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Social media analytics for nonprofit marketing: #Downsyndrome on Twitter and Instagram

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Abstract

Introduction: Social media listening and monitoring of user-generated content (UGC) in commercial marketing is central to measuring social media users' perceptions of a brand or company. Applications of social media analytics (SMA) have become common practice in marketing and are employed to predict consumer behavior. However, critical reflections on SMA applications to nonprofit marketing are lacking, despite the increased usage of SMA by nonprofit organizations.

Objective: The article proposes to apply SMA to analyze UGC and identify how computational methodologies can help bolster strategic communication for nonprofit organizations and drive marketing strategy.

Methodology: The article presents results from a 2-year (October 2017–January 2020) social media monitoring of the hashtag #DownSyndrome on Twitter and Instagram. SMA tools will be used. Specifically, sentiment analysis and topic modeling are employed to analyze tweets and Instagram posts, while image classification is used to analyze Instagram images.

Findings: The results highlight a strong stereotypical characterization of people with Down syndrome in content that is generated by social media users and identify possibilities and challenges ahead of nonprofit organizations pushing specific agendas.

Originality and Contribution: This study is the first to offer a review of SMA, apply them to a nonprofit context and reflect on aspects of representation and stereotypization through them. It ultimately proposes to support nonprofit and voluntary marketing research and practice by integrating UGC research and computational techniques into the broader discussion of ethical content strategy in social media nonprofit marketing.

KEYWORDS
Down syndrome, non-profit marketing, predictive analytics, social media analytics, social media listening, user-generated content

1 | INTRODUCTION

In August 2017, the American channel CBS News uncovered Iceland's investments in the use of advanced pregnancy scanning technologies to minimize the birth of children with Down syndrome (Quinones & Lajka, 2017). Shortly after airing, the exposé went viral and sparked heated debates on social media. These were flanked by passionate discussions about the moral and ethical implications of choosing to terminate pregnancies as well as sympathetic messages about celebrating life and embracing living with disabilities.

Down syndrome and people with Down syndrome do not tend to be a focus of social media marketing or nonprofit marketing practice and research. Similarly, they remain a marginalized market segment on social media platforms (Dias de Faria & Moreira Casotti, 2019). However, people with Down syndrome are increasingly participating on social media, and organizations that support people with Down syndrome and their carers are, like other nonprofit organizations, increasingly relying on social media for their marketing and communication efforts. Therefore, this case study offers a unique opportunity to operationalize social media analytics (SMA) to understand how user-generated content (UGC)—which can be defined as content that is freely and created by social media users on social media—can contribute to discussions of nonprofit communication and marketing. This information can offer a unique advantage for designing and implementing successful social media campaigns.

2 | CONTRIBUTION OF THIS STUDY

The term SMA describes the process of employing computational methodologies, data analytics and machine learning to measure and improve the effectiveness of social media marketing campaigns, predict audiences' responses to a campaign and campaigns' results (Yun et al., 2020). While research on applications of computational methodologies have started to be produced, a more focused approach on how these methodologies and applications can benefit nonprofit and voluntary sector marketing is needed. Therefore, the objective of this article is twofold: we apply SMA and advanced image processing techniques to identify how they can bolster nonprofit marketing and communication efforts; we also propose to operationalize the applications of SMA in nonprofit marketing by reflecting on the important role of ethical content creation, which is to be balanced with the need to generate engagement on social media platforms. To the best of the authors' knowledge, there are no articles that have focused on these two aspects in the context of digital and content-driven strategy in nonprofit marketing. The focus is on the hashtag #DownSyndrome and its uses on two main platforms: Twitter and Instagram. These two platforms are analyzed using the #DownSyndrome hashtag because the objective is to understand the narratives that emerge on the platforms and to identify patterns and major differences between them and reflect on the ethical aspects of nonprofit social media marketing content strategy.

Twitter, a multimedia platform and microblog, is chosen due to the immediacy of its content. Given the limited number of characters users have at their disposal (280 characters), Twitter tends to be used as a colloquial platform where users post short comments (i.e., tweets) and "like" or reply to other people's posts (e.g., via retweets). In contrast, Instagram is chosen due to its visual nature. Unlike on Twitter, Instagram users must include a picture in each post. As such, Instagram has become a "curated space" where users are prompted to engage in "filtering, cropping, blurring, [*and*] image manipulation" (Zappavigna, 2016, p. 273). The stark differences between these two platforms make an analysis of UGC-driven SMA extremely important from a marketing perspective. In fact, while Twitter presents an interesting textual narrative, Instagram offers an unprecedented insight into the visual narratives that emerge around Down syndrome, enabling a unique comparative study of how the same topic is discussed across different platforms. The article is especially relevant for organizations that seek to maximize the use of social media and conduct social media marketing research in the field of nonprofit marketing. The article further contributes to expanding research on the applications of SMA in social media strategy by connecting SMA with audiences' reception of social and humanitarian causes and with ethical content strategies.

2.1 | Literature review

2.1.1 | User-generated content and nonprofit marketing

Social media play a significant role in communication strategy. Both commercial and nonprofit organizations attempt to capitalize on new opportunities that social networking platforms offer to help maximize reach and return on investment while minimizing advertising and marketing costs (Chaffey & Smith, 2017; Chaffey & Ellis-Chadwick, 2019). In this scenario, nonprofit organizations work to "marshal their limited and variable resources into marketing with a high potential for return" (Jordan et al., 2019, 232). Such strategic relevance is further accentuated by the role of UGC (i.e., what is being discussed on such platforms by social media users).

UGC refers to the content that active social media users produce. This content spans all types of topics and issues and includes brand loyalty, complaints, and dislikes (Steenkamp, 2017). Branding strategy emphasizes UGC because effective product and branding propositions lead to consumers creating content for the brand, discussing it, and helping it to gain market share at virtually no cost; this is typically called "earned content" (Charis et al., 2016; Cheregi, 2018; Quoquab et al., 2019). As Zhang et al. argue, "social media reflect underlying social dynamics and values" and provide a "treasure" to social media marketers, strategic communicators, and institutional actors alike (Zhang et al., 2019, p. 182). The opportunities offered by UGC in humanitarian emergencies and natural disasters, as well as in nonprofit marketing and crisis management situations, have been well documented (Akhgar et al., 2017; Marland & DeCillia, 2020; Ozanne et al., 2020). UGC is usually monitored and analyzed in real-time through automated processes, with the aim of being able to adapt and change tactics and thus potentially improve an overall social media marketing strategy. As a result, UGC offers a unique method for both commercial and nonprofit campaigns to monitor what is being produced and discussed on social media and to adapt to any eventualities that might arise.

SMA includes techniques for the capture and analysis of UGC that are widely applied in commercial, strategic, and political marketing (Neudert et al., 2019). These techniques consist of a series of computational and mixed-method approaches that allow a company or a brand to monitor campaigns and consumers' attitudes, responses, and overall sentiments toward their company, brand, or product (Laine & Frühwirth, 2010; Mattke et al., 2019). Monitoring platforms such as Hootsuite, SocialMention, and Salesforce offer real-time insights, but they may be cost-prohibitive for organizations and other actors in the third sector. The third sector has not fully embraced social media monitoring for broader strategic communication purposes (Klassen et al., 2018), restricting itself to the assessment of campaign-specific goals and associated results (Jordan et al., 2019).

2.2 | SMA: Techniques and applications

To date, the most widely applied computational techniques for SMA are sentiment analysis and topic modeling (Yun et al., 2020), while little to no research is available on applications of computer vision in marketing contexts.

Sentiment analysis and topic modeling are also specifically relevant to this article. These are techniques that are applied to text-based documents. Sentiment analysis is a form of unsupervised learning that enables the discovery of *positive*, *negative*, and *neutral* sentiment of words and sentences (Kharde & Sonawane, 2016); it can be used to analyze either long or short forms of text. Sentiment usually shifts from -1 (extremely negative) to $+1$ (extremely positive), with 0 being the neutral cut-off point. This process is considered unsupervised because the algorithms associate the sentiment to the word or the sentence; the analysis is therefore undertaken directly by the algorithm without any human intervention. Topic modeling is also an unsupervised form of learning that helps group and categorize topics that emerge in a given text. This technique is specifically designed to allow the discovery of the most relevant—or frequent—terms that reoccur in a text, which can, again, be either long or short (Liu et al., 2016). Combined, these two techniques can help map what people are talking about and how. This is the most valuable aspect of these two unsupervised techniques (Hastie et al., 2009).

On the other hand, image recognition is a computational technique that helps classify images by identifying important elements within an image (e.g., a face or a tree). The objective of this technique is to train algorithms to recognize images and discern them; in search engine and neuromarketing, image recognition can help predict what people will click on or what kind of imagery will have the highest probability of being considered (Glova & Mudryk, 2020). However, in the case of this article, this technique is used specifically to understand how people with Down syndrome are represented in UGC discussions and the visual narrative that surrounds them. Given the complex nature of images, while image classification is also unsupervised, algorithms cannot automatically "learn" and need some human supervision. Such supervision comes in the form of datasets that are trained, or annotated, by humans to help the algorithm detect categories or specific aspects of an image. Image recognition is used to classify images on search engines, thus greatly contributing to relevant search engine optimization (SEO) strategies.

Despite being a powerful and useful technique, image classification and analysis are not really embedded in any SMA techniques applied to marketing strategy, while sentiment analysis and other text-based analyses, such as topic modeling, are usually considered SMA and systematically applied in marketing strategy.

From a data perspective, the best and most effective way to apply SMA is through the monitoring and analysis of campaign-related or user-created hashtags. A hashtag is "a word or phrase marked with '#' to identify an idea or topic and facilitate a search for it". It is also an "affordance" of social media platforms for people to "create discursive clusters around a shared interest" (Bode et al., 2015, p. 149). Studies have relied on hashtag usage to map political networks beyond the simple objective of a given campaign or candidate, to identify discourse streams (Papacharissi & De Fatima Oliveira, 2012), and to study the coordination of collective action messages (Freelon et al., 2017). Hashtags are also widely used in marketing to create "discursive spaces for individuals to participate in cultural creations of meanings around a wide range of topics" (Xu & Zhou, 2020, p. 89). Such discursive spaces are specific to social media and can be used across multiple platforms (Kuo, 2018). Hashtag conversations thus create topic-driven networks that move away from networks of connections such as the "friends" structure on Facebook or the "following/followers" structure that is typical of Twitter and Instagram (Bruns & Burgess, 2015). At times, marketers have little to no control of UGC hashtags, and monitoring is therefore necessary to inform strategy and minimize risks of negative sentiment spreading online. These results in the hashtag helping to create implicit and temporary virtual communities whose members gather due to their interests or around a topic or event rather than through friendship-based solidarity.

The third sector has largely been unable to harness the full potential of SMA, UGC, and hashtag monitoring. This is due not only to the prohibitive costs of using platforms but also to the uniqueness of nonprofit marketing, which, unlike commercial marketing, may not offer immediate rewards (Šebestová & Šebestová, 2020). More importantly, an analysis of the Down syndrome discourse requires the use of more nuanced analytical and methodological frameworks that efficiently employ UGC and hashtag analysis to evaluate the impact of users' discussions, feelings, and perceptions beyond campaign-specific goals (i.e., raising donations with a specific social media campaign). This article develops such nuanced frameworks with the aim of maximizing the opportunities offered by social media marketing while also highlighting the important role of ethical representation of people with Down syndrome and discussing how marketing and communication strategists should consider issues of essentialization and representation of the person with Down syndrome. It will do so using UGC as an important tool for audience response analysis and using strategic information to design effective yet realistic communication strategies and value propositions (Lee, 2019; Saleem et al., 2019).

2.3 | Online discussions: Vitriolic messages, stereotype, and essentialization

Nonprofit social media marketing requires consideration of the specificities of the platforms on which organizations choose to operate and of the negative discourses that can emerge on them. Twitter's vitriolic nature and Instagram users' tendency to shame have been widely discussed in academic literature (Badawy & Ferrara, 2018; Wang et al., 2017). However, there has been less research investigating the issue of essentialization and stereotyping on social media and the effects these can have on marketing campaigns, especially in the third sector. However, the exponential growth of social media marketing applications creates the need for a way of transforming conversations into information. Equally, it ought to be recognized that organizations that want to raise awareness and generate interest around an important social issue or give a platform to marginalized voices may seek to maximize their reach and presence on social media through campaigns that utilize hashtags. Knowing how to maximize the ways in which these hashtags are used by social media users can help to effectively monitor campaigns and inform future strategies.

Undoubtedly, the use of social media to raise awareness about marginalized people—like people with Down syndrome—and engage with potential donors or volunteers forces us to consider issues of prejudice and stereotyping. While there exists a critique of stereotyping and prejudice in marketing and advertising (Bauer et al., 2018; Bendle & Thomson, 2016; Foster Davis, 2017; Saint Claire et al., 2017), these are very focused on gender and race and are further limited to specific advertising campaigns. Down syndrome awareness campaigns have increasingly gained attention in practice-led literature (McAteer, 2019), but much more could and should be done to fully explore stereotypical characterizations of people with Down syndrome—along with any other under-researched and under-represented segments of society—on social media in order to offer insights to practitioners and researchers in the field of nonprofit marketing.

Theoretical frameworks that might be considered when researching marginalized groups on social media and UGC are those offered by social and behavioral sciences that have at length studied how some groups can be easy victims of *infra-humanization* and *essentialization*. While infra-humanization can be defined as the perception of the superiority of one group over another, essentialization can be defined as the perception of a specific group as "naturally" lacking certain characteristics such as "intelligence, language and sentiments" (Chisango, 2012, 72). Sociological research on infra-humanization and essentialization has identified issues of *benevolent prejudice* and *paternalistic stereotypes*. These are forms of positive stereotypical characterizations of people or groups considered "different"; they are characterized by an attitude of pity toward a specific group, an attitude that "carries overtones of compassion, sympathy and even tenderness" (Fiske et al., 2002, p. 880). Benevolent prejudice and paternalistic stereotypes emerge in so-called inter-group relations, that is, in relations between a group that is perceived as homogenous and predominant and one that is usually perceived as alien or different. Research on infra-humanization and essentialization focuses on the perception of specific groups' low (intellectual) competence and high degree of warmth (Hadarics & Kende, 2018). These frameworks have been applied to analyses of race and gender (where they have been discussed in terms of *benevolent sexism*). Though they have never been applied in a systematic analysis of the perception and representation of people with Down syndrome and other under-researched segments in marketing research, these concepts offer a methodologically and theoretically rich framework and will be applied in this study in order to evaluate if (and how) UGC-driven conversations about Down syndrome have the traits identified by behavioral scientists in terms of infra-humanization and essentialization. Identifying issues of essentialization and infra-humanization is paramount for creating campaigns that elicit sympathy but avoid stereotyping people with Down syndrome. Social marketing research has started to tackle stereotypes around Down syndrome, although not systematically, by problematizing romanticized portrayals of people with Down syndrome as consumers. Although never directly using terms such as stereotypization and prejudicial representation, existing research in this field has assessed the characterization of people with Down syndrome as eternal children that are affectionate but also "everlastingly dependent" (Chisango, 2012; Dias de Faria & Moreira Casotti, 2019, 2260). Research has also identified an emerging narrative in the ways in which people with Down syndrome are portrayed in pictures. In fact, while children with Down syndrome appear in pictures with young family members, the situation drastically changes when pictures of adults with Down syndrome are considered. In this latter case, the adult with Down syndrome tends to appear with older members of the family, very seldom enjoying any time with peers or siblings (Dias de Faria & Moreira Casotti, 2019). These concepts—which have never been used in social media marketing research for nonprofit organizations—can help with interpreting the results, given the specific characteristics of the two platforms considered in this analysis.

2.3.1 | Research design and methodology

The #DownSyndrome hashtag offered a useful starting point to monitor and gather insights about UGC on Down syndrome narratives. This hashtag was chosen because the UGC that followed the CBS News report prompted an abundance of discussions on both Twitter and Instagram, thus offering a unique opportunity to gauge the rhetoric of the opinions that were shared as well as the possibility of discovering other hashtags. Specifically, #DownSyndrome was associated with over 1 million tweets and 1.4 million Instagram posts.

To avoid biased conversations following the CBS News report, data covering the Iceland report was disregarded (Grisby, 2018). For this reason, the #DownSyndrome hashtag was monitored over time, not only to obtain a reasonably large dataset but also to identify the most salient aspects of Twitter and Instagram discussions on the topic, beyond the highly controversial report itself. The data presented in this article was mined from Twitter and Instagram posts from October 2017 to January 2020.

Tweets were computationally analyzed using two text-based techniques: sentiment analysis and topic modeling. The sentiment analysis was undertaken using the R Packages tidy and syuzhet. While tidy allows for the cataloging of sentiment (positive, negative, and neutral) as well as topic, Suyzhet helps to further contextualize the emotions associated with the sentiment. The syuzhet package builds upon multiple dictionaries and can classify tweets into six clusters or emotions that are automatically detected: anger, fear, disgust, surprise, anticipation, joy, and trust. While the package does not specifically classify these emotions in positive and negative, it is usually accepted that disgust, fear, and anger belong to a more negative sphere while emotions like joy and trust can be associated with more positive sentiment; anticipation and surprise, however, are more difficult to detect and associate with either a positive sentiment or a negative sentiment. Therefore, the authors chose to combine the two packages to better understand the context of the tweet within the corpus. To further obtain robust results of the corpus, topic modeling was also undertaken. The analysis of Instagram images drew upon the proprietary platform Google Cloud AutoML for machine learning. This tool has been designed by Google for developers with limited expertise in machine learning to build reliable models from annotated images. Being free to use and quite user-friendly, AutoML offers the perfect tool for bulk annotation and the building of a model that can predict the salient elements within an image.

It ought to be clarified that while text analysis for English text is advanced and no human coding was needed for Twitter and Instagram posts, computer vision still depends upon human coding. Consequently, Instagram images were first organized to create a training sample, for example, a sample that identifies the most representative features of an image and creates a statistical model used to analyze new, unknown images. This intermediate step is necessary to ensure that the algorithms are valid and statistically relevant. Having no knowledge of how to select the images to operationalize a representative image classification model, an exploratory analysis of tweets was prioritized. As such, an exploratory sentiment analysis was undertaken on the Twitter dataset (659,145 tweets) and later refined (362,987 tweets) to undertake sentiment analysis and topic modeling of the tweets using the tidy and syuzhet packages.

This text-driven analysis led to the initial consideration of how social media users engage with the hashtag #DownSyndrome in order to identify any major emerging patterns. These insights subsequently provided the authors with a better understanding of how to select the sample of Instagram images. A total of 14,294 Instagram pictures[1] carrying the hashtag #DownSyndrome were mined using proprietary software for image and associated caption retrieval.[2] Using Google AutoML it was possible to capture the most relevant categories that emerged in the training set (238 images) and compile them to gather more robust results.

These computational methodologies were supported by qualitative approaches. To enhance the algorithm used to identify core aspects of the large dataset of images, the training set (238 images) was further analyzed using NVivo. The context of each image was analyzed by looking at categories such as who the person with Down syndrome appears to be in the picture, what they appear to be doing and their apparent age.

2.3.2 | Findings

Twitter analysis results

The hashtag #DownSyndrome led to the discovery of other salient hashtags (Table 1).

An exploratory sentiment analysis was undertaken with 659,145 tweets. This initial dataset was subsequently refined to eliminate bots and tweets produced by institutional accounts and well-known organizations. A further exploratory analysis of the dataset highlighted a high level of sarcasm in the tweets from August to October 2017, which was mainly linked to Iceland's CBSN exposé. Consequently, tweets carrying #Iceland were removed from the main dataset and analyzed separately to avoid outliers. This led to a final clean dataset of 362,987 tweets. The posting dates and the geographical distribution of tweets were prioritized, followed by a more in-depth analysis of the text using topic modeling and sentiment analysis. The analysis revealed a sparse geographical distribution of the participation in the Twitter discussions (Figure 1), though it also illustrated specific peaks of activity (Figure 2). Finally, given that the dataset included tweets in multiple languages, manual translation of tweets into English was required to achieve a unified corpus.[3]

The mean distribution of the tweets showed that the unusual peaks of activities coincided with three key periods: March 2018, March 2019, and May 2019. These surges correspond to three main events. Those in March 2018 and March 2019 coincided with the annual World Down Syndrome Day, which takes place on 21st March and involves a series of activities that aim to raise awareness about Down syndrome. In contrast, the May 2019 surge can be attributed to tweets celebrating life with Down syndrome from a parent's perspective. Though it remains unclear what prompted this latter surge, there had been tweets celebrating the life of Alfie Evans, an infant boy born with an undiagnosed neuro-degenerative problem, and similar cases of parents caring for children with disabilities.

The results evidenced an intensification of Twitter activities during Down Syndrome Awareness Month, with an average of 15% more tweets published in 2019 than in 2018 (Figure 3).

However, apart from these peaks, the flow of discussion remains limited, confirming the marginality of discussions about Down syndrome from UGC on social media (Watchman, 2014). The results further highlight the pivotal roles played by ad hoc events such as World Down Syndrome Day and by nonprofit communication and social

TABLE 1 Hashtag co-occurrence analysis

#blessed	#nothingdownaboutit	#DownSyndromeAware	#DownSyndromeawareness	#autism
#disabilityawareness	#downsyndromeadoption	#extrachromosome	#downsyndrome	#makeupjunkie
#endangeredspecies	#downsyndrome	#downsyndromelove	#downsyndromemom	#cerebralpalsy
#morealikethandifferent				

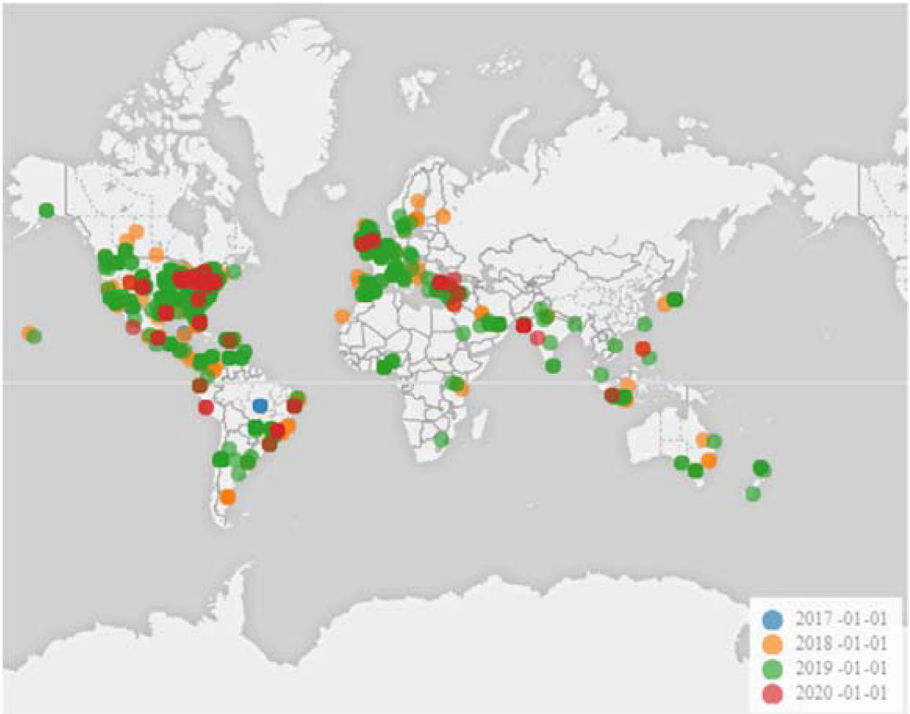

FIGURE 1 Tweets' geographical distribution over time (years)

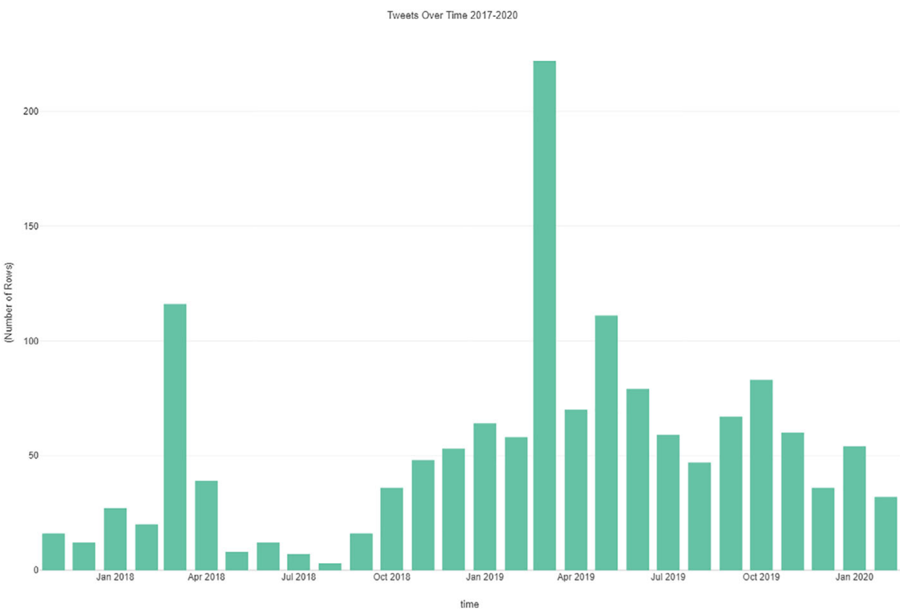

FIGURE 2 Tweets' distribution over time (years)

media activities. As a result, focus and attention are maintained, in great part, by organizations that work to raise awareness of and promote inclusive attitudes toward people with Down syndrome.

These observations led to further examination of the text to determine how Down syndrome is discussed on Twitter. Given the vitriolic nature of Twitter, the authors anticipated that negative

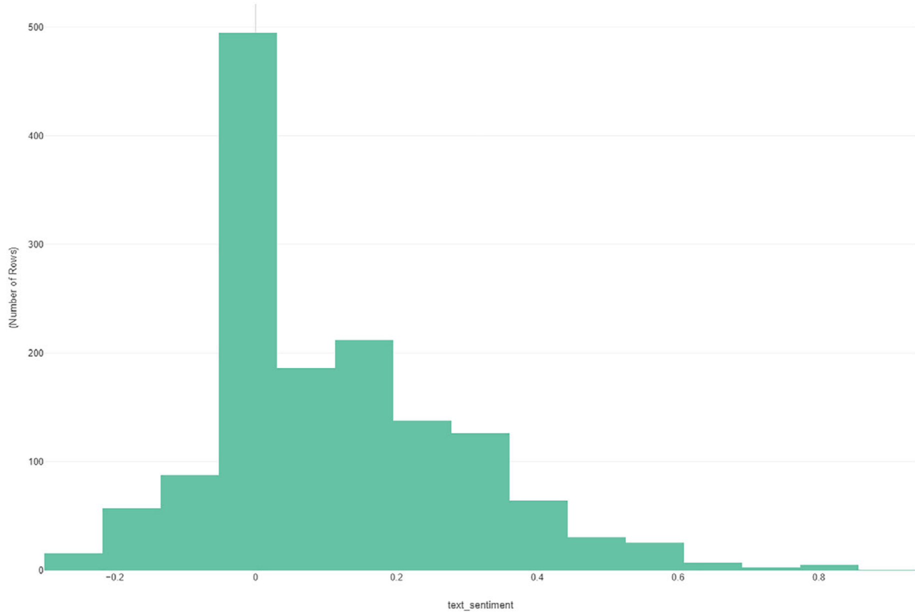

FIGURE 3 Sentiment mean distribution

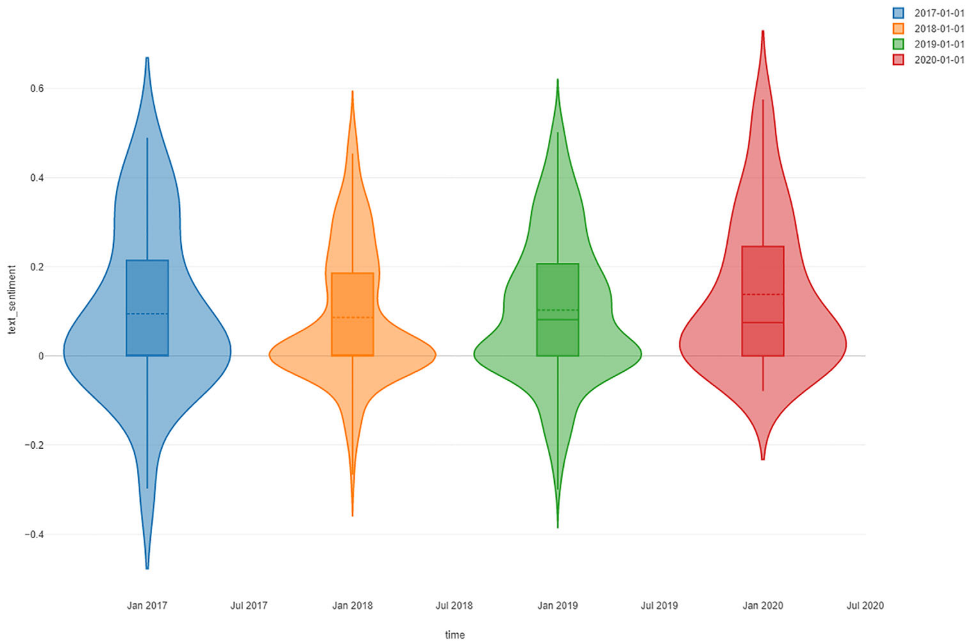

FIGURE 4 Tweets' mean and median sentiment distribution (years)

tweets would be found. Therefore, as a second step, sentiment analysis of tweets was undertaken with the aim of identifying significant shifts in rhetoric and the overall sentiments of tweets between 2017 and 2020 (Figure 3). The analysis, which is a standard aspect of social media monitoring tools and practices (Laine & Frühwirth, 2010), indicated the predominance of positive sentiment among those involved in the conversations, further indicating that the tweets were generally positive.

The sentiment analysis evidenced positive tones and sentiments in conversations carrying the #DownSyndrome hashtag, with the distribution of the sentiment following a multimodal Gaussian distribution, and the mean of the sentiment at 0.20 (positive sentiment comprises values between 0 and 1).

A more detailed analysis of the sentiment of tweets over the years (Figure 4) also demonstrated that in 2018, the sentiment of tweets was more negative (median sentiment distribution set at 0.08) than in 2019 (median sentiment distribution set at 1.2). They also highlighted a much larger dispersion of the sentiment in 2017 compared to the following year.

The sentiment analysis was applied to tweets as sentences, meaning that the tweets in their entirety (and not the individual words within the tweets) were analyzed and evaluated. This allowed for a

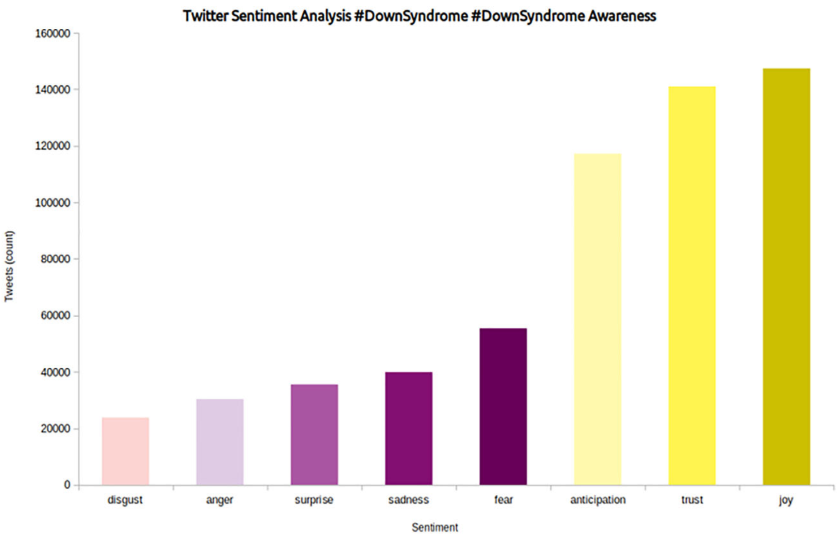

FIGURE 5 Detailed sentiment analysis

TABLE 2 Topic modeling: Topics distribution and sentiment

Topic	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	TOTAL
Dis/able/ita/ability/d	2531	11,997	2400	11,719	18,188	6387	2059	13,389	68,670
people	4388	9491	3210	5596	14,840	4623	5175	10,818	58,141
wdsd	787	13,324	478	9752	13,185	1361	2767	14,290	55,944
Abort/ion/o/ing	5170	5790	7578	8733	6077	8524	1880	7713	51,465
love/ing/love−/ly/d	2138	8493	1359	3379	13,481	2948	4060	8822	44,680
child/children	2253	9551	2055	3740	10,289	3064	3451	7995	42,398
life/pro−/life−/lives	3393	7431	2609	5000	8196	3443	3729	7946	41,747
God−/s	467	9449	352	9380	9477	749	752	9457	40,083
grow/ing	22	8384	36	8107	8384	51	87	8384	33,455

more comprehensive understanding of the sentiment of UGC carrying the #DownSyndrome hashtag on Twitter.

This overview prompted a more in-depth and emotion-based sentiment analysis with the aim of further classifying the sentiments associated with the topics that emerged as more prominent. This specific analysis allowed for the testing of sentiment (i.e., positive, negative, or neutral) on given topics within the context of the sentence (i.e., the tweet) and the identification of associated emotions (e.g., negative sentiments such as anger, disgust, fear, and sadness, and positive sentiments such as anticipation, trust, joy, and surprise) and key terms (e.g., frequency of topics discussed) within the entire corpus. This provided a method for accessing the robust sentiment extraction tool, which is more detailed than a generalized sentiment analysis that solely clusters tweets as negative, neutral, or positive (Mohammad & Turney, 2013), thus enriching current SMA research and practice. This in-depth computational analysis was used to produce a better understanding of the emotions that emerge around the topic of Down syndrome on Twitter and identify any emerging patterns of discussion that could be of strategic importance.

The refined and in-depth analysis revealed a different picture from the initial results (Figure 5). Positive sentiments of joy, anticipation, and trust overwhelmingly emerged in the tweets. Such positivity is associated with very specific topics that emerged through the topic modeling.

In fact, as Table 2 indicates, the 10 terms that emerged the most were "disability" and "World Down syndrome Day" (WDSD). Another emerging topic was "people" ($f = 58{,}141$), which occurred mainly in relation to the positive emotions of "joy" ($f = 14{,}840$ or 25%), "trust" ($f = 10{,}818$ or 18.6%), and "anticipation" ($f = 9491$ or 16.3%). However, it was difficult to place or explain the significance of the topic within the context of the dataset, given the lack of contextual specificity of the occurrence of the word.

Looking specifically at the negative sentiment, feelings of anger, disgust, or sadness emerged through the occurrence of very specific terms such as "abortion" ($f = 51{,}465$), most commonly used in association with negative emotions such as "fear" ($f = 8733$ or 17%), "sadness" ($f = 8524$ or 16.5%), or "disgust" ($f = 7578$ or 14.72%), but also with the positive emotion "trust" ($f = 7713$ or 14.99%). This negativity emerges in stark contrast to the positivity accompanying references to the term "life/pro-life" ($f = 41{,}747$), which appeared to be associated with positive emotions of "joy" and "anticipation." This tension in the corpus confirms the tension that surrounds discussions around Down syndrome but also around disability in general (Ellis & Kent, 2011; Nelson, 1994; Trevisan, 2017). Pro-life rhetoric can also be found in the repeated use of the terms "child" or "children" ($f = 42{,}398$ and among the top 10 most relevant topics recurring in tweets) and "God" ($f = 40{,}083$), which were found in co-occurrence with sentiments of "joy" ($f = 9477$ or 23.64), "trust" ($f = 9457$ or 23.59%), and "anticipation" ($f = 9449$ or 23.57%). These overtones of positivity, anticipation, and joy offer a novel understanding of stereotyping and essentialization of people with Down syndrome, and to the knowledge of the authors, this is the first study to confirm the complexity of social media users' conceptualization of people with Down syndrome, bringing to light the need to better understand the contribution of UGC not only to behavioral science studies and disability studies but also to marketing and strategic communication (in both social marketing and health communication).

Instagram analysis and results

Unlike on Twitter, images from specific dates cannot be retrieved on Instagram; instead, random images must be retrieved. Additionally, removing specific Instagram handles—or usernames—from the dataset is difficult. Therefore, the images that were processed included UGC as well as institutional account posts. Instagram has been widely researched in social and cultural studies, and the role of filters has also been at the center of digital ethnographic work (Pink, 2013). However, thus far, research on hashtag conversations on Instagram is lacking, despite the increased focus on emotional imaging in marketing and health communication (Gendall et al., 2018; Yung et al., 2019). Instagram posts were thus retrieved, and images were analyzed separately from the accompanying text using Google AutoML. The Instagram sample consisted of 14,294 unique posts; only images were extracted. To make the Google AutoML algorithm correctly classify images, a sample of Instagram images was selected and annotated as "training sample."[4] Based on the Twitter analysis, images were clustered to differentiate between three categories: "child," "youth," and "adult" (Bisong, 2019). At this stage, the main objective of this unsupervised learning was to assess whether the person with Down syndrome is somehow trapped into a stereotypical representation of a child-like person, in line with social marketing research but also by the Twitter analysis so far discussed.

The findings confirmed the predominance of pictures of children (item = "child" had a weighted score of 0.73, indicating that 73% of the images tested for the model were of children) and teenagers or young adults (item = "youth" had a weighted score of 0.26, showing that 26% of the tested pictures carried this label). Finally, adults represented less than 1% of the dataset. These results indicate a major distance between the frequency of images of children and the frequency of images of older people with Down syndrome within the platform, confirming both existing research findings and the Twitter analysis findings from this study.

The images in the training set were further analyzed using a qualitative approach; the 238 images were coded with NVivo. Although the Twitter results were taken into consideration, the coding process was inductive. In fact, rather than using any specific literature on essentialization or stereotyping, the images were coded with the aim of identifying specific themes and sub-themes (Elliot, 2018; Fereday & Muir-Cochrane, 2006) as they emerged during the coding process, almost following a grounded theory approach. The images were consequently coded; coders' cross-validation occurred through the exchange of samples and the re-coding of the images by the two authors with the help of an external researcher to ensure the rigorous coding of the images. This enabled the assessment of the results' validity, evaluation of other aspects of the image, and agreement on key visual narratives. Specifically, it enabled the discovery of what the person with Down syndrome appears to be doing in the picture, who appears in the pictures with them, and the space (e.g., indoor or outdoor) where the picture was taken.

Multiple categories could be associated with a single picture, allowing for one picture to be tagged multiple times with various themes and sub-themes. This allowed the analysis to determine which characterizations were most visible (Table 3) and what visual narrative about people with Down syndrome emerged based on the selected dataset of Instagram images.

The results confirmed the predominant presence of children and the setting and the context of the picture (i.e., the background) could be seen more clearly. Children's happiness in family settings was the most prevalent theme in pictures of children. The narrative for teenagers with Down syndrome was instead one of achievement, where the young people were pictured receiving a diploma or participating in an athletic competition. These pictures commonly represented teenagers either posing for a picture with a medal or diploma or engaging in sports or physical exercise. These photographs additionally depicted teenagers spending time and having fun with volunteers and, at times, engaged in field trips, events, or parties. Finally, a small number of pictures showed teenagers involved in fashion shows or school performances. In line with existing research, the Instagram analysis revealed that adults with Down syndrome were frequently accompanied by adult family members, volunteers, or staff of caring facilities or hospitals. The latter were recognizable due to the use of watermarked pictures or, in the case of staff from caring facilities, the uniforms typically worn by those appearing in the pictures with the adults with Down syndrome.

TABLE 3 Qualitative analysis

Category	Count of characters	Happiness	Achievement (more than able)	Family	Volunteers	Hospital/uniformed staff
Child	85	53	13	39	0	19
Teenager	94	11	47	16	80	0
Adult	59	17	20	8	37	1
Total	**238**	81	80	43	117	20

3 | DISCUSSION, PRACTICAL IMPLICATIONS, AND LIMITATIONS

The results of the analysis of #DownSyndrome on Twitter and Instagram confirmed some degrees of benevolent prejudice toward people with Down syndrome while also illuminating three important points. The first is the unique rhetoric that emerged on the two platforms. Although the same hashtag was used to retrieve data and analyze its textual and visual narrative, it emerged that each platform had its own specific rhetoric and stereotypical characterization of people with Down syndrome. However, this study identified the emergence of certain patterns common to both platforms that promoted the characterization of the person with Down syndrome as jovial, youthful, and innocent.

Twitter was revealed to be a more polarized, aggressive, and extreme platform, with religious overtones that exposed the debate between pro-life and pro-choice advocates. Conversely, the visual narrative that emerged on Instagram presented the imagery of the child more positively, albeit with curated content that did not necessarily imply a more inclusive attitude toward people with Down syndrome. As previously mentioned, this difference pertains to the platforms' specific characteristics, which must be carefully considered. Twitter is more immediate, and the limited space of a tweet makes it more susceptible to extreme or vitriolic comments and potentially offensive discussions (Recuero et al., 2019). On the other hand, Instagram's features and its structural characteristics make it a curated space with activities such as post-processing, filtering, and enhancement of some parts of images for esthetic purposes (Zappavigna, 2016). All these features are part of the application and are entrenched in the process of posting an image to a network of followers. These factors highlight the fact that, despite the different ways in which benevolent prejudice is channeled, the stereotypical representations of Down syndrome manifest constantly. The stereotypes that emerged in this analysis clearly represent a major challenge for health and nonprofit communication practitioners.

The second key point arising from the results of this investigation, therefore, is the need for a challenging discussion about more realistic portrayals of people with Down syndrome as part of awareness campaigns and general health communication efforts. As the results revealed, the tone and the overall content used in conversations carrying #DownSyndrome confirm the need to systematically undertake social media listening to inform communication strategies but, most importantly, creative and content-driven effective social media campaigns. This would, in turn, assist organizations and institutional bodies in moving beyond traditional understandings of social media campaign effectiveness and allow them to take other significant factors into consideration. The article evidenced the ethical challenges associated with social media marketing in the context of nonprofit strategies. The results in fact show that although it is paramount to elicit sympathy for people with Down syndrome, organizations must also carefully consider the ethical implications of perpetuating stereotypical and prejudicial characterizations of marginalized and under-researched segments of society. These discussions are needed to inform researchers and practitioners about the ways in which disabled and other marginalized people are portrayed on social media platforms.

Third, and perhaps most importantly, the results evidenced the important role of social media monitoring techniques, which, in combination with mixed methods, allow for a more in-depth evaluation of UGC. The major limitation of this research is the limited engagement with the qualitative aspect of the findings. While computational techniques can evidence patterns, the granularity of the data is lost. A well-rounded methodological approach would include qualitative analysis of meaningfully representative datasets. Research is increasingly moving toward "big qualitative data" studies (Davidson et al., 2019), and a mixed computational and qualitative analysis of UGC is necessary in the context of nonprofit and institutional marketing. The expertise and the interdisciplinarity required to undertake such mixed methods research, however, are beyond the scope of this article.

4 | CONCLUSION

This article demonstrated the important role that UGC plays in understanding how social media conversations can inform communication and marketing campaigns. The computational analysis undertaken on Twitter and Instagram posts confirmed the persistence of stereotypes while also illuminating the different shades of benevolent stereotypes and prejudicial representations of people with Down syndrome. The sentiment analysis and topic modeling of Twitter results indicate a polarization in discussions about Down syndrome with which neither disability studies nor media and marketing research have engaged. While some stereotypical depictions of people with Down syndrome align existing research, the tweets highlighted the emergence of religious overtones that appear on the platform. Likewise, the image-based research undertaken on Instagram emphasized the persistent presence of children on the platform, while the computational analysis confirmed the persistent presence of child imagery, confirming current social marketing research (Dias de Faria & Moreira Casotti, 2019).

The images posted on Instagram, when directly compared to existing research on intra-group relations and stereotypical media representations of disability, reveal several important imageries. First, the representation of people with Down syndrome as warm indicated what social and behavioral studies have identified as the paternalistic stereotype (Fiske et al., 2002). This emerges in the presentation of the visual narrative of Instagram. The images, in fact, evidenced the prevalence of children and a celebration of their happiness. When children become teenagers, their achievements receive more attention. In line with Nelson's model, it could be argued that teenagers with Down syndrome fall into the category of the "supercrip," a person who *despite* their condition can celebrate achievements like anyone else (i.e., like their *normal* peers), thus further stressing the paternalistic stereotype that has been discussed in behavioral sciences and disability studies alike.

Finally, the role of adults in the pictures analyzed corroborates research on paternalistic stereotyping, stressing the pitiable and tender nature of the adult with Down syndrome and positing that once the person with Down syndrome becomes an adult, their role changes from being a loving yet dependent child to being a member of society that needs support. Although none of the photographs of adults with Down syndrome carry any overtly negative tones, the possibility of a negative characterization of an adult with Down syndrome undeniably emerges. Overall, the research indicated that Instagram images were far more positive than the tweets and tended to induce sympathy toward young people with Down syndrome and those around them (organizations, families, or carers). Although there were no overtones of pity, the images clearly illustrated a form of stereotyping that would be difficult to capture with computational analysis, while also showing the work that remains to be done by non-profit organizations, health communication specialists, and social marketers from a visual communication perspective.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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ENDNOTES

[1] It will not be possible to use pictures for this article due to the funding body's request that we avoid sharing visuals of vulnerable people. Access to the dataset can be requested by contacting the corresponding author.

[2] The dataset comprises consists of 75,697 videos and pictures and their associated captions. Further research on this dataset is currently taking place. The tool that was used, and which is usually used in social media marketing intelligence, is 4KStogram.

[3] Although multilingual sentiment analysis is improving, social sciences are still encountering some issues with the successful implementation of available packages.

[4] The number was initially set to 238 to allow for an equal split between categories. The low presence of mature adults with Down syndrome necessarily impacted the final number of images that could be included in the training set. However, as the number of retrieved images has kept on growing, the training set is constantly being increased and the model enriched.

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