generated social media posts by brand managers to trigger greater CESM.

Dependent variables. Regarding the dependent variable, CESM behavior is definitely not conceptualized nor measured in a universal way either. For instance, Liu *et al*. (2021) draw upon the COBRA model (Muntinga *et al*., 2011), which conceives CESM as a continuum of three social media usage types connotated by increasing levels of activeness, respectively consuming (that is, participation without active contribution), contributing (that is, conversation on the brand social media page), and creating (that is, active production and publication of brand-related content). Similarly, the SMEB framework (Dolan *et al*., 2019; Dolan, Conduit, Fahy, and Goodman, 2015) translates CESM in four consumers behaviors that vary in terms of intensity (low-high), but also valence (positive-negative). Along similar lines, Vlacvei *et al*. (2021) rely upon de Oliveira *et al*. (2020)'s three-stage CESM framework, where engagement moves from relationship formation, where trust and commitment affect satisfaction and positive emotions, to creation, where CESM is originated from consumer satisfaction, positive emotions, trust, and commitment, to contribution, where CESM contributes directly and indirectly to firm performance. Moreover, two further layers of complication fragment this subfield even further. First, several publications, despite what is measured on the platform being the same, adopt different labels for their dependent variables. In other words, the same built-in CESM metrics such as "Like", "Comment", "Share" or "Retweet" are used to measure constructs named differently from CESM, including, among others, "content virality" (Pacer *et al*., 2019; Tellis *et al*., 2019), "eWOM" (Kim, Kim, and Kim, 2019; Swani, Milne, and Brown, 2013), "post popularity" (Sabate *et al*., 2014; Swani and Milne, 2017; Swani, Milne, Brown, Assaf, and Donthu, 2017), "pass-along behaviors" (Araujo, Neijens, Vliegenthart, 2015), and "consumer involvement" (Cruz *et al*., 2017). Second, in other works the opposite case take place instead. That is to say, despite the dependent variable being labelled in the same way (namely, CESM), the way it was actually measured differ. For example, some studies include also passive CESM behaviors like click-throughs or impressions (e.g., Moran, Muzellec, and Johnson, 2019; Dolan *et al*., 2019; Lee *et al*., 2018). Others also consider the valence dimension of CESM (Kim *et al*., 2019; Shahabaznezahd *et al*., 2021). Others include within-comment thresholds dynamics (Dhaoui and Webster 2021; Liu, Shin, and Burns, 2021) and feedback effects between the dependent variables (see engagement effect, Shahabaznezahd *et al*., 2021). Finally, others use engagement scores provided by third parties instead of the mentioned built-in ones (Ashley and Tuten, 2015). This conceptualization-level as well as measurement-level lack of agreement might very likely impact discriminant validity of CESM investigations.

All in all, the emerging CESM field study stream of literature thus appears as quite fragmented, which prompts three main concerns. First, a lack of a unified vocabulary and the presence of little agreement on how constructs are conceptualized as well as operationalized not only hampers robust comparison among studies, but also prevents to offer brand and social media managers the normative guidance needed to best design their brand post content. Second, we spot a monitoring shortcoming, since in the reviewed literature, despite few exceptions, CESM is operationalized mainly in volumed-based terms. Even though early works defined the affective dimension of CBE as strictly "positively-valenced" (Hollebeek *et al*., 2014: 154), more recent contributions recognize also a negative nature of engagement, since the two valence dimensions of CBE are not necessarily orthogonal (Bowden, Conduit, Hollebeek, Luoma-Aho, and Solem, 2017; Hollebeek and Macky, 2019). In other words, a specific brand-generated social media post might record a very high volume of user-generated comments, which however could be negative in tone or discussing harmful topics, as in the case of online firestorms and retaliations. Therefore, assessing the variety and semantic nature of CESM beyond volume-based metrics is mandatory to make sense of the effectiveness of brand communication on social media (Shaefers, Falk, Kumar, and Schamari, 2021; Unnava and Aravindakshan, 2021). Failing to develop and implement an all-encompassing CESM measurement could very likely lead to biased or unreliable results, as already happens with off-the-shelf social media monitoring analytics (Hayes, Britt, Evans, Rush, Towery, and Adamson, 2021).

Third, as if brand communication happened in a sociological vacuum, the context in which the brand-generated messages of the tested campaigns take place is left out by most studies. Traditional communication theories and message routes are used to make sense of the effectiveness of brand communication on social media platforms without considering that consumers' expectations and relationships with both brands and such platforms has importantly changed (Appel *et al*., 2020). In this vein, consumers now require brands to act and communicate beyond their businesses sphere of competence, by taking overt stances about hot sociopolitical issues (Schimdt, Ind, Guzman, and Kennedy, 2021; Vredenburg, Kapitan, Spry, and Kemper; 2020). Brand activism communication plays a much greater role in the communication mix of brands, though few include or distinguish these strategies from traditional communication appeals (Milfelfd and Flint, 2020; Mirzaei, Wilkie, and Siuki, 2022).

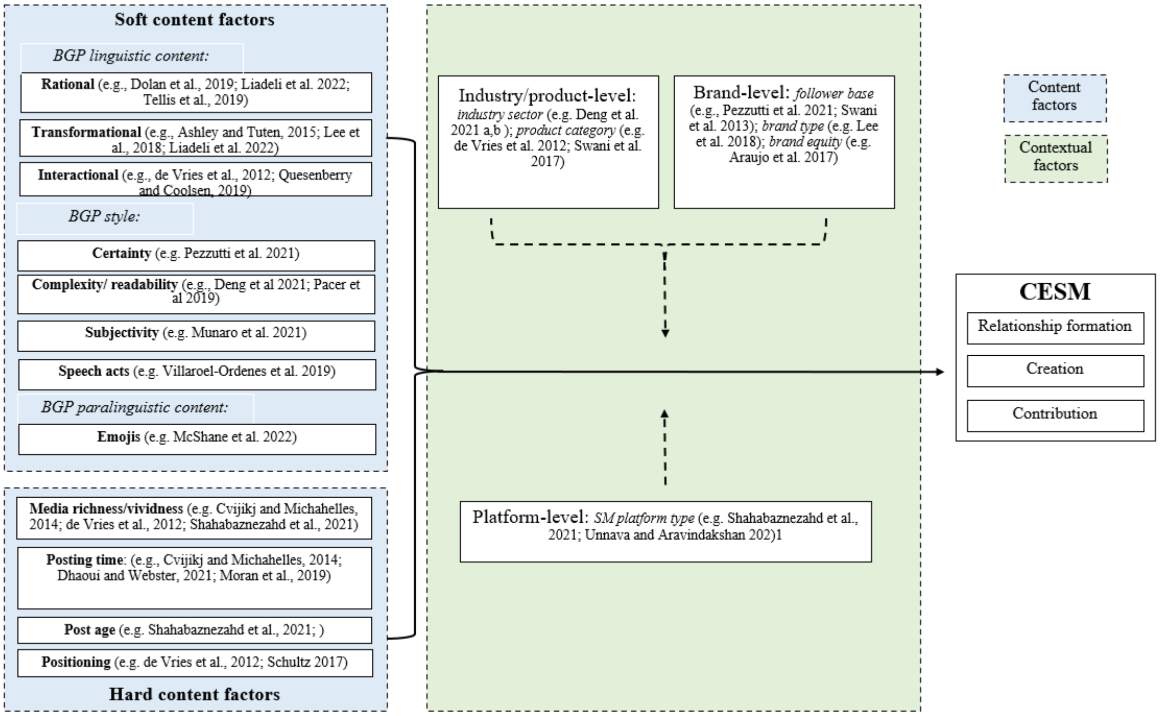

Figure 2: Drivers of CESM initiated by brand communication on social media.

1.2 Epistemological and methodological foundations

Being social media platforms at the core of this work, it should not be surprising that the epistemological, methodological as well as overarching theoretical foundations on which its three essays lay were chosen to best accommodate research dealing with digital techno-mediated phenomena and behaviors. As we introduced above, despite social media platforms were initially conceived and approached as a migration of traditional communication media into digital realms (after all, as Caliandro and Gandini [2016] underline, the term media is a component of the “social -media” bigram itself), soon researchers from various fields realized that, also due to the nature and magnitude of their effects on the broader society, social media could not be treated and studied as mere broadcasting media. These platforms represented indeed a brand-new ecosystem for social interactions endowed with peculiar forms of agency (Callon, 1986) which, on one side, offered to users untapped avenues for practicing new activities, enacting new roles and instantiating new behaviors, in a climate of interconnection and real-timeness (boyd and Ellison, 2007). On the other side, they contributed to the digitalization of identities (Belk, 2013), and to the platformisation and "appification" of societies and markets (Humphreys, 2021). As a result, they have contributed to generate and unleash a deluge of unstructured data not accessible before (Balducci and Marinova, 2019), especially in the form of text, broadly meant as the fabric resulting from any combination of alpha-numeric (or symbolic) code within a market (Humphreys, 2021).

This data deluge necessarily prompted scholars to adapt the way they approach, design, and conduct their research in, or about, social media. In particular, the follwoing essays draw inspiration from two schools that can to all effects be defined as opposed - if not antipodal - in their stances vis-à-vis digital textual data on social media; though, which are increasingly asked to bridge and synergistically cooperate to best deal with the challenge of navigating big unstructured data for social scientists (Aranda , Sele, Etchanchu, Guyt, and Vaara, 2021; Breiger *et al* 2018; Di Maggio, Nag, and Blei, 2013): the quantitative "big data" approach (Grimmer, Roberts, and Stewart, 2021; Humphreys, 2021; Huh, 2017; Hargittai, 2018) and the more qualitative and interpretivist approach of the Digital Methods (Rogers, 2019; 2013).

The paradigm known as Digital Methods (Rogers, 2019; 2013; 2010) indicates a methodological outlook stemming from Internet research scholarship which aims at repurposing those data collection and analytical strategies that are natively digital for social research scopes that instead go beyond the study of online culture. Revolving around the motto "follow the medium" (Rogers, 2013), and recalling McLuhan's seminal lesson (McLuhan and Fiore, 1967), the Digital Methods paradigm invites social researches to resort on and exploit the features, architectures and logics idiosyncratic of digital media – what are referred to as "affordances", like the famous hashtags or the recommendation systems and seeding algorithms typical of social media platforms– to treat the Web as a source of research methods rather than as a topic of investigation per se. In this vein, Digital Methods are not a virtualization or the digital analogue of traditional, offline research methods. They represent instead an approach aimed at making the most of the "online groundedness" of modern societal conditions and cultural changes, whereby "the Internet is a research site where one can ground findings about reality" (Rogers, 2010: 243). Even though recent events, like the global political fight around personal data and online privacy, are threatening those conditions of data public availability and transparency that fueled this methodological framework, Digital Methods researchers are creatively coming up with new strategies to continue this promising tradition also in a post-API environment (Caliandro, 2021; Tromble, 2021). Common methods used to conduct research in digital environments according to this paradigm comprise, for instance, Social Network Analysis, as well as various type of content analysis. We used both to answer to inform the research questions of our first essay (Chapter 2).

Conversely, the so-called "big data" approach to textual data (Humphreys 2021; Huh, 2017; Hargittai, 2018) refers to the use of computational approaches, like machine learning (Grimmer *et al*., 2021), to analyze large amounts of unstructured textual data and infer latent meanings and relations otherwise unseeable at human eye. Fostering a new spring to the "linguistic turn" of management and marketing research (Hannigan, Haans, Vakili, Tchalian, Glaser, Wang, Kaplan, and Jennings, 2020), various techniques of analysis have been developed to navigate large volumes of textual data and map underpinning meanings at a broader level through means of data quantification and visualization. This set of techniques, used for tasks that span from sentiment analysis to document clustering to topic discovery, are often referred to as "text-mining" (Feldman and Sanger, 2007), "automated text analysis" (Berger *et al*., 2019; Humphreys and Wang, 2018), or "computer-aided textual analysis" (Brunzel, 2021). Independently from the name adopted, these approaches share the same key assumption about textual data: in order for the latter to be usable for a computational approach, they must be translated or better "represented" in structured formats, like a matrix or vector form, to allow mathematical or statistical comparisons and measurements. Despite its "data mining" nature, this approach should not be confused with the fields it draws upon, like computational linguistics or Natural Language Processing (NLP). As a matter of facts, whilst the former is interested in language and linguistic patterns per se, automated text analysis is concerned about the cognitive, behavioral, and cultural phenomena that can be expressed and conveyed by textual data. In addition, automated text analysis also differs from NLP, a branch of Artificial Intelligence, in that its main purpose is not to understand and operationally replicate what natural (that is, human), language does (Jurasfky and Martin 2014), but rather to operationalize methodologically various theoretical constructs expressed via language (Hannigan *et al*., 2019; Humphreys and Wang, 2018). In other words, according to the big data approach, researchers apply NLP functionalities to social scientific data to discover new concept or adapt old ones, to measure them, assess causality and make predictions, finally allowing to "break free from the deductive mindset that was previously necessitated by data scarcity [...] to adopt a more inductive approach, which involves sequential and iterative inferences" (Grimmer *et al*., 2021: 396). We adopt this approach especially in the deployment of our second (Chapter 3) and third (Chapter 4) essay, where we inform our research questions through the use of topic modeling algorithms like the Structural Topic Model (Roberts, Stewart, Tingley, Lucas, *et al*., 2014) and aspect-based sentiment analysis (Dehler-Holland, Okoh, and Keles, 2022).

Despite stark differences, both approaches are useful to exploit real data in unabridged settings and maintain the concurrent representative nature of unstructured textual data (Balducci and Marinova, 2019), meaning that studying the same textual unit from one perspective does not affect its quality, and thus does not prevent the possibility to assess it also with the other stance. Moreover, we contend that both, to different extents, rely on the same epistemological assumption, somehow rooted in a structurationist perspective whereby behavior can strongly differ among individuals, but at the aggregate level is normalized into "social structures", and thus is by itself predictable (Giddens, 1984). In this stance, CESM behavior can differ from user to user, for instance, based on their personality traits, identity-projects, self-presentation aims, but there are structural factors of brand-generated social media engagement initiatives that, taken at an aggregate level, can predict the likelihood of various CESM behaviors. In other words, in our essays we aim perform a "distant reading" (Moretti, 2013) of aggregated social media data to infer latent social structures connectible to engagement which, at the same time, do not infringe micro-level variations.

Chapter 2. Branding Rhetoric in Times of a Global Pandemic: A Text-Mining Analysis

In collaboration with Giuseppe Pedeliento (University of Bergamo) and Daniela Andreini (University of Bergamo)[7]

2.1 Introduction

During the first semester of 2020, people from all over the world had to cope with the most challenging global crisis of recent human history: the Covid-19 pandemic. The pandemic-induced lockdown, and the forced social and physical distancing it provoked in almost every country of the world, reset movements and activities of people, who were obliged to stay all day long within their home walls. These unexpected circumstances did not only separate consumers from their relatives and affections; they also forced brands to stay away from their audiences, with potential harmful drawbacks on the relationships they have with actual and prospect customers. Thus, very soon, both the academia and the media (e.g. Taylor, 2020; Cole, 2020) wondered about whether and how brands should change and adapt their advertising and communication efforts during the pandemic to make them more resonant toward their audiences. This was particularly urgent given that the time spent by consumers on social media peaked dramatically during the lockdown (Gfk, 2020). Though, despite studies on the relationship between brand communication and consumers' social media engagement with brands (CESM, Schivinski *et al*., 2016) has flourished in recent years (Araujo *et al*., 2015; Lee *et al*., 2019, Ordenes *et al*., 2018; Pezzuti *et al*., 2021), current research lacks sufficient empirical evidences to advise brands on how they could better adapt their advertising and communication efforts to stay relevant and to keep consumers engaged in times of high uncertainty and turbulence, such as those implied in a global pandemic (Karpen and Conduit, 2020; Lee *et al*., 2018; Tuzovic *et al*., 2017).

[7] Published in a different version on *Journal of Advertising* (Mangiò *et al.*, 2021).

This research contributes to bridging this gap in two ways: first, it explores whether and how the pandemic outbreak changed the rhetorical appeals brands used on social media (in particular on Twitter). Second, it tests whether eventual changes in the rhetorical appeals affect CESM. The institutional logics perspective (see Thornton *et al*., 2012) is used to make theoretical sense of the findings, while the Aristotelian persuasion categories of logos, ethos and pathos (Aristotle and Roberts, 2004) are resorted to signify changes in logics induced by the Covid-19 pandemic.

These premises done, this research addresses the following research questions:

RQ1) How and to what extent have the rhetorical appeals brands employed on social media changed during the pandemic?

RQ2) How did the different persuasion appeals the brands employed, affect CESM?

To answer these questions, we collected and processed a unique cross-industry dataset comprising ca. 12,000 tweets posted by 76 brands before, during and after the lockdown. The research was conducted in Italy, the first Western country to decree a complete lockdown to counteract the virus. We used an exploratory analysis involving document similarity (Gomaa and Fahmy, 2013) and hashtags network analysis (Caliandro and Gandini, 2016) to assess whether the pandemic led brands modify their rhetorical appeal on Twitter, and to determine whether brands changed their vocabulary in such communication. Next, we applied a top-down automated text analysis (Humphreys and Wang, 2018) to operationalize the rhetorical appeals and to track their evolution across the selected industries before, during and after the lockdown. Finally, we tested whether and to what extent such rhetorical appeals affected CESM before and after the pandemic's spread. The discussion of the empirical result is then followed by conclusions, where we specify implications, limitations and suggestion for further research.

2.2 Theoretical background

A landmark theory in organization and management studies, the institutional logics perspective (Thornton *et al*., 2012) is gaining momentum also in marketing research (Slimane *et al*., 2019). Defined "as the socially constructed, historical pattern of material practices, assumptions, values, beliefs, and rules by which individuals produce and reproduce their material subsistence, organize time and space, and provide meaning to their social reality" (Thornton and Ocasio, 1999: 804) the concept of an institutional logic signifies a set of tacit and explicit rules that shape how social actors think and act within a certain area of social life. Being rooted on the tenets of institutional theory, an institutional logic is often framed as a normative structure that exists insofar actors implicitly or explicitly refer to it to guide their actions and interactions (Hirsch and Lounsbury, 1997; Thornton *et al.*, 2012). Yet, despite of their normative structure, logics can be changed either by internal forces, e.g. by the transformative work of institutional actors (Beckert, 1999), or by external forces, e.g. by exogenous events that may disrupt and change even the most institutionalized and taken-for-granted conventions that grant field stability overtime (Fligstein and McAdam, 2012). The Covid-19 pandemic undoubtedly falls under this latter circumstance. Given the magnitude and unpredictability of its consequences (Kirk and Rifkin, 2020) and the impact it had on business life, the pandemic has quickly altered dominant and time-persistent logics (Gümüsay *et al*., 2020) including the traditional dominant market logic that imprints brands' communication and advertising efforts (Thornton *et al*., 2012). A brand's persistent stickiness to this logic throughout the pandemic may in fact lead consumers to perceive it as acting egoistically and to be disrespectful of what is happening around (Kirk and Rifkin, 2020), eventually sparking phenomena of de-legitimation (Ahmed *et al*., 2020). Although research has shown that institutional logic changes can be inferred through several key constructs, changes taking place in the communication realm are deemed to be particularly suited to this purpose (Brown *et al*., 2012; Ocasio *et al*., 2015). Connecting "macrostructural aspects of collective meaning structures with the microinteractional level where much of the negotiation of meaning takes place" (Cornelissen *et al*., 2015: 20), the focus on communication allows accessing how logics are instantiated (Ocasio *et al*., 2015) and how new issues are framed (Humphreys, 2010). Supporting this theoretical posture, and in line with similar studies (Hartman and Coslor, 2019) this research focuses on changes in brands' communication on social media to account for and make sense of institutional logic shifts. In addition, it also assesses whether such changes are rewarded or penalized by consumers that may increase or reduce their CESM depending on the rhetorical appeal brands use. Brands' rhetorical appeal is formalized restoring the Aristotelian persuasion categories of logos, ethos and pathos (Aristotle and Robers, 2004). In brief, logos refers to the way of persuading an audience with reason, using facts and figures; ethos, signifies the means of convincing others via the authority or credibility of the persuader; pathos, deals with the way of convincing the other by creating an emotional response to an impassioned plea or a convincing story. Previous contributions confirmed that the Aristotelian categories of persuasion are well suited to make sense of how brands relate to consumers (Auger 2014; Bonfanti *et al*., 2016; Panygirakis *et al*., 2019) and have shown that they differently predict consumers' social media engagement with brands (Lee *et al*., 2018). In addition, the rhetorical appeal used by brands has been suggested to be paramount especially when brands are trying to cope with exogenous crises to create or re-create a positive relationship climate with customers. For example, research has shown that following the 2007-2008 financial collapse, players of the financial sector have shifted their advertising strategy from a performance based to a more informative-based rhetorical appeal to reassure consumers and to be perceived more trustworthy (Lee *et al*., 2011). Others have shown that focusing on consumers' safety needs can outperform other narratives to favor the recovery of the tourism and travel industry following a natural disaster (Finsterwalden, 2010).

2.3 Methodology

2.3.1 Brand selection and data collection

Tweets posted from December 1st, 2019, to July 1st, 2020 by a representative sample of 76 brands competing in seven industrial sectors were scraped through Twitter API. Data collection started on July the 30th, i.e. thirty days after the end of the period under investigation, to guarantee enough time for digital interaction with every tweet considered. Consistent with extant research (Farace *et al*., 2020; Liu *et al*., 2017), Twitter was chosen despite not being the most widely used social media platform in Italy (Statista, 2020) because it provides a free and easy access to data (Kumar *et al*., 2014), because it has been proven as an insightful real-time information network and because Twitter is sufficiently ubiquitous to cover a wide array of communicators and publics (Liu *et al*., 2017). We selected seven different industries - automobile, fashion and beauty, banking and finance, fast moving consumer goods (FMCG), retail, pharmaceutics, and travel and tourism - considering how much the pandemic had impacted them (Cerved, 2020). Specifically, we selected these brands based on their appearance in rankings like Interbrand and BrandZ, their market share, and Twitter activity, i.e. only those brands that posted regularly during the entire six-month period were included (see Appendix A for the complete list of brands). Following these brands provided us with 13,033 tweets, which were then skimmed through language identification algorithms to grant data homogeneity (Ooms, 2020). Thus, 11,888 tweets were retained for the analysis (avg. tweet length = 26 words; σ= 10.83; min: 2; max: 74) (Table 1).

Industry	**N° brands (%)**	**N° tweets (%)**
Automobile	18 (23.7)	2,164 (18.2)
Fashion and Beauty	15 (19.7)	717 (6.0)
Banking and Finance	4 (5.3)	1,581 (13.3)
FMCG	7 (9.2)	1,325 (11.1)
Retail	14 (18.4)	1,390 (11.7)
Pharmaceutic	9 (11.8)	3,536 (29.7)
Travel and Tourism	9 (11.8)	1,175 (9.9)
Tot.	*76*	*11,888 (100)*

Table 1: Number of brands and tweets, per industry.

2.3.2 Analytical procedure

We analyzed the selected tweets by following the most recent methodological guidelines (Berger *et al*., 2019). First, we divided the corpus into three different groups distinguished according to three periods of publication identified as ‘Pre-lockdown’ (phase 1), December 1st, 2019 to March 7th, 2020; ‘Lockdown’ (phase 2), March 8th to May 4th, 2020; ‘Post-lockdown’ (phase 3), May 5th to July 1st, 2020. In the preliminary stage, the analysis was limited to hashtags which were inspected through a document similarity analysis and a hashtag network analysis. On these preliminary results, we then proceeded with a top-down automated text analysis to assess the presence of each of the rhetorical appeals of logos, ethos, and pathos within the textual corpus we collected. In addition, we also tested whether changes of the rhetorical appeal affected CESM.

2.4 Analyses

2.4.1 Preliminary analysis

The preliminary stage involved a document similarity analysis and a subsequent hashtags network analysis. Before any computation, we went through a document preparation and data pre-processing phase consisting in cleansing the textual database to minimize noise effects, grant the quality of textual data and make text suitable for text mining (Berger *et al*., 2019; Welbers *et al*., 2017). Textual data cleaning is particularly important for social media data which, despite being informative, can be highly sparse and scattered (Liu *et al*., 2017). In this preliminary phase we performed a customized rule-based normalization procedure aimed at fixing encoding issues. For example, we transformed emoticons and emojis into their closest textual semantic descriptions. We then removed non-relevant features like punctuation, separation, URLs or other useless hyperlinks; deleted typical stop words (Wilbur and Sirotkin, 1992) like articles, conjunctions and prepositions and others which could potentially amplify the noise; we also lower-cased and stemmed the features and finally proceeded by tokenizing, i.e. splitting the text data to the smallest computational unit intended by the researchers, the cleansed text at the word level (Benoit *et al*., 2018). After pre-processing, we represented documents according to a bag-of-word model, a simple but effective representation approach which ignores word order and derives textual meaning from word occurrences only (Humphreys and Wang, 2018).

As first exploratory analysis, document similarity was assessed via cosine distance[8] (Gomaa and Fahmy, 2013). The results suggest that the Covid-19 outbreak has significantly changed the way in which brands communicate via Twitter: the set of hashtags used in phase 3 have a higher level of similarity with those retrieved in phase 2 (.56) than with those of phase 1 (.49). The highest similarity score is between phase 2 and phase 3 (.69). As robustness check, we also investigated how the stock of hashtags used by brands changed along the three phases. Being #hashtags flexible and dynamic social media affordances rife with sociological

[8] Cosine distance is commonly used as a text similarity metrics in information retrieval domains, as it is based on the representation of each document as a vector of feature occurrences on an inner product multidimensional space (Huang, 2008). The higher the vectors' similarity, the more they point toward the same direction in the multidimensional space. Thus, a cosine of the angle dividing each vector equal to zero indicates absolute dissimilarity; on the contrary, a cosine equal one indicates perfect similarity.

meaning, used for self-presentation purposes, and employed to signal membership to a group or cause or to convey non-verbal ideas (Lin and Margolin, 2014), they have been suggested to be particularly useful to represent the online discourse taking place in specific point in time (Arvidsson and Caliandro, 2016; Caliandro and Gandini, 2016; Lewis *et al*., 2013; Bruns, 2012). The results suggest that the Covid-19 outbreak brought an entirely new set of hashtags that remained in used throughout the pandemic; the share of new hashtags never used in phase 1, but included in tweets during phase 2 and 3, was respectively 50% and 86%. This evidence suggests that the pandemic outbreak triggered significant modifications of the online discourse and modified established mechanisms through which users' attention can be catch.

As for the hashtag network analysis, we first weighted hashtags' frequency of occurrence by TF-IDF (Spärck Jones, 1972); then, three researchers coded the most salient hashtags (n=590) by assigning each of them to some categories ($.792<\alpha<.827$; Krippendorff, 2010). Next, we plotted three undirected networks of hashtags representing phase 1, 2, and 3 on Gephy via Force Atlas2 algorithm (Jacomy *et al*., 2014). We detected communities based on modularity class (MC) (Barber, 2007), and ranked nodes by betweenness centrality[9] (BC) (Freeman 1977) (Table 2). As a robustness check, in a post-hoc analysis nodes were ranked by an alternative centrality measure specified by Sainaghi and Baggio (2014), leading to similar results (see Appendix B) The distribution of brand-generated hashtags confirmed that Covid-19 appeals took on brands' tweets as soon as the virus gained media traction during the first weeks of March (Figure 3).

[9] Modularity class (MC) is a measure of network structure which assesses the strength of the division between modules or communities (Barber, 2007). The calculation of MC was then followed by a further test of betweenness centrality (Freeman, 1977) (BC) to weight how much a given node in a network (a #hashtag in our case) is in-between others. The score of BC is moderated by the total number of shortest paths existing between any couple of nodes of the network. Thus, the higher the value of BC of a target (such as a #hashtag), the higher the frequency with which it appears in many shortest paths (Perez and Germon, 2016).

Before the lockdown (Nodes:200; Edges: 617)			During the lockdown (Nodes: 192; Edges: 578)			After the lockdown (Nodes: 198, Edges: 673)		
	BC	*MC*		*BC*	*MC*		*BC*	*MC*
Max.	4,114.33	30	Max.	6,019.62	23	Max.	7,009.17	25
Min.	0	0	Min.	0	0	Min.	0	0
Avg.	190.885	-	Avg.	144.40	9.59	Avg.	146.71	13.201
Dev. Std.	571.38	-	Dev. Std.	540.96	6.26	Dev. Std.	557.85	5.55
Mode	-	20	Mode	-	5	Mode	-	16

Table 2: Hashtag Network Analysis: descriptive statistics.

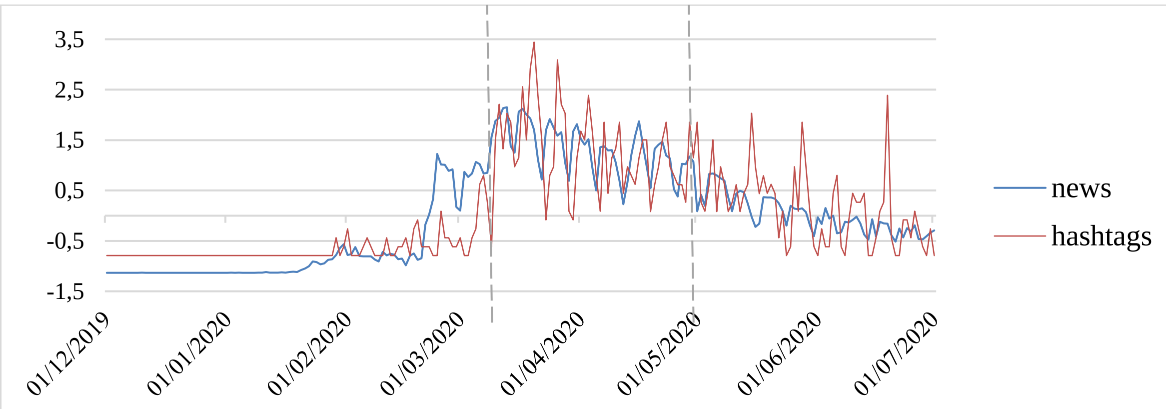

Figure 3: Covid-related Italian media news vs covid-related brand tweets[10].

#Covid19 and its synonyms not only have the highest BC score, but also the widest community in both phase 2 and 3: once the lockdown was mandated, brands rapidly replaced the set of brand-specific hashtags, such as #bestwestern_ita or #suzuki, or the activity-related hashtags, such as #sostenibilità (#sustainability) with new ones related to the pandemic crisis. In phase 1, the analysis revealed the predominance of four clusters in the hashtag network. The first, named #Events, includes hashtags having a link with a specific event or occurrence like #sanremo2020, a popular music festival in Italy (BC=495, MC=22) and #natale (#Xmas,

[10] The distribution of Italian news articles covering the pandemic was retrieved from Mediacloud's "Italy" collection (www.mediacloud.org), using the keyword: "Covid-19 OR Coronavirus" (N= 183.803). The distribution of tweets containing #covid19 or #coronavirus was obtained filtering our sample over the period of investigation (N= 959). As we expected, these two distributions are strongly and positively correlated over the entire period of analysis (0.75, p<.05), even much if we simply consider the first and second phase only (0.82, p<.05). Frequencies are absolute count, normalized.

BC=4,082, MC=30). The second, named #Places, contains hashtags that have an indexical connection with specific cities, like #Milano (BC=1,952, MC=17) and #Palermo (BC=1,516, MC=2). The third, named #CSR, groups hashtags with some factual connection to the realm of corporate social responsibility (CSR) like #sostenibilità (#sustainability, BC=2,039, MC=17) and #ambiente (#environment, BC=461, BC=17). The last cluster, named #Industry, contains the sparse and heterogeneous set of hashtags brands used to identify their name, e.g. #bestwestern_ita (BC=4.114, MC=20), or others used to establish a clear connection with their sector of activity e.g. #visititaly (BC=758, MC=20) in the tourism industry (Figure 4).

In phase 1 the network analysis seems to suggest a generalized tendency of brands to use Twitter hashtags to boost brand awareness and brand online circulation and to advertise and account CSR activities they make confirming previous studies that have recommended Twitter to display CSR activities due to the platform's ability to foster dialogue and content diffusion (Araujo and Kollat, 2018).

In phase 2, the results revealed the emergence of new hashtags and of new clusters. The first of the new clusters, named #Coronavirus, contains hashtags that are clearly connected to the pandemic. Examples are #covid19 (BC=6,020, MC=5), #coronavirusitalia (BC=121, MC=5), #covid_19 (BC=1,473, MC=12), and #pandemia (#pandemic, BC=57, MC=5). The second collects hashtags that are aimed at fostering the recipients' sense of community and emotional closeness, such as #distantimauniti (#farbutclose, BC=375, MC=4) and #insiemecelaferemo (#togetherwemakeit BC=922, MC=8). This cluster of #hashtags was labelled as #EmotionalSolidarity, a set of feelings, emotional ties and shared individual experiences characterized by perceived emotional closeness and contact like help and support which binds individuals together and fosters a *we together* versus *the others* mentality (Woosnam and Norman, 2010).

The third cluster identified contains the set of #hashtags that have been used by brands to label those call-to-action-like campaigns to raise awareness of Covid-induced threats, precautionary measures and behaviors needed to contain the pandemic and safeguard public health. Examples of popular #hashtags here included are #iorestoacasa (BC=3750, MC=4), #sicurezza (#*safety*, BC=394, MC=5) and #responsabilità (#*accountability*, BC=123, MC=5), but also #fakenews (BC= 360, MC=16), a widely used #hashtag to stop the uncontrolled circulation of false information that could undermine cogent norms, social restrictions and other measures aimed at obstacle the circulation of the virus. This cluster of #hashtags was labelled #Safety[11] (Figure 5).

Reading the phase-one hashtags against phase two's confirms that the pandemic drastically modified the way brands use Twitter. Despite brands have undoubtedly made an opportunistic use of pandemic-related hashtags to boost their online visibility, opportunism cannot thoroughly explain brands' changes in Twitter activity. Some brands used #Coronavirus or similar to advertise their offer especially in regard to those products that were in high-demand or in short supply at the inception of the pandemic. Others began using their profiles to broadcast messages of fraternity, social inclusion, and emotional closeness (#EmotionalSolidarity). As our results confirm, usage of these hashtags was so massive that the network shape and structure were substantially remodeled and displayed higher homogeneity. The cluster of #EmotionalSolidarity overcame sectorial confines, and formed a brand-new vocabulary used by a great share of brands.

In phase 3, an additional cluster was identified, i.e. #EconomicRecovery, containing hashtags with a factual connection to the ongoing debate about the post-Covid economic recovery. Hashtags included in this class are, for example, #fase2 (#phase2, BC=902, MC=16), #ripartenza (#restart, BC=223, MC=16), and #nuovanormalità (#newnormal, BC=183, MC=13). The hashtag network painted in phase 3 reveals continuity with phase 2 as brands seem to keep on using social media communication (also) to broadcast positive messages of sociality and civic commitment. However, with the pandemic subsiding and people gradually going back to their pre-Covid life, brands devised a new space for communication which related to the need to recover an economy severely battered by two whole months of inactivity. Phase 3 hence, witnessed the contemporary presence of two major hashtags' clusters corresponding to as many ways for brands to frame the pandemic issue. The first, relates to brands' leveraging, evoking and exploiting the connection between them and the

[11] Worth mentioning, the brands inspected did not merely adopted these hashtags pandering an emerging thread of topics. Rather, they seemed to be putting in place some degrees of personalization and differentiation effort, so that the #Safety-related appeal lead the players of the *retail* and *FMCG* industry to generate hashtags like #iorestoacasaecucino (#Istayhomeandcook, BC=25, MC=4) or those of the *travel & tourism* industry to inspire a temporary paradigmatic change in their services through hashtags like #viaggiaconlafantasia (#travelwithyourfantasy, BC=8, MC=4).

sense of community the pandemic fostered; the second, relates to brands' leveraging the individual recipients' actions and will to take active role toward recovery through, for example, conscious and purposeful buying choices (Figure 6). This cluster contains those #hashtags that have a factual connection with the ongoing discourse and debate about the economic recovery, i.e. the process by which businesses and local economies return to conditions of stability, often referred to as a "new normal" state, following a disaster (Sima *et al.*, 2017). #Hashtags selected for this class are, for example, #fase2 (#phase2, BC=902, MC=16), #ripartenza (#restart, BC=223, MC=16), #nuovanormalità (#newnormality, BC=183, MC=13) and #postcovid (BC=64, MC=5). The cluster was labelled as #EconomicRecovery[12].

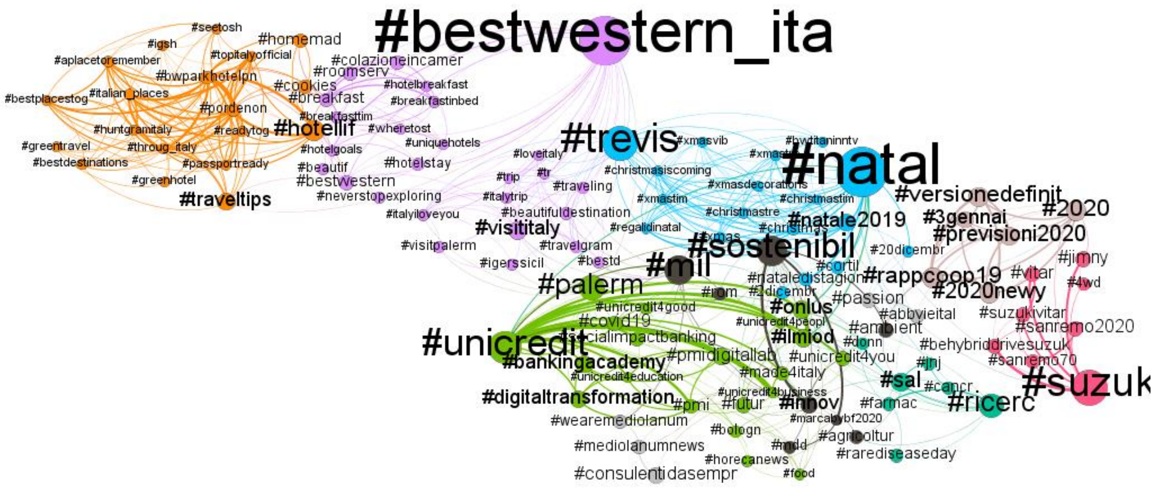

Figure 4: Hashtag network graph (pre-lockdown).

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[12] Worth noticing is the fact that hashtags falling under the cluster of #Industry, although overwhelmed by the trending hashtags related to the pandemic, did not truly disappear neither during, nor after the lockdown. In the banking & finance industry for example, #unicredit or #bancamediolanum (two important national bank institutes) were present – though with different frequency and centrality - in all periods (respectively, 'lockdown' BC=564, MC=2; BC=582, MC=8; 'post-lockdown BC=1,128, MC=9; BC=171, MC=12). Hashtags like #GDO (i.e. #groceryretail, BC=1,090, MC=18) or #Coop (a leading brand of the grocery retail industry, BC=258, MC=12) became highly central in the 'lockdown' phase – when going to the grocery store was the only activity unrestricted – and almost disappeared in the 'post-lockdown' phase, whilst travel and tourism-related #hashtags like #estatepostcovid (#postcovidsummer, BC= 25, MC= 5) popped up and gained importance in the post-lockdown phase.

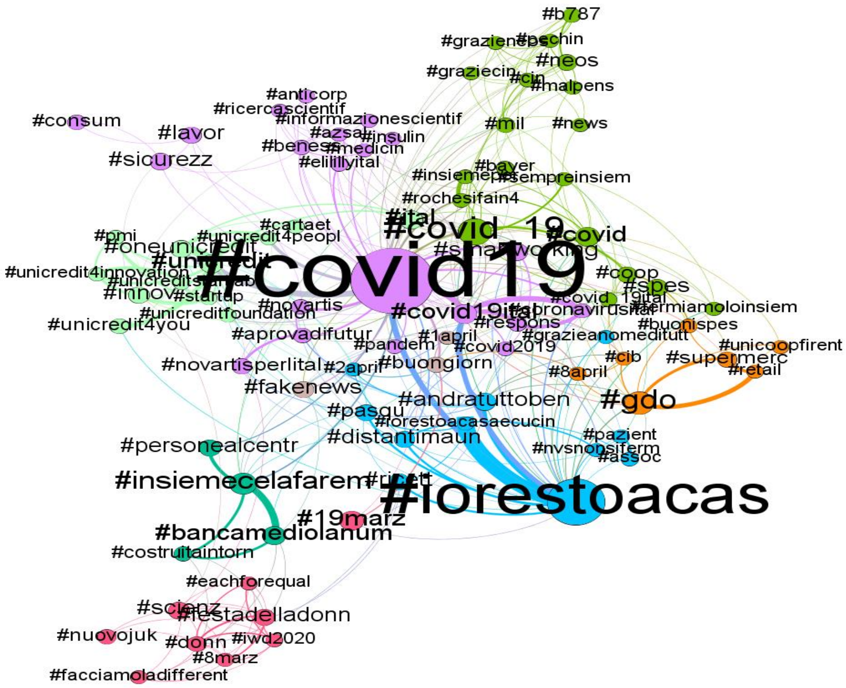

Figure 5: Hashtag network graph (lockdown).

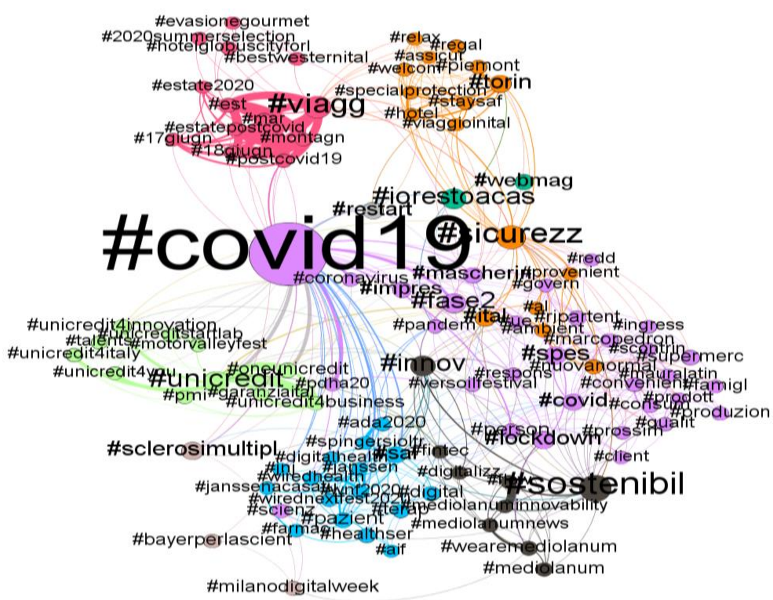

Figure 6: Hashtag network graph (post-lockdown).

2.4.2 Automated text analysis

An automated text analysis on the entire corpus of tweets was run to operationalize the brands' rhetorical appeals and to assess their change over time. This analysis consisted of a combination of top-down methods, including dictionary and rule-based approaches (Humphreys and Wang, 2018). Dictionaries are among the widest-used text mining techniques: they are relatively straightforward to deploy and interpret; they can be accessed and validated also by non-specialists; they permit an easy operationalization of the concepts and of the theories used not necessarily stemming from the linguistic domain (Humphreys and Wang, 2018). Dictionaries, in particular, represent a useful technique to summarize textual characteristics and semantic patterns characterizing a given corpus (Berger *et al.* 2019). Rule-based approaches (e.g. Van Laer *et al.*, 2019) instead imply the development of a customized code aimed at identifying predetermined linguistic elements like punctuations, symbols, parts of speeches in the target text corpus. As the textual analysis performed in this study was informed by the well-established framework of *logos*, *ethos* and *pathos* (Aristotle and Roberts, 2004), we adapted or created original dictionaries and rules for each of these three persuasion categories, following typical conservative protocols (Hayden *et al.*, 2018). For operationalizing *logos*, we developed and validated a dictionary including a lexicon focused on informative and factual content, such as promotions, prices, and statistics, and including symbols like % or currency symbols like £, $, and € (Panigyrakis *et al.*, 2019; Auger, 2014). For *ethos*, we composed a dictionary which consists of the lexicon of trust (Mohammad and Turney, 2010) integrated with the use of links to external sources such as URLs and mentions (i.e. @). As *ethos* relates to a persuasion rhetoric connected to the source's trustworthiness and credibility, URLs and mentions are used because they have been proven to increase a tweet's credibility (Castillo *et al.*, 2011; Auger, 2014). For *pathos*, we relied on the pre-built Italian version of the NRC-Emolex dictionary[13] (Mohammad and

[13] The NRC-Emolex is a crowd-sourced word-emotion association dictionary (available in 20 languages) containing roughly 14,200 unigrams, each labelled with ten affect categories embedded in text, namely two sentiments - *negative* and *positive*, and the eight basic emotions of *fear, surprise, sadness, disgust, joy, anticipation, trust* and *anger* (Plutchick, 2001). Borrowing from Cambria *et al.* (2012), we conceptualize positive and negative emotions based on their level of activation, leading to operationalize a dimension of *negative pathos* resulting from the aggregation, after filtering out potential duplicates, of the dictionaries of

Turney, 2010). Based on the results of the exploratory analysis, we built and validated a further dictionary to measure the emotive appeal of tweets aimed at inspiring or nudging the recipients to behave coherently with the collective safety and good. We summarized these in a new dimension of pathos, labelled *social pathos*.

Terms composing each dictionary were tested for internal validity through three researchers' subjective coding. To reduce false positive observations and include omitted ones (Humpreys and Wang, 2018), post-measurement validation of the dictionaries was made via comparison with 15 human coders ($.619<\alpha<.854$; Krippendorff, 2010) (see Table 3). We used the validated dictionaries to enrich the corpus of collected tweets by computing a dictionary index for each persuasive dimension as the sum of the dictionary words found per tweets divided by the total tokens per tweet. To balance the effect of Twitter daily traffic, we averaged the aforementioned dictionary indexes at the day-level and grouped them by industry.

As textual data are generally non-normally distributed and skewed[14] (Humphreys and Wang, 2018), we ran a Welch's ANOVA model on Tukey-transformed data to assess whether brands adopted the rhetorical appeals differently across phases 1, 2, and 3[15]. Only when the null hypothesis was rejected, the Games-Howell post-hoc test with Bonferroni-adjusted *p*-values to compute pair-wise multiple comparisons was performed (Ruxton and Beauchamp 2008).

sadness, disgust, surprise, fear and *negative sentiment*, and a dimension of *positive pathos* that aggregated dictionaries of *joy, anticipation, anger* and *positive sentiment*.

[14] Accordingly, dictionary scores failed the Shapiro-Wilk test for normality (i.e. with $p < .05$).

[15] For exploratory purposes, beforehand we checked for the presence of statistically significant differences among the seven industries analysed over the entire period considered (Welch's $F_{logos} = 83.872$, $p < .001$; Welch's $F_{ethos} = 35.243$, $p < .001$; Welch's $F_{positive\ pathos} = 26.839$, $p < .001$; Welch's $F_{negative\ pathos} = 108.127$, $p < .001$; Welch's $F_{social\ pathos} = 23.941$, $p < .001$) Results of the post-hoc Games-Howell test for significant pairwise comparison among industries are displayed in Appendix C).

Construct		Source	N° original terms	N° retained terms	N° wild cards	Regex	**Examples** (top 5 features by TF-IDF, translated)
Negative pathos	*Negative Sentiment*	*NRC*	3324	1518	-	-	emergency (624), disease (242), against (210), difficulty (188), crisis (183)
	Fear		1476	428	-	-	tumor (213), lose (133), pain (63), fear (26), panic (22)
	Surprise		534	225	-	-	risk (420), wait (49), beginning (40), anxiety (34), call (19)
	Sadness		1191	320	-	-	depression (199), stress (81), consequences (54), isolation (64), damages (23)
	Disgust		1058	295	-	-	pollution (38), wreak (16), failure (12), nightmare (15), indignant (15)
Positive pathos	*Positive Sentiment*	*NRC*	2312	1434	-	-	commitment (410), innovation (356), future (297), discover (286), special (259),
	Joy		689	320	-	-	well (181), beauty (160), success (156), love (152), create (50),
	Anticipation		839	158	-	-	unveil (189), gift (187), opportunity (160), visit (37), soon (35)
	Anger		1247	102	-	-	challenge (185), revolution (101), powerful (56), react (19), stigma (31)
Social pathos	*Emotional Solidarity*	*pers.el.*		32	25	-	together (508), thank (473), sustain (231), support (224), community (200)
	Economic Recovery	*pers.el.*		26	15	-	restart (176), recovery (79), normality (73), post-covid (62), reopening (57)
	Security	*pers.el.*		27	27	-	home (501), safety (367), prevention (183), protect (92), safeguard (90)
Ethos	*Trust*	*NRC*		329	-		President (202), advice (232), disposition (143), Ministry (128), trust (105)
	Mention	*pers.el*		-	-	@ URL	@coopitalia (506), '@intesasanpaolo (147), '@reglombardia (151), '@masterchef_it (262), '@corriere (150)
Logos	*Logos*	*pers.el.*		31	5	%, $, €	% (514), € (382), research (304), million (249), study (187)

Table 3: Dictionaries and Rules composition.

2.5 Results

The results provided evidence that the rhetorical appeals had changed across the three phases. *Social pathos* is the only one displaying a significant positive increase during phase 2 for all the industries: *automobile* (F=9.882, p < .001); *fashion and beauty* (F=9.862, p< .001); *banking and finance* (F=5.057, p < .05); *FMCG* (F=18.424, p < .001); *retail* (F=10.714, p < .001); *pharmaceutics* (F=3.629, p < .05); *travel and tourism* (F=7.512, p < .001). This result reveals that the shared tendency of brands to carry an identical rhetorical appeal to reduce the risks individual communication failures entail is insensitive to industry-based differences. Nudging to *social pathos* was perhaps considered by brands to be 'safer' or 'more universal' compared to other rhetorical options that could have been perceived as an authority abuse (in the case of *ethos*), too technical to be understood by non-experts (in the case of *logos*), or too much skewed toward an intimate emotional response (in the case of pure *pathos*).

The resort to *logos* increased for the *pharmaceutics industry* (F= 9.509, p < .001) and for *travel and tourism* (F=4.289, p < .05) in both phases 2 and 3, lost ground in the *automobile* industry (F=3.316, p < .05) in phase 2, while remaining unvaried for all other industries. For pharmaceutical companies the higher resort to *logos* can be explained by the fact that the pandemic became an opportunity for them to make greater use of a scientific lexicon through which inform and reassure an increasingly health-concerned audience. For those in the *travel and tourism* industry, the resort to *logos* intensified in phase 3 because of a more frequent use of facts and figures that underline the sector's economic relevance and the severity of the economic backlash they need to recover. In contrast, the *automobile* industry, which was severely hit by the pandemic, partly gave up its traditional *logos* appeal in phase 2, opening space for the emotionally directed appeal of *social pathos*.

The resort to *ethos* remained stable throughout the three phases, excepting for the *fashion and beauty* industry, which witnessed a slight increase in phase 2, but reverted to phase 1 levels in phase 3 (F=6.965, p < .01). As soon as the pandemic started to slow down, brands featuring in this industry rapidly returned to their pre-Covid communication style, centered around "pathetic" values of authenticity (Beverland, 2006) and exclusivity (Fionda and Moore, 2009).

The resort to *positive pathos* decreased in the *pharmaceutics* industry both in phases 2 and 3 (F= 10.087, p < .001), slightly increased in the *fashion and beauty* industry in phase 2, to contract again in phase 3 (F= 8.488, p < .01). *Positive pathos* remained unvaried for all of the other industries we analyzed. The resort to *negative pathos* became more relevant only in the *banking and finance* industry in phase 3 (F= 3.518, $p < .05$). Table 4 displays the results of the post-hoc Games-Howell test for significant pairwise comparison among phases.

Automobile							
	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Logos	1	98	.0427	.00169		-.01605*	-.00122
	2	56	.0266	.00148			.01483
	3	58	.0415	.0018			
Social pathos	1	98	.0417	.00167		.0405*	.0108
	2	56	.0822	.00387			-.0296
	3	58	.0525	.00184			
Fashion and Beauty							
	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Ethos	1	97	.0428	.00222		.02748*	-.00073
	2	54	.0703	.00217			-.02821*
	3	50	.0421	.00205			
Positive pathos	1	97	.117	.00205		.04339*	-.00274
	2	54	.16	.00557			-.04613*
	3	50	.114	.00607			
Social pathos	1	97	.0145	.00064		.0257*	.0151
	2	54	.0402	.00207			-.0106
	3	50	.0296	.00222			
Banking and Finance							
	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Negative pathos	1	82	.019	.000213		.00636	.00853*
	2	49	.0254	.000389			.00217
	3	46	.0275	.000481			
Social pathos	1	82	.0473	.002091		.01872*	.0126
	2	49	.066	.001028			-.00612
	3	46	.0599	.000861			
FMCG							
	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Social pathos	1	92	.0512	.00133		.04512*	.00962
	2	53	.0964	.00216			-.0355*
	3	57	.0609	.00231			

	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Retail							
Social pathos	1	96	.0643	.00294		.0364*	.0191
	2	57	.1007	.00175			-.0173
	3	58	.0834	.00326			
Pharmaceuticals							
	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Positive pathos	1	98	.225	.00326		-.0134	-.0364*
	2	57	.212	.00171			-.023**
	3	58	.189	.00196			
Logos	1	98	0.066	.0012		0.036**	0.027**
	2	57	0.102	.00178			-0.009
	3	58	0.093	.00123			
Social pathos	1	98	.0894	.00465		.0242**	.0096
	2	57	.1136	.00209			-.0146
	3	58	.099	.00151			
Travel and tourism							
	Phase	*Sample*	*Mean*	*Var.*	1	2	3
Logos	1	98	.027	.001759		-.0091	.00988
	2	57	.0179	.000934			.01898**
	3	58	.0368	.001696			
Social pathos	1	98	.0845	.00785		.045*	.0209
	2	57	.1296	.00324			-.0242
	3	58	.1054	.0039			

* $p < .05$ ** $p < .001$. All other values are significant at 95%.

Table 4: Rhetorical appeals evolution, among phases: Games Howell comparison.

2.5.1 Rhetorical appeals and CESM

How did the different persuasion appeals the selected brands employed, affect CESM? Consistent with its conceptualization (see Schivinski *et al.*, 2016), CESM was operationalized as the sum of retweets and likes each tweet received (Pezzuti *et al.*, 2021). We included a dummy variable for the seven considered industries, controlled for each brand's popularity including the number of followers at the data scraping date, and opted for running count models like negative binomial regression, which takes the response variable's overdispersion into account (Table 5). We ran two individual models on the data aggregated by average at the day-level before (661 observations) and after (768 observations) the lockdown was decreed, March 7th, 2020. To measure the effect size, we computed the incidence rate ratio (IRR), indicating how much CESM is expected to change if a persuasion appeal and the size of the account were to increase by one standard deviation.

	Before March 7th, 2020	**After March 7th, 2020**
Industry	*Mean (Std. Dev.)*	*Mean (Std. Dev.)*
Automobile	32.98 (-21.76)	28.29 (24.17)
Fashion and Beauty	10.62 (24.82)	11.76 (24.34)
Banking and Finance	27.94 (80.51)	24.77 (23.95)
FMCG	5.81 (4.87)	10.10 (14.39)
Retail	9.96 (22.62)	12.53 (23.91)
Pharmaceuticals	25.66 (-54.12)	29.97 (51.32)
Travel and tourism	6.12 (3.33)	17.41 (43.68)
Shapiro-Wilk's W:	*.33187****	*.48315****
Skewness	*8.619*	*6.241*

Table 5: CESM with brands: descriptive statistics.

Both models showed a good fit (*Model₁*: $\chi 2$ (14) = 12,502.51, *p*<.001; *Model₂*: $\chi 2$ (14) = 32,733.16, *p*<.001) (Table 6). Before the lockdown was imposed (*Model₁*), only *negative pathos* was not significant in relation to CESM (β=-.80, IRR=.45, *p*>.05). *Logos* and *positive pathos* were found to be significantly but negatively related to CESM (respectively, β=-1.96, IRR=.14, *p*<.05 and β=-4.40, IRR=.01, *p*<.001), while the relationship between rhetorical appeal and CESM was found significant and positive for *social pathos* (β=2.03, IRR=7.63, p<.05) and for *ethos* (β=2.69, IRR=14.72, *p*<.01). The results show that although the number of followers has a null effect on CESM (β=.00, IRR=1.00, *p*<.001), the test for the model effects indicates that the categorical variable 'industry' was statistically significant (Wald X^2 (6):51.163, *p*<.001). After March 7th, 2020 (*Model₂*), *logos* and *pathos* seem to exert no statistically significant effect on CESM (*logos* β=.69, IRR=1.99, *p*> .05; *positive pathos* β=.70, IRR=2.00, *p*>.05; *negative pathos* β=1.02, IRR=2.76, *p*>.05), while the positive effect of *ethos* and *social pathos* persist, but with the latter now playing the utmost role (*ethos* β=3.68, IRR=39.74, *p*<.001; *social pathos* β=4.51, IRR=91.25, *p*<.001). The number of followers remains a negligible predictor of CESM (β=0.00, IRR=1.00, *p*<.001). In all, these results indicate that during the pandemic CESM was connected to brands' ability to shift their rhetorical appeal toward more socially-conscious issues. *Social pathos*, became the leading CESM driver in both phases 2 and 3. Regarding *ethos*, the results reveal this appeal to be a strong CESM driver, both before and after the Covid-19 emergency, confirming previous studies that equally revealed the higher the source's standing and credibility, the higher the engagement it generates (Chu and Kim, 2011). Our results establish that in phase 1 *positive pathos* was negatively related to SME, while *negative pathos* showed no significant effect. Considering the affective valence embedded in the rhetorical appeal of *pathos*, the result is in line with those of previous studies that adopted a similar approach (Pezzuti *et al.*, 2021). In phase 1, *logos* is related to lower levels of SME, providing support to previous studies that have similarly shown the relatively lower level of engagement informative brand messages generate in contrast to more entertaining ones (Lee *et al.*, 2018). Defying expectations, both *logos* and (*negative* and *positive*) *pathos* showed no significant effect on CESM in both phases 2 and 3.

Model 1 ***Before*** **March 7th** (N:661)				**Model 2** ***After*** **March 7th** (N:784)			
	β	(SE)	IRR		β	(SE)	IRR
Logos	-1.96	(.78)*	.14	Logos	.69	-.81	1.99
Positive Pathos	-4.40	(.87) ***	.01	Positive Pathos	.70	-.8	2.00
Negative Pathos	-.80	-1.66	.45	Negative Pathos	1.02	-1.68	2.76
Ethos	2.69	(.81)**	14.72	Ethos	3.68	(.77)***	39.74
Social Pathos	2.03	(.89)*	7.63	Social Pathos	4.51	(.87)***	91.25
Followers	.00	(.00)***	1.00	Followers	.00	(.00)***	1.00
Fashion and Beauty	-1.76	(.14)***	.17	Fashion and Beauty	- 1.28	(.14)***	.28
Banking and Finance	-.19	-.15	.83	Banking and Finance	-.23	-0.15	.80
FMCG	-1.81	(.14)***	.16	FMCG	-.97	(.13)***	.38
Retail	-1.19	(.13)***	.31	Retail	-.90	(.13)***	.41
Pharmaceuticals	-.17	-.15	.84	Pharmaceuticals	-.10	-.15	.91
Travel and tourism	-1.64	(.13)***	.19	Travel and tourism	-.43	(.12)**	.65
Wald Chi^2 (Change df)		51.163 (6)***		Wald Chi^2 (Change df)		21.668 (6)***	
McFadden's pseudo R^2		.068		McFadden's pseudo R^2		.051	

$*p < .05$; $**p < .01$; $***p < .001$.

Table 6: Effects of the persuasion categories and control variables on CESM.

2.6 General discussion

This study shows that during the pandemic brands have profoundly modified the way they remained resonant and engaging towards their audiences. Brands opted for changing their rhetorical appeals as the dramatic conditions of the lockdown unfolded and have used Twitter specially to foster, or pander to, the recipients' sense of community and social and economic solidarity. The regression analysis indicates that the brands' ability to adapt their rhetorical appeal with the emergent pandemic scenario was prized by consumers with higher rates of SME. However, besides having diagnostic value, the results have also theoretical relevance.

The perspective known as institutional logic offers robust theoretical underpinnings to make theoretical sense of our empirical results. Despite competitive dynamics push firms to exploit differentiation and to appear and be perceived different vis-à-vis their counterparts, institutional theory postulates a firms' natural tendency to behave isomorphically when the rules of the game are clear and stable (DiMaggio and Powell, 1983). Indeed, the results clearly identify that in stable conditions like in phase 1, brands tend to adhere to a rhetorical appeal aligned to the dominant market logic. As a matter of facts, the prevalent jargon adopted by brands in phase 1 was manifestly activity-related and industry-specific, showing conformity to an established logic whereby social media are used to strengthen brand image, create awareness, improve customer relationships, and boost sales (Culnan *et al.*, 2010). Conversely, when a field is shaken by exogeneous forces such as a global pandemic, a deep modification of time-persistent institutional logics is likely to occur (Fligstein and McAdam, 2012). Our analysis supports that this was undoubtfully the case of the Covid-19 outbreak which dismantled the prevailing cultural conventions guiding how brands advertise and communicate (Gümüsay *et al.,* 2020). With firms unable to trade and consumers forced to a home-detention, the traditional logic was forced to a rapid change and led brands leaning to the rhetorical appeal of *social pathos*. The rhetorical shifts occurring in phase 2 reflected and instantiated an institutional shift from a market and profit-making centered logic to an emergent prosocial one (Suchman, 1995). In other words, despite one can be easily tempted to blame brands to act as parasites (Holt, 2006) and to make opportunistic use of trending topics (Sobande, 2020), our analysis suggests that brands still sought to align their communication to emergent conditions to gain legitimacy (Suddaby and Greenwood, 2005). Indeed, as Kirk and Rifkin (2020) have warned, the hard times of the pandemic make the risks of a non-conforming behavior too high to be run. Such risks – for example –have been deemed to be unaffordable even for a global brand like Coca-Cola that because of the pandemic has purposefully stopped every social media activity.

Conversely, in phase 3, we unveiled vivid signs of institutional complexity, i.e. a situation in which plural institutional logics are contemporarily at play offering potentially problematic prescriptions and proscription to field players (Cherrier *et al.*, 2018). As soon as the lockdown restrictions were relaxed, brands found themselves in the need to take simultaneously into account prosocial issues and the needs associated with the economic recovery and the return to new normalcy. As our analysis outlines, the jargon used in phase 3 was a syncretic form of those established in phase 1 and 2. Moreover, the results show that brands framed the same central topic of the pandemic differently overtime: depicted as an opportunity to shift from individualism towards a new model of shared responsibility and civic commitment in phase 2, the symbolic construction of the new emerging logic was conveyed also by frames underlying the economic backlash induced by the pandemic in phase 3. Despite institutional complexity is often associated with the emergence of conflicts (Dunn and Jones, 2010), plural logics are typically associated to fields that are lowly structured and where a dominant logic is yet to be formed. In the specific context we study, i.e. the current pandemic, it is hence likely that the presence of plural logics is more an outcome of loose institutional boundaries than of the presence of conflicting logics.

Our analysis also validates the underexplored connection between institutional logics and persuasive appeals (Cornellisen *et al.*, 2015). It is in fact through the latter that the former are made visible (Hartman and Coslor, 2019). Accordingly, the more a logic is established and taken for granted, the more the rhetoric vocabulary through which such logic materializes itself tends to be equally structured and take for granted (Tracey, 2016). However, our results seem to be contradicting in this stance. We in fact found that it is especially in phase 2, when uncertainty was at its highest point, that the rhetoric brands used showed the highest similarity and converged around the dominant appeal of *social pathos* with no industry-based differences.

Finally, the results are also theoretically interesting for the link they have with one of the most relevant topics in the agenda of institutional studies: legitimacy (Durand and Thornton, 2018). Although we did not provide any direct measure or any direct observation of legitimacy, we can speculate on the results connecting CESM and rhetorical appeal and affirm that since *social pathos* was highly used by brands and awarded by consumers with higher rates of CESM, this rhetorical appeal is the one that received the higher level of legitimacy compared to others.

2.7 Conclusion, limitations, and future research

The research contributes to extending the debate on how brands can cope with the effects a "black swan" event (Taleb, 2007) like a pandemic brings to their business and to their communication activities (Kirk and Rifkin, 2020; Taylor, 2020). Despite this study shedding new light on this phenomenon, two major limitations should be mentioned to inspire further research. First, the study uses only data retrieved from Twitter. Further research is needed to validate our findings using data retrieved from other social media platforms like Facebook or Instagram. Second, we collected data in a single country. Although the case of Italy is highly important due to it being the first Western country to suffer the human and social tragedy Covid-19 brought, and the first to issue a complete lockdown, further cross-country studies are needed to assess our findings' external validity.

Chapter 3. Woke brand communication and consumers' social media engagement: the role of brand stereotypes and language expectancy.

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3.1 Introduction

The established body of Corporate Social Responsibility (CSR) literature has so far provided strong evidence that brands taking a stand on issues that go beyond their core business and their shareholders' expectations, and claiming this stand in their communication efforts, outperform competing brands that prefer staying neutral and not to take any position (Du, Bhattacharya, and Sen, 2010; Weinzimmer and Esken, 2016; Saxton, Gómez, Ngoh, Lin, and Dietrich, 2019). Though, if traditional CSR issues, like socioeconomic and environmental sustainability, have to date acquired a status of generalized acceptance, in the recent period brands have been increasingly asked to take a stance also on other issues that instead are perceived as divisive and controversial (Schmidt *et al*., 2021). The peculiar form of communication where brands publicize their direct support towards these causes is called woke communication (Mirzaei *et al*., 2021; Feng *et al*., 2021; Middleton & Turnbull, 2021). A term of Afro-American origin, woke signifies the brand's active effort to increase awareness about, and encourage socio political change toward, socially relevant issues. These include, to name a few, the defense of LGBTQIA+ rights, race discrimination, the right to abortion, the active support to people during big crisis like the last pandemic (Mirzaei *et al*., 2022; Jungblunt *et al*., 2021; Schmidt *et al*., 2021; Feng *et al*., 2021; Vrendeburg *et al*., 2021;

[16] Published in a different version on *Journal of Brand Management* (Mangiò *et al.*, 2023a).

Middleton & Turnbull, 2021; Sobande 2019). Examples of brands that have embraced woke communication are now countless. To mention some, the worldwide famous Dove 's "Real Beauty" campaign, which began in 2004 and is still ongoing, was released to put forth the brand's rejection of an unreal aesthetic that was and still is served up by the vast majority of brands operating in this industry. Heineken broadcasted the 'Worlds Apart' to raise awareness on gender diversity and feminism and on the need to face these issues in a constructive rather than disruptive way. Burger King released an ad addressing mental health combating the stigma of mental distress, while Nike took a strong stance to support black people rights and Colin Kaepernick fight to racism under the tagline 'Believe in something, even if it means sacrificing everything'. Through these campaigns, brands instantiate to all effects a form of brand activism (Vrendeburg *et al*., 2021; Swaminathan *et al*., 2020; Mooreman 2020). However, being the socio-political initiatives and activities promoted by a woke campaign public, strongly connected to a brand's higher purpose values, not necessarily tied to the brand's core-business, not targeting a broad and inclusive audience, and, above all, revolving around an intrinsically controversial issue which carries risks for the brand, woke communication differs from other forms of brand activism that have been previously investigated like Cause-Related Marketing (CRM), Corporate Social Initiatives, and Corporate Social Advocacy (Mirzaei *et al*., 2022; Bhagwat *et al*., 2020; Austin & Geither 2016; Warren 2022; Rim *et al*., 2020, Hydock *et al*., 2020; 2019; Johnen & Jungblunt 2021 -Table 7**)**. Moreover, despite the number of brands embracing woke communication is booming (Thompson & Kumar, 2022), research shedding light on the outcomes of this form of communication is in short offer (Feng *et al*., 2021; Abbas *et al*., 2022, Vredeburg *et al*., 2020) and has often led to conflicting results (Hydock *et al*., 2019; Weinzimmer & Esken, 2016). Whilst some argue that brands engaging in woke communication enjoy higher consumers' support and higher levels of product use than their counterparts (Schmidt *et al*., 2021; Bravo *et al*., 2019; Austin *et al*., 2019; Li *et al*., 2019), others posit that taking a stance is risky for brands, as it exerts an overall negative effect on stakeholders' attitudes and behaviors (Wang *et al*., *forthcoming*; Mukherejee & Althuizen 2020; Abitbol *et al*., 2018), on brand image (Jungblunt & Johnen 2021), on brand perceptions (Klosterman *et al*., 2021) and on stock market performances (Bhagwat *et al*., 2020). For example, the aforementioned

Nike's commercial supporting Kaepernick's fight for black-people rights caused the brand's profits soaring to $6bn right after the ad launch (The Guardian, 2019). Table 8 provides an overview on the emergent body of literature on woke communication, which bears three bold limitations. First, no study to date has compared the persuasive effects of woke communication with those prompted by other more traditional forms of brand communication. Recent research investigated which consumers' reactions are more likely to be elicited by woke communication (Wang *et al*., *forthcoming*; Yang *et al*., 2021; Feng *et al*., 2021) but do not provide any factual assessment for whether woke communication is more, less, or equally persuasive than other more mainstream of more orthodox forms of brand communication (Milfied & Flynt, 2020). Moreover, beyond the pivotal inquiry about whether undertaking a woke campaign is overall beneficial or not (Wang *et al*., *forthcoming*; Mukherejee & Althuizen 2020), research is needed to identify for which type of brand this communication strategy is most effective. Second, despite recent calls to investigate the myriad of social issues that woke communication can sustain (Feng *et al*. 2021), current research is redundantly skewed towards a narrow set of popular and blatantly partisan campaigns, like femvertising and pro-black people rights campaigns, while other socially relevant causes that may give ground to woke communication are hardy found in the literature. Third, excluding two very recent exceptions (Mirzaei *et al*., 2022; Feng *et al*., 2021), since social media platforms provide built-in response options through which consumers can interact with brand-generated content in real time (Kabadayi and Price, 2014), studies so far evaluated consumers' online reactions to woke communication via structural volume-based metrics, such as the cumulated number of likes, views, or followers (Wang *et al*., *forthcoming*; Shaefers *et al*., 2021), while other 'thicker' and finer-grained metrics have been neglected. Differently stated, although we know that some posts can generate higher consumer engagement expressed in volume-based metrics, we have very limited knowledge about the semantic nature of what consumers' write in the thread of comments forming under a brand-generated social media post (Unnava & Aravindakshan 2021; Swani & Labreque 2020). The analysis of user-generated comments can enrich our understanding of consumer reactions by revealing the existence of both positive and negative topics (Moro *et al*., 2018; Tellis *et al*., 2014).

The aim of this study is thus to provide solution to these gaps and to answer the following research questions: 1) does woke communication affect consumer engagement on social media (CESM from now on) differently compared to traditional appeals? 2) Does woke communication affect conversation topics in consumers' social media comments differently compared to traditional appeals adopted by brands? 3) For which type of brand is woke communication on social media most effective?

To address these questions, we develop a theoretical model based on a combination of language expectancy theory (LET) (Burgoon *et al*., 2002), the brands as intentional agents framework (BIAF) (Kervyn *et al*., 2012), and the thriving literature on CESM (Santini *et al*., 2020) and test it through a multi-industry, CATA-based field study which investigates both the volume and semantic virality patterns of traditional (emotional, informative, credibility) and woke communication cues brands adopt on social media platform. The reminder of this research is structured as follows: First it reviews LET, BIAF, and previous CESM literature, based on which it develops the theoretical model and provides justification for the tested hypotheses. This is followed by a methodological section in which we provide information about the research context and give details about the data collection and the two CATA protocols used, whose results are presented separately. Finally, we present general discussion of the results, and conclude with the implications, the study's limitations, and some concluding remarks.

	Corporate Social Responsibility	**Cause-Related Marketing**	**Corporate Social Marketing**	**Corporate Political Activity**	**Political Brand Communication**	**Brand Activism, Corporate Sociopolitical Advocacy**	**Woke communication**	**Femvertising**
	The company's status and activities with respect to its perceived societal obligations (Brown and Dacin, 1997)	Marketing activities that are characterized by an offer from the firm to contribute a specified amount to a designated cause when customers engage in revenue-providing exchanges that satisfy organizational and individual objectives (Varadarajan and Menon, 1988)	Strategy that uses marketing principles and techniques to foster behavior change in a target population, improving society while at the same time building markets for products or services (Kotler and Lee, 2005)	Form of non-market strategy broadly defined as firms' efforts to influence or manage political entities (Lux *et al.*, 2011)	A brand's public expression of a stance toward a political issue that has no direct relation to a brand's business model (Jugblunt and Johnen, 2021)	Purpose- and values-driven strategy in which a brand adopts a nonneutral stance on institutionally contested sociopolitical issues, to create social change and marketing success (Vredenburg *et al.*, 2020)	Communication strategy whereby brands attempt to signal to their audiences their supportive position towards controversial socio-political issues (this study)	Growing marketing trend utilized by large brands that appropriates feminist values and female empowerment to encourage brand consumption (Akestam *et al.*, 2017)
Activity type:								
-practices	✔	✔		✔		✔		
-communication	✔	✔	✔	✔	✔	✔	✔	✔
Issue nature:								
-controversial						✔	✔	✔
- non-controversial	✔	✔	✔	✔	✔			
Issue type:	socio-environmental	socio-environmental	socio-environmental	political	political	socio-poli-env-eco-legal	socio-poli-env-eco-legal	social
Core business fit	High	High	Medium	High	Low	Medium	Low	Low

Table 7: Defining woke communication.

Author	Method	Data and Sample	Controversial issue	Theoretical background	Antecedents	Dependent variable	Findings
Mirzaei *et al.*, (2022)	unsupervised ATA	Facebook (?), 46,000 and 34,000 UGC, 2 brands	femvertising*[17] and anti-racism	Brand authenticity (Morhart *et al.*, 2015)	-	-	Woke authenticity is influenced social context independency, perceived inclusion, profit sacrifice, actual practice, and underpinning motivation.
Abitbol *et al.*, (2018)	mixed methods case study	Twitter; 226 tweets; 4 employees (interviews); historical secondary data (2012-2016); 1 brand	anti-racism	Company-cause fit (Varadarajan and Menon, 1988)	-	-	Consumer reactions towards the woke campaign are polarized but predominantly negative, criticizing its poor execution, political skewness, logistic and setting inappropriateness, and perceived hypocrisy. Employees reactions include complains about a lack of communication between organizers and employees and about a lack of participation among employees, but also manifestations of pride in being a partner. Employees' perception of the brand did not change. No evidence of financial effects and ambiguous effect on reputation detected.
Austin *et al.*, (2016)	content analysis	Twitter, 917 UGC from 200 brand-generated posts ;1 brand	anti-obesity, femvertising, sustainability	Typology of CSI types (Kotler and Lee 2005a, 2005b)	CSI types, CSR topics	favorability of public comments	Posts emphasizing socially responsible business practices gain the most favorable public response, while posts focused on cause promotion gain the most negative ones. Brand communication is less effective when the issue and advocated behavior change appears to be acting against the brand's interests.
Feng *et al.*, (2019)	supervised ATA	YouTube; 20,419 UGC; 1 brand	femvertising	Reception theory (Calhoun 2002)	-	-	Consumers discuss both adversarial and supporting topics towards the sociopolitical stance, namely ad skepticism, beauty definition, praise, and discussion of broader issues.

[17] *Gillette's 'We believe: the best man can be' campaign; **Nike's 30th Anniversary 'Just Do It' campaign, featuring Colin Kaepernick.

Feng *et al.*, (2021)	supervised ATA (study 1); online experiment (study 2)	YouTube; 125,481 UGC (study 1); 1,139 users (study 2); 1 brand	femvertising*	Social Norms Theory (Perkins and Berkowitz 1986; Aijzen 1991); Social Identity Model of Deindividuation effects (SIDE; Reichter *et al.*,1995); Information Cascades (Duan *et al.*, 2009)	social norm conditions	consumer reaction (type of comment); ad attitude; brand attitudes; purchase intentions; demographics	When evaluating a YouTube-based woke advertisement, consumers without social norms condition are more likely than those in the static social norms condition to generate positive ad attitudes, positive brand attitudes and high purchase intentions; consumers exposed to a dynamic social norms condition are more likely to be influenced by the prevailing norms than those in a static social norms condition; conservative men tend to post more negative comments; liberal women tend to post more positive comments; consumers responses on social media are more negative than those from self-report data.
Yang *et al.*, (2021)	supervised ATA	Instagram, 32.702 UGC; 110 accounts between brands and social media influencers	anti-racism	source-message fit; especially in the context of CSR (Aaker and Keller 1990); consumer engagement (Kumar *et al.*, 2010)	type of social media account (brand vs social media influencer; black vs non-black)	consumer engagement ratios, sentiment, and topics	Woke content promoted by social media influencers generates more engagement than brand-promoted woke content. Criticism is most frequently observed for woke posts of brands, followed by non-black social media influencers. Nonblack social media influencers register a higher percentage of negative comments than black influencers; purchase and boycotts is present only under brand-generated posts, anger/frustration toward racism, intention to share/engage, endorsement intention, and showing empathy through personal stories is observed only from influencer-generated posts.
Austin *et al.*, (2019)	survey	1,214 participants, 3 brands	diversity**, gun control, femvertising*	Public Interest Research and CSR			Public support for brand advocating for social issues variesby political viewpoints, age, income, education, and gender. Liberal and younger respondents are more likely to support compared to older and conservative respondents. Higher levels of income, education, and overall concern for social issues

							also play a role in perceptions of corporate engagement with social issues.
Bravo *et al*., (2019)	online experiments	288 students, 1 fictitious brand	health care and abolition of death penalty	Social Judgment Theory (SJT, Sherif and Hovland, 1961)	Issue involvement, message agreement	attitude towards the ad, attitude towards the brand, intention to support the behavior advocated in the ad, purchase intention.	Among millennials, message agreement mediates the effect of issue involvement on purchase intention and intention to support the behavior advocated in the advocacy ad. High issue involvement exerts a positive effect on attitude towards the persuasive message in the advocacy ad, on purchase intention and intention to support the behavior advocated in the ad.
Champlin *et al*., (2019)	inductive qualitative analysis	19 commercials	femvertising	target audience brand-cause fit (Barone, Norman, and Miyazaki 2007)	-	-	In their femvertising practices, brands instantiate different forms of 'brand-cause fit' that are built on three types of matches: a *functional* match,; an *image* match, a *target audience* match
Jungblut and Johnen, (2021)	online experiments	158 respondents, 2 FMCG brands (study 1) ;805 respondents, 2 fictional brands (study 2)	immigration; gun control	political consumerism (Copeland and Boulianne, 2020); Balance Theory (Heider, 1946)	strength and valence of individual opinion toward the brand's political brand communication, category involvement, consumer political interest, ad skepticism (control)	brand image (study 1); purchase intention (study 2)	When brands engage in political communication, the negative effects on brand image and purchase intention of disapproving consumers (boycotters) outweighs the positive effects of approving consumers (buycotters) and the magnitude of this effect decreases for higher levels of consumers' political interest and low levels of category involvement.
Li *et al.*, (2019)	survey	345 American citizens; 1 brand	diversity**	consumer involvement theory and stakeholder theory (Laurent and Kapferer, 1985)	issue involvement factors (cognitive and affective), brand attachment factors (brand-self connection; brand attitude)	CSA attitudes, negative and positive WOM	Consumers that find the sociopolitical stand taken by the brand as important, meaningful, and/or positively emotional are more likely to show support for such campaign and the company that chose to advocate for the issue. Favorable attitude towards the campaign is driven by issue, personality and value alignment

							between consumers and the brand. CSA can also attract consumers with an originally low attachment to the brand if the latter advocates a sociopolitical issue supported by the former.
Milfield and Flynt (2020)	phenomenological semi structured IDI	24 respondents, 1 brand	femvertising*	brand storytelling (Kao *et al*., 2019); narrative transportation theory (Green and Brock, 2000)	-	-	Social narrative cues embedded in brand videos create a polarizing effect capable of both resolving tensions and creating new ones among the audience at the same time. This polarizing effect depends on the (dis)connection between consumers and the brand-intended story.
Parcha *et al*., (2020)	online experiment	677 millennials, 1 fictitious brand	gun control; transgender rights	Elaboration Likelihood Model (Petty and Cacioppo, 1986)	involvement (outcome-relevant and value-relevant involvement), advocacy fit, corporate credibility, bandwagon heuristic	attitude change toward the corporation's position	CSA changes consumer's attitudes in four conditions: a) the more a sociopolitical issue personally affects one's goals, the more a woke statement on a low-fit issue changes an consumer's attitude; b) the more a sociopolitical issue personally affects one's goals, the more a woke statement supported by a large number of other brands changed a consumer's attitude; c) the less a sociopolitical issue personally affects one's goals, the more a woke statement supported by only a few other brands changes a consumer's attitude; d) the less a sociopolitical issue is important to one's values, the more a woke statement supported by only a few other corporations changes an consumer's attitude.
Park (2021)	survey	960 respondents, 1 fictitious brand	fictitious	Signaling theory (Spence, 1974)	consumer-company identification, corporate issue identification, CSR skepticism; controls: age, gender, income, education, CSA	brand trust, brand loyalty	A brand's strong and clear identification with a controversial sociopolitical issue is positively associated with brand trust and loyalty and is mediated by reduced skepticism towards corporate non-market activities, especially when consumers have a favorable attitude toward the company.

					familiarity, attitude towards the company)		
Rim *et al.*, (2020)	social network analysis, quantitative content analysis	Twitter, 17,821 tweets from 4 hashtags, 2 brands	immigration	situational theory of publics (Grunig, 1997)	-	-	Within polarized social media communities emerged in response to woke stances endorsed by brands, disapproving consumers (boycotters) appear not only in the aggregated brand boycotting networks, but also in the approving consumers' (advocators) networks; boycotters' activities targ*et al*so other brands or organizations that took similar stances compared to the target brand.
Schmidt *et al.*, (2021)	focus groups (study 1), online survey (study 2), consumer experiments (study 3, 4)	5 groups with an average of 10 college students each (study 1); 33 brand managers (study 2); 99 and 107 business students (study 3); 208 respondents (study 4)	diversity**, gender rights	socio-cultural perspective on brands and brand authenticity (e.g. Beverland and Farrelly, 2010)	sociopolitical brand or not	brand personality appeal, brand attitude, product use	Brands take sociopolitical stances for both cause-driven and for consumer-driven goals; authenticity is a key construct and brands need to approach sociopolitical issues by translating them into actions that have meaning for consumers and remain consistent in the long-run . Socio-politically active brands are seen more positively by consumers; women are more likely than men to think positively about the socio-politically active brand; sociopolitical activeness results in more positive levels of product use than a non-socio-politically active brand.
Xu *et al.*, (2021)	online experiment	296 respondents, 2 fictitious brands	various	Construal Level Theory (Trope and Liberman, 2007)	perceived psychological distance, consumer-company identification (mediator), political partisanship	expectations for the company's CSA, attitudes towards company, buycott and boycott intentions	Psychological distance to the brand affects consumer's expectations about the brand engagement to the sociopolitical issue, but not their attitudinal responses to CSA. Greater perceived psychological distance decreases intention to buycott and increases intention to boycott the politically liberal brand, with boycott intention particularly salient among Republicans.

Bhagwat *et al.* (2020)	event study	293 CSA events initiated by 149 brands across 39 industries	various	Signaling and Screening theories (Spence, 1974; Connelly *et al.* 2011)	CSA event, form of support, announcement source stature, business interest communication, coalition size, deviation from customer values, deviation from employee values, deviation from government values, deviation from brand image; controls: industry and time- specific control variables	stock price response (abnormal returns)	Investors' reactions to CSA are on average negative. They deteriorate when CSA deviates from stakeholders' political values, takes the form of actions compared to statements, is announced by the CEO compared to another actor within the firm, does not explicitly communicate any business interests, and is undertaken by a brand alone compared to in coalition with others. CSA is rewarded when it closely resonates with their personal values.
Klostermann *et al.* (2021)	event study	106 CPA events	various	Brand-consumer overlap and negative effects of corporate political advocacy; self-brand similarity; online protests; effort; concurrence	CPA behaviour (effort, concurrence), online protest (mediator), control variables (brand awareness, alignment, event time, controversy)	cumulated abnormal value of brand perception	CPA has a negative effect on consumers' brand perceptions; this effect is stronger for customers relative to non-customers; effort and concurrence moderates CPA's effect consumer perceptions..
Villagra *et al*. (2021)	event study	stock prices of 33 listed companies, 1 event	hate speech	Corporate activism and brand boycott	-	stock price response (abnormal returns)	Corporate activism, when directed at a firm, has a negative effect on the stock market value of the firm, but does not have a positive effect on the stock market that benefits the companies involved, especially if this action is carried out as a group.

Table 6: A summary of studies on brand's public engagement towards a partisan sociopolitical issue.

3.2 Theoretical background

3.2.1. Language expectancy theory

Language expectancy theory (LET) (Burgoon, Denning, and Roberts, 2002; Burgoon, 1995) is a message-centered theory of persuasion which posits that the persuasive ability of a message depends on both the message's features and style, and the expectancies held by its recipients. According to LET, expectancies are both *framing devices* that affect and define interpersonal interactions, and *perceptual filters* (Burgoon, 1993: 32) through which receivers process social information. Expectancies depend on communicator's features (such as linguistic style or credibility), on relationship factors among message sender and receiver, and on situational factors that are contingent to specific contexts. Despite being originally formulated for interpersonal communication exchanges, LET has been fruitfully applied also in technology-mediated settings, like online product reviews (Jensen, Averbeck, and Zhang, 2013; Wu, Shen, Fan, and Mattila, 2017), service encounters context (Choi, Liu, and Mattila, 2019), and crowdfunding (Parhankangas and Renko, 2017). Central to LET is the concept of *expectancy violations*, which occur anytime a communicator, more or less consciously, performs a persuasive attempt which falls outside its bandwidth, consequently failing to pander with the receivers' linguistic expectations. According to LET, a communicator's persuasion attempt can trigger two kinds of expectancy violations in the receiver: positive and negative (Jensen *et al* 2013). Negative violations occur when a message breaches cultural and social conversational norms. For this reason, negative violations lead to a no attitude change, or to an attitude change and consistent behavioral response opposite to what intended by the source (e.g., low CESM). Positive violations instead occur whenever a message is more preferred to contextual cultural and social conversational norms, or when negatively evaluated sources better comply with these norms. For these reasons, positive violations foster persuasion and lead to the formation of a positive attitude and consistent behavioral response by the receiver (e.g., high CESM). Previous research drawing on LET has formulated different language expectations regarding both linguistic style and content words. For instance, research has found that the suasory effect of highly intense messages is inhibited when recipients are in a state of arousal or anxiety (Burgoon *et al* 2002); instead, research has found that a large amount of technical jargon is more credible and induces a positive expectancy violation (Jensen *et al* 2013). In the specific realm of advertising, assertive ad messages have been found to be more persuasive when the issue at stake is perceived as important by the recipients, and when the advertised product is hedonic (Kronrod *et al* 2012a, b). In short, according to LET, the persuasive effect of a message depends on the generalized linguistic expectations stemming from socio-cultural conversational norms that are learnt and shared by individuals in a specific communication context, such as a social media platform. To derive such conversational norms in the context of brand communication on social media, this paper draws on the literature dealing with brand communication and CESM, as shown next.

3.2.2. Brand communication and consumer social media engagement

Given the increasing ubiquity and importance of social media (Alawan *et al.*, 2017; Kaplan and Haenlein, 2010), research shedding light on the suasory effects of brand communication via social media has gained academic traction in the last decade (Hollebeek *et al.*, 2021; Voorveld *et al.*, 2018; Kumar *et al.*, 2016; Brodie *et al.*, 2013; Gummerus *et al.*, 2012). The effectiveness of social media brand communication has been conceptualized in various ways, including post popularity (de Vries *et al.*, 2012; Swani *et al.*, 2013; Swani and Milne 2017; Sabate *et al.*, 2014), pass-along behaviour (Arujo *et al.*, 2015), eWOM (Bowen *et al.*, 2022; Kim, Kim, and Kim 2019; Swani *et al.*, 2013), and receptivity (Kumar *et al.*, 2016), and has been assessed through a myriad of theoretical lenses including psychological motivation theory (Tellis *et al.*, 2019), linguistic and communication theory (Deng *et al.*, 2021a; Villaroel *et al.*, 2019), uses and gratification theory (Vlacvei *et al.*, 2021; Dolan *et al.*, 2019) and traditional advertising effectiveness models (Tafesse and Wien 2018; Lee *et al.*, 2018). Once scattered, the body of literature focusing on brand communication's effectiveness on social media has recently converged on CESM as an effective and readily available measure of brand-generated messages' persuasiveness and effectiveness (Shahabaznezahd *et al.*, 2021; Pezzutti *et al.*, 2021; Santini *et al.*, 2020; Swani and Labreque 2020; Munaro *et al.*, 2021; Ashley and Tuten 2014). Owing to the consumer-brand engagement literature (Hollebeek *et al.*, 2014; Brodie *et al.*, 2010), CESM is a multilevel and multidimensional phenomenon involving varying levels of users' commitment and interactions towards brands and their activities on SM. CESM results from the specific experiences that consumers live whilst being exposed to brand-generated contents on social media (Voorveld *et al.*, 2018). Thus, CESM stays at the crossroad of users' engagement behaviors (Gummerus *et al.*, 2012; Van Doorn *et al.*, 2010) and brands' communication features, such as content and media type, posting frequency, and posting time (Shahbaznezhad *et al.*, 2021; Deng *et al.*, 2021; McShane *et al.*, 2021: Pezzutti *et al.*, 2021; Dolan *et al.*, 2019; Schivinski *et al.*, 2016; Barger *et al.*, 2016). In this research we draw on a notion of CESM as "consumer's behavioral manifestations that have a social media focus beyond purchase, resulting from motivational drivers" (Dolan *et al.*, 2016, p. 265). Starting from the assumption that consumers are cognitively, affectively, and conatively affected by brands' communication (Barry and Howard, 1990), we operationalize CESM as a cumulative phenomenon occurring along three stages of "*relationship formation*" (cognitive dimension) "*creation of engagement*" (affective dimension) and "*contribution*" (conative dimension) (Santini *et al.*, 2020; Vlachvei *et al.*, 2021; Swani and Labreque 2020).

Brands willing to foster CESM can choose among three main traditional appeals: *logos*, refers to ways of persuading people by appealing to their rationality using facts, figures, and by conveying information-based and/or remunerative contents; *pathos*, refers to ways of convincing the other by creating an emotional response to an impassioned plea or a convincing story, through the use of emotional and/or entertaining content; *ethos*, finally, which signifies the means of convincing others by signaling the persuader's credibility and trustworthiness (Mangiò *et al.*, 2022; Panigyrakis *et al.*, 2020; Lee *et al.*, 2018).

According to previous research, all of the three rhetorical strategies brands can use in social media contribute to brands' attempt to generate CESM across the three aforementioned stages through which CESM is formed, i.e., relationship formation, creation of engagement, and contribution (Vlachvei *et al.*, 2021) (Figure 7).

There is in fact wide evidence suggesting that social media are now increasingly used as information sources (Alawan, 2018; Dwiwedi, Kapoor, and Chen, 2015; Westerman, Spence, and Van Der Heide, 2014) including the retrieval of product information such as availability, prices, discounts, and promotions (Bowen, Wen, and Kim 2022; Moro, Pires, Rita, and Cortez, 2018; Heinonen 2011) and that brand communication via social media featuring a high degree of information content is particularly effective (Eigernraam *et al.*, 2020; Dolan *et al.*, 2019; Swani *et al.*, 2017; Araujo *et al.*, 2015; Kim *et al.*, 2015; De Vries *et al.*, 2012; Cvijikj and Michahelles, 2013; Muntinga *et al.*, 2011). In addition to their informative content, brand communication over social media is also often characterized for it holding an emotional and/or entertaining tone (Tellis *et al.*, 2019). Being social media online arenas where consumers can express their emotions and feelings and increase their self-enhancement and social connections, they expect emotions also being implied in their interactions with brands (Swani *et al.*, 2017;2014; Ashley and Tuten, 2015). As a matter of fact, previous research has shown that emotionally charged brand-generated posts are more likely to generate CESM (Santini *et al.*, 2020; Rietved *et al.*, 2020; Tellis *et al.*, 2019; Kim *et al.*, 2019; Tafesse and Wien 2018; Lee *et al.*, 2018; Swani *et al.*, 2017) and are more likely to be shared compared to non-emotional ones (Tellis *et al.*, 2019; Akpinar and Berger, 2017; Berger and Milkman 2012).

Extent research also offers wide evidence that credibility, i.e., believability of information and of its source (Hovland *et al.*, 1953), positively affects consumer attitudes towards brands in the context of social media where the idiosyncratic functioning of their affordances makes it difficult for users to assess the veracity of information shared therein (Di Domenico *et al.*, 2021; Sundar, 2008). Studies have in fact found that a communicator's credibility can boost followers' brand awareness, attitudes, and trust between senders and receivers in social media (Gvili and Levy; 2018; Wang and Scheinbau, 2018; Lou and Youan, 2019; Hung and Li, 2007).

Based on empirical evidences of previous research and based on the principal tenets of LET we can assume that brand communications on social media that appeal to consumers' rationality (*logos* appeal), that evoke consumers' positive emotions (*pathos* appeal), and that express the persuader's credibility and trustworthiness (*ethos* appeal) can represent a conversational norm on social media and, as such, will positively contribute to the formation of CESM in the three stages of relationship formation, creation of engagement, and contribution.

In addition to the above-mentioned traditional persuasive appeals, woke communication has recently emerged as a new CESM initiative which brands employ to be resonant with their audiences. Acknowledging these trends, Mangiò *et al* (2021) expanded the traditional persuasion toolkit of brands by adding a further persuasive appeal, "social pathos", which specifically panders to recipients' positive emotions, i.e., it is pathetic in nature but leverages on social-sensitive issues and showcases a brand's support for a controversial social cause. For this reason, social pathos is a persuasive appeal which underpins authentic woke values (Karpen and Conduit 2020; Sobande 2020). Brands engage in woke communication especially via social media because of these platforms' ability to reach a wide audience quickly and conveniently (Mizrei *et al*. 2022; Feng *et al* 2021). They do so either proactively, whenever they are inherently conscientious (Iglesias and Ind 2020; Grewal *et al*. 2017), but also reactively, seeking compliance with organizational legitimacy pressures. Despite extensive research postulating that amidst the recent upsurge of responsible and ethical consumerism (Giesler and Veresiu 2014; Uusitalo and Oksanen 2004) brands must be increasingly sensitive to these appeals (Kantar 2020), due to their divisive nature woke pervasive appeals are less mainstream and less expected by consumers than traditional ones (Bhagwhat *et al* 2020; Hydock *et al* 2020; Jungblut and Johnen 2021). Applying the lenses of LET, we contend that brand-generated posts adopting social pathos positively violate consumer linguistic expectancies and thus generate and attitudinal and behavioral change in their recipients which translates in higher levels of CESM. This paper therefore hypothesizes the following:

H1. Brand posts using *social pathos* generate higher CESM along the three stages of relationship formation (H1a), creation of engagement (H1b), and contribution (H1c) than the other rhetorical appeals of ethos, pathos, and logos.

3.2.2. Brands as intentional agents framework

Consistently with the tenets of LET, this paper contends that the persuasiveness of brand communication on social media does not depend only on the message content; it also depends on the idiosyncratic features of the communicator (Burgoon *et al* 2002). In other words, since not every brand communication works in the same way for every brand, the overall effectiveness of brand communication depends on consumers' perceptions of the brand undertaking it (Eigenraam *et al* 2021). In this vein, the brands-as-intentional-agents framework (BIAF) proposes that brands are not merely names or symbols conveying functional features of product and services; rather, they are intentional social actors ontologically comparable to people (Kervyn *et al* 2012; Fiske *et al* 2002). Stemming from the influential perception content model (Fiske *et al* 2002), the BIAF has extended two of its fundamental dimensions recognized as underpinning social perceptions – namely “warmth” and “competence” – to the domain of consumer’s perceptions about brands. Perceptions of warmth depend on a brand’s ability to convey trustworthiness, sincerity, kindness, and friendliness, whilst perceptions of competence are associated with a brand’s efficiency, skill, confidence, and intelligence (Cuddy *et al* 2008). Previous studies contend that perceptions of brand warmth and competence come along with consumers’ expectations of specific brand actions (Eigenraam *et al* 2021; Magee 2022; Ren *et al* 2023). Warm brands are associated with the fulfillment of emotional or hedonic needs, whilst competent brands are related to the fulfillment of functional or utilitarian needs (Eigenraam *et al* 2021; Tellis *et al* 2019). Indeed, Eigernraam *et al* (2021) found that emotional communication is perceived by consumers as more authentic when it is practiced by brands which are perceived as more suitable to fulfilling emotional needs (i.e. warm) compared to those which are perceived as more suitable to fulfilling functional needs (i.e. competent). This reasoning can also be extended to woke communication, which by its very nature relates more to emotional than functional needs. Indeed, the design and management of woke communication have been referred to as an ‘authenticity challenge’ (Nunes *et al* 2021). Similarly to CSR communication (Du *et al* 2010; Kim and Rim 2019; Love *et al* 2022), the effectiveness of woke campaigns is challenged when consumers become skeptical about a brand’s real motives for engaging in these communications (Shoenberger *et al* 2021). Woke communication risks being downgraded to ‘woke washing’– that is, the instantiation of “*inauthentic* brand activism in which activist marketing messaging about the focal sociopolitical issues is not aligned with a brand’s purpose, values, and corporate practice” (Vrendeburg *et al* 2021, p. 445) – precisely when the messages communicated by activist brands are perceived as insincere by the recipients, thus triggering in the latter negative reactions like skepticism (Park 2021), consumer backlashes or flaming (Feng *et al* 2021) and even boycotts (Klostermann *et al* 2021). It is argued that, to remain resonant while pursuing woke communication, brands should convey their authenticity to their audiences by optimizing the fit between consumers’ brand perceptions and actual behavior (Li *et al* 2022; Parcha *et al* 2020; Park 2021). From the lenses of LET, if a competent brand, which is generally expected not to engage in emotionally skewed communication, does so, it will negatively breach consumers' expectancies, inhibiting CESM. Conversely, because consumers can expect any kind of brand to engage in informative and credible communication (Eigenraam *et al* 2021; Ismagilova *et al* 2020), these CESM initiatives will prove to be effective regardless of whether the brand is perceived as warm or competent.

In line with this reasoning, this paper hypothesizes the following:

H2. Relationship formation (H2a), creation of engagement (H2b), and contribution (H2c) are higher for warm brands than for competent brands using pathos appeal and social pathos appeal.

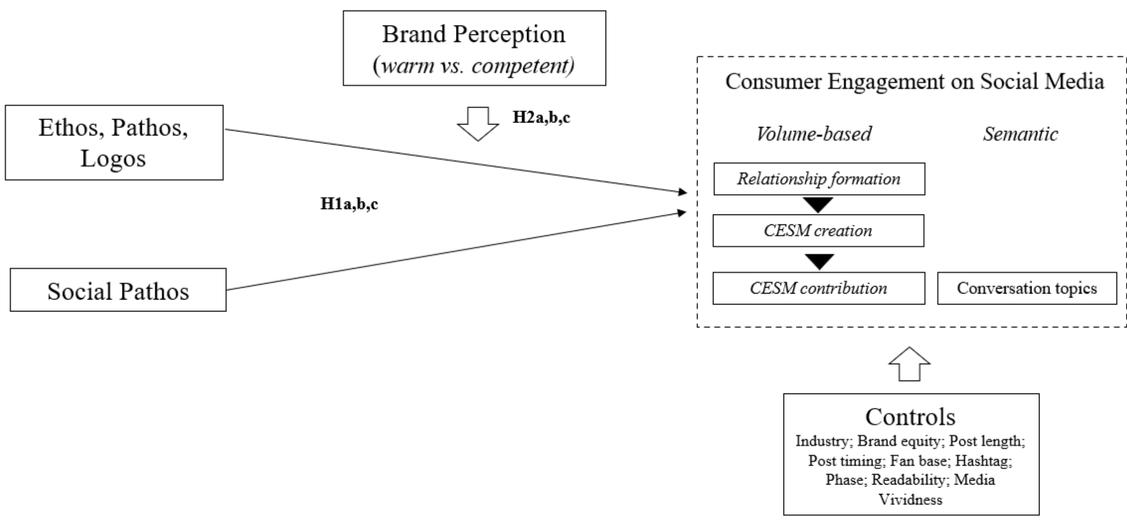

Figure 7: Proposed conceptual framework and hypotheses.

3.3 Data collection and analytical procedure

To answer our research questions, we designed and implemented a big-data, CATA-based field study (Brunzel, 2021; Kim *et al.*, 2019) to analyze publicly available consumer online reactions to woke communication embedded in prosocial covid-19 campaigns extensively put forth by brands during the entire 2020. Being the pandemic a hot social issue with enormous socio-economic consequences for the broader society (Taylor, 2020), about which brands took a divisive stance by communicating their active public health and economic support in terms of donations, countermeasures, and advocacy (Hesse *et al.*, 2021; Mangiò *et al.*, 2021), brands' pandemic-focused communication has been referred to as one of the widest and most ubiquitous brand woke communication campaigns (Sobande 2020; Chatzidakis and Litter, 2021). Thus, it represents a suitable natural experiment to study the phenomenon under investigation. We collected Facebook data from a representative sample of 24 Italian brands operating in seven industries during the whole 2020 (Jan 1st, 2020 - Dec 31st, 2020 - see Table 9). Similarly to previous research (Mangiò *et al.*, 2021; Visentin *et al.*, 2021), we focused on the Italian brandscape as Italy was the first Western country to mandate a national-level lockdown. Among the various social media platforms available, Facebook was selected because it is characterized by higher levels of active rather than passive engagement compared to other platforms (Kübler *et al.*, 2020; Shahabaznezahd *et al.*, 2021). Brands were carefully chosen based on two criteria: they are listed on reliable international brand value rankings (BrandZ, 2019), and they have a verified Facebook public page for Italy which remained active during the period of investigation. Once that the brands' official accounts were identified, we proceeded to collect their posts published in the period considered. In absence of a dedicated public API (Caliandro, 2021), we proceeded to develop a custom scraping protocol to obtain both brand and audience related information. This procedure was conducted three times a week until one month after the end of the period considered in different schedules to update the dataset and avoid biases associated with the day of collection (Pezzuti *et al.*, 2021). Although we selected Italian brands only, since many of the brands identified have a worldwide reputation and serve a global market, we automatically detected and translated posts and comments written in languages different than Italian via Google Translate API to ensure data homogeneity. For the same reason, brand-generated comments different from posts, such as social media managers' moderation responses, were deleted. To comply with research ethical standards, all references to users' identifiers like names and mentions were removed. The final dataset consisted of 3,252 brand-generated posts and 262,019 user-generated comments (avg. post length = 10.83

words, σ = 13.31; avg. comment length = 14.70, σ = 22.01). Once that the data wrangling stage was over, we prepared the data for CATA and split it into two different datasets: one including brand-generated posts, and one including users' comments. These were then preprocessed and analyzed respectively through both top-down and bottom-up protocols (Humphreys and Wang, 2018). The first step consisted in a volume-based CESM analysis involving the automatic classification of brand-generated posts according to their persuasive appeal. This analysis is hence aimed at assessing the extent to which different rhetorical appeals used in brand communication (namely social pathos, pathos, ethos and logos) are associated to different levels of volume-based CESM. The second step consisted in a semantic CESM analysis on user-generated comments through a computational content-analysis involving both the semantic and affective aspects of CESM and applying topic modeling (Roberts *et al.*, 2019) and controversy detection analysis (Garimella *et al.*, 2018). Figure 8 depicts the data collection and analysis protocols followed.

Industry	***N* Brands *(%)***	***N* Posts (%)**	***N* Comments (%)**
Automobile	3 (13%)	339 (10%)	57,504 (20%)
Banking and Finance	4 (13%)	225 (7%)	31,340 (11%)
Energy	5 (13%)	148 (5%)	1,786 (1%)
Fashion	6 (25%)	1,765 (54%)	54,312 (19%)
FMCG	5 (21%)	221 (7%)	46,109 (16%)
Telecommunications	2 (8%)	313 (10%)	65,315 (23%)
Travel and Tourism	3 (8%)	241 (7%)	28,080 (10%)
Total	**24**	**3,252**	**284,446**

Table 7: Number of brands, posts, and comments, per industry.

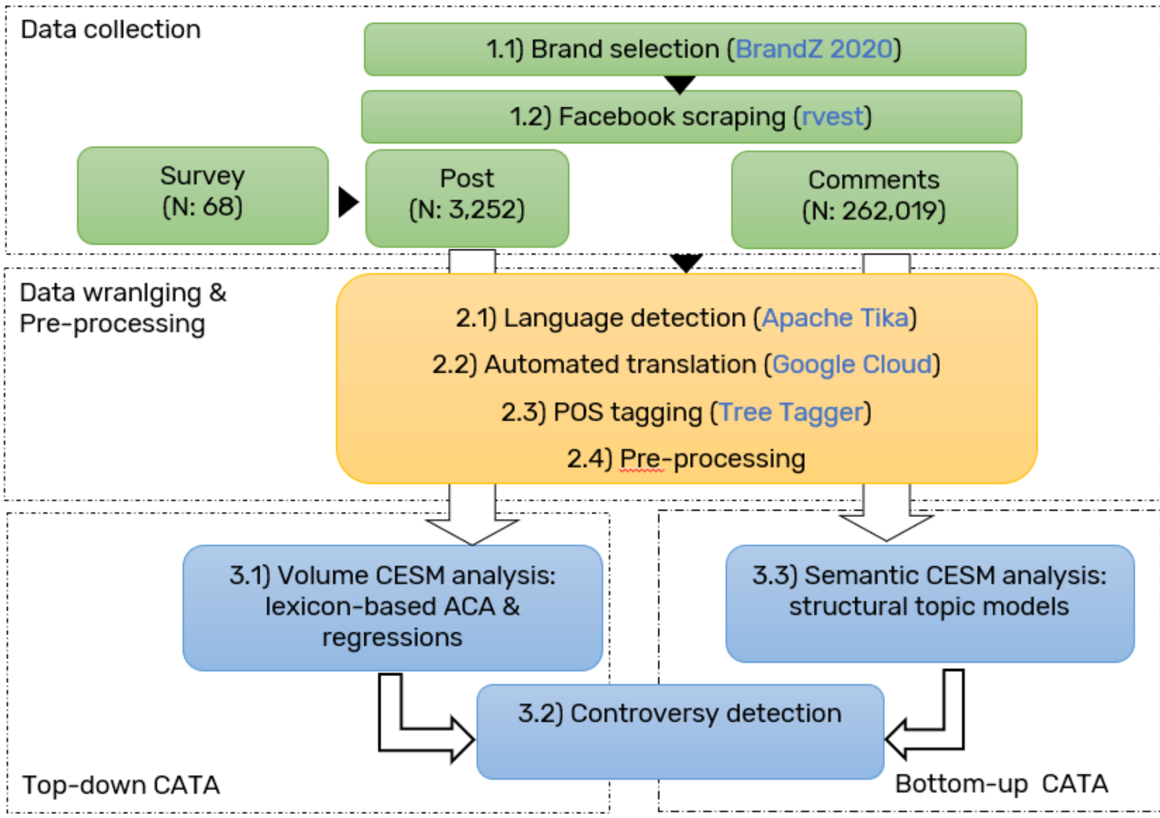

Figure 8: Data collection and analytical strategy.

3.3.1 Volume-based CESM analysis

CESM is operationalized via three volume-based metrics achieved by each brand-generated post over the period considered: number of likes ("*relationship formation*"), number of comments ("*creation of engagement*"), and number of shares ("*contribution*") (Santini *et al.*, 2020; Vlachvei *et al.*, 2021; Swani and Labreque 2020). Brand rhetorical appeals were operationalized through four pre-built lexicons used in previous research (Mangiò *et al.*, 2021). Aligned with methodological suggestions to top-down automated text analysis (Humphreys and Wang, 2018), the presence of each construct was operationalized as the token-weighted proportion of target lemmas in each document of the corpus (i.e. brand-generated post). Brand stereotypes were assessed through a survey, administered to a convenience sample of Italian active Facebook users (N: 68) during summer 2021, in which recipients were asked to rate their perceptions of warmth and competence of each one of the

24 Italian brands considered using available scales (Aaker *et al.*, 2010; Bernritter *et al.*, 2015). The results of this survey enabled us to recodify brand perception with a dummy variable based on the median value, where 1 indicates that the brand is predominantly warm, and 0 that the brand is predominantly competent brands. Following previous studies on CESM (Moran *et al.*, 2019; Araujo *et al.*, 2015), nine control variables were also included: 1) *Post timing* which assumes value 1 if the post was published on weekends, or 0 otherwise; 2) *Phase*, indicating the four phases of the evolution of the pandemic waves occurred during 2020; 3) *Industry*, a qualitative variable indicating which of the seven industries consider the brand belongs to; 4) *Readability*, a variable aimed at assessing the ease of understanding of each brand-generated post based on its writing style, measured through the Gulpease index for the Italian language (Lucisano and Piemontese, 1988); 5) *Fan base,* indicating the number of active followers registered on each brand's official Facebook page at the posting day; 6) *Brand equity,* operationalized with the BrandZ (2021) valuation, which measures the share of the brand's financial value generated by the brand alone; 7) *Media vividness*, recoded through a qualitative variable, where 2 indicated the presence of videos (high vividness), 1 the presence of pictures (mid vividness), 0 the presence of raw text (low vividness) in the brand-generated post; 8) *Post length*, operationalized as the word count of each brand-generated post; 9) *Hashtag*, a dummy indicating whether the brand-generated post included (1) a hashtag (#) or not (0).

As per Aiken and West (1991), before any computation all measures obtained through a lexicon-based approach were scaled and mean-centered (via z-score) and shifted so that the minimum is equal to zero. The descriptive statistics of each variable are detailed in Table 10 and Table 11. To test hypotheses H1-H2, we run three sets of stepwise negative binomial regressions with maximum-likelihood estimation. Generalized linear models such as negative binomial regression are better suited to account for the overdispersion of the dependent variables which are positively skewed, like count-data ($skew_{Likes}$ 6.29; $skew_{Comments}$ 9.51; $skew_{Shares}$ 8.21).

Variable		Share (%) in the full dataset	Min	Max	Mean	SD
N° Likes			4	40,000	1,305.365	2,907.964
N° Comments			0	3,963	68.957	162.188
N° Shares			1	4,679	97.518	187.849
Fan Base			27,195	31,407,454	5,725,196	6,493,854
Pathos			0	10.636	3.173	1
Logos			0	13.169	0.277	1
Ethos			0	14.429	0.476	1
Social pathos			0	15.438	0.409	1
Readability			0	6.762	1.105	1
Post length			1	291	38.585	30.126
Hashtag			0	13	1.761	1.709
Brand equity			0	4.67	0.61	1
Media vividness	*low*	12.2%				
	medium	58.3%				
	high	29.5%				
Industry	*Automobile*	10.5%				
	Bank and *Finance*	6.9%				
	Energy	4.5%				
	Fashion	54.2%				
	FMCG	6.8%				
	Telecom	9.7%				
	Travel	7.4%				
Phase	*1*	28.9%				
	2	17.9%				
	3	32.7%				
	4	20.4%				
Brand Perception	*warm*	50.0%				
	competent	50.0%				
Post timing (*weekend*)	*no*	75.3%				
	yes	24.7%				

Table 10: CESM volume-based analysis: descriptive statistics.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. N° Likes	1																
2. N° Comments	0.262	1															
3. N° Shares	0.288	0.504	1														
4. N° Followers	0.319	0.206	0.308	1													
5. Pathos	0.074	0.061	0.087	0.157	1												
6. Logos	-0.059	0.044	-0.042	-0.115	*-0.025*	1											
7. Ethos	*0.018*	*-0.008*	0.049	*-0.012*	0.119	*0.019*	1										
8. Social pathos	*-0.018*	0.088	0.061	*-0.014*	0.119	*0.024*	*0.012*	1									
9 Readability	*-0.008*	*-0.004*	*-0.01*	-0.095	-0.119	-0.05	-0.101	*-0.022*	1								
10. Post length	*-0.028*	-0.039	*0.03*	0.061	0.048	0.132	0.091	0.119	-0.273	1							
11. Hashtag	*0.019*	-0.099	*0.002*	0.006	-0.126	-0.085	*0.01*	-0.141	-0.237	0.059	1						
12. Brand equity	0.133	0.071	0.063	0.584	*-0.026*	*-0.026*	-0.046	*0.008*	-0.062	0.255	-0.197	1					
13. Media richness	-0.035	0.078	0.08	*0.017*	0.119	*0.004*	*0.033*	0.068	-0.073	*0.016*	-0.078	*0.001*	1				
14. Industry	-0.209	0.078	-0.238	-0.132	*-0.008*	*0.002*	-0.138	0.068	0.042	-0.124	-0.038	0.032	0.072	1			
15. Phase	*-0.018*	*0.034*	0.112	0.087	*0.015*	*0.004*	*-0.015*	0.057	0.077	0.164	-0.089	0.17	0.047	-0.044	1		
16. Brand stereotype	0.146	0.174	0.273	0.165	0.144	*0.007*	*0.009*	0.145	0.217	-0.066	-0.206	-0.176	0.067	-0.126	*0.026*	1	
17. Weekend	*-0.002*	*0.003*	*0.024*	*0.034*	*0.016*	-0.076	*-0.005*	*-0.031*	*-0.002*	-0.035	0.047	*-0.006*	*0.013*	*-0.027*	0.148	-0.064	1

Note: figures in italics are non-significant at C.I. 95%

Table 8: Variables correlations.

3.3.2 Results

Table 11 presents the regression results along the three stages of CESM for both the direct and interaction effects. For the sake of interpretation ease, we computed and reported the incidence rate ratio (IRR) of the β coefficients from the regression results. The results of the likelihood ratio test indicate a good fit for all the negative binomial regression models (see Table 11). No multicollinearity issues were detected, as VIF for all predictors in the direct effects models is lower than 5 (James, Witten, Hastie, and Tibshirani, 2017).

To test H1 postulating that brand posts using *social pathos* generate higher CESM along the three stages of relationship formation (H1a), creation of engagement (H1b), and contribution (H1c) than the other rhetorical appeals of ethos, pathos and logos, we first tested the impact of each of the rhetorical appeals brands can use on the three stages of CESM.

The rhetorical appeal *pathos* was found to be non-significantly associated with two of the three stages of CESM (relationship formation and creation of engagement) except for the last stage (contribution) which was found significant but negative. Similarly, *logos* was found to be significantly and negatively related to the first (relationship formation) and last (contribution) stage of CESM, whilst non-significant for the second (creation of engagement) stage. Regarding the credibility appeal (*ethos*) the results show a significant and positive effect on relationship formation and creation of engagement, whilst effect was found non-significant for contribution.

As far as social pathos is concerned, the results show that this rhetorical appeal has a significant and positive effect on all of the three stages of CESM, i.e., relationship formation, contribution, and creation of engagement, and that the impact of social pathos compared to the other rhetorical appeal of the three stages of CESM is by far the strongest compared to other appeals. H1 is thus fully confirmed.

Regarding control variables, we found significant differences between posting time periods, day of the week, and industries, corroborating that social media content scheduling is pivotal (Vlachvei *et al.*, 2021) and that different industries resort to both different media types and different content orientations while reaching their online audiences (Swani and Milne 2017; Tafesse and Wien 2018; Lee *et al.*, 2018). As expected, the readability of a brand-generated posts significantly affects the first and last stages of CESM, i.e., relationship formation and creation, corroborating that the more readable a post is, the more it is able to trigger CESM (Pancer *et al.*, 2019). Similarly, we lend empirical support that the size of the brand has a positive effect on engagement behaviors (Araujo *et al.*, 2015), as both fan base and brand equity positively affect all stages of CESM. As for media vividness, pictorial posts enhance only the liking behavior, whilst highly vivid brand-generated posts including videos enhance sharing behaviors (Shahabaznezahd *et al.*, 2021). Lastly, we also corroborate that the use of linguistic features and affordances that favor cognitive processing enhance CESM (Deng *et al.*, 2021c, Arujo *et al.*, 2015), as post length and hashtags were found to significantly and positively impact all CESM stages.

Dependent variable	N° Likes				N° Comments				N° Shares			
Independent variables	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE	IRR	SE
Logos	0.96 *	0.02	0.93 ***	0.02	1.03	0.02	1.04	0.03	0.95 **	0.02	0.94 **	0.02
Pathos	0.99	0.02	0.95 *	0.02	0.96	0.02	0.96	0.03	0.97*	0.02	0.90 ***	0.02
Ethos	1.05 **	0.02	1.05 *	0.02	1	0.02	1	0.03	1.05 **	0.02	1.05 *	0.03
Social pathos	1.06 **	0.02	1.02	0.03	1.10 ***	0.02	1.05	0.03	1.10 ***	0.02	1.14 ***	0.03
Brand stereotype (warm)	1.25 ***	0.08	0.95	0.12	1.22 **	0.09	1.22	0.19	1.57 ***	0.1	1.07	0.14
vividness (pictorial)	1.13 *	0.06	1.13 *	0.06	0.92	0.06	0.92	0.06	0.94	0.05	0.94	0.05
vividness (video)	0.86 **	0.05	0.86 *	0.05	0.98	0.07	0.98	0.07	1.35 ***	0.08	1.36 ***	0.08
weekends (yes)	1.16 ***	0.05	1.16 ***	0.05	1.06	0.05	1.06	0.05	1.16 ***	0.05	1.15 ***	0.05
N° followers	1.00 ***	0	1.00 ***	0	1.00 ***	0	1.00 **	0	1.00 ***	0	1.00 ***	0
Banking and *Finance*	0.25 ***	0.03	0.22 ***	0.02	0.37 ***	0.04	0.36 ***	0.04	0.70 ***	0.07	0.71 **	0.08
Energy	0.05 ***	0.01	0.05 ***	0.01	0.07 ***	0.01	0.07 ***	0.01	0.24 ***	0.03	0.24 ***	0.03
Fashion	0.44 ***	0.03	0.43 ***	0.03	0.17 ***	0.02	0.17 ***	0.02	0.36 ***	0.03	0.36 ***	0.03
FMCG	0.62 ***	0.05	0.60 ***	0.05	1.05	0.11	1.05	0.11	0.60 ***	0.05	0.59 ***	0.05
Telecommunications	0.14 ***	0.01	0.14 ***	0.01	1.29 *	0.16	1.27	0.16	0.22 ***	0.02	0.21 ***	0.02
Travel and *Tourism*	0.20 ***	0.02	0.19 ***	0.02	0.93	0.1	0.89	0.09	0.32 ***	0.03	0.33 ***	0.03
Hashtag	1.05 ***	0.01	1.04 ***	0.01	0.97 *	0.01	0.96 **	0.01	1.05 ***	0.01	1.05 ***	0.01
Brand equity	1.19 ***	0.03	1.19 ***	0.03	1.16 ***	0.04	1.16 ***	0.04	1.07 *	0.03	1.07 *	0.03
Readability	1	0	1.00 *	0	1	0	1	0	1.00 **	0	1.00 **	0
Post length	1	0	1	0	1.00 **	0	1.00 **	0	1.00 **	0	1.00 **	0

Phase	0.93 ***	0.01	0.93 ***	0.01	1.10 ***	0.02	1.10 ***	0.02	1.10 ***	0.02	1.11 ***	0.02
*Logos *brand stereotype (warm)*	-	-	1.11	0.04	-	-	0.95	0.04	-	-	1.04	0.04
*Pathos * brand stereotype (warm)*	-	-	1.08 *	0.04	-	-	0.99	0.04	-	-	1.13 ***	0.04
*Ethos * brand stereotype (warm)*	-	-	1	0.03	-	-	1	0.04	-	-	0.98	0.03
*Social pathos *brand stereotype (warm)*	-	-	1.07*	0.04	-	-	1.11 *	0.05	-	-	0.93	0.03
Nagelkerke R^2	0.614		0.618		0.65		0.651		0.557		0.561	
Wald Chi2 (Change df)	4858763*** (22)		4835687***(26)		287582***(22)		283378***(26)		315382 ***(22)		314006 ***(26)	
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '°' 0.1												

Table 9: CESM volume-based analysis: results.

To test H2, we evaluated the interaction between the rhetorical appeals adopted by brands and the brand stereotypes perceived by consumers (Table 11). The moderation analysis supports that the interaction between *social pathos* and brand stereotype has a positive and significant effect on the first two stages of CESM, whilst a non-significant effect on the last one. Social pathos is more likely to trigger forms of engagement like liking and commenting if this rhetorical appeal is resorted by brands that are perceived by consumers as warm rather than competent. Regarding the other appeals, *pathos* is more effective for warm brands in terms of liking and sharing while the interaction between *logos* and *ethos* and brand stereotype is non-significant across all stages of CESM. Thus, H2 is partially confirmed.

3.3.3 Robustness test

To validate the predictive capabilities of the volume-based analysis, following previous studies on content virality (Tellis *et al.*, 2019) we conducted an out-of-sample predictive analysis. In particular, we built a Support Vector Machine (SVM) model for each CESM stage to assess whether the factors that were significant in the volume-based CESM analysis would actually predict the different engagement behaviors of consumers on the social media platform. Brand-generated posts were divided into two categories "highly engaging" and "lowly engaging", based on the distributions of the number of likes received. Similarly, continuous independent variables were recoded into high and low based on their average. We performed tenfold cross validation to prevent one-shot sampling biases. The same procedure was repeated also for the number of comments and the number of shares. We used mainstream scores to evaluate the predictive capabilities of each model (i.e. precision, recall, and macro-average F1; see **Table 12**). The high predictive accuracy of the three models suggests that the predictors included in the volume-based CESM analyses are not idiosyncratic and thus potentially generalizable.

	Precision	Recall	F1
N° Likes	66.2%	95.1%	78.1%
N° Comments	83.7%	66.5%	74.1%
N° Shares	72.7%	69.5%	71.0%

Table 10: Performance of the predictive analysis.

3.3.4 Semantic CESM analysis

To assess the semantic dimension of CESM generated by brand-generated posts that conveyed different rhetorical appeals, the second step of our analytical procedure involved a topic modeling on the user-generated comments. Topic modeling covers a wide group of algorithms aimed at soft-clustering and discovering hidden thematic structures in large unstructured textual datasets without the need of a priori classification (Airoldi *et al.*, 2015; Blei *et al.*, 2012). The advantages that make topic modeling an increasingly used toolkit for conducting social science (Van Dick *et al.*, 2018) lays in it being explicit, automated, inductive, and naturally keen to navigate the relational nature of textual data (Di Maggio *et al.*, 2013). Among the various techniques refined over the years, generative models-based techniques such as latent Dirichlect allocation (LDA, Blei *et al.*, 2003) have been found to be particularly effective to analyze social media users' comments (e.g. Mirzaei *et al.*, 2022). However, LDA comes with some limitations: model estimation occurs without taking into account relevant document-level covariates that affect the topical prevalence (i.e., the frequency with which a specific topic is discussed) and the topical content (i.e., the differences in the language used to discuss a given topic) and without the possibility to detect correlated topics, that is themes that tend to occur in the same documents (Hu *et al.*, 2019; Lindstedt *et al.*, 2019). To overcome such limitations, we built a model of online comments in response to brand-generated posts employing the structural topic model (STM, Roberts *et al.*, 2014). A recent extension of LDA and correlated topic models (Blei and Lafferty, 2007), STM has already been fruitfully used in a variety of research domains like political science (Bauer *et al.*, 2018), journalism studies (Jacoby *et al.*, 2016), management and organization studies (Innis 2022; Aranda , Sele, Etchanchu, Guyt, and Vaara, 2021), but marginally employed in marketing and brand communication research (Fresneda *et al.*, 2021;

Reisenbichler and Reutterer, 2019). Compared to previous generative models, the advantage of STM is that it allows to explore the relationships between the identified topics and other variables by including pertinent document-level metadata during the model estimation, and by weighting for between-topics correlations (Schmiedel *et al.*, 2019).

3.3.5 Text preprocessing and model specification

Before conducting STM, we performed a thorough document-preparation and text preprocessing. We removed invalid records (such as comments with no words or duplicates), performed tokenization at the word level, document cleaning (e.g. removing hyperlinks such as URLs and https from the comments), enrichment (adding relevant bi-grams and tri-grams collocations), stopword-removal, word normalization (e.g. lowercasing and spelling). We also removed highly infrequent words, setting the minimum document occurrence at the conservative threshold of five (Banks *et al.*, 2018). The final corpus contained 45,020 unique comments, 6,984 unique terms, and 323,002 tokens. After data-wrangling and corpus pre-processing, the model was set up by defining topic prevalence as a generalized linear function of post type, brand stereotype, industry, and time of publication:

*Topic prevalence = g (post type, brand stereotype, post type*brand stereotype, industry, s (time of publication))*

where *post type* and *brand stereotype* are dummy variables with factors corresponding to the rhetorical appeal most prevalent in the post each comment is associated to and the brand stereotype perceived by consumers, obtained in the first step of this study; *industry* is a dummy variable with factors corresponding to the seven industries investigated, and *time of publication* is operationalized as a spline function of the week of the year during which the user-generated comment was posted in order to account for non-linearity of the time effects. After setting up the model, we selected the number of topics (K) for the STM. K represents one the most important user-specified parameters for topic modeling, though the literature warns that there is no one-size-fits-all procedure for identifying a number of topics that is the best under both the analytical and interpretative standpoints (Schmiedel *et al.*, 2019; Hu *et al.*, 2019). We thus initially run estimates for K in between 10 and 100, with an increment of five topics at each step, given the intrinsic nature of our corpus which comprises several thousands of short user-generated documents (Lindstedt, 2019; Banks *et al.*, 2018). Then, we compared the models through STM-specific diagnostics, namely held-out likelihood, exclusivity, and semantic coherence (Figure 9), which informed us that the best models occur when $40 \leq K \leq 50$ as differences in terms of held-out likelihood are small and most importantly the trade-off between semantic coherence and exclusivity is most marked (Roberts *et al.*, 2014). Despite the higher the number of topics the higher the level of exclusivity, more informative solutions can be reached if exclusivity and semantic coherence are balanced. As with other clustering algorithms (Reisenbichler and Reutterer, 2019), purely relying on these quantitative diagnostics is not sufficient. For this reason we qualitatively inspected the solutions of the models between 30 and 50 to check for the stability of topics among neighboring models, and we finally selected the 40 topics solution.

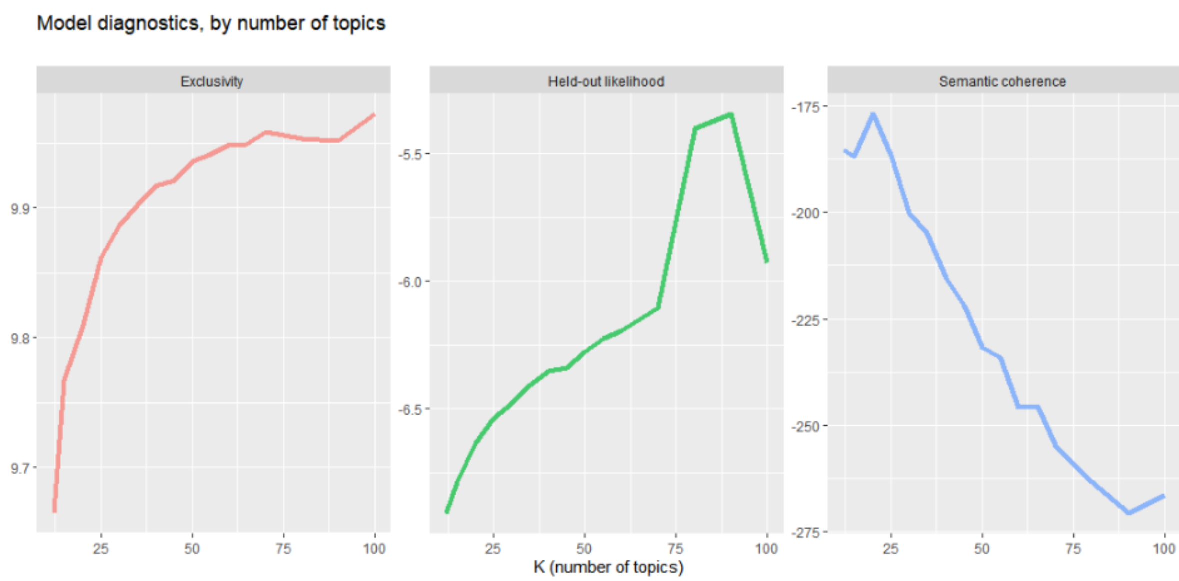

Figure 4: STM diagnostics: held-out likelihood, semantic coherence, exclusivity, by K.

3.3.6 Topic interpretation and validation

Despite it greatly helps researchers to computationally assess extremely large textual data quickly and effectively, the interpretation of the results obtained through topic modeling techniques requires an interpretative inferential task and demand expertise on the part of the researcher (Aranda *et al.*, 2021; Di Maggio and Blei, 2013). For this reason, two researchers with extensive knowledge of the branding literature were employed to assign a label to each emergent topic on the basis of the underlying meanings of each of the top words and most representative comments that were automatically grouped together under the same cluster (Hu *et al.*, 2019). Top words were identified with the FREX criterion (Roberts *et al.*, 2014). Overall, 33 topics expressed themes coherent and exclusive enough to be associated with a unique, single and concrete concept. To internally validate the results of the structural topic model, two authors coded a sample of the most representative comments per topic to assess if the model discriminates adequately. External validity was assessed by inspecting each topic's performance with respect to its time distributions and prevalence over the time period considered (Grimmer and Stewart, 2013). After topic interpretation and validation, three authors grouped the 33 topics in seven distinct thematic clusters representative of as many second order constructs based on previous literature and inter-topic correlations (Hu *et al.*, 2020). Finally, STM was complemented with a controversy detection analysis (Garimella *et al.*, 2018; Choi *et al.*, 2010). The aim of the controversy detection analysis is to identify controversial topics, i.e., topics that are capable to generate significant online debate (Garimella *et al.*, 2018). Among the different methods, we quantify controversy through a text and sentiment-analysis approach (Choi *et al.*, 2010). Owing to the fact that the brands included in the analysis are well-known and that their social media presence is professionally managed (Kübler *et al.*, 2020), we opted for an aspect-based sentiment-analysis (Dehler-Holland , Okoh, and Keles, 2022) which relies on a combination of the distribution of words of each topic identified via the STM with a selected lexicon. For the latter, the Italian version of the NRC-Emolex lexicon (Mohammad and Turney, 2010) was chosen, adapted, and validated to our domain (see Appendix D for additional details). To handle negations and valence shifters, we parsed the comments at sentence-level and shifted the emotional polarity only when the grammatical relationship between the emotional lemmas and the negation was relevant (Herausen *et al.*, 2019). Given the role recognized to paralinguistic non textual cues such as emoticons and emojis (McShane *et al.*, 2021), sentiment was operationalized also via a rules-based approach which enabled us detecting and giving a score to representative static emoticons and emojis selected due to their embedded sentiment polarity (Novak *et al.*, 2015). Thus, for each topic, sentiment was computed following Dehler-Holland , Okoh, and Keles' (2022) approach as the normalized sum of the overall sentiment score per topic weighted with the word occurrence probability for each topic estimated by the STM (β_{wt}), where overall sentiment score for each lemma is the difference between positive emotion score and negative emotion score according to the sentiment lexicon.

$$Topic\ sentiment\ (TS) = \Sigma_{w \in polita} (POSITIVITY^{polita} - NEGATIVITY^{polita})_w * \beta_{wt}$$

As topic variance represents a reliable indication of controversy (Garimella *et al.*, 2018), we proceeded to aggregate topic sentiment scores at thematic cluster level and compute each cluster's sentiment variance.

3.3.7 Results

Figure 10 represents the network with 33 topics discussed by consumers in reaction to brand-generated posts. Within this network we identified five discourses (Philips *et al.*, 2004) widely investigated in the branding literature, i.e., *brand-consumer co-creation* (cluster 1), *positivity towards brands* (cluster 2), *brand referral* (cluster 3), *negativity towards brands* (cluster 4), and *nostalgia* (cluster 6), and two more idiosyncratic discourses, namely *mixed feelings* (cluster 5), and *covid complaints* (cluster 7). A detailed description of each cluster and the topics included therein is provided in Appendix E.

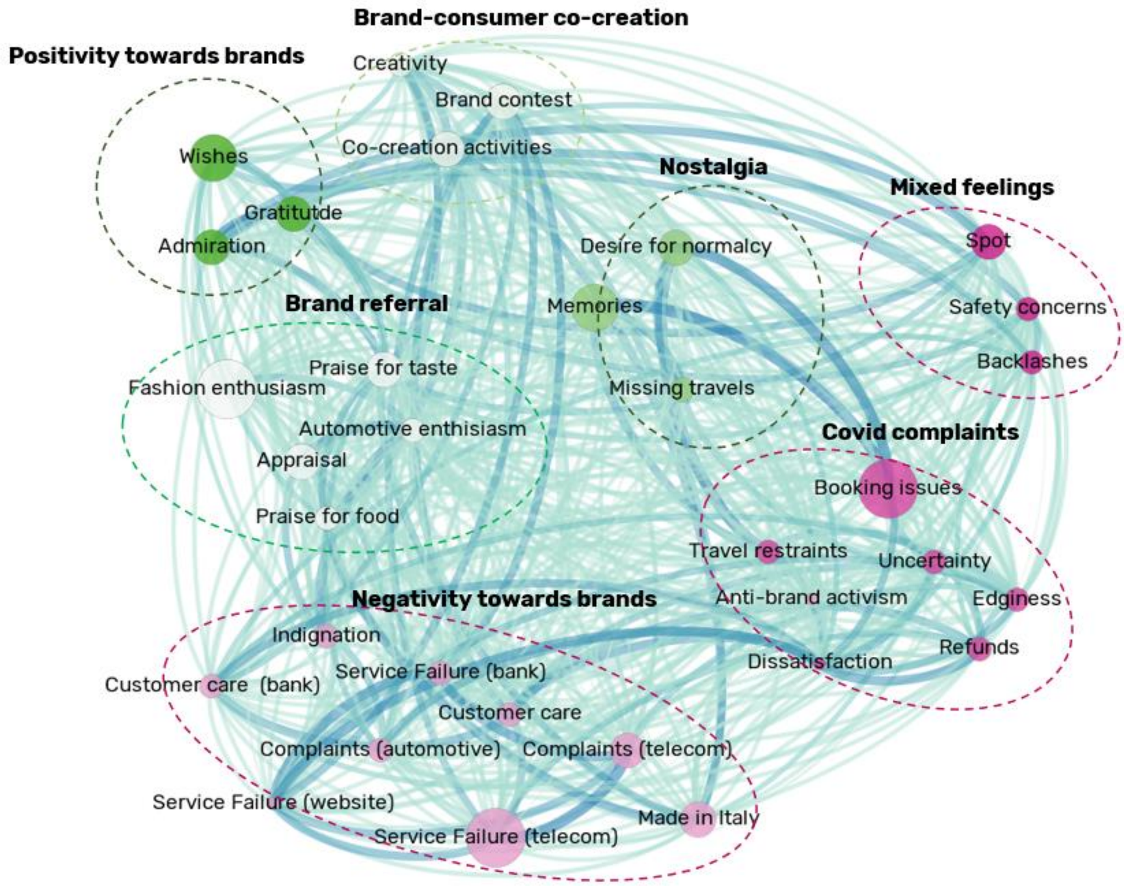

Figure 5: STM topic network graph.

Note: Nodes represent the 33 topics identified via STM. Edges represent the correlation among topics. The color of the cluster's circle indicates the average sentiment of the respective thematic cluster.

The controversy detection analysis reveals that the seven clusters differ in terms of controversy, and in particular that cluster 5 (*mixed feelings*) has the highest sentiment variance, and thus contains the most polarized reactions ($\sigma^2_{TS(1)}$: 18.484, $\sigma^2_{TS(2)}$: 20.436, $\sigma^2_{TS(3)}$: 16.691, $\sigma^2_{TS(4)}$: 18.218, $\sigma^2_{TS(5)}$: 22.223,$\sigma^2_{TS(6)}$: 18.772; $\sigma^2_{TS(7)}$: 19.616 ; Bartlett's K^2 (39) = 1000.1***). Including the post type variable as a covariate in the STM estimation allowed modelling how the different rhetorical appeals used by brands triggered the prevalence of topics occurring in consumer-generated comments. In other words, this feature of STM enabled to obtain the proportion of each topic associated with all four brand rhetorical appeals used for the classification task in the volume-based CESM analysis, and to assess whether the association between topics and rhetorical appeal is statistically significant. The estimated differences in topic proportions for the four rhetorical appeals at the 95% confidence interval are respectively shown in Figure 11.

As visible, consumer reactions that we identified as intrinsically polarized (*cluster 5*) are statistically more prevalent below brand-generated posts that are imbued with *social pathos*, i.e., with the rhetorical appeal that characterizes woke communication. In other words, we have empirical evidence that woke communication cues are controversial (Garimella *et al.*, 2018). Somewhat interestingly, brand-generated posts dominated by the informative rhetorical appeal (*logos*) are associated with highly negative consumers' reactions on the platform (*cluster 4*).

In addition, we could further test the moderation role of brand stereotypes. Results further corroborate H2: polarized consumers' reactions (cluster 5) are more prevalent when social pathos is resorted by brands perceived as competent compared to those perceived as warm. Conversely, when brands perceived as warm use a woke appeal, they are more likely to trigger consumers' positive discourses like those included in cluster 6 (Figure 12).

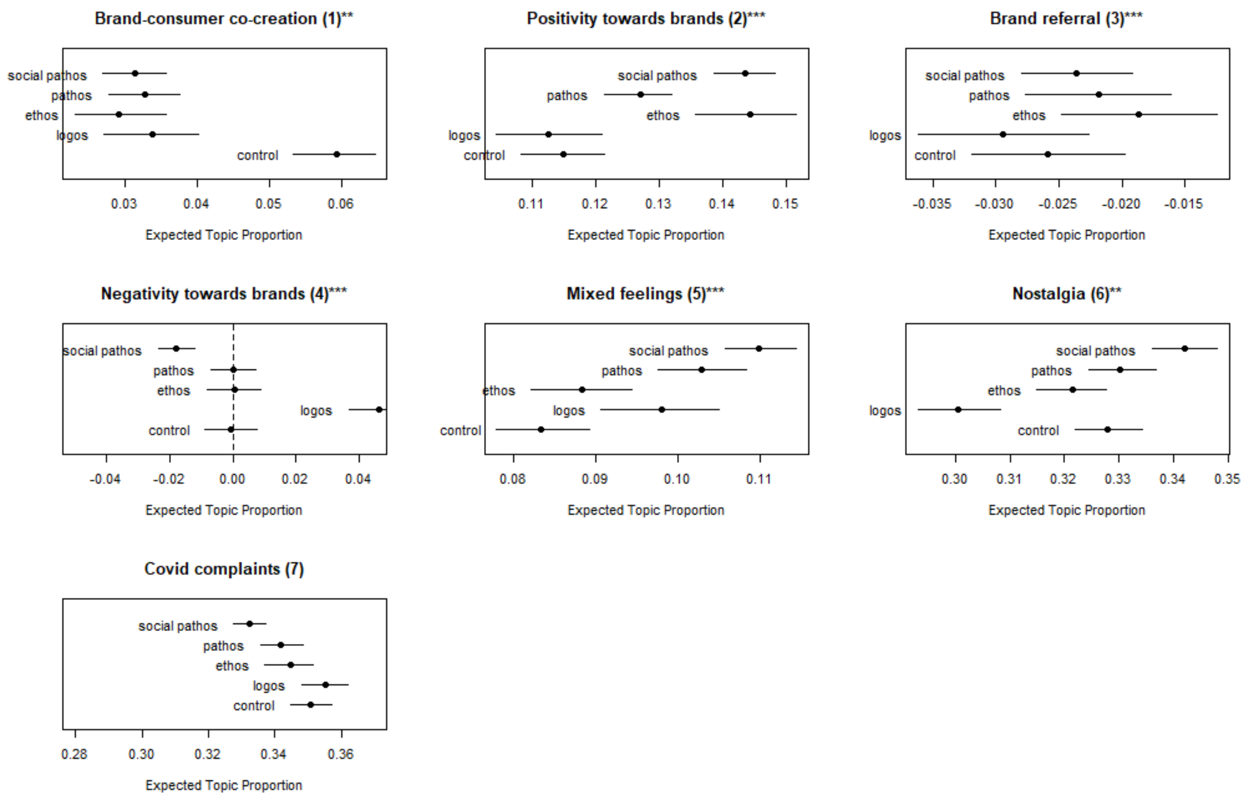

Figure 6: Thematic cluster prevalence, by post type.

Note: Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '°' 0.1

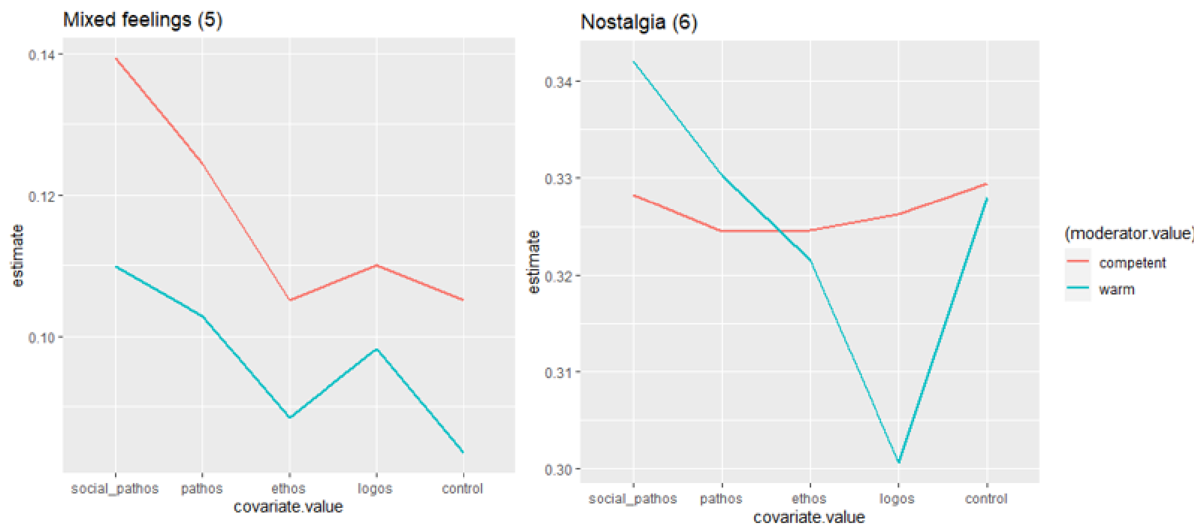

Figure 7: Thematic cluster prevalence, moderation of brand stereotypes.

3.4 General Discussion

Bridging LET, CE, and BIAF, and through a big-data, CATA-based field study comprising both top-down and bottom-up approaches, this study shed light on the overlooked effectiveness of woke brand communication in SM, and most importantly provides guidance about which brands should better employ this emerging rhetorical appeal, and which instead should better stick to traditional forms of brand communication. First, the volume-based CESM analysis corroborates that brand woke communication, operationalized through the social pathos appeal, is able to trigger more CESM along the phases of relationship formation, creation, and contribution compared to traditional credibility, emotional, and informative rhetorical appeals, i.e. ethos, pathos, logos. Though, this is particularly true for brands that are perceived as warm rather than competent by consumers. Second, the topic modeling and controversy detection analysis further supported and offered finer-grained understanding of these results, since brand-generated posts framed with social pathos are statistically associated with the most polarized consumer comments especially when they are posted by competent brands. In this way, our study also demonstrates that volume-based analyses alone cannot provide an all-encompassing picture of CESM dynamics, answering to recent calls to consider also the semantic-nature of CESM behaviors (Unnava & Aravindakshan 2021; Swani & Labreque 2020). The contributions of this study are thus threefold. First, we contribute to the emerging literature about woke branding (Mirzaei *et al*., 2022; Feng *et al*., 2021; Schmidt *et al*., 2021) by expanding the debate beyond the inquiry of whether it is beneficial or not for a brand to be sociopolitical (Wang *et al*., *forthcoming*; Mukherejee & Althuizen 2020; Jungblunt & Johnen 2021) and shifting the focus on identifying *who* should pursue such communication strategies instead. In particular, we do so without directly framing the management of a woke campaign as an authenticity challenge. Indeed, authenticity is a nebulous concept that, eluding a precise definition and practical operationalization, leaves brands and marketers with the burden of navigating who and what determines what being authentic really is (Thompson and Kumar, 2022; Nunes, Ordanini, and Giambastiani, 2021). Along this line, we instead contend that categorizing the effects of woke communication based on a much more measurable reference like the warmth and competence stereotypes embedded in the BIAF would provide clear normative guidance to brands considering woke communication in SM.

Second, theoretically, this study contributes to communication theory by advancing the underexplored application of L*Et al*so in social media contexts (Lee and Yu, 2020). Previous studies applying LET, a message-centered theoretical framework mainly devised for interpersonal communication (Burgoon *et al.*, 2002), in online settings, did so in technology-mediated contexts where the communication exchange occurred between human actors, for instance in the case of online reviews (Folse, Porter III, Godbole, and Reynolds, 2016; Jensen, Averbeck, Zhang, and Wright., 2013; Wu, Shen, Fan, and Mattila, 2017). In our study, we validate LET openness (Burgoon, 1995) by demonstrating that its precepts hold also in techno-mediated contexts where communication exchange unfolds between human (i.e., consumer audiences) and non-human (i.e., brands) actors, in lines with the brand anthropomorphism supporters (Aggarwal and McGill, 2012; Fournier, 1998).

Third, this study contributes to the rising literature focused on brand polarization (Osuna Ramirez *et al*., 2019). Conversely to the current view whereby the phenomenon of polarization is depicted as a strategic asset in control of the brands (Mafael *et al* 2016; Luo *et al* 2013), capable of bringing many advantages to multiple parties (Osuna Ramirez *et al*

2019), this study posits that polarization is not always a deliberate and manageable choice for brands and brand managers. Similar to the case of social narrative videos (Mylfield & Flynt, 2020), social pathos turned out to be divisive and polarizing appeal, despite it was not deliberately conceived so by brands. Although already during the first stages of the pandemic some scholars blamed brands for using a socially oriented rhetoric opportunistically (Nolan, 2020; Sobande, 2020), the majority of brands did not engage in this communication style to divide, but rather to instill in their recipients a deeper sense of emotional attachment (Hang *et al*., 2020) and to cultivate feelings of compassion, resilience and care (Ertimur & Coskuner-Balli, 2021). Moreover, this study contributes to the brand polarization scholarship also from a methodological standpoint, as related studies so far employed qualitative methods (Mylfied & Flynt, 2020; Osuna Ramirez *et al*., 2019) or focused on targeted idiosyncratic communities (Rim *et al*., 2020; Jungblunt *et al*., 2021).

3.5. Conclusions, limitations, and future research

This study contributes to the unfolding scholarly debate about brand woke communication shedding light upon its CESM dynamics and, most importantly, identifying for which type of brand this recent appeal is most effective. Though, the results of this study come with some limitations as well, which open avenues for further research. Firstly, despite the choice of Italy as research context was not random, focusing on a single country might provide only a partial explanation of the phenomenon investigated. The brand-consumer interactions which took place on the Facebook pages of Italian brands could be biased by cultural dynamics. Future studies should hence test the identified relationship between social pathos and polarized consumers' reactions in cross-country, cross-cultural settings. Secondly, computational methods such as those employed in this study offer many advantages; however, blending aspects of multimodal communication phenomena, they necessarily gloss over nuance. Qualitative in-depth investigations could infer finer-grained nuances of the brand polarization phenomenon on social media. Along this lines, computational social media analysis does not allow to investigate this phenomenon at the micro level, gauging the individual details and features of the commentors engaged in sharing polarized comments.

Indeed, we still know very little about who is lying behind such behavior. Further studies adopting methods framed by more controllable settings like experimental design can infer what are the more recurrent socio-cognitive factors and personality traits most likely associated with consumers posting polarized reactions towards brands on social media.

Chapter 4. All that glitters is not *real* affiliation: how to handle affiliate marketing programs in the era of falsity

In collaboration with Giandomenico Di Domenico (Cardiff University)[18]

4.1 Affiliate Marketing Programs In The Era Of Falsity

From Amazon to Instagram and Snapchat, from BuzzFeed to YouTube and Twitch, affiliate marketing programs have flooded the web 2.0, often even without us noticing it. Every time we come across sentences like: "*this content is sponsored by*" or we hear our favorite content creators and social media influencers exclaiming: "*swipe up to take advantage of this incredible sale in my bio!*", chances are high that we are moving in the space of affiliate marketing programs. Amid the recent digital marketing revolution that has seen brands increasingly abandon owned media in favor of earned media, *affiliate* or *partnership* marketing programs represent one of the most dominant digital tools for online marketers, with as much as 15% of global digital media revenues generated through them (CHEQ, 2021), and the great majority of marketing executives globally eager to invest in this channel (Enberg, 2021). When first introduced, these programs were implemented with excitement by advertisers, who saw in this tool a safer means to implement online marketing (Edelman and Brandi, 2015). The initial adopters of affiliate marketing programs were small partners using their blogs or websites to earn money on commissions. Nowadays, social media influencers have increasingly become an integral part of affiliate programs, raising the complexity of the affiliate marketing landscape, and exposing brands to new, subtler perils. Affiliate marketing programs show indeed some structural flaws, mainly stemming from the affordances of digital environments (Di Domenico *et al.*, 2021), where fraudsters can develop and refine various forms of deceptive behaviors, from digitally advanced techniques such as cookie stuffing (Chachra *et al.*, 2015), to more social media-sized frauds such as engagement

[18] Published in a different version on *Business Horizon* (Mangiò & Di Domenico, 2022).

manipulation (Alba, 2019). Affiliate falsity threatens brands' image, reputation, and economic resources: in 2020 affiliate frauds cost brands $1.4 billion (CHEQ, 2021).
As the size of the affiliate marketing industry continues to grow, worth more than $15 billion in 2020 (CHEQ, 2021), how can marketers protect their affiliate marketing programs from falsity? Affiliate frauds can take many forms and thus there is no "silver bullet" for handling this problem. Moreover, the gray and academic literatures to date have failed to provide a meaningful characterization of affiliate frauds that would help brands to better understand the various facets of this phenomenon and plan appropriate coping strategies. Seizing this opportunity, in this article we provide an original classification of affiliate frauds based on the identity of the affiliate. In this sense, we distinguish between *non-influencer* and *influencer* falsity, describing the impact that the various tactics belonging to each category exert on brands. For both the affiliate falsity categories, we also outline the appropriate strategies that brands can implement to identify frauds and preserve their economic and reputational integrity. Then, we propose a two-stage protocol that specifically helps brands to manage influencer affiliate falsity with the support of computer-aided textual analyses (CATA from here on; Brunzel, 2021). We conclude with an illustrative case in which this protocol is applied on real influencer affiliate data.

4.2. Affiliate Falsity: What Is It, And Why Does It Matter?

Affiliate marketing programs are a performance-based online marketing strategy whereby an actor (merchant) makes an agreement with another actor (affiliate or publisher) to feature a link from its websites on affiliated sites (Dwivedi *et al.*, 2017). In particular, an affiliate earns a commission if 1) a user browses to an affiliate's site or social media account, 2) clicks the affiliates link to the merchant, and 3) makes a purchase from the merchant (Edelman and Brandi, 2015). Initially, affiliate marketing programs were proclaimed "the Holy Grail of advertising" (The Economist, 2005) as the Pay-Per-Sale mechanism they are based on promised to liberate brands from blindly investing resources in advertising through the older Pay-Per-Thousands mechanism. Back then, affiliates used to be small publishers who posted their affiliate links on websites, discussion forums or blogs to redirect users to the merchants' websites (Enberg, 2021). However, social media influencers have increasingly become an integral part of digital marketing strategies, leveraging the influence they hold on their follower base to promote products and services (Leung *et al.*, 2022). More importantly, they started to earn commissions within affiliate marketing programs, giving rise to the practice of influencer affiliate marketing (Bradley, 2021). In this article, we adopt the distinction between *influencer* and *non-influencer affiliate marketing* to illustrate how affiliates use falsity in both realms, instantiating *affiliate frauds*, i.e. activities which are explicitly forbidden under the terms and conditions of affiliate programs or by the law (Snyder and Kanich, 2016). Our distinction builds on the identity and modus operandi of the affiliate. Influencer affiliate marketing refers to instances in which the affiliate is a social media influencer, i.e. an individual with a considerable network of followers who creates and shares content on social media (Campbell and Grimm, 2019). Non-influencer affiliate marketing instead defines the programs enforced by other actors who use different digital marketing tools (such as websites, email marketing, or banner ads) for their affiliate marketing activities. This distinction is relevant for two reasons. First, it helps to better understand the ways in which affiliate frauds are perpetrated. While social media represents fertile ground for fraudster influencers, non-influencer affiliate frauds are realized by hidden fraudsters who exploit the shortcomings of the digital world outside social media platforms. Second, influencer and non-influencer affiliate falsity have different impacts on brands and consumers. On the one hand, non-influencer affiliate falsity exerts a direct economic impact on brands due to the misattribution of sales and commissions to the deceptive affiliate. In these cases, consumers are usually unaware of the fraud being realized and are not impacted. On the other hand, influencer affiliate falsity impacts brands directly and indirectly. The direct effect is due to deceptive influencers who buy fake followers and ask for a higher compensation to promote the brand. The indirect effect instead passes through consumers, as a lack of transparency from the influencer can inhibit perceived trustworthiness and engagement with social media posts on the side of consumers (Karagür, Becker, Klein, and Edeling, 2022), ultimately hampering the performance of the campaign and potentially the brand’s reputation. Therefore, our classification helps to reconcile the knowledge about the different types of affiliate frauds, clarifying how they are carried out, their impact on brands and consumers, and the different solutions that brands can adopt to prevent them. Figure 13 summarizes our classification.

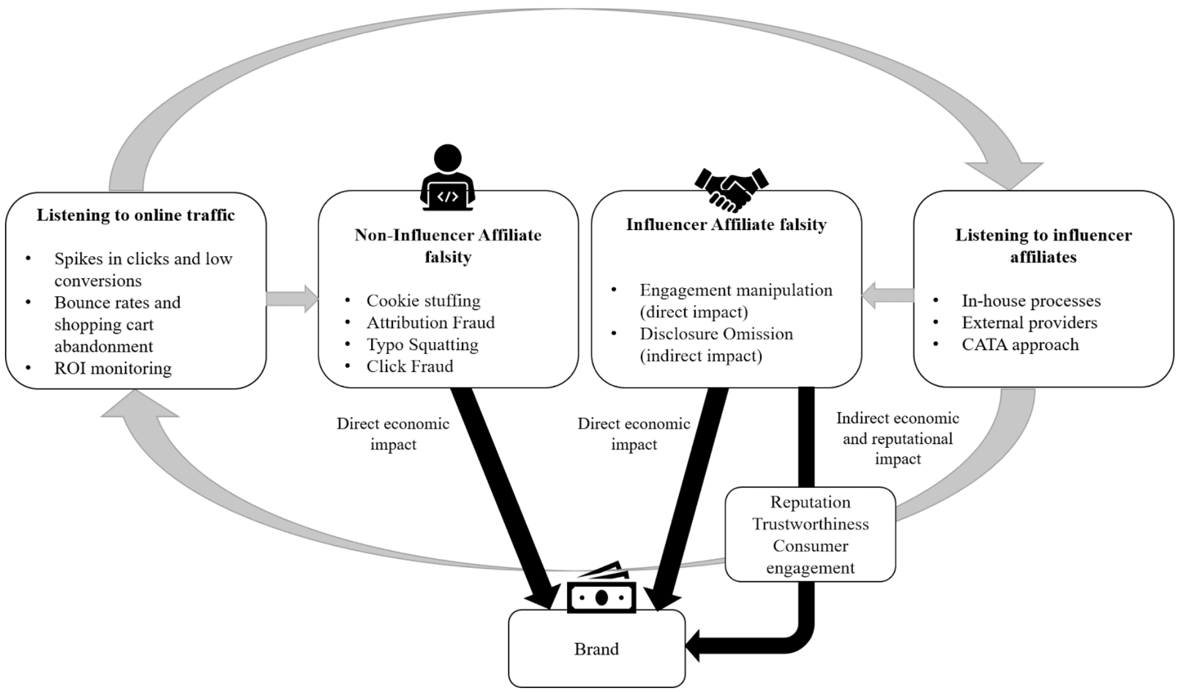

Figure 8: Affiliate falsity classification and brand's coping strategies.

4.2.1 Non-Influencer Affiliate Falsity: Frauds and Scams, From Cookies to Farms

Non-influencer affiliate falsity is performed by those fraudsters that, exploiting or forcing technical shortcomings in the affiliate tracking and attribution systems, receive commissions they should not really earn. As the misattribution of commissions results in a direct economic cost for the brand, these frauds have represented to date the main concern of marketers engaging in affiliate marketing programs. Non-influencer affiliate falsity involves many activities, often undertaken by the same actor simultaneously and automatized through bots. The activities that most frequently affect brands are *cookie stuffing, attribution frauds, typo squatting* and *click frauds*. Through *cookie stuffing*, fraudulent affiliates drop small HTTP files, named "tracking-cookies", from third-party advertisers onto the users' browsing history every time they visit their websites. In this way, if the user subsequently visits one advertiser and completes a purchase, the fraudster can claim a commission without actually having directed the user to the advertiser. Given their invisibility and ubiquity online, cookies can be dropped in multiple ways without getting noticed, for example including them in decoy pictures and in redirect links. Usually placed on the websites of big retailers such as Walmart, Amazon, and eBay, cookie stuffing costs brands thousands of dollars every year. For example, in 2014, an elaborated cookie stuffing scheme cost eBay $28 million in online marketing fees (Chachra *et al.*, 2015). Despite the global digital marketing ecosystem eventually moving towards a "cookieless future", with companies like Apple and Google planning a complete ban of third-party cookies (Fou, 2021), cookie stuffing is still going to represent a real threat for affiliate marketing, at least in the upcoming future. As nowadays not all the global Internet users navigate the web via cookie-free browsers, like Safari and Firefox, they are still easy targets for cookie-stuffing frauds.

Another way in which fraudsters manipulate the affiliate system is through the *attribution fraud* of fake app installs. This fraud allows deceptive affiliates to claim credits for app installs not generated by them performing sophisticated and subtle techniques. One of the most common is called "click injection". Fraudsters develop a mobile app that, once installed by users on their smartphones, tracks the download of any other app. When fraudsters realize that an app has been downloaded, they generate new windows and force users to perform a series of clicks before the app installation is completed. In this way, the tracking system is deceived, and the installation is attributed to the fraudulent source. Such activities infest ad networks with hundreds of thousand malicious apps (Benes, 2018). For instance, Uber wasted more than $100 million in affiliate marketing investments due to attribution fraud (Silverman, 2018).

The third type of non-influencer affiliate falsity is called *typo squatting*. With this illegal tactic, affiliates register online domains that show poor grammar or misspellings of an actual merchant's domain, tricking users into believing to click on the actual website's link. Conversely, by clicking on hijacked URLs such as those depicted in **Figure 14**, the user is ultimately redirected to the merchant's website, but the affiliate will collect a commission not rightfully earned. To avoid consumers' backlashes, some brands preventively register typo versions of their domains to anticipate fraudsters, but this is not always effective. For example, in 2006 the affiliate program Land's End proved in court that its affiliates registered a variety of domains misspelling the original Land's End website to earn commission from simply redirecting users to their website.

Figure 9: Examples of common typo-squatting techniques affecting affiliate programs.

Lastly, we have click frauds. In the beginning, fraudsters would create computer programs specifically designed to generate fake clicks, also called "click bots", to artificially inflate the revenues from affiliate marketing. Companies then started to protect themselves by applying CAPTCHA tools (i.e. systems intended to tell humans from machine inputs apart) on their websites to block such malicious click bots. However, fraudulent affiliates responded by creating even more sophisticated automated fraud schemes able to bypass CAPTCHA. Alongside this, fraudsters started to use humans to overcome the evolving anti-frauds systems as well. This is the case of *human click farms*, where real people click on ads, fill out forms, and even put items into online carts to trick marketers and merchants into thinking they are getting real leads. Usually click farms are located in countries where the labor cost is minimal and outweighed by profits. Indeed, click farms workers in Bangladesh or India get paid as much as $120 per year (The Guardian, 2013), whereas the industry of click farms generates $152 billion yearly (CHEQ, 2021).

4.2.2. What Can Brands Do About Non-Influencer Affiliate Falsity?

As frauds can come in many forms, there is no "one-size-fits-all" solution for managers to protect their brands. However, monitoring the traffic quality represents a proper practice. There are three indicators to keep track of that might signal the brand is under affiliate fraud attack:

- *Spike in clicks and low conversions*: if the number of clicks suddenly increases and it is not followed by a proportional increase in conversions, that very likely proves that bots or click farms are in action. Also, managers should keep track of sources of traffic, as very unfamiliar sources or same IP addresses can be evidence of bots or click farms.
- *High bounce rates and shopping cart abandonment*: brand managers could notice that a great number of users immediately abandon the brand's website after a visit. The duration of the session provides insights to spot the action of malicious actors. If users stay on the website for zero seconds, then these users are very likely to be bots and the brand might be under attack of click frauds. However, sometimes bots are trained to disguise themselves as humans so that they fill in shopping carts. Though, since bots cannot purchase anything, they bounce and abandon the cart. High shopping carts abandonment rates might signal bots are in action.
- *Budget and falling ROI*: brand managers should always keep an eye on the budget and ROI of affiliate campaigns. The performance of affiliate campaigns could be affected by a variety of factors, such as industry trends or other crises, that managers should constantly monitor. However, if an unexpected bad performance cannot be attributed to any other factors, this should be a warning sign of the brand being under attack by affiliate fraud.
- Despite being not an easy task to accomplish, spotting and preventing non-influencer falsity and frauds is possible through a continuous and deep monitoring of the traffic. Fortunately, brand managers have various third-party solutions available for them to better understand the effectiveness of their affiliate marketing campaigns. Among them Anura.io (www.anura.io) and SEON.io (www.seon.io) offer brands the

opportunity to develop tailored traffic monitoring solutions that aim to uncover hidden fraudsters and detect suspicious usage.

4.2.3 Influencer Affiliate Falsity: Mocking the System Through Engagement Manipulation and Disclosure Omission.

Influencer affiliate falsity occurs anytime a deceptive affiliate exploits those logics at the base of influencer marketing to earn from undue affiliate commissions, brand promotions, and partnerships. In this stance, influencer affiliate falsity activities represent not only a direct but also an indirect cost for the brand, as it may cause an erosion of reputation and consumer trust for being associated with deceptive and unlawful influencer affiliates (Leung *et al.*, 2022). Different types of influencers populate the social media landscape, fulfilling different purposes (Bentley *et al.*, 2021). Typically, the scale of influencers, ranging from Nano-influencers (0 - 10k followers) to Celebrity influencers (1m+ followers), affects their perceived level of authenticity, cultural impact, and defines the relationship they have with their network (Campbell and Farrell, 2020). The influencer falsity tactics that we describe might be applied by the influencers of all sizes. However, in the domain of affiliate marketing frauds, several reasons suggest brand managers to monitor smaller-scaled influencers. First, while the partnerships with celebrity influencers are regulated by well-established contracts, this is generally not the case of smaller influencers who might escape the brand control over their operations (especially for brands owning large portfolios of influencers). Second, celebrity influencers already detain a large network of followers. Nano- and Micro-influencers might be more tempted to give an initial "boost" to their influencer activity, for example purchasing fake followers or trying to preserve their perceived "authenticity" (Campbell and Farrell, 2020) by not disclosing the commercial nature of the post.

Influencer affiliates perform falsity in two main ways: inflating the engagement metrics of social media (*engagement manipulation*) or concealing their commercial identity (*disclosure omission*).

The influencer's follower base and the engagement rates represent the major criteria brands adopt in choosing the social media influencers they work with (Leung *et al.*, 2022), so fraudsters attempt to strategically manipulate these criteria at their own benefit, asking higher compensation for the partnership. As such, engagement manipulation represents a direct economic cost to the brand. Similar to click frauds, engagement metrics can be artificially inflated through both human and computer-based tactics. Among the human tactics, a common fraud is *sock-puppeting*, i.e. the administration of plural, fake accounts by one single actual user. Hiding behind puppet profiles and pseudonyms, the scammers manage to interact at will with online contents to amplify the metrics on which their income depends. Another mainstream human-based affiliate fraud consists of the lobbying activities executed by *pod-communities*, secret groups of online users who systematically endorse in a mutual exchange of fictitious online engagement interactions during planned drops that exploit the affordances of specific social media platforms. For example, through the systematic share of threads as "#likeforlikes" or "#followforfollows", pod-groups on Instagram hack the platform's ranking algorithm placing among the first results posts that record sky-high numbers of false likes overnight. Conversely, computer-based fraud tactics involve the use of computer programs that grant the actual *purchase of followers*, and the activity of *bots*, specifically designed to artificially increase engagement metrics by creating false accounts. Despite attempts by social media platforms to curtail this engagement manipulation activities, it is still simple for users to buy fake engagement. With an expense as cheap as $330 it is possible to purchase over 3,500 comments, 25,000 likes, and 5,000 followers (Alba, 2019).

The second influencer affiliate falsity strategy, *disclosure omission*, is instead aimed at concealing the commercial nature behind the affiliate's online activity in the eyes of their audiences. To regulate the digital advertising environment, consumer protection authorities like the Federal Trade Commission (FTC) require content-creators to clearly disclose to users their relationships with merchants every time an affiliation link is presented in online advertising content (Campbell and Grimm, 2019). Thus, influencer affiliate contents must include endorser-advertising disclosures. These can span from indirect ones like *affiliate links* disclosures (merely specifying the merchant nature of the URLs embedded in content) and *channel support* disclosures (promoting a financial contribution to the content-creator from users to support their channel), to more explanatory disclosures, where the endorsers explicitly state they receive commissions upon click-throughs (*explanation* disclosures;

Mathur *et al.*, 2018). However, recent studies found that only less than 10% of affiliates on YouTube disclose the presence of affiliate links in their videos (Mathur *et al.*, 2018), not only violating international advertising regulations, but also posing indirect threats to the advertised brands who could suffer reputation damages for being associated with bad influencer affiliates. Recent evidence indeed suggests that consumers are nowadays more knowledgeable about the commercial nature of social media influencer posts (Statista, 2019) and thus expect the existence of a commercial/affiliate relationship between the brand and influencer even when not explicitly disclosed. Consequently, not disclosing a commercial partnership decreases the perceptions of trustworthiness of the influencer and the intentions to engage with the social media post (Karagür *et al.*, 2022), with indirect negative consequences for the brand.

4.2.4 What Can Brands Do About Influencer Affiliate Falsity?

To face the challenge of managing the affiliate-influencer landscape, today brands can rely on two options (Edelman and Brandi, 2015). The first one involves implementing in-house processes specifically aimed at selecting, verifying, and monitoring everything that is said in the name of the brand by all the publishers, brand ambassadors, and influencers. For example, global consumer goods leader Unilever has recently devised a multi-layered internal procedure specifically designed to enhance its long-term relationship with the influencers of its many brands, making sure that virtuous influencers are rewarded whilst inauthentic ones staved off. Otherwise, influencer management tasks can be outsourced to external service providers. The market of influencer marketing platforms is fertile and expanding, as many specialized providers like Upfeat (www.upfeat.com), SEON.io (www.seon.io) or Feedzai (www.feedzai.com) offer AI-driven solutions aimed at helping their clients to minimize the cost of influencer frauds with relatively low effort from their clients' side. However, although useful, these solutions can be problematic for brands for two reasons. First, as with Social Media Analytics more in general (Lee, 2018), not every brand has the possibility of devoting part of their marketing budget to outsource influencer fraud management processes. Second, even when managers rely on external providers, they would need to understand the underpinnings of the statistical and AI tools used by influencer marketing platforms to better evaluate their value proposition and avoid being deceived by the hype surrounding these buzzwordy technologies. To account for these issues, we thus propose that CATA can offer an effective and affordable way for brands of all sizes to navigate the complex intersection between influencer marketing and affiliate marketing programs.

4.3 How to Use CATA to Prevent Influencer Affiliate Falsity

It is no breaking news for marketers and academicians alike to acknowledge that consumers, brands, and influencers live and operate in an increasingly datafied and platformised society. In current markets, where the bulk of transactions are performed on, and customer-brand relationships take place across, online platforms, text broadly meant as a configuration of alphanumeric signs (Humphreys 2021) represents more than ever the pivotal medium of everything that brands do, share, and are concerned about. As a matter of fact, consumers can write unsolicited product reviews on platforms like Yelp or Amazon. Brands can remain resonant with their audiences by incessantly sharing messages about their activities, promotions, and new product launches on social media platforms like Twitter and Facebook in real-time. Likewise, influencers can post video-content on their official accounts of platforms like Instagram, TikTok, Snap Chat and YouTube to connect with their followers, pander to their expectations, and earn from affiliate programs– content which, transformed into transcriptions and captions, still presents itself in a textual format. It is thus evident that brands are immersed in an ocean of unstructured textual data. As put forth also by recent contributions endorsing the pressing call for a better understanding of big-data-friendly sources and techniques (Bendle and Wang, 2016; Lee, 2017; Kaplan and Haenlein, 2009; Brunzel 2021), brands urgently need to conceive and master protocols designed to make the most out of this unstructured data deluge. In particular, this seems crucial in the context of influencer marketing, given that a greater extent of related content actually eludes brands control. As reviewed earlier, noisy and potentially detrimental brand-related textual data in the form of fake reviews, false accounts, and deceptive posts is created everyday by unscrupulous deceptive influencers allured by affiliate marketing dynamics, at the expenses of brands' image and reputation.

To face this challenge, today brands can resort to CATA and fine-tune a ad hoc affiliate listening protocol. Among the methods stemming from the intersection of computer science, linguistics, and AI domain, CATA has recently gained academic and practitioners' attention (Brunzel, 2021; Berger *et al.*, 2019). CATA comprises a wide family of techniques and tools ranging from sentiment analysis, text categorization, to information extraction that merge statistics, rule-based, and AI approaches for making replicable and valid inferences from textual data at large scale. Bridging quantitative and qualitative methods, CATA not only outperforms traditional qualitative business research, but also allows brands to extract additional insights from the ocean of textual data that in the past have been left untouched. In general terms, the broad umbrella of CATA approaches can be split up into two groups: top-down and bottom-up approaches (Humphreys and Wang 2018; Grimmer and Stewart 2013). Top-down approaches are those in which the analysts know a priori which construct they are interested to gauge in the textual data, and a proper measurement to operationalize its presence is available. Close-based tools like dictionaries and lexicons – that is, lists of validated lemmas and expressions deemed representative of a specific cultural or psycholinguistic construct- are typical CATA approaches that fall into the top-down category. Conversely, bottom-up approaches are those in which an operationalization of the construct of interest is missing in advance. A classification of the textual data must be provided either by the analysts (in the case of supervised machine learning) or inductively inferred by the structures latent in the textual data themselves (in the case of unsupervised machine learning). Topic modeling algorithms like Latent Dirichlect Allocation (LDA, see Bendle and Wang 2016 for an introduction) for instance represent a popular top-down CATA approach adopted to soft-cluster textual data and detect the latent topics embedded in the online discussions. Per sè, none of these two approaches is better than the other, as both are characterized by advantages and pitfalls, with top-down methods generally being more user-friendly and straightforward to use, but static and context-dependent, and bottom-up approaches being more flexible but harder to implement. The choice is always driven by the research question and aim, with top-down approaches more driven by theory whilst bottom-up approaches by data-grounded advances. If once CATA was strictly a prerogative of researchers and coders only, today instead brands successfully introduce CATA protocols into their marketing intelligence routines, and use them for several scopes and purposes. Social Media Analytics, under which also influencer analysis falls, is precisely one of them (Delbaere *et al.*, 2021; Lee, 2018). We suggest that brands can independently and systematically monitor their affiliate space through the two-stage CATA-based protocol shown in Figure 15. Stage 1 involves the selection of the influencer marketing campaigns, the social media platform where it takes place, and the collection of online textual data. Stage 2 focuses on how to spot compliant and deceptive influencers based on the digital traces they leave on social media platforms. Despite CATA can include very sophisticated techniques, we posit that the steps included in this protocol can be learnt and performed by any social media manager with a basic background in data management and analysis, given that user-friendly and scalable visual-programming CATA software are increasingly available (Ordenes and Silipo, 2021).

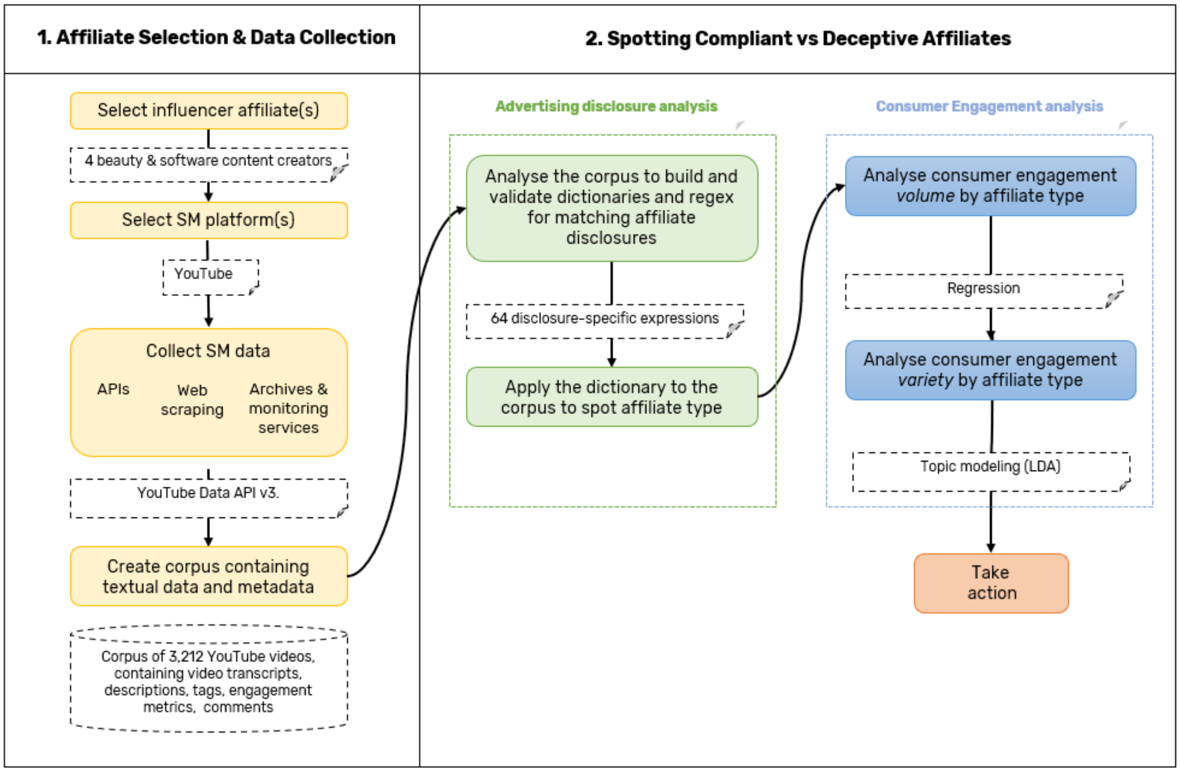

Figure 10: Stages of influencer affiliate CATA-based listening protocol.

4.3.1. Stage 1: Affiliate Selection and Online Textual Data Collection

The first stage regards the identification and selection of the proper social media platform and influencer affiliates to focus on. Influencer affiliate marketing programs have flooded social media platforms that foster influencer-follower interactions through interactive content, like TikTok, YouTube, or Instagram. The analyst can focus either on one single platform or more simultaneously, as affiliate marketing campaigns are often performed on multiple platforms. Similarly, the analyst can decide whether to focus on the content related to one specific campaign and influencer, or multiple ones at the same time. The selection of a specific platform also involves some technical considerations regarding how to collect large volumes of brand-related textual data online. Indeed, analysts can do so in three ways: calling an Application Programming Interface (API), web scraping, or accessing online archives offered by external providers.

APIs are "*a set of rules that allows programmers to develop software for a particular operating system without having to be completely familiar with that operating system"* (Merriam-Webster). In more trivial words, an API puts in place a means for two software to communicate to each other, enabling the calling machine to exploit some functionalities (for example, retrieving data) embedded in the called machine without the need to operate directly on this latter. Given the fact that APIs provide access to potentially sensitive data, their use is often governed by strict security requirements restricting the type of data that can be retrieved, the number of calls launched per session, and the temporal and/or geographical extent of the data collection. To allow and control the use of an API, its developer thus grants the access only to other software or apps developers which firstly authenticated themselves of the API's platform using an API key or OAuth token. The advantages of APIs lie in the fact that they are relatively user-friendly and their usage for non-commercial purposes is generally granted for free. However, if till a few years ago the use of API was proliferating and getting mainstream also in non- computer science research given the availability of these gateways to big data, in the aftermath of online privacy scandals and data breaches like Cambridge Analytics many social media companies curtailed APIs, making it harder and harder to conduct digital research (Caliandro, 2021).

This can lead the analyst to employ the second online data collection method, that is web scraping, i.e. the automatic extraction of structured information from unstructured sources on the web (Boegershausen *et al*., 2022). The logics underpinning scraping is to exploit a preexisting socio-technical infrastructure of the online sources that the analyst wants to retrieve relevant information from – the most common being the HTML structure of the websites – and look for specific identifiers associated to the desired data on the website. Scraping dramatically enhances the relevance of big data online, which per se are noisy and unfocused. Though, compared to the use of APIs, it is not as user-friendly, especially for researchers lacking coding skills. The analyst doesn't need to only know how the source to be scraped is structured (e.g. the general rules used in HTML), but also be able to interpret how these changes from website to website and customize the scraper accordingly. Moreover, from an ethical and oftentimes legal perspective, web scraping is framed as an ambiguous activity, as it may lead the analyst to breach the data privacy and security policies of the target online source. For this reason, website and online platforms have begun to intensify domain protection protocols via data blockades, making the use of scrapers oftentimes problematic. One last convenient option is to resort to the online archival and monitoring services provided by external content marketing platform such as CrowdTangle (www.crowdtangle.com) and BuzzSumo (www.buzzsumo.com), which provide multi-platform interfaces able to return the most relevant influencers data for target domains or keywords. Once the analyst identified the target influencers, the social media platform, and gathered enough textual data through APIs, scraping, or archival sources, it is time to delve deeper into the influencer-follower interactions.

4.3.2. Stage 2: Spotting Compliant and Deceptive Influencers

The second stage concerns spotting who is a compliant influencer against who instead is a fraudster. To do so, brands can follow the digital traces that fraudsters leave behind online. Some of these "red flags" can be manually checked, e.g. examining the influencers' accounts to check for missing information in the bios, strange or misspelt usernames, and geographical locations far away from the actual market served. However, in a big data environment, a sounder strategy is to implement automated CATA approaches to detect frauds. We specifically focus on two of them: *advertising disclosure* and *consumer social media engagement analysis*.

The aim of advertising disclosure analysis is to tell regulation-compliant content creators and fraudsters apart by mapping the presence of affiliate disclosures in endorsed content through processes that count the presence (or absence) of disclosure statements. The analysis proceeds along two steps. First, the analyst performs preliminary content inspection of the textual data gathered, looking for textual patterns through which affiliates disclose the nature of their partnership (e.g., "*I can receive commission if you click on this link*"), aided by keyword-in-context analysis (Luhn, 1966). In this way, the analyst proceeds to build up what is called a custom dictionary, that is a textual list containing recurring affiliate link, channel-support, and explanation disclosure statements, or a regular expression ("regex") able to match them. Second, once validated, these dictionaries and rules are processed by word-count software, like LIWC (http://liwc.wpengine.com), Provalis Research's Wordstat (www.provalisresearch.com)Gate (www.gate.ac.uk), to check the presence of disclosure statements in the areas of the entire influencer-generated textual data supposed to contain affiliate links, e.g., YouTube video descriptions sections or Instagram and TikTok content captions. In this way, the analyst can determine which affiliate is compliant with online advertising regulations.

The second fraud detection analysis involves the systematic assessment of the consumer engagement generated on the social media platform. Consumer engagement is a multi-dimensional phenomenon of particular interest to brands and marketers due to its predictive power on consumer and firm outcomes (de Oliveira Santini *et al.*, 2020). In social media contexts, it is commonly operationalized and tracked through the accumulated volume of likes, comments, and shares that a specific brand-related content records. Different types of influencers are characterized by different follower bases and different engagement relationships (Campbell and Farrell, 2020; Britt *et al.*, 2020). Thus, analysts can control whether consumer engagement is aligned with expectations in terms of two dimensions: volume and variety.

- *Volume*: given that influencer affiliate fraudsters inflate their engagement metrics through, among other, sock-puppets, bots and pods, they hardly create sustained engagement interactions in terms of volume of likes, favorites, and comments with their audiences. Therefore, spikes in followers counts reached overnight should represent a first alarm signaling the presence of a fraudster, along with distribution of engagement metrics that differ too much from the ordinary, or followers-to-engagement ratios too large given the actual size of the influencer's network. These can be analyzed with several statistical and CATA techniques, like gaussian-curve analysis, with suspicious outliers falling far away from the CSME median representing potential bots; by computing followers-to-engagement ratios, or directly testing the influencers' contents ability to generate CSME via regression models analysis, with fraudster showing on average lower levels of engagement per followers; or finally by assessing the position held by the influencer in ego engagement networks (e.g. reply or mention networks) through Social Network

Analysis, with fraudsters holding more peripherical roles given the fake nature of their interactions with followers

- *Variety*: analysts should also consider the affective and semantic variety of consumer engagement interactions. In other words, the *actual content* of the user-generated comments. For instance, Micro-influencers tend to build and maintain more intimate connections with their followers, engaging in considerably more two-way and personalized interactions than their Mega counterparts (Britt *et al.*, 2020). For example, the comments generated by pod groups tend to be very generic and decontextualized, like low-informative emojis ("🔥") and very generic comments ("*love this*"). Such textual patterns can be automatically identified through topic discovery algorithms like topic modeling and traced back to the creators they are associated with. Luckily, to perform these analyses, the analyst does not necessarily need an in-house data science function. Today both commercial (like Provalis Research's Wordstat [www.provalisresearch.com], MeaningCloud [www.meaningcloud.com], and Leximancer [https://www.leximancer.com]) and non-commercial Software-as-a-Service providers (like Knime Analytics [www.knime.com] and RapidMiner [www.rapidminer.com] text mining extensions) offer point-and-click, visual programming platforms to perform CATA without any kind of coding requirement, making it easier to include these tools in business intelligence operations.

4.4. An Illustration: Influencer Affiliate Analysis on YouTube

The next section shows how the protocol illustrated above can be practically performed with real influencer affiliate data. We selected eight popular content creators operating in two industries where affiliate marketing is a predominant advertising strategy (beauty and cosmetics and consumer software) for the analysis. Then, we proceeded with the two-stage protocol. First, we decided to focus on YouTube. To collect the data, we called YouTube

Data API v3 first from the Youtube Data Module provided by the Digital Methods Initiative[19]. Starting from the eight channels owned by each content-creator, we obtain a tabular file containing the URLs of all the videos published on each channel along their metadata. Then, we enrich this file reaccessing the API from "youtubecaption" R package (Seo and Choi, 2020) to retrieve the transcripts of each affiliate's video by exploiting the subtitles. This enabled us to create a dataset where each row corresponds to one of the 3,212 videos posted overtime by the content creators, and each column contains textual data about the videos and the related engagement metrics (Table 13). Then, we create a second dataset starting from the same video list and retrieving from "vosonSML" R package (Graham *et al.* 2020) the UG comments posted below each video. Next, we applied advertising disclosure and consumer social media engagement analyses to identify compliant and fraudster influencers.

Category	Videos	Views	Net likes	Comments	Duration (sec)
Beauty	1,577	477,863 (893,199)	19,091 (30,517)	1,496 (2,282)	737 (382)
deceptive	*625*	*818,534 (1,213,799)*	*31,964 (37,593)*	*2,422 (2,636)*	*749 (361)*
compliant	*952*	*254,208 (478,609)*	*10,569 (20,825)*	*790 (1,652)*	*730 (395)*
Software	1,735	181,271 (442,802)	5,214 (13,083)	258 (555)	735(469)
deceptive	*811*	*245359 (532,603)*	*8,797 (16,997)*	*302 (455)*	*803 (584)*
compliant	*924*	*125021 (335,620)*	*2,070 (6,912)*	*219 (627)*	*676 (327)*

Table 11: Number of videos collected, and mean engagement metrics (SD).

After data collection, before proceeding with the next stages, we preprocessed the YouTube textual data. Pre-processing is a fundamental step in CATA, as its performance is highly impacted by the degree of structure and consistency of the textual input data (Humphreys and Wang 2018). We performed common steps in the field, namely:

[19] https://tools.digitalmethods.net/netvizz/youtube/mod_videos_list.php

1. Applied language identification algorithms and retained only English text (Ooms, 2020);
2. Substituted internet slang (e.g., “NV” with “nevermind”, “YOLO” with “you only live once”) through the lexicon R package (Rinker, 2018);
3. Substituted emojis and emoticons with their descriptions with the emoji sentiment ranking v1 provided by Novak *et al*. (2015);
4. Tokenized at word level;
5. Normalization word (i.e., lowercasing and spelling);
6. Removed punctuation, symbols, numbers, and English stopwords (marimo);
7. Pruned and trimmed the comments corpus, conservatively removing features with absolute frequency lower than 10, and that occurred in less than 5% of the documents or in more than 95%.

To tell authentic and false influencers apart, we then applied some of the CATA approaches illustrated above: a top-down content analysis for checking the presence of advertising disclosures; a regression analysis on CSME; and finally a semantic analysis of CSME through topic modelling.

As for the first analysis, we created a script containing words and sentences expressing affiliate disclosures and applied it to the description section and to the transcripts of the YouTube videos. This allowed us to identify the videos from compliant (1,848) and deceptive (1,465) influencers, whereby compliant affiliates are those writing or mentioning an affiliate disclosure in their content. For the consumer engagement analysis, we firstly analyzed the volume of consumer engagement generated by the two types of affiliates with regression analysis. A dummy indicating the affiliate influencer type (compliant vs deceptive) based on whether the video included an affiliate disclosure or not served as independent variable, along with other relevant control variables suggested by the literature (e.g., Munaro *et al.* 2019), namely, the complexity, length, and type of content, measured respectively via words and prepositions count, duration of the videos, and YouTube tags and video category associated. Consumer engagement, operationalized as the sum of views, net likes, and comments count, served as the dependent variable. Table 14 shows the descriptive statistics.

Variables (*N*: 517)		Mean	SD	Min	Max
Duration (sec)		694.841	217.414	60	1600
Complexity	Word Count	1919.368	661.696	1	5508
	Prepositions	12.019	1.625	0	15.47
Tags count		33.753	15.709	0	63.125
CESM		10020.89	9210.85	0	69851.86

Table 12: Disclosure omission analysis: descriptive statistics.

A negative binomial regression was run on weekly-aggregated data. Figure 4 shows the effects of these variables on the log count of consumer engagement as well as their significance, indicated by the error bars. As the coefficient of compliant influencer is significantly higher than that of their deceptive counterparts, keeping the effect of control variables constant, the regression analysis confirms that compliant content creators are able to generate more volume of consumer engagement than deceptive ones.

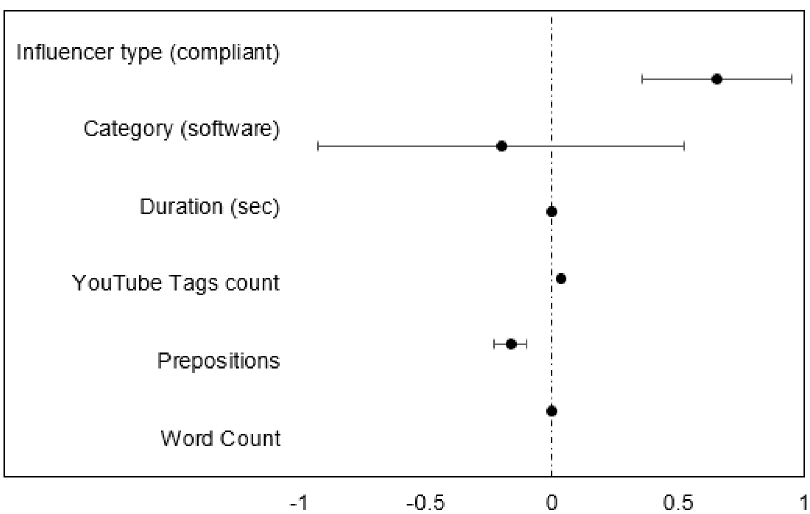

Figure 11: Effects of affiliate influencer type and controls on CESM.

Note: McFadden's Pseudo R^2: .016; AIC: 10.215; N: 517. Black lines represent error bars.

Finally, we further analyzed the variety of consumer engagement triggered by the two types of content creators by performing an automated detection of the topics discussed by their followers in about 300,000 unique comments left below the videos. We applied an extension of the Latent Dirichl*et al*location topic modeling algorithm that can take into account the same regressors used for the previous analysis (namely, structural topic model, Roberts *et al.* 2019). We then statistically tested whether the identified topics are more or less strongly associated to the type of content creators. We identified 11 unique topics discussed by users in reaction to the videos which were interpreted and labelled based on their most probable words (Figure 17) and most representative comments. The results of this analysis allow the analyst to disentangle with more granularity the variety of consumer engagement the content creators are able to elicit on the platform. Figure 18 shows how prevalent each of the 11 topics identified is among the comments left below the videos of the two types of influencer affiliates, which lay at the two sides of a continuum. Clearly, compliant content creators generate more engaged reactions then their counterparts. For example, followers are likely to express "gratitude", thanking the influencers for their contents (e.g. "*Wow, thank you so very very much, this is something I was in the need of for some years, thank you*!") or share engaged "suggestions" about the products being advertised (e.g. "*I have all three 2 Pro, Air 2 and Mini 2. All three are good for the distance at 10km. But the 2 Pro is the best…*"). Conversely, prevalent among the comments to the videos of deceptive content creators are very cold topics that share deal-oriented tones (e.g. "How do contributors to free sites get rewarded?"; "use my links please!" [topic "links"]) or very generic ones, typical of pods communities ("love it", "OMG" [topic "generic"]).

Figure 12: Wordclouds of high probability words (selected examples: a) topic *gratitude*; b) topic *links*).

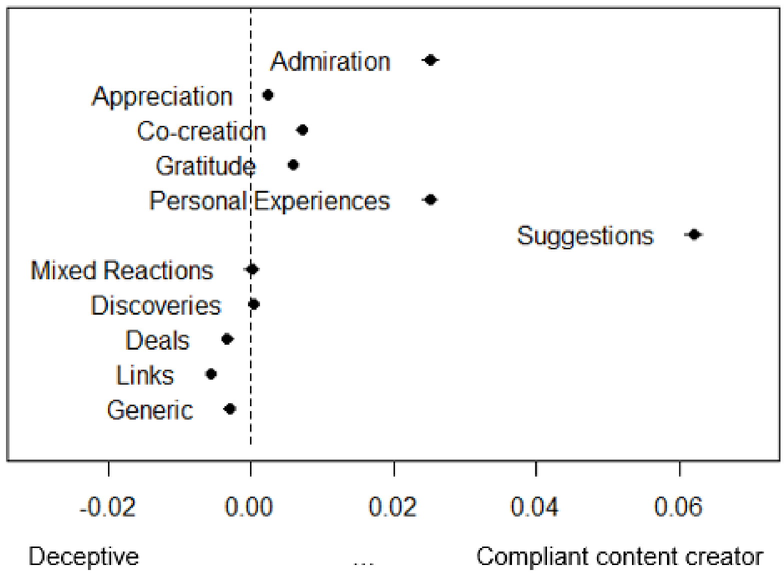

Figure 13: Prevalence of consumer discussion topics, by affiliate influencer type.

The illustrative case shows that CATA can be used to build straightforward but predictive protocols that can help brand managers to identify and prioritize affiliate influencers by analyzing in a big-data-friendly way the relationship between their contents and consumer engagement. Although more complex protocols and models are available, relevant signals and trends that should sound an alarm regarding the presence of deceptive behaviors in online brand-related contexts can be quickly and automatically grasped already through these CATA. In particular, by using this protocol, we discovered that compliant content creators stimulate more engaged reactions in their followers, who not only show appreciation and gratitude for the influencer's activity but are also engaged more in meaningful brand- or product-related discussions. On the other hand, the engagement stimulated by deceptive content creators likely comes from pods communities, is less authentic, and more oriented towards exploiting community-based mechanisms in the affiliate environment. Even if in this illustrative case we focused on the comparison of two relevant groups of affiliate influencers, the same approach can be easily adapted for other affiliate management analyses illustrated in this paper, such as the detection of overnight spikes in followers count by including time variables in the CATA. In the same vein, the proposed techniques are able to spot fraudulent activities enforced by any scale influencers.

4.5. Listen, Act, And Repeat

In an ever-more content-driven digital economy, affiliate marketing programs present real and florid opportunities for brands to reach consumers in new, meaningful ways. As the size of e-commerce is steadily growing, so are revenues from and investments in affiliate marketing (CHEQ Report, 2021). Relatedly, affiliate partnerships represent a key monetization source for social media influencers of all sizes (Enberg, 2021). As a matter of fact, just recently the leading social media platform Instagram launched a native affiliation tool that allows users to include affiliate links into their stories, and sell their merchandise (Instagram, 2021). Therefore, brand managers should be proactive in their approaches to these digital marketing tools, seizing the vast opportunities they offer. This, first and foremost, entails being able to protect the brand from the different types of deceptive behaviors that both influencer and non-influencer affiliates put in practice online. To effectively manage their brands in an era of increasing falsity, we suggest that brand managers should follow the “Listen, Act, and Repeat” guideline. By listening to specific indicators relative to online traffic (such as bounce rates, shopping cart abandonment, spikes in clicks and low conversions), as well as to the affiliates’ online activities (such as volume and variety of consumer engagement generated) managers not only will get a more meaningful understanding of their digital marketing dynamics and performance, but will also disentangle potential frauds from deceptive affiliates in short time. Not all frauds are created equal, and thus recognizing in which domain of affiliate falsity a brand is eventually trapped allows to fine-tune the most proper copying strategies. Also, systematically monitoring the affiliates activity is pivotal to keep the brand under control and prevent cost and reputational damages from escalating. Though, this should be done without hampering the partners' ability to create content freely and creatively. Among the different tools and techniques that brands have at their disposal to analyze the influencer affiliate ecosystem, CATA approaches precisely allow monitoring in almost real-time, but without being intrusive. By adopting the protocol we propose in this article, marketers can also develop a profound knowledge of their influencer affiliates and be able to select the compliant ones, amplifying the reach of the brand, opening more market opportunities, and protecting themselves from being associated with deceptive affiliates. Finally, and most importantly, this whole process should not be intended as exclusive and one-shot, as the various monitoring solutions should be applied in parallel and constantly to protect brands more efficiently.

Conclusions

Despite social media platforms being one of the most emblematic technological – but not strictly so (Appel *et al.*, 2020) – ecosystems of our age, and academic research investigating its complex nature flourishing, various conceptual, methodological as well as empirical questions remain unanswered, prompting the necessity of investigating the evolving landscape of marketing communication and advertising in such ecosystem even further (Li *et* al., 202; MSI, 2020; Voorveld, 2019). This work was precisely aimed at contributing to fill gaps that revolve around three main trends occurring at the societal, brand-consumer, and platform level of the social media ecosystem. In doing so, we contend that the three original essays included in this work contribute, to different extents, to both marketing theory and practice. At the same time, investigating only indirectly some phenomena and dynamics and being structurally constrained by some limitations, these studies also inspire future research in this field. We present contributions and future research avenues next.

The first essay (Chapter 2), through the examination of how the rhetorical appeals adopted on Twitter by brands evolved during the Covid-19 pandemic, offers a twofold contribution. First, by means of what, with hindsight, could be acknowledged as a unique natural experiment, this study helped solving the puzzling dilemma about whether and how brand should adapt their communication during "black swan" crises (Taleb, 2007). Previous crisis communication theorists indeed focused on, and offered guidance about, somehow "narrower" types of crises, which in other words regarded either single products, like in the case of product harm crises (Yuan *et al.*, 2020), or single brands, like in the case of brand scandals (e.g., Humphreys and Thompson, 2014), or, in the widest configurations, single industries or single markets (e.g., Corciolani, Gistri, and Pace, 2019; Piazza and Perretti, 2015). Additionally, even when previous literature investigated communication dynamics unfolding in the context of exogenous crises, their focus was placed on more or less "restricted" crises, such as acute natural disasters (like the 2012 Hurricane Sandy [Spence, Lachlan, Lin, and del Greco, 2015] or the 2013 Colorado floods [Li and Yu, 2020]). The case of the Covid-19-induced crisis was inherently different. It represented an exogenous crisis of global scale, which did not hit a single, or a narrow set of market actors, but rather the entire global economic system at almost the same time. Thus, the seminal response strategies prescribed by the situational crisis communication theory's paradigm (SCCT; Coombs, 2007) offered poor support, as they can be implemented only once the brand's initial crisis responsibility, the crisis history, and the brand's prior relational reputation are identified (2007:166-167). Of these key factors, only prior relational reputation could be accounted for in a context such as a global pandemic[20], which indeed had no precedents at all (thus, no crisis history could be detected), and for which brands cannot be blamed in the first place (thus, brands' initial responsibility could not be found as well). As a matter of fact, despite covid-19 pandemic being to all effects a natural disaster, thus falling in the crisis cluster characterized by weak attribution (i.e., the "victim" cluster; Coombs, 2007:168), our study shows instead that undertaking traditional strategies - like "victimage", "justification" or "scapegoating" - would have turned out to be not as effective as the original "social pathos" strategy instantiated by brands conversely was. In addition, even though extents of "rebuild" crisis response strategies (for example, in the form of "economic recovery" topics) were found, they tended to occur in later stages of the pandemic, thus giving a central role to more social sensitive response strategies. In this vein, our study thus contributes to SCCT, by pointing out a novel crisis response strategy that was not investigated earlier. Future studies can empirically test whether this peculiar crisis response strategy works best also for other types of crises, as well as in other contexts. Moreover, despite the rhetorical strategy that we labelled as "social pathos" permeated also other media different from Twitter (Hesse et al., 2021; Sobande, 2020), we argue that the specific technological affordances of this social media platform could have likely played an important role in spreading such novel appeal. Thus, future studies can dig deeper into the algorithmic influence of specific social media platforms in constraining or enabling rhetorical evolutions during similar circumstances. Second, this essay contributes to the broad academic field grounded on institutional logics (Thornton *et al*., 2012). Field theorists indeed prescribes that one a field is shaken by

[20] Indeed, we do so in the second essay, by including brand stereotypes from the BIAF as moderators of the effect of social pathos on CESM.

exogeneous forces - such as the global covid-19 pandemic- dominant institutional logics are very likely to undergo a deep modification (Fligstein and McAdam 2012) and, therefore, also the rhetorical vocabulary through which the logics are instantiated is expected to change (Tracey 2016). As a matter of fact, our study precisely monitored this process, providing empirical evidence of a relevant and prolonged linguistic change in the brand communication posted on Twitter over the period investigated. However, our results seem to also provide a different picture on institutional logics dynamics. If institutional theorists contend that firms have a natural tendency to disaply organizational isomorphism overtime (DiMaggio and Powell, 1983). Still, in this instance our results seem to provide a different picture, we somehow differently found that especially in phase two, when the dominant logic was shattered and uncertainty was at its highest, brands tended to converge, communication wise, on adapting the same rhetorical appeal (that is, *social pathos*), with very few differences among industries. In other words, isomorphism took place almost immediately, whilst institutional complexity, materialized through different communication choices, took place in the immediate aftermath of this crisis peak period, as the outcome of loose institutional boundaries. These counterintuitive results offer indeed a novel perspective on institutional change, based on which we thus contend that whenever the change is particularly abrupt - as in the case of exogenous crises- we should expect an initial form of intra-field isomorphism performed by field actors as a copying mechanism, followed by the presence of different and contrasting logics only in a subsequent moment. Future studies could focus on this specific step of this dynamic, providing a finer-grained explanation of the shift from “temporary” dominant logic to subsequent institutional complexity.

The second essay (Chapter 3), by investigating the effectiveness of woke brand communication on social media from LET and BIAF perspectives, offers several contributions as well. First, it advances the emerging body of research focused on woke branding and advertising, by expanding the debate beyond the inquiry of whether it is beneficial or not for a brand to be woke, and indicating for which type of brand is best to pursue, or to avoid, such communication strategy. In particular, it does so without framing the management of a woke campaign in somehow vague terms of authenticity lack (Thompson and Kumar, 2022; Nunes *et al*, 2021), but rather resorting to more operational references (namely, warmth and competence stereotypes), which can be strategically and purposefully monitored by brands and practitioners. In this vein, it could be interesting for future research to investigate how concepts and constructs closely related to the elements of the BIAF, like brand personality and brand emotions (Ivy *et al*., 2015), relate to brand woke communication effectiveness on SM. Second, it contributes also to the CESM body of literature, shedding lights on an overlooked transformational content-level CESM factor, and importantly proving and all-encompassing picture of CESM behaviors, that is not just based on volume and variety, but also on the semantic nature of UGC (Unnava and Aravindakshan 2021; Swani and Labreque 2020). Monitoring CESM also through the inspection of the actual consumer discussions, as scholars have recently started to emphasize (Swaminathan *et al*., 2022), has a strong managerial implication, which corroborates an old (and often unheeded) warning put forth by computational scientists which warn against an acritical use of off-the-shelves digital marketing analytics (Grimmer and Stewart 2013). In the run towards data-driven, easy-to-implement services, practitioners run the risk of overlooking the fact that metrics taken out of their context can be highly unrepresentative of what's actually happening in the conundrum of big data, and thus of backing their decisions on misleading inferences (Hayes et al., 2021). As we show, this can be prevented if semantic dimensions of CESM are taken into consideration. Third, this study contributes to the similarly recent debate about brand polarization (Osuna Ramirez et al., 2019), pointing out that, differently to shared views (Mafael et al 2016; Luo et al 2013), polarization is not always a deliberate and manageable choice for brands and brand managers. As for avenues for future research in these directions, even though we discovered something more about which brands should better communicate divisive cues such woke-related ones, but much has to be discovered at the individual consumer-level. Future research, relying for instance on experimental research designs, could explore the socio-cognitive factors and personality traits most likely associated with consumers reactions towards such brand communication on social media.

Finally, the third essays (Chapter 4), by surveying and characterizing various ways through which affiliate marketing programs are affected by deceptive behaviors, and by proposing and showing a two-stage affiliate listening protocol, it offers both conceptual and practical guidance on how to differentiate and handle *non-influencer* and *influencer* falsity by leveraging on affordable but effective procedures. Since false behaviors and deceptive activities evolve as the technology evolves (Di Domenico *et al*., 2020), future studies are needed to update and expand our original categorization by including novel deception techniques – as well as proper countermeasures – in the domain of affiliate marketing programs. In addition, since the illustrative case focus on disclosure omission and CESM analysis on YouTube content, future studies could test the applicability of the described protocol also in other social media platforms, like Instagram and Facebook, where disclosure statements are included in more subtle ways.

All in all, the studies included in this work lend empirical support the idea that social media platforms cannot be interpreted, and studied, as mere broadcasting media. Rather, we should better acknowledge their central role of enablers of the participatory digital culture (Jenkins, 2009). In particular, from the perspective of brand communication, resorting to McLuhan's lesson we can contend that social media should be managed, to all extents, as "warm" media, meaning that the features and logics of both "hot" and "cool" media (McLuhan and Fiore, 1967) must be purposefully balanced. Indeed, on one hand brands and brand managers should systematically plan, implement, and monitor social media content in a top-down and controlled manner in order to avoid a loss of control which can finally hamper brand identity, reputation, and equity; on the other hand, they should at the same time empower their consumers, by granting enough room for interaction, expression, and co-creation within this ecosystem.

Appendices

Appendix 1 - List of brand official X accounts investigated, by industry.

Automobile	**Fashion and Beauty**	**Banking and Finance**	**FMCG**	**Retail**
AudiIT	armani	BancaMediolanum	Barilla	Bennet_official
BMWItalia	CollistarBeauty	GeneraliItalia	BirraPeroniNews	CarrefourItalia
citroenitalia	dolcegabbana	intesasanpaolo	CocaColaIT	Conad
Fiat_IT	Elena_Miro	UniCredit_IT	lavazzagroup	Coopitalia
forditalia	Fendi	**Travel and Tourism**	Nutella_Italia	cortilia
JaguarItalia	Ferragamo	Alitalia	PassioneCirio	EuronicsItalia
JeepItalia	KikoMilanoIT	AlpitourWorld	theonlyparmesan	EurospinItalia
MercedesBenz_IT	lorealitalia	best_westernITA	**Pharmaceutic**	GruppoSelex
MINI_Italia	Luxottica	costacrociere	AbbVieItalia	LidlItalia
Nissanitalia	MaisonValentino	lonelyplanet_it	AlfasigmaSpa	Media_World
OpelItalia	myrinascimento	MSC_Crociere	BayerItalia	Nova_Coop
peugeotitalia	Prada	nhhotelsit	EliLillyItalia	quomi_it
renaultitalia	SephoraItalia	presstours	JanssenITA	TronyOfficial
SEATItalia	zarait	TripAdvisorIT	msdsalute	UnieuroNews
smart_Italia	Zegna		NovartisItalia	
SuzukiIT			RocheItalia	
toyota_italia			SanofiIT	
Volkswagen_IT				

Appendix 2- Top 10 hashtag ranked by betweenness centrality (BC) vs normalized importance (NI) index – across phases.

	PHASE 1			
	hashtag	**BC**	**hashtag**	**NI**
1	#bestwestern_ita	4114.33	#natal	2.300495
2	#natal	4082.449	#trevis	2.204847
3	#suzuk	2646.064	#bestwestern_ita	2.045825
4	#trevis	2526.535	#unicredit	1.703967
5	#unicredit	2315.195	#natale2019	1.594547
6	#sostenibil	2039.115	#hotellif	1.479094
7	#mil	1952.007	#mil	1.450806
8	#palerm	1516.844	#sostenibil	1.434697
9	#ricerc	1448.232	#visititaly	1.39335
10	#hotellif	1037.144	#palerm	1.294923
	PHASE 2			
	hashtag	**BC**	**hashtag**	**NI**
1	#covid19	6019.619	#covid19	2.509058
2	#iorestoacas	3750.12	#iorestoacas	1.996966
3	#covid_19	1473.232	#covid_19	1.603963
4	#gdo	1089.332	#covid19ital	1.362254
5	#insiemecelafarem	921.8024	#covid	1.207525
6	#covid19ital	698.8476	#gdo	1.17467
7	#19marz	666.3435	#unicredit	1.130667
8	#covid	654.2286	#ital	1.096955
9	#bancamediolanum	581.9763	#andratuttoben	1.093944
10	#unicredit	564.8066	#insiemecelafarem	1.053661
	PHASE 3			
	hashtag	**BC**	**hashtag**	**NI**
1	#covid19	7009.173	#covid19	2.520722
2	#sostenibil	1868.805	#sicurezz	1.757676
3	#sicurezz	1473.137	#sostenibil	1.612134
4	#viagg	1325.635	#viagg	1.570144
5	#unicredit	1128.59	#innov	1.495972
6	#innov	1033.216	#spes	1.400083
7	#iorestoacas	1023.616	#unicredit	1.378189
8	#fase2	901.923	#sal	1.255326
9	#spes	708.2185	#fase2	1.249099
10	#torin	665.1151	#covid	1.245829

Note: Normalized degree Importance (NI) is computed as the geometric mean of each node's closeness, normalized degree, betweenness centrality, eigenvector centrality and clustering coefficient (Sainaghi and Baggio, 2014).

Appendix 3- Rhetorical appeal usage, among industries (Games-Howell comparisons).

Logos				**Games-Howell Comparison** (differences)					
Industry	*N*	*μ*	*σ*	Fashion and Beauty	Banking and Finance	FMCG	Retail	Pharma	Travel and Tourism
Automobile	212	.038	.002	-.020**	.082**	-.0173**	.0228**	.014	-.010
Fashion and Beauty	201	.017	.001		.103**	.003	.043**	.035**	.009
Banking and Finance	177	.120	.006			-0.09**	-.059**	-.068**	-.093**
FMCG	202	.020	.002				.040**	.031**	.006
Retail	211	.060	.002					-.008	-.033**
Pharma	213	.052	.001						-.025**
Travel and Tourism	213	.027	.002						

Positive Pathos									
Industry	*N*	*μ*	*σ*	Fashion and Beauty	Banking and Finance	FMCG	Retail	Pharma	Travel and Tourism
Automobile	212	.15	.002	- .021*	- .010	-.036**	-.006	.003	-.013
Fashion and Beauty	201	.128	.004		.011	-.014	.015	.025**	.008
Banking and Finance	177	.139	.002			- .026**	.003	.013*	-.003
FMCG	202	.113	.001				.029**	.040**	.023**
Retail	211	.143	.002					.010	-.006
Pharma	213	.153	0.002						-.017*
Travel and Tourism	213	.136	0.001						

Negative Pathos									
Industry	*N*	*μ*	*σ*	Fashion and Beauty	Banking and Finance	FMCG	Retail	Pharma	Travel and Tourism
Automobile	212	.017	.001	-.002	0.005*	-.004	.004	.049**	.0007
Fashion and Beauty	201	.014	.000		.008**	-.001	.007	.051**	0.003
Banking and Finance	177	.023	.000			-.010**	-.001	.043**	-0.005
FMCG	202	.012	.000				.009**	.053**	.005
Retail	211	.021	.000					.044**	-.003
Pharma	213	.066	.001						-.048**
Travel and Tourism	213	.017	.000						

Social Pathos									
Industry	*N*	*μ*	*σ*	Fashion and Beauty	Banking and Finance	FMCG	Retail	Pharma	Travel and Tourism
Automobile	212	.0553	.003	-.030**	.0003	.010	.002	.003	-.005
Fashion and Beauty	201	.0252	.001		.030**	.040**	.0328**	.033**	.024**
Banking and Finance	177	.0557	.001			.010	.002	.002	-.005
FMCG	202	.0658	.002				-.007	-.007	-.015*
Retail	211	.0579	.002					.0006	-.007
Pharma	213	.0585	.001						-.008
Travel and Tourism	213	.0501	.002						

Ethos									
Industry	*N*	μ	σ	Fashion and Beauty	Banking and Finance	FMCG	Retail	Pharma	Travel and Tourism
Automobile	212	.0793	.002	-.0292**	.014*	-.017*	.006	.016*	-.018**
Fashion and Beauty	201	.05	.002		.044**	.0113	.035**	.045**	.010
Banking and Finance	177	.094	.001			-.032**	-.008	.001	-.033**
FMCG	202	.0615	.002				.024**	.034**	-.0008
Retail	211	.0859	.003					.010	-.025**
Pharma	213	.096	.002						-.035**
Travel and Tourism	213	.0608	.001						

Note: * $p < .05$ ** $p < .001$. All other values are significant at 95%.

Appendix 4- Supplemental material: "Unpacking brand communication on social media through top-down and bottom-up text-mining".

In collaboration with Giuseppe Pedeliento (University of Bergamo) and Daniela Andreini (University of Bergamo)[21].

Project Overview and Context

The study presented in this research method case was conducted as part of wide-ranging brand monitoring and social media (SM) listening research project conducted at the Department of Management of the University of Bergamo (Italy). The research started as the Covid-19 pandemic began to severely hit Italy, during the first weeks of 2020. The project monitored how Italian brands across various industries coped, communication-wise, with this socio-sanitary and economic crisis, and how consumer's perception of brands changed, through a large-scale analysis of brand-generated (BGC) as well as user-generated content (UGC) published in social media platforms. In particular, the specific study discussed in this research method case was aimed to understand whether, and to what extents, Italian brands modified their communication on Twitter as well as to identify which was the most effective communication strategy during an unexpected and exogenous crisis. The research resulted in the publication of a paper in the pages of the Journal of Advertising (Mangiò, Pedeliento, and Andreini, 2021). Although the literature on crisis communication (Coombs, 2007) and brand communication on social media is fertile (Voorveld, 2019), extant research lacks sufficient empirical evidence to advise brands on how they should adapt their advertising and communication efforts to stay relevant and to keep consumers engaged in times of unprecedent uncertainty and turbulence. Against this background, we designed and conducted a text-mining study to address two research questions that are, respectively, inductive and deductive in nature: How and to what extent has brand communication on

[21] Published in different version in *Sage Research Methods: Business* (Mangiò *et al.*, 2023b).

social media changed during the pandemic? How did the different persuasion appeals the brands employed affect consumer engagement on SM? Given these research questions, and the timeliness of the phenomenon under investigation, conducting a mixed method study which included both top-down (i.e. deductive) and bottom-up (i.e. inductive) text mining approaches represented the most appropriate research method. The combination of inductive and deductive methods allows in fact to investigate large volumes of unstructured textual data quickly and reliably, to boost the study's ecological validity, and to explore new phenomena for which conventional dataset are not yet available. In particular, top-down dictionary and rule-based analysis allowed to test which rhetorical appeals working in traditional communication contexts (Aristotle and Roberts, 2004) would be effective also in this novel crisis context; bottom-up hashtag network analysis, instead, allowed to explore the brand communication evolution as it unfolded via an interpretivist epistemological approach, and to adapt the theoretical framework to the specific contingencies of the investigated context.

Section Summary

- The key goal of the study was to unveil if, and the extent to which, brand communication on social media changed during an exogenous crisis such as the Covid-19 pandemic, and to shed light upon how brands should best communicate to remain resonant towards their online audiences.
- Due to large-scale volume and due to the unstructured nature of the textual data, a text-mining approach was chosen.
- A bottom-up approach consisting of hashtag network analysis was employed to carry on the inductive phases of the study; a top-down approach consisting of dictionary and rule-based methods was employed for the deductive phases of the study.

Research Design

As previously mentioned, this study was aimed at understanding how and the extent to which the pandemic led to changes in the way in which brands communicate on social media, and to understand whether the different persuasion appeals the brands employed during the pandemic affected consumer engagement on social media. To fulfil these aims a three-stage analytical procedure encompassing different text-mining techniques was implemented.

In their seminal book, Ronen Feldman and James Sanger define text mining as a "knowledge-intensive process in which a user interacts with a document collection over time by using a suite of analysis tools […] to extract useful information from data sources through the identification and exploration of interesting patterns" (2006:1). Despite its origins are traced back to the first half of the 20th century with early implementations of automated content analysis, text mining evolved thereafter boosted by methodological advancements in fields like computational linguistics, statistics, and Natural Language Processing (NLP). Regardless of its origins, text mining has been always aimed at reaching one specific goal: transforming unstructured text into structured information, which can then be processed with traditional research methods to distill knowledge. Thus, it is somehow commonsensical to note that the adoption of text-mining has intensified precisely in the last decades, concurrently with the ever-greater supply of unstructured data unleashed by the big data deluge. Indeed, text mining does not include one single specific technique but it covers an expanding family of techniques which vary in scope, task, and complexity, and include, among others, information extraction, sentiment analysis and opinion mining, topic modeling, and text clustering. Text mining techniques do not deal merely with language and text per se. Rather, they help unravel the cognitive, behavioral, and cultural meanings that are more or less explicitly implicated in the production of textual data. Differently stated, text mining techniques allow to make the very cognitive, behavioral, and cultural structure that underpin the way social actors interact visible. Accordingly, text mining can be thus used to answer questions aimed to advance heterogenous knowledge domains, ranging from psychology to marketing, from political science to media studies. Indeed, also brands and practitioners have recently begun to include text-mining techniques among their marketing intelligence routines to monitor their brand reputation, listen to their audience's sentiment, and map the competitive arena (Brunzel, 2021). Though, text mining should not be considered a silver bullet. It is particularly helpful when observational data represent the most natural way to study a phenomenon, to measure linguistic changes over time, and to perform group comparisons. Conversely, it should not be preferred to other methods when inferential causation related to psychological mechanism or nuanced meanings, such as irony, are the focus.

In our study, the analytical procedure included the following stages which are typical of text-mining research designs:

1. Data collection, comprising source selection, data sampling, and extraction;
2. Data wrangling and corpus pre-processing;
3. Data analysis, via text-mining top-down and bottom-up approaches.

The overall goal of this procedure was to allow the researchers to move the collected data forward two directions: from online data displayed in multiple web units (like tweets), to offline data stably stored in one single dataset; from unstructured data like text, symbols, and hyperlinks, to structured data like numbers displayed in a matrix. Bitty Balducci and Detelina Marinova (2018) posit that unstructured data are non-numeric and multifaceted, given that the same single unit of text conveys information about multiple phenomena, and are concurrent representation meaning that the same unit allows to represent different phenomena at the same time. As we will see, compared to traditional methods, text mining is particularly well suited to deal with unstructured data.

Data collection

Since this project dealt with social media, data collection required making choices about several aspects that are idiosyncratic of the digital realm. First, we had to select the data source and type of social media platform. This choice depends on balancing out research validity, technical feasibility, but also ethicality and legal risks. Three main ways to automatically collect large-scale volumes of web data can be considered. First, web scraping, i.e., the extrapolation of web data from non-individual databases like websites, platforms, blogs, and forums through the means of custom software that exploits their native infrastructure (e.g., HTML), is highly flexible and does not depend on data providers, but is generally difficult and time-consuming to implement and risky from an ethical and legal standpoint. Second, calling an Application Programming Interface (API), i.e., a software purposefully developed to let the researcher's machine communicating with the source where the data are stored, allows to, after the completion of an authorization process, directly access part of the data provider's dataset at scale. If used properly, calling APIs is rather user-friendly, usually free of charge or very affordable, and involves few ethical and legal risks. However, APIs generally give access to data that, due to privacy and security issues, can be restricted in terms of volume, quality, or time covered. Lastly, web data can be collected from online archives or data aggregators, like Dataverse (https://dataverse.org) and Crowdtangle (www.crowdtangle.com). These sources are technically straightforward to access, but either limited in scope or very expensive. Considering these trade-offs and our research goals, we selected Twitter, as it covers a wide range of communicators and audience groups, while providing free and easy access to data through its Twitter Academic Research API (https://developer.twitter.com/en/products/twitter-api/academic-research) that allowed us to gather the data covering our period of investigation.

Data wrangling and corpus pre-processing

Once the data collection was complete, we proceeded with the data wrangling and corpus pre-processing stages. The former is aimed at merging and homogenizing data retrieved via multiple API calls. Indeed, Twitter APIs provided data in JSON format which had to be transformed in one single, more software-digestible text format, like a .csv file. This unique file containing all the brands' tweets (i.e., documents) is called "corpus" in textual research. The purpose of the corpus pre-processing stage is precisely to prepare the corpus for further analysis. We adopted a Bag-of-Word approach, which focuses on word frequencies and not on their order and on grammar, and split each tweet at the word level ("tokenization"). We also cleansed the corpus by removing irrelevant words like stop-words, punctuation, or URLs, and by solving encoding issues, lower-casing, turning each word to its dictionary form ("lemmatizing") and to its root ("stemming"), and finally substituting emojis and emoticons with their textual description.

Data Analysis

Text mining techniques can be split in two groups, depending on whether the construct or category of interest can be clearly identified a priori (Humphreys and Wang, 2018; Grimmer and Stewart, 2013). Both approaches favor the concurrent representations typical of textual data, meaning that a single unit can be assessed via different approaches without influencing the quality of the data. Top-down approaches pertain to those text mining analyses whereby the construct of interest and its textual operationalization are identified by the researcher before starting the analysis. In our case, the theory informed us that social media communicators, including brands, can persuade their audiences using rational, emotional, and credibility-based rhetorical appeals (Lee *et al*, 2018; Aristotle and Roberts, 2004). Thus we chose, adapted, validated, and applied three dictionaries – i.e. list of lemmas or multi-word expressions representative of a construct or category – and regular expressions – i.e. arithmetic patterns designed to match a particular alphanumeric expression in textual data – to measure and "count" how much the brands resorted to rational, emotional, and credibility appeals in their tweets. Data-wise, this top-down analysis provided weighted frequency counts for each category. Then, these quantitative data were first used to compare brands by industry groups through ANOVA; second, to determine the effectiveness of each appeal indicated by the social media engagement (i.e. cumulative number of favorites and retweets each tweet recorded), through a regression analysis.

Conversely, bottom-up approaches are used when the construct is still unclear and relatively latent, and thus textual patterns must be explored inductively and then interpreted to propose more advanced theoretical explanations (Humphreys and Wang, 2018). Accordingly, we employed a bottom-up approach to inductively explore whether and how brand communication on Twitter evolved during three key phases (before, during, and after the first national lockdown). This also served the purpose of updating and adapting the theoretical framework used to the uniqueness of the context in which such framework was used as an intelligible lens. In particular, we performed a topic detection task through hashtag network analysis.

Being able to leverage on the specific social media affordances characterizing Twitter, i.e., hashtags, hashtag network analysis can effectively reveal the existence of network connections that might otherwise go unnoticed (Tremayne, 2014). Combining this approach with an in-depth qualitative analysis of the texts in which these affordances appeared, i.e., the tweet itself, the hashtag network analysis allowed inferring the emergence of novel thematic clusters and the diffusion of a new emotive appeal aimed at inspiring or nudging the recipients to behave consistently with the collective safety and good (that we named "social pathos"). This not only evidenced a communicative evolution; but also allowed to enrich to the aforementioned set of appeals to be tested in a top-down fashion.

To sum up, a text mining approach was chosen as research method for the following advantages:

- It allows researchers to reliably investigate large-scale volumes of unstructured data, and to detect patterns that would be otherwise unnoticed by human eyes.
- It allows researchers to investigate phenomena whose linguistic representations take place spontaneously in natural and unabridged settings, thus boosting ecological validity.
- It is agnostic to research paradigms, as it can serve both inductive (theory discovery) and deductive (theory testing) research designs.

Section Summary

- SM data were retrieved by calling a social media-dedicated API, considering its availability, scalability, and ethical/legal compliance.
- Data wrangling and corpus pre-processing were performed to merge, standardize, and prepare the textual data for subsequent analysis.
- Dictionaries and rule-based top-down methods were used to test theory, whilst hashtag networks were inductively inspected to map the brand communication evolution and expand the theoretical framework.

Research Practicalities

In this section we present the key practical and ethical considerations and challenges faced during the three stages of the analytical procedure. For this project, we worked mainly in the

R environment and on the Gephi software. Other languages (e.g. Python) or visual-programming text-mining solutions (Ordenes and Silipo, 2021) can alternatively be used to achieve the same results.

Sampling social media data

Sampling web data like social media data bears some additional challenges compared to traditional research designs. Accessing the entire dataset of a social media platform is very difficult if not impossible, and algorithmic interference as well as the rate at which websites and online platforms change makes automatic data scraping often unfeasible (Boegershausen *et al.*, 2022). To draw a valid and representative sample of brand-generated tweets, we thus referred to external sources like international rankings such as Brand Z and Interbrand to identify about 30 Italian leading brands operating in seven industries. Hence, we manually collected the tags of brands' account (such as @Gucci) and used them as seeds to retrieve their tweets posted over a specific time frame. However, we discovered that this strategy led to collect too few units (i.e. tweets) to inform the research questions, since some of these brands in the sample are not very active on social media, or deliberately remained silent during the pandemic, as in the case of Coca-Cola Company. Therefore, we decided to expand the list of seeds by including other leading brands which were not identified in the first round. In particular, we selected the top brands by market share for each of the seven industries considered, allowing us to finally obtain 11,888 tweets posted by 76 brands. Moreover, since the API allowed to retrieve only the 3,200 most recent tweets posted by each brand on its timeline, we scheduled and reiterated all the 76 API calls several times during the data collection period, so to be sure to cover the entire period of investigation. Since social media engagement is a cumulative phenomenon, meaning that popular tweets recording high volumes of favorites and retweets can circulate for a while, the last call was performed one month after the end of the third phase considered, which made sure that the engagement metrics of all tweets were properly updated.

Validating text-mining models

The two text-mining stages are here presented one after the other for the sake of clarity, though they were conducted reiteratively.

As for the dictionary and rule-based method, we first came up with a clear and stable definition of the rhetorical appeals informed by the literature, or by our grounded exploration of the data in the bottom-up stage (Corbin and Strauss 2014). Then, we checked whether dictionaries and/or rules used by previous studies that would match these construct conceptualizations existed, or whether we had to build custom ones from scratch. The former was the case of the emotional, informative, and credibility appeals, for which we listed a set of existing Italian dictionaries such as the Italian version of LIWC (Agosti and Rellini, 2007), SentITA (Bosco *et al.* 2015) and the NRC-Emolex (Mohammad and Turney, 2010) whose performances were exploratively compared by applying them iteratively to our corpus of tweets. The latter was the case of the brand new "social pathos" construct, for which we built a custom dictionary. In the first case, despite an off-the-shelf list of lemmas was selected (NRC-Emolex), we did not apply it blindly to our corpus, but proceeded to adapt and validate it. Validating the performance of text-mining models is a crucial phase, often taken-for-granted or overlooked. In their seminal paper Justin Grimmer and Brandon Stewart (2013) warn that, given the complexity of language, all quantitative language models - even the most advanced ones- are wrong to some extent, as they cannot fully grasp the subtleties and nuances of meaning embedded in textual data. Therefore, the blind use of any text-mining method without proper validation must be avoided to prevent the risk of drawing conclusions driven by biased results. To validate our top-down investigation, we followed this strategy. First, we applied the selected dictionaries and rules in their original form and, to control that their lemmas did not appear in ambiguous semantic circumstances in our corpus, we randomly extracted subsamples of the classified tweets and evaluated them qualitatively. Ambiguous or irrelevant lemmas were removed, and the final list of retained lemmas was inspected by three external coders who, uninformed of the research goal, evaluated whether they actually reflected the respective construct's definitions. In the following step, after applying the refined dictionaries to our corpus, random subsamples (about 10%) of best and worst performing tweets per each construct were extracted and evaluated by 80 respondents, reached via a survey. Each respondent was provided with the construct definition along with an example of its potential textual operationalization, and was asked to classify the subsample without seeing how the algorithm actually classified them. Then, we proceeded to compute machine-to-human intercoder reliability with tools like ReCal3, (http://dfreelon.org/utils/recalfront/recal3/) adjusting the dictionaries, and repeating the whole process until a satisfactory reliability score was achieved. The same approach was followed also for the "social pathos" dictionary, with the difference that, since an existing dictionary was not available, we had to build an original list of valid lemmas. To this purpose, we started by listing the vocabulary of the tweets that inspired this construct during the bottom-up analysis. Then, we enlarged this list in two ways: first, by inspecting the vocabulary used in scales and measurements of already existing constructs conceptually close to our definition of social pathos like "emotional solidarity" (Woosnam and Norman, 2010); second, by exploring the "synsets", that is a group of synonyms which can be described by a unique definition, of our initial list of words through WordNet (https://wordnet.princeton.edu/). Once the lemmas were chosen, also the custom dictionary was inspected through the validation process described above.

As for the hashtag network analysis, we first decided to explore the entire set of hashtags produced by brands. However, acknowledging that its size prevented any meaningful qualitative inspection, we opted for selecting just the most viral ones for the graph plotting, weighting their frequency of occurrence by TF-IDF, an adjusted word-frequency measure which is commonly in text-mining research (Sparck Jones, 1972). Then, three researchers coded the top-ranked 600 hashtags by assigning each of them to particular categories following an interpretivist approach (Corbin and Strauss, 2014). Next, three undirected networks of hashtags representing as many temporal phases were plotted on Gephy via the Force Atlas2 algorithm (Jacomy *et al.*, 2014). Communities were identified based on modularity class (Barber, 2007), and hashtags-nodes by betweenness centrality (Freeman, 1977). Similarly to the top-down analysis, validation was pivotal for the bottom-up investigation as well. To do so, we thus performed a document-similarity analysis by measuring the cosine-distance (Gomaa and Fahmy, 2013) between the brand-generated tweets aggregated by phase, that corroborated the evidence that brand communication changed along the period considered.

Ethical considerations

Three ethical concerns were particularly important during this project.

- Privacy: we secured the privacy of each account investigated in the social media analysis. Despite we focused only on public actors like brands, and on public data posted on verified pages accessible to anyone by mere browsing, we still pseudonymized or anonymized any mention (i.e., tags, e.g., "@userA") to private accounts or potentially sensible information in the corpus.
- Security: we granted the security of the retrieved data, which were stored in private, password-protected laptops accessible to only members of the research team.
- Transparency: we maximized protocol transparency, recording and stating each choice made during the data collection, wrangling, and corpus pre-processing stages, as well as regarding the composition of the dictionaries. Not disclosing or keeping such decisions unclear prevents study replication, as each one of these choices highly affects the final performance of text-mining analyses.

Section Summary

- Sampling of social media data must take into consideration technical feasibility, the affordances of the data source, and the research aim.
- Before drawing any meaningful conclusion, thorough validation is necessary for every text-mining approach.
- From an ethical standpoint, safeguarding account privacy, granting data security, maximizing the transparency regarding each influential choice undertaken during the analytical protocol is required.

Method in Action

This section reviews some of the unplanned bumps in the road that we came across during the project, and the tactics that were reactively conceived to try and solve them. During the data collection – which lasted several weeks - carrying out multiple rounds of API calls, each one of them composed of 76 queries (one per brand), turned out to be more demanding and time consuming than expected. As a matter of fact, we discovered that, despite the API authentication, sending too many calls from one single laptop could run the risk of our API account being blocked and temporarily suspended, due to the anti-bot countermeasures often implemented by social media providers. Moreover, a non-secondary issue was that using a single laptop for data collection necessarily meant that it was completely busy doing one single task due to memory shortage, implying a considerable opportunity cost for the research team. To solve both issues, after a few trials, we thus decided to split the data collection tasks among different machines, each with an IP located in a different region, so to avoid being banned and so to share the memory burden among more laptops, which in the meantime could be used for conducting other stages of the analytical procedure. Data wrangling and corpus pre-processing also turned out to be extremely demanding. The main issue here related to the fact that most text-mining packages and sources are developed for the English language. Thus, not only it is more difficult to find the required tool for other languages like Italian, but also, when the tool is available, given that it is used and tested in way fewer occasions that in the English case, its validation turns out to be more burdensome. For instance, we could not tokenize or stem our tweets with a default algorithm without validating its performance; similarly, some sources, like the translation of emoticons and emojis, did not even exist for the Italian context and had to be translated. These inconveniences extended the duration of the corpus pre-processing stage to a good extent compared to expectations.

Finally, regarding the analytics stages, we faced the challenges embedded in modeling the "numeric translations" of textual data. Indeed, when textual data get transformed in their structured version, they rarely meet mainstream statistical assumptions, like normal distribution or homoskedasticity. The frequency with which words occur in natural language, for instance, tends to follow the Zipf's law, according to which word frequency and rank are inversely, and sharply, correlated. This implies that just few, very common words tend to account for the widest share of a corpus. This, compounded with the fact that the dictionary method inflates zeroes among the observations (that is, tweets which do not record any dictionary score), made our dataset very scattered. On top of that, also our dependent variable (SM engagement) did not follow normal distribution, but was very skewed and asymmetric, as typical of count data. Thus, applying "traditional" statistical tests, like Pearson correlations or OLS linear regressions, would have led to highly biased results. This represented a challenge, because in lack of a one-size-fits-all solutions on how to overcome such issues, we had to try different tactics, like data transformations and non-parametric, zero-inflated analyses which relax some of the mentioned assumptions but forced us to step outside the "comfort zone" of mainstream statistical analysis.

Section Summary

- Splitting data collection among various servers can reduce time and opportunity costs.
- Since most text-mining applications are developed and tested for English text, assessing other less-diffused languages involves some extra efforts.
- Given the statistical properties of unstructured textual data and social media data, conducting text-mining analyses in this realm implies stepping outside the "comfort zone" of mainstream statistical modeling.

Practical Lessons Learned

With the benefit of hindsight, some lessons emerged from this project that could not but be learned through direct experience during the design and implementation of the protocol. They were inferred from this project, but we contend that they can be generalizable for any top-down and/or bottom-up based text-mining research project.

- Theory always comes first: Since natural language is intrinsically complex, so are the phenomena and behaviors conveyed by it, which implies that, as emphasized by Justin Grimmer and Brandon Stewart (2013), every text-mining model is inaccurate to some extent. Acknowledging this, beyond the general distinction between top-down (deductive) and bottom-up (inductive) approaches and their fit with the research questions, text-mining is not a silver bullet, and there is no agreement about which the best model is to inform research questions. Many alternative techniques exist for each task, and knowing which one performs best for the specific case is difficult to tell beforehand. However, trying all of them for a specific task and compare their performances afterwards can turn out to be so time-consuming to outweigh the time and scalability benefits for which a text-mining is selected in the first place. A better strategy is to reduce the techniques consideration set by following theory and reviewing previous studies, and to devote the saved time to perform a through adaptation and validation of the selected technique to the specific corpus investigated.

- Be tidy and methodical: Research projects involving text-mining analysis rarely proceed linearly, but imply a going back and forth from one step to another. Since this reiteration can occur many times, and a change along the protocol tends to affect every other step, systematically keeping track of the choices undertaken is fundamental. So, being tidy, orderly, and methodical is of utmost importance. To this purpose, keeping an updated research project diary shared with the research team, where all choices are noted and time-stamped, is an effective strategy, which also prevents transparency concerns during further evaluation and review processes.
- Don't replace human abilities, augment them: All in all, text-mining techniques should not be used to blindly automate research and leave the researcher out, minimizing her/his involvement in the analytical stages of the project. As expressed about the relevance of validating models' performance, text-mining should augment the abilities of the researcher, who should still guarantee contextual sensitivity and systematic rigor of the analyses performed.

Section Summary

- Theory and context sensitivity, not mere methodological advancement, should always guide the selection of the best text-mining techniques.
- Given the complex and reiterative nature of text-mining protocols, being tidy, orderly, and methodical is of utmost importance

Conclusion

This research method case illustrated how the effectiveness of brand communication in social media can be unraveled, reliably and at scale, via a combination of top-down and bottom-up text-mining techniques. This approach turned out to be productive given its ability to assess large volumes of unstructured textual data and to detect patterns that would be otherwise unnoticed by human eyes, to boost the study's ecological validity by investigating phenomena whose linguistic representations take place spontaneously in natural and unabridged settings, and to explore new phenomena for which conventional dataset are not available. As this kind of analytical protocols encompasses several linked steps, the researcher needs to be systematically rigorous and methodical throughout its whole deployment. Moreover, we underlined that, irrespective of the degree of complexity and sophistication of the technique adopted, text-mining tools cannot be applied as they are offered off-the-shelf, but a thorough validation effort must be undertaken. Finally, the specific context of this study was brand communication on social media. Though, being text-mining agnostic to research paradigms, and given the pervasiveness of unstructured text in modern societies and markets, we outline that this approach can be similarly adopted in a wide range of research and business settings, like customer profiling and competitors listening.

Appendix 5 - Sentiment Analysis “polita” dictionary composition.

Construct	Source	Lemmas	Wildcards	Emojis	Top items, by TF-IDF
Positivity	Italian sentiment: NRC Emolex (Mohammad *et al.*, 2011); Emojis: Novak *et al.* (2015)	180	49	107	love emoji (92355), good (10090), cheers (9911)
Negativity		241	21	42	hate emoji (5893), problem (2903), shame (879)

Appendix 6- Sample brand-generated posts for each persuasive appeal.

Persuasive appeal	**Example** (translated)
Pathos	“Big or small, simple or elaborated, expected or unexpected: no matter how your present is, your love is what makes it perfect #Nutellawithlove”
Logos	“A2A aims at reducing carbon emission by 30% by 2030. This new target was analyzed by the #ScienceBasedTargets initiative to verify the alignment of industry and Paris COP21's goals. More information here: https bit.ly/2wvpDmR”
Ethos	“The main global stock exchanges closed August with record sales. Trust or enthusiasm? Here's the opinion of V.G., asset management director of Banca Mediolanum, for Panorama.it”
Social Pathos	“This emergency has put us to the test by redefining the way we work, teaching us to communicate in a new way. We stepped up to the plate for the community, without giving up, we went forward: fast, united, and together because we are Fastweb. Simply, #ConnectedTogether”

Appendix 7- Structural Topic Model summary table

Thematic cluster	Description	Literature	Mean Cluster Sentiment ($\sigma 2$)	Topics	FREX (top 10*)	Representative documents*
(1) Brand consumer co-creation	This cluster contains topics discussed by consumers that reflect the active engagement of the users as members of the brand community, for example in the form of personal suggestions on how to improve products and services to other users.	Vallaster and von Wallpach (2013)	-1.04 (18.485)	(1) Creativity	too, top, good, fond, yummy, family, surprise, find, anna, share	*"What a lovely product to be enjoyed with families, I have goosebumps! :D"*
				(2) Co-creation activities	years, son, daughter, inside, children, gift, eggs, surprise, made, name	*"Here's a tiny artefact made by my 8-year-old daughter for school <3"*
				(22) Brand contest	branch, app, respond, access, bank transfer, account, earn, reward, code, credentials	*"Good morning, I am attaching my code so that you can register and enter the *** code. You will earn stars and medals and you can win great prizes, such as food packs, entrance tickets to cinemas, gyms, restaurants and attractions and even collectible LPs? Remember that those who already have the app but have not entered a friend code can reinstall it to be allowed to log in?"*
(2) Positivity towards brands	This cluster gathers consumers' comments containing extremely positive emotions towards the brands and/or their activities, for example feelings of appraisal, gratitude and admiration of consumes for brands and their representatives.	Batra *et al* (2012)	0.644 (20.437)	(7) Admiration	suspension, excellent, gentle, united, grand, ennio, need, employees, very good, courage	*"Great Director?! You're one in a million, and one of us!"*
				(21) Wishes	great, good, celebration, happy, greetings, hello, good wishes, recovery, Sunday,	*"Good wishes to all the dads all over the world!"*
				(28) Gratitude	thank, teacher, proud, energetic, gesture, immense, extraordinary, honor, human, reconversion	*"About thirty years of continuous work, to date there is no bank in Italy closest to the needs of companies. Personally we can only thank them, a very long partnership that has allowed us to grow by navigating in any weather conditions … Thanks :"-)"*
(3) Brand referral	This cluster includes comments expressing varying consumer's instantiations of referral regarding the brands and/or its value proposition, not necessarily directly related to what the brands did amidst the pandemic, for example in the form of voluntary reviews of products and services advertised via social media.	Shan and King (2015)	-1.119 (16.691)	(3) Fashion enthusiasm	shoe, fashion, dress, perfection, clothes, collect, glasses, adorable, amazing, collection	*"Adorable colours! I would like to buy the yellow top "*
				(14) Appraisal	tipo, punto, panda, finally, version, thousand, oil, satisfied, cross, gpl	*"Feel free not to believe it, but my natural power model has covered ONLY one million km, with only ordinary maintenance! <3 <3 <3"*
				(20) Praise for food	great, idea, yummy, taste, jar, cerals, small, smooth, rocher, mango	*"I tasted the mango and maracuja one, simply delicious. I'll taste the blueberry and cranberry one as well!"*
				(36) Automotive enthusiasm	aston, martin, car, rear, grill, design, sports car, supercar, iconic, colour	*"I love it! The rear looks like a Corvette, whilst the back is a mixture of Aston Martin and Porsche"*
				(37) Praise for taste	always, choco, cocco, family, all, chosen, smile, take, best, nice	*"Too good…. I always keep the "mini" in my pocket…for moments of weakness, not for gluttony…. yeah, no-one could believe it! :P"*

(4) Negativity towards brands	This cluster gathers all those topics that manifest varying degrees of consumers' dissatisfaction with brands, expressed through online complaints, overt criticism, and verbal protests. For instance, consumers use the brand's social media page to complain about service failures, product malfunctioning or customer care inadequacies, but also to perform anti-brand activism and other forms of consumer resistance.	Ramirez *et al* (2019); Zarantonello *et al* (2018)	-1.586 (18.219)	(4) Indignation	car, enzo, shame, leclerc, bignotto, vettel, mercedes, pilot, track, drive	*"Unwatchable .... you have the best pilots, and you give them the worse car ... zero evolution, zero updates ... simply disgusting and embarrassing ... F. go away, you are destroying a myth …"*
				(9) Customer care	question, service, why, write, read, understand, ask, work, say, not at all,	*"Too bad you do not answer the phones and do not call back !!! so I would like to know how to make an appointment with you. People have deadlines and you have to respect them, because delays do not affect the bank, but US !!! Answer or listen to the messages left on your answering machine"*
				(13) Made in Italy	pasta, wheat, glutin, eat, lactose, italian, jars, packaging, provenance, slice,	*"I invite all consumers to stop buying XX pasta made with Canadian grain full of glyphosate which causes many very serious diseases, most of them fatal. The wording "only Italian wheat" on packages is a scam!"*
				(15) Complaints (telecom)	fiber, modem, bill, connection, giga, fixed, bill, adsl, activation, unlimited	*"Dear XX, your contribution would be that our fixed and mobile lines worked properly but since yesterday morning I have had no fixed line, and the mobile line is not even reliable."*
				(17) Service Failure (telecom)	private, solve, feedback, contacted, report, certified email, bad, reply, problem	*"After sending you the requested data, I have been waiting for an answer for about two weeks"*
				(26) Service Failure (website)	can, must, none, purchase, having, problems, lament, pro, interested, discount	*"Speaking of TIME, FOR HEAVEN'S SAKE INCREASE THE WEB SESSION TIMEOUT! INCREASE THE WEB SESSION TIMEOUT! INCREASE THE WEB SESSION TIMEOUT! INCREASE THE WEB SESSION TIMEOUT! INCREASE THE WEB SESSION TIMEOUT!"*
				(27) Customer care (bank)	need, rest, comments, few, not even, negative, atm, instead, advance, take off	*"If you manage not to permanently close the branches, customers could also access them. See for example Corso Moncalieri and Via Val della Torre in Turin."*
				(31) Anti-brand activism	immediately, sanpaolo, want, carbon, fossils, finance, sources, stop, climate, #dirtyalliance	*"XX, if you want to defend the climate you must immediately stop financing coal and fossil fuels! We do not want #dirtalliance Renounce to finance Adani and the controversial project to exploit a coal field in Australia, where millions of animals and entire forests have been engulfed by fires."*
				(32) Service Failure (bank)	card, credit, info, step, site, web, canon, order, home, reload	*"The app never recognizes the payment QR code…and I have an Iphone pro, not a low-quality smartphone"*
				(35) Complaints (automotive)	time, issues, loose, price, old, capital, damage, errors, guaranteed, system	*"Speaking of injustice ... even your prices don't allow people with lower incomes to afford them? I don't think your prices are justified by their production costs. Your brand benefits from social differences (brands as status symbols) and justifies this system by making your stuff accessible only to people with higher incomes. It would be easy for your business to produce a cheaper line and make it more accessible."*

(5) Mixed feelings	This cluster contains polarized social media users' reactions to social media communication that brands undertook during the pandemic, ranging from expression of deep admiration, skepticism, perceived opportunism and even disgust.	-	-2.223 (22.215)	(10) Spot	ad, masterpiece, amazing, spot, proud, bad, people, chaplin, rich, evil	*"A memorable speech by Charlie Chaplin was used to advertise the coffee ... it's really embarrassing ..."*
				(11) Safety concerns	part, work, employees, proud, important, must, central, excellence, yet	*"A proper cleaning of the branches .. Sanitization in the rooms of firms????? No??? !!!!"*
				(29) Backlashes	moment, south, masks, lombardy, hospitals, govern, shame, suspend, hard, difficult	*"But do you know the situation in Lombardy ????? Do you fucking read how many infections there are in Lombardy? In my opinion you don't even look, and talk as usual just to let your breath out ... Even in difficult moments"*
(6) Nostalgia	This cluster gathers consumers' expression of nostalgia for the brand and/or its activities and contexts.	Heinberg *et al* (2020); Merchant and Rose (2013); Brown *et al* (2003)	-0.106 (18.773)	(16) Memories	memories, santorini, magnifique, delicious, greece, fabulous, unforgettable, islands, go back,	*"I visited both of them…. Palma and Santorini…Santorini has had a special place in my heart since then <3"*
				(25) Missing travels	miss, sea, balcony, hikes, buffet, restaurant, fun, relax, shows, pleasure	*"I miss everything about the cruise!!!The halls, the swimming pools, the restaurants, the samsara, the parties, I miss the love of the crews of every sector!!!"*
				(34) Desire for normalcy	hope, soon, can't wait, restart, go back, end, marvelous, miss, #restarttogether, jump on	*"I hope it will happen very soon :) we all need to start again.. and to find you on board again "*
(7) Covid complaints	This cluster gathers topics that manifest varying degrees of consumers' dissatisfaction with brands, but contextual to Covid-19	-	-2.02 (19.607)	(33) Edginess	now, less, area, cases, continue, desire, availability, countermeasures, coronavirus, none	*"Dear friends of XX, I have been in the red zone since February, the very first town that was closed. I have not received the infamous message to have the possibility to use the giga in an unlimited way!"*
				(5) Travel restraints	cruising, holiday, book, hope, miss, decision, cancelled, news, anxiety, positive	*"Stop it! Stop and be done with it, you're making fools of yourselves. You and your decisions really let me down. I won't travel with you any more in the future! You are irresponsible!"*
				(8) Uncertainty	certainly, must, passengers, possibility, bad, remain, next, certainty, host, situation	*"My wife and I have to go on a cruise in March. Oman and Jordan have already issued orders not to accept Italians. If other states forbid us from disembarking, do we risk spending all the time on the ship?"*
				(19) Refunds	know, voucher, client, penalties, closed, refund, avoid, date, distance, right	*"Manager, you should allow your clients to freely choose between refunds and vouchers according to their needs "*
				(38) Booking issues	smeralda, booking, grandiosa, caribbean, leave, september, august, emirates, may, route	*"I have a reservation for the April departure with XX: even if the departure from Savona is confirmed, will there be any changes of itinerary considering the closures of France and Spain?"*
				(40) Dissatisfaction	exchange, again, happen, visit, fear, treated, expire, decline, visibility, suggest	*"From this emergency I have truly understood that you are highly disorganized, and that information does not pass correctly between you. As soon as everything ends, I will do the subrogation of the mortgages, just to have no more to deal with you! "*
Excluded	*This cluster gathers consumer topics which were not theoretically*	-	-	*(18) San Remo festival*	song, great, congrats, diodato, festival, gabbani,	*"The true winner of the Festival, Gabbani the best! Great song and*

relevant (i.e. topic 18) or that were deemed not interpretable by the research team.		sanremo, winner, amadeus, deserve	*great music, enjoyable, joyful, nice, bravo Gabbani! :) :) :)"*
	(6) undefined	something, think, should, sure, doubt, worse, was, guess, worst, sorry	-
	(12) undefined	things, world, god, sure, mister, bless, fan, have, world, learn	-
	(23) undefined	well, want, see, words, maybe, go, thought, moving, one, hear	-
	(24) undefined	never, better, this way, that is, maybe, hard, sorry, late, change, unfortunately	-
	(30) undefined	people, do, say, really, by the way, understand, page, other, pay, look for	-
	(39) undefined	same, thing, more, value, suggestion, happening, say, sky, guys, imagine	-

Notes: * translated from Italian to English

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