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Typology of Tweets and User Engagement Generated by U.S. Companies Involved in Developing COVID-19 Vaccines

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Abstract

This study analyzes 295 tweets by four U.S. companies engaged in discovering a vaccine for COVID-19. Tweets were analyzed to understand how their Twitter feeds balanced corporate and product branding (vaccine, medicines, etc.) and disseminated scientific information relating to COVID-19. The results suggest that these companies were actively embedding technical information about COVID-19 in their corporate and product branding. Tweets providing technical and scientific information about the

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progress made toward developing a COVID-19 vaccine garnered high levels of user engagement from their target audience. Findings from this study indicate the growing importance of technical communication in corporate settings during a public health crisis.

Keywords
COVID-19 vaccines, COVID-19, Twitter, branding, content analysis

The coronavirus disease (COVID-19) has unleashed a pandemic that has evoked serious public health concerns across the globe. The epidemic began in December 2019 when a new virus, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), spread from Wuhan, China, to 114 countries within 3 months, forcing the World Health Organization (WHO) to declare a global pandemic. With no clinical therapeutic cure in sight, most administrative bodies enforced stringent social distancing and quarantine measures as preventive strategies. At the same time, national governments, large pharmaceutical companies, and biotechnology start-ups, alone or in collaboration, started redirecting a considerable proportion of their resources toward developing new or repurposed drug compounds to provide a medical solution. To address some of the health concerns, experts used social media as a tool to disseminate public health information regarding COVID-19 based on the latest updates about vaccine trials.

In the race to find a cure for COVID-19, corporate entities, particularly pharmaceutical and biotech companies, have frequently shared information about therapeutic discoveries via social media in order to keep users informed about the emergence of a cure. Indeed, a survey conducted by Pew Research Center indicated that about 70% of Americans were optimistic that medical breakthroughs to successfully combat the coronavirus were on the horizon (Thigpen & Funk, 2020). In December 2020, Moderna's COVID-19 vaccine was at the cusp of being approved by the Food and Drug Administration (FDA). Candidate vaccines of two other U.S. biotechnology and pharmaceutical companies, Novavax and Johnson & Johnson (J&J), were in Phase 3 of a clinical trial while that of Inovio Pharmaceuticals (Inovio) was in Phase 2 (WHO, 2020).

As Thigpen and Funk (2020) reported, companies have used Twitter particularly to keep people informed about the latest status of their vaccines. As a fast, low-cost, interactive, and informal medium for communication between companies, stakeholders, and consumers (Xiong et al., 2018), Twitter has been used by corporate entities for product marketing (Taecharungroj, 2017), corporate communication (Mamic & Almaraz, 2013), and crisis communication (Stieglitz et al., 2018). Although the micro-blogging nature of Twitter imposes restrictions on the complexity of information that can be communicated, studies have confirmed the successful use of Twitter by for-profit companies for science communication (Lee et al., 2020), health communication (Park et al., 2016), financial disclosures (Xiong et al., 2016), and even technical support (Lam & Hannah, 2017).

The few studies that investigated social media strategies of organizations during global health crises focused almost exclusively on the risk communication efforts undertaken by government or nonprofit health organizations. We have found no studies that have investigated how for-profit science-based companies (e.g., biotechnology and pharmaceutical companies) engaged their consumers and stakeholders during such a global emergency. Thus, for this study, we developed a coarse-grained typology of tweets, focusing on tweets generated by four such for-profit companies—Moderna, Novavax, J&J, and Inovio—during the first months of the COVID-19 pandemic in the United States, using these categories to identify the types of tweets that generated a high level of user engagement.

Additionally, given Americans' general optimism regarding an imminent medical breakthrough on an effective vaccine against COVID-19, we specifically investigated how these companies shared technical information related to their COVID-19 vaccines via Twitter and how users responded to these messages. While categorizing the corpus of tweets broadens our understanding of how these companies used Twitter during this unprecedented pandemic, ranking the tweet categories according to the level of user engagement sheds light on how for-profit entities can further refine their Twitter strategies to induce higher levels of user engagement that could increase their visibility on this platform. Consequently, our overarching goal for this study is to analyze companies' dissemination of information about their COVID-19 vaccine from the sides of supply and demand. From the supply side, we study how frequently tweets of different categories appear. From the demand side, we analyze how user engagement varied across the tweet categories. Infrequently generated tweet categories that garner a high level of user engagement would inform the organizations about a potential mismatch between the information that the audience seeks and the information that the organizations have provided. This study, then, contributes to the literature on Twitter use in corporate communication by identifying such easily understandable and interpretable supply and demand categories of tweets. Categorizing tweets is not an end in itself but rather forms the foundation for analyzing the interplay between supply and demand information about COVID-19 vaccines on Twitter.

Before we present our study, we provide a background of studies that have been conducted on Twitter use in corporate communication. Then, we describe our research questions and method for the study, report the results, and discuss our findings. Finally, we consider the study's implications for practitioners, limitations, and future directions.

Studies on Twitter Use in Corporate Communication

Twitter has played an integral part in corporate communication policies. Several studies have investigated how large companies use their dedicated Twitter account to establish an informal communication channel with consumers, stakeholders, and relevant interest groups (Kaplan & Haenlein, 2010; Rybalko & Seltzer, 2010; Zhang et al., 2020). There are two main categories of studies investigating Twitter: (a) studies analyzing the content of tweets generated to perform specific types of communication, such as corporate social responsibility (Araujo & Kollat, 2018), customer service (Berry, 2018), financial reporting (Xiong et al., 2019), and health promotion (Park et al., 2016) and (b) studies focusing on the structural properties of tweets, such as tweet frequency and the use of hashtags, links, and visuals (Mamic, & Almaraz, 2013) and the ways that tweets were used to induce a dialogue between the audience and sender (Rybalko & Seltzer, 2010). But only a few studies have systematically analyzed the contents of corporate tweets in order to develop a typology of company-generated tweets.

Recently, Zhang et al. (2020) provided a comprehensive analysis of the tweets generated by large information technology (IT) companies and arrived at three main tweet categories—corporate communication, technical communication, and marketing communication—and a fourth category of tweets involving combinations of those three categories. In essence, they identified in the tweet content a set of relevant features whose presence or absence determines a tweet's category. In contrast, Lee et al. (2020) analyzed the purpose of the tweet content of one company, 23andMe, a direct to consumers (DTC) genetic-testing company, and derived five categories: provide company-related information, directly promote a product, share scientific information about human genetics, share science more generally, and communicate product benefits. These five categories could be merged into the three categories proposed by Zhang et al. (2020) by including the product-promotion and product-benefit content in the marketing communication category, the two types of scientific information content in the technical communication category, and the company-related content in the corporate communication category.

Tweets conveying corporate communication attempt to build community relations and enhance the company's reputation by promoting community activities, explaining corporate social responsibilities, announcing collaborations and alliances, and describing company work culture and recognizing employees and corporate achievements. All these features align with a deliberate organizational communication strategy that focuses on building community, developing relationships, disseminating information, and monitoring public opinion and stakeholder responses (Frandsen & Johansen, 2018). Both Zhang et al. (2020) and Lee et al. (2020) found that tweets performing corporate communication were dominant in their analysis of tweets generated by IT companies and 23 and Me, respectively.

Turning to tweets generated for marketing communication, studies have reported that pharmaceutical companies spend more than $2.5 billion dollars on DTC advertising (Deshpande et al., 2004). The main goal of the DTC approach is "to create market recognition of a brand [in order] to sell a product" (Coney, 2002, p. 214). Given its ability to attract consumer attention and promote word-of-mouth communication (Jansen et al., 2009), Twitter has the potential to be an effective medium for advertisement and sales promotion. Zhang et al. (2020) revealed that marketing-oriented tweets conveyed product features, product benefits, direct advertising and sales promotions, and third-party testimonials. Thus, product name branding and direct calls to purchase form an integral part of the DTC marketing strategy and communication. In contrast, in a business-to-business setting, companies are more likely to highlight corporate name branding (Swani et al., 2014).

Gottfried and Funk (2017) reported that a considerable fraction of the U.S. population receives scientific news from social media. Consequently, science and technology-based companies often use social media channels to disseminate information about technical aspects of their products and services and offer related scientific information to educate consumers (Lee et al., 2020). Corporate tweets that primarily convey technical communication, then, provide scientific or technical information about company products, offer information about technical product updates, and disseminate general scientific or technical information on specialized topics. For such companies, both Zhang et al. (2020) and Lee et al. (2020) found this category of tweets to be the second most abundant, with tweets devoted to traditional corporate communication being the most abundant.

Studies have also shown that organizations use social media during and after events of natural disasters, social unrest, and violent incidents (Al-Saggaf & Simmons, 2015; Gaspar et al., 2016; Heverin & Zach, 2012; Oh et al., 2013; Panagiotopoulos et al., 2016) for *risk communication*, defined as the "exchange of information among interested parties about the nature, magnitude, significance, or control of a risk" (Covello, 1992, p. 359). In fact, Turoff et al. (2013) argued that organizations should more optimally use social media's penetration and knowledge-decentralization capabilities to engage with the public during emergencies. Guidry et al. (2017) observed that prominent health organizations extensively used both Twitter and Instagram for communicating health risks during the Ebola outbreak. As such, from the perspective of strategic communication theory on health risks, we can argue that social media can play a critical role in managing health crises (Guidry et al., 2017; Tirkkonen & Luoma-aho, 2011). In particular, Tirkkonen and Luoma-aho (2011) posited that strategic use of social media during a crisis can motivate the public to take actions to mitigate the risk.

From these studies, we can glean insight into the types of Twitter content that science and technology companies generate. Additionally, some of these studies also investigated the association between user engagement and tweet characteristics (Guidry et al., 2017; Lee et al., 2020), identifying a set of tweet characteristics that highly correlate with user engagement. But none of these studies examined a potential mismatch between the demand and supply of tweet categories. Further, the set of tweet features that showed significant association with user engagement may not always be useful to corporate tweet writers in crafting messages. Consequently, these findings may have limited use to practitioners. We addressed this gap in the research by developing an empirical procedure that would help practitioners fine-tune the supply of different tweet categories by considering the user engagement that these categories elicited.

Developing Research Questions

To explain how we developed our research questions, we first discuss how we developed tweet categories and characterized user engagement. Then we report how we generated the frequency of each category and the user engagement it elicited. Finding which tweet categories have low generation frequency but high engagement, or vice versa, reveals what tweet categories should be emphasized and what ones should be deprioritized.

Characterizing Contents of Corporate Tweets

Given our focus on corporations, we expected that our focal companies would mostly generate tweets aimed at providing general corporate communication. We also expected that these companies would generate marketing-oriented tweets that offer information about (or promote) their existing or future products. Although the product portfolios of Inovio, Moderna, and Novavax were not substantial enough to engage in direct sales promotion or product advertisement, the companies routinely provided information about their product pipeline and kept their audiences updated about their research and development breakthroughs. Acknowledging the difference between the marketing tweets generated by these four organizations, we defined a broader tweet feature—*brand orientation*—that captured the corporate-branding and product-branding strategies.

Next, from the empirical evidence provided by Zhang et al. (2020) and Lee et al. (2020), we expected that the companies would use Twitter to disseminate both product-specific and topic-specific scientific and technical information. Hence, we defined a *science/technical orientation* feature to identify the tweets that disseminated any form of scientific or technical information.

Finally, following the strategic communication theory on health risks and the empirical evidence of health organizations' heavy use of social media during the Ebola outbreak (Guidry et al., 2017), we expected that corporate entities at the forefront of developing a vaccine for COVID-19 would also use Twitter to disseminate COVID-19-related information in order to keep the population aware of the health risks and available protective strategies. Consequently, we defined a third feature—*COVID-19 orientation.* Including this last feature provided insight into how the companies generated public-interest messages during the pandemic.

Our three features captured three distinct aspects of each tweet; thus, each tweet could be represented by the values assigned to either brand orientation, science/technical orientation, or COVID-19 orientation. We posited that these features would serve this study's purpose of examining how frequently the companies used Twitter to disseminate scientific and technical information about their COVID-19 vaccine. Therefore, our first research question investigated the frequency of the following characteristics in the contents of the companies' tweets:

Research question (RQ) 1: What proportion of tweets generated by U.S. for-profit biotech and pharmaceutical companies that were engaged in developing the COVID-19 vaccine from March 01, 2020, through May 24, 2020, were (a) performing corporate branding, (b) performing product branding, (c) sharing scientific or technical information, (d) sharing COVID-19 related information, and (e) disseminating scientific information about the company's own COVID-19 vaccine?

Assessing User Engagement

In an unmoderated setting, users can interact freely with social media. Alhabash and McAlister (2015) defined such interactive behavior as the "virility" of the message. *Message virility* consists of viral reach (i.e., retweeting in Twitter), affective evaluation (i.e., favoriting in Twitter), and message deliberation (i.e., replying in Twitter). We could, therefore, assess the effectiveness of the communication strategies by analyzing the virility of the messages. Since the Twitter application programming interface readily provides retweet and favorite counts for each tweet, we could use virile reach and affective evaluation to assess the level of user engagement in the tweets.

Previous studies examining user engagement in company tweets reported that under normal circumstances, tweets providing general corporate information and those sharing general scientific discoveries elicited significantly higher retweets and favorites than did other types of company tweets (Lee et al., 2020). But during an emergency, Twitter can turn out to be an excellent platform for disseminating crisis-related information (Panagiotopoulos et al., 2016). The risk information seeking and processing (RISP) model predicts users' behavior in seeking information from multiple channels (Griffin et al., 1999). Such behavior can be motivated during pandemics (Holton, 2010; Morahan-Martin, 2004; Wang & Ahern, 2015); on Twitter it can manifest in the form of retweeting because, according to Metaxas et al. (2014), people retweet when they find a message to be interesting, trustworthy, informational, or agreeable. Therefore, our second research question assessed user engagement in the company tweets in order to reveal users' behavior in seeking information related to COVID-19:

RQ2: Overall, which category of tweets generated by U.S. for-profit biotech and pharmaceutical companies that were engaged in developing the COVID-19 vaccine from March 01, 2020, through May 24, 2020, elicited (a) the most retweets and (b) the most favorites?

Bandwagon Effect

The association between tweet category and user engagement is susceptible to severe discrepancies according to the number of followers associated with each Twitter account. The disproportionately greater popularity of J&J compared to the other three companies in our study could have confounded the relationship between tweet category and user engagement. That is, because it had such a huge follower base, if followers of J&J retweeted a certain tweet category and none of the followers of the other three companies retweeted that category, the outcome of RQ2a would show that the corresponding tweet category generated the most retweets in the entire tweet corpus. Therefore, to properly interpret the findings of RQ2, we needed to establish that the user engagement across different categories was not overly influenced by the user engagement generated by the company having the largest number of followers.

Theoretically, the association between user engagement and the number of followers of a social media account can be explained from the perspective of "bandwagon heuristics": That is, "if others think that something is good, then I should think so too" (Sundar, 2008, p. 83). Lee and Sundar (2013) operationalized the bandwagon cue in Twitter as the number of followers that a profile has and experimentally demonstrated the significant positive impact of a high bandwagon condition on the popularity and trustworthiness of a source. Flanagin and Metzger (2013) used the bandwagon effect to explain Twitter users' reliance on retweeted messages in order to formulate quick judgments and decisions about products or brands. Liu et al. (2017) also reported a positive association between number of followers and user engagement in health communication on Sina Weibo. Hence, our third research question assessed user engagement to determine which category of tweets elicited the most retweets and favorites after we adjusted for the bandwagon effect:

RQ3: Which category of tweets generated by U.S. for-profit biotech and pharmaceutical companies that were engaged in developing the COVID-19 vaccine from March 01, 2020, through May 24, 2020, elicited (a) the most bandwagon-adjusted retweets and (b) the most bandwagon-adjusted favorites?

If the bandwagon-adjusted scores in the retweet and favorite dimensions of user engagement showed significant positive correlation with their unadjusted counterparts (as obtained from RQ2), then it would suggest that the discrepancy in the size of the follower base of the different companies did not reverse the user-engagement pattern revealed in RQ2.

Method

To address our research questions and hypotheses, we performed a quantitative content analysis of the Twitter content generated by four U.S. companies—Moderna, Novavax, J&J, and Inovio—the only four U.S. companies working on a COVID-19 vaccine during our study period (March 1–May 24, 2020). We used tweets generated on May 25 through May 31, 2020, to develop a codebook establishing the precise operational definitions for each category, so we did not include those tweets in the final sample. We chose March 1 as the start date because around this time, arguably the first experimental broad-spectrum antiviral drug—NHC, EIDD-1931—was reported to deliver promising results against multiple coronaviruses, including SARS-CoV-2 (Sheahan et al., 2020). Further, the first week of March 2020 marked the beginning of the first wave of COVID-19 in the United States. We chose this period specifically to restrict our study to the first wave of the COVID-19 epidemic in the United States (The New York Times, 2021).[1]

Our initial sample consisted of a total of 317 tweets posted from the companies' principal Twitter handle (see Appendix for a profile of each company and the twitter handles we used to collect data) during the study period. Using Twitter's developer account, we downloaded and saved all the tweets. We retained texts, audiovisual contents, and external links embedded in the posts and discarded emojis because they were symbolic and did not represent textual or verbal communication. We also discarded all direct replies because these were not company generated.

Variables

Our unit of analysis was the individual tweet. Each tweet was represented by three features, brand orientation, science/technical orientation, and COVID-19 orientation. But a tweet could be both brand oriented and scientifically oriented. To obtain a finer resolution, then, we divided the brand orientation feature into three more specific features: *corporate branding* tweets, which shared corporate information; *product branding* tweets, which shared product-related information; and *no branding* tweets, which shared neither corporate nor product related information. Then we categorized each of the tweets in our sample according to these five features: corporate branding, product branding, no branding, science/technical orientation, and COVID-19 orientation.

Corporate Branding. We adapted the findings of Zhang et al. (2020) and Swani et al. (2013, 2014) to define the aspects of tweets performing corporate branding. In particular, we defined seven corporate-centric aspects: (a) community relations, (b) corporate social responsibility, (c) company-specific business insight, (d) partner relations, (e) human resources and job postings, (f) corporate achievements, and (g) corporate–government relations. If at least one of these corporate-centric aspects was present in a tweet, we classified it as corporate branding. Tweets that made any reference to the product–service portfolio of the company were not considered as corporate-branding tweets.

Product Branding. We identified tweets focusing on specific products or services as product-centric tweets. Following Zhang et al. (2020), we defined product-centric attributes as (a) product related research and development information, (b) product branding, (c) commercial advertising, (d) product launch, (e) sales promotion, and (f) third-party testimonials. If at least one of these product-centric attributes was present in a tweet, we classified it as product branding.

No Branding. We identified tweets whose focus was neither corporate nor product branding as no branding. Typically, these tweets contained information that kept users updated about developments that were not strictly connected to either corporate or product branding.

Science/Technical Orientation. We identified a tweet as having a science/technical orientation if it had at least one of the following characteristics: (a) reference to company-specific scientific research; (b) referenced to any scientific documents (links, text, videos, audio files); (c) opinions of scientists, health care professionals, or technical personnel; (d) technical information about specialized topics; (e) scientific or technical updates about products or services; and (f) technical instructions to users.

COVID-19 Orientation. We identified tweets containing mentions or descriptions of any of the following 12 COVID-19-specific attributes (adapted from Guidry et al., 2017) as being *COVID-19 oriented*: (a) news about COVID-19, (b) COVID-19 symptoms, (c) the spread of COVID-19, (d) the nature and forms of COVID-19 transmission, (e) preventative measures against COVID-19, (f) misinformation about COVID-19, (g) travel restrictions, (h) mandatory quarantines, (i) reassurance about COVID-19, (j) crisis-response measures, (k) survivor stories, and (l) COVID-19 medication.

We paired the tweets identified as corporate branding, product branding, or no branding, features which were all mutually exclusive, with the tweets that had a science or technical orientation, a COVID-19 orientation, or both, resulting in a total of 12 tweet categories (see Table 1). We coded each tweet with one content category only. We removed from further analysis any tweet that could not be categorized into any of these categories, resulting in a final sample of 295 tweets. Our sample, then, consisted of most of the entire corpus of tweets generated by the four companies during our study period.

Finally, following Lee and Sundar (2013) and Liu et al. (2017), we tracked the number of followers for each of the corporate Twitter accounts daily during the study period and averaged them to approximate the size of each company's follower base. Then we computed the bandwagon-adjusted retweet or favorite scores for each tweet category using the following formula:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{y_{i,C}}{n_{i,C} * f_i},$$

In this formula, $y_{i,C}$ denotes the total number of retweets or favorites associated with a category (C) and company (i), $n_{i,C}$ the total number of tweets generated in the category (C) by company (i), f_i the approximate size of the follower base of the company (i), and N denotes the number of companies. A score of 0 was assigned when $n_{i,C}$ turned out to be null. Subsequently, we compared these bandwagon-adjusted numbers with the unadjusted number of retweets or favorites obtained from RQ2.

Coding and Reliability

Two out of three authors served as principal coders, developing the codebook for the tweets we collected during the last week of May 2020. Both coders individually coded this set of tweets in order to achieve consistency in interpreting the coding scheme. Once an acceptable intercoder reliability was achieved on this set of tweets, the corpus of tweets in the study sample was evenly split between the two principal coders. All three of us intensively examined the text of each tweet. We investigated the audio and video files embedded in the tweets and visited any link posted in the tweet to make sure that the text in the tweet agreed with the external content. We then held multiple rounds of discussion to refine the codebook and resolve the ambiguity in some of the tweets in our corpus. The two principal coders independently coded a random sample of 102 tweets to arrive at the final reliability estimate. Krippendorf's alpha indicated a high level of intercoder reliability for all variables: brand orientation [$\alpha = 0.8351$, 95% confidence interval (CI) = (0.745, 0.925)], COVID-19 related [$\alpha = 0.8373$, 95% CI = (0.702, 0.946)], science/technical orientation [$\alpha = 0.7694$, 95% CI = (0.631, 0.908)].

Table 1. Typology of Corporate Tweets ($N = 295$).

Content Category	Example	Frequency (%)
Corporate branding, nontechnical, unrelated to COVID-19	"We just announced first quarter 2020 financial results & business updates. Read more: https://t.co/5XdkPGIpUw https://t.co/mDxW528M6 h 5/7/2020" (Moderna, 2020b)	33 (11.2)
Corporate branding, nontechnical, COVID-19 related	"#JNJ is proud to honor the frontline health workers courageously leading our communities through the #COVID19 crisis. Watch to meet some of these fearless frontline heroes, and learn how you can join J&J." (Johnson & Johnson, 2020b)	44 (14.9)
Corporate branding, technical, unrelated to COVID-19	"One way #JNJ helps support nurse-led innovation: with programs like the Nurse Innovation Fellowship, which helps strengthen nurses' leadership & entrepreneurial skills. Learn more about the program from Lynda Benton, Senior Director, Corporate Equity, J&J. https://t.co/aZsGpPWyza" (Johnson & Johnson, 2020c)	5 (1.7)
Corporate branding, technical, COVID-19 related	"How is #JNJ working to ensure our supply chain remains strong during the #COVID19 pandemic? Kathy Wengel, CSCO, J&J, shares how her team is helping meet the needs of the patients and consumers who rely on us—all while ensuring our employees' wellbeing: https://t.co/ReNFYF7KIZ https://t.co/perS7ejrZS" (Johnson & Johnson, 2020a)	13 (4.4)
Product branding, nontechnical, unrelated to COVID-19	"BREAKING: @NovavaxInc has inked a deal for its seasonal flu vaccine with another Gaithersburg biotech… https://t.co/odnofgmyTv" (Novavax, 2020a)	3 (1.0)
Product branding,	"Inovio Pharmaceuticals™ race to create a vaccine began when the genetic	17 (5.8)

(continued)

Table 1. (continued)

Content Category	Example	Frequency (%)
nontechnical, COVID-19 related	sequence of COVID-19 was posted online by Chinese scientists just weeks after the outbreak was identified. https://t.co/tJfgmAnJ00 https://t.co/kawgGgbtZb" (Inovio Pharmaceuticals, 2020a)	
Product branding, technical, unrelated to COVID-19	"INOVIO released data for newly diagnosed #glioblastoma multiforme (#GBM) patients who received our DNA medicine INO-5401 in combination w/ a PD-1 inhibitor. Results will be presented at #ASCO20 Virtual Scientific Program: https://t.co/4I8DPlY5qJ #DNAMedicines #DNAImmunotherapy https://t.co/b7QTxBDWUE" (Inovio Pharmaceuticals, 2020b)	21 (7.1)
Product branding, technical, COVID-19 related	"Today we announced an INOVIO study published in peer-reviewed journal @NatureComms about the robust preclinical immune response, including both neutralizing antibodies and T cell responses, of INOVIO™s COVID-19 DNA vaccine: https://t.co/nrysBJAO70 #DNAMedicines #DNAVaccines https://t.co/MJsJSEMOXL" (Inovio Pharmaceuticals, 2020c)	68 (23)
No branding, nontechnical, unrelated to COVID-19	"CDC estimates that between Oct. 1 and March 14, at least 38 million people were sick with #flu. https://t.co/pWousIjU41" (Novavax, 2020b)	5 (1.7)
No branding, nontechnical, COVID-19 related	"#coronavirus #COVID19 https://t.co/8pkD5sogYB" (Novavax, 2020c)	31 (10.5)
No branding, technical, unrelated to COVID-19	"Professor Paul Heath of @StGeorgesUni is now presenting an overview of #immunization https://t.co/QarYYSCebm" (Moderna, 2020a)	9 (3.1)

(continued)

Table 1. (continued)

Content Category	Example	Frequency (%)
No branding, technical, COVID-19 related	"Current understanding is #COVID19 spreads mostly from person to person through respiratory droplets produced when a person coughs or sneezes, similar to how flu spreads. Learn more at https://t.co/ Vvlzx7O3 mM https://t.co/ MiHHHyCfTa" (Novavax, 2020d)	46 (15.6)

Note. Here nontechnical tweets are those that did not contain any scientific or technical information.

Results

To determine the proportion of tweets that performed corporate branding (RQ1a), performed product branding (RQ1b), shared scientific or technical information (RQ1c), shared COVID-19 related information (RQ1d), and disseminated scientific information about the company's COVID-19 vaccine (RQ1e), we analyzed the frequency of each of the 12 tweet categories (see Table 1). We found that the companies struck a balance between corporate branding (32%) and product branding (37%). About 55% of the tweets shared some form of scientific or technical information, with 43% of the tweets sharing scientific or technical information on COVID-19-related topics. And a large majority (74%) of the tweets disseminated COVID-19-related information. Although we observed features of corporate branding in a number of tweets that were primarily geared to disseminate COVID-19-related information (19%), some of the tweets (16%) simply conveyed scientific information about the disease without including any form of corporate or product branding. Finally, about 23% of the tweets conveyed scientific information about the COVID-19 vaccines that these companies were developing. As such, out of the 12 tweet categories, the most frequently occurring category performed product branding while offering scientific or technical information about COVID-19-related topics.

To determine which category of tweets overall elicited the most retweets (RQ2a) and the most favorites (RQ2b), we calculated the average number of retweets and favorites per day for each tweet category (see Table 2). We observed the highest user engagement in the product-branding category that conveyed COVID-19-related information. In other words, tweets containing information about COVID-19 vaccines tended to elicit maximum user responses. Users mostly retweeted tweets related to COVID-19 vaccines that did not contain any scientific or technical information; however, tweets containing scientific information related to COVID-19 vaccines earned the most favorites.

We used Kruskal–Wallis tests to determine if there were significant differences in retweet and favorite frequencies (count variables) across the tweet categories. Both the mean retweet and the mean favorite frequencies differed significantly across tweet categories ($p < .001$). Subsequently, we performed post hoc pairwise comparisons using the Mann–Whitney two-

Table 2. Mean Number of Unadjusted Retweets and Favorites Elicited by Each of the 12 Tweet Categories.

Content Category	Retweets *M* (*SD*)	Favorites *M* (*SD*)
Corporate branding, nontechnical, unrelated to COVID-19	14.94 (29.59)	26.45 (23.66)
Corporate branding, nontechnical, COVID-19 related	38.64 (67.08)	60.14 (68.13)
Corporate branding, technical, unrelated to COVID-19	8.60 (4.16)	18.80 (23.42)
Corporate branding, technical, COVID-19 related	49.15 (68.50)	42 (70.04)
Product branding, nontechnical, unrelated to COVID-19	16.33 (14.01)	25.67 (38.55)
Product branding, nontechnical, COVID-19 related	164.12 (265.31)	180.82 (435.04)
Product branding, technical, unrelated to COVID-19	10.95 (11.06)	32.48 (43.08)
Product branding, technical, COVID-19 related	119.37 (338.35)	198.18 (448.22)
No branding, nontechnical, unrelated to COVID-19	21 (36.159)	6.40 (6.23)
No branding, nontechnical, COVID-19 related	17.26 (16.91)	22.77 (36.56)
No branding, technical, unrelated to COVID-19	5.78 (6.47)	20.67 (14.92)
No branding, technical, COVID-19 related	87.35 (307.05)	38.96 (51.34)

sample procedure with Bonferroni corrections for multiple comparisons. The resulting *p*-values suggested that the frequency of retweets elicited by the product-branding tweets providing technical information on COVID-19-related topics was significantly different from the frequency of retweets elicited by the (a) corporate-branding tweets providing nontechnical information on COVID-19-related topics ($p < .001$), (b) product-branding tweets providing technical information on topics unrelated to COVID-19 ($p = .001$), (c) no-branding tweets providing technical information on topics unrelated to COVID-19 ($p = .001$), and (d) no-branding tweets providing nontechnical information on COVID-19-related topics ($p = .014$).

We found a significant difference in retweeting behavior between product-branding tweets providing non-technical information on COVID-19-related topics and (a) corporate-branding tweets providing nontechnical information that was unrelated to COVID-19 ($p = .001$), (b) product-branding tweets providing technical information that was unrelated to COVID-19 ($p = .004$), and (c) no-branding tweets providing technical information that was unrelated to COVID-19 ($p = .001$).

Regarding the frequency of favorites elicited by the tweet categories, the adjusted *p*-values suggest that the frequency of favorites elicited by the product-branding tweets providing technical information about COVID-19-related topics was significantly different from the frequency of favorites elicited by the (a) corporate-branding tweets providing nontechnical information unrelated to COVID-19 ($p = .001$), (b) corporate-branding tweets providing technical information on COVID-19-related topics ($p = .038$), (c) product-branding tweets providing technical information unrelated to COVID-19 ($p = .010$), (d) no-branding tweets providing nontechnical information unrelated to COVID-19 ($p = .030$), (e) no-branding tweets providing nontechnical information on COVID-19 ($p < .001$), and (f) no-branding tweets providing technical information on COVID-19 ($p = .001$).

The results were particularly interesting when we ranked the 12 tweet categories according to both their relative frequency of occurrence and their user engagement. We found that the top-three tweet categories in terms of occurrence were product branding providing technical information related to COVID-19, no branding providing technical information on COVID-19, and corporate branding providing nontechnical information on COVID-19, respectively. In terms of retweets, the top-three tweet categories were product branding providing non-technical information on COVID-19, product branding providing technical information on COVID-19, and no branding providing technical information on COVID-19, respectively. And in terms of eliciting favorites, the top-three tweet categories were product branding providing technical information on COVID-19, product branding providing nontechnical information on COVID-19, and corporate branding providing nontechnical information on COVID-19, respectively. To determine if the bandwagon effect had an impact on these overall rankings, we need to examine company-specific rankings of popular tweet categories.

Thus, to examine which category of tweets elicited the most bandwagon-adjusted retweets (RQ3a) and the most bandwagon-adjusted favorites (RQ3b), we calculated the average number of followers of each corporate Twitter account and the total number of tweets generated by each account during our study period (see Table 3). Table 4 displays the mean number of bandwagon-adjusted retweets and favorites for each tweet category along with their unadjusted counterparts.

To assess whether there was an agreement in the adjusted and unadjusted mean scores, we computed a Pearson's correlation coefficient. For RQ3a, we found no significant correlation in the retweet dimension of user engagement [ρ=0.40,95% *CI*=(-0.22,0.79)]. For RQ3b, we found a significant positive correlation between the adjusted and the unadjusted scores in the favorite dimension of user engagement [ρ=0.71,95% *CI*=(0.24,0.91)]. Since a potential bandwagon effect was indicated in the retweet dimension of user engagement, the top-three most retweeted categories shown in Table 2 could have been dominated by the user engagement generated by J&J because of its considerably larger follower base. Therefore, we investigated company-specific retweeting behavior. Table 5 shows the top-three tweet categories for each company ranked according to the average number of retweets that each category generated per day. The fact that J&J's top-two retweeted categories matches the overall top-two retweeted categories clearly indicates the bandwagon effect.

Table 3. Company-Specific Analysis of Twitter Activities and User Engagement.

Company	Followers (*M*)	Relevant Tweets *n*
Inovio	10,600	40
Novavax	4,582	67
Moderna	22,500	40
J&J	197,500	148

Table 4. Mean Number of Bandwagon-Adjusted Retweets and Favorites Elicited by Each of the 12 Tweet Categories.

Content Category	*M* Adjusted (Unadjusted) Retweets	*M* Adjusted (Unadjusted) favorites
Corporate branding, nontechnical, unrelated to COVID-19	0.43 (14.94)	2.16 (26.45)
Corporate branding, nontechnical, COVID-19 related	2.72 (38.64)	4.26 (60.14)
Corporate branding, technical, unrelated to COVID-19	0.15 (8.60)	0.60 (18.80)
Corporate branding, technical, COVID-19 related	3.36 (49.15)	3.49 (42)
Product branding, nontechnical, unrelated to COVID-19	0.89 (16.33)	1.40 (25.67)
Product branding, nontechnical, COVID-19 related	1.39 (164.12)	2.33 (180.82)
Product branding, technical, unrelated to COVID-19	1.21 (10.95)	4.55 (32.48)
Product branding, technical, COVID-19 related	5.71 (119.37)	11.11 (198.18)
No branding, nontechnical, unrelated to COVID-19	1.26 (21)	0.44 (6.40)
No branding, nontechnical, COVID-19 related	0.20 (17.26)	1.24 (22.77)
No branding, technical, unrelated to COVID-19	0.18 (5.78)	0.77 (20.67)
No branding, technical, COVID-19 related	20.58 (87.35)	1.30 (38.96)

Discussion

The purpose of this study was to categorize the corpus of tweets that U.S. biotech or pharmaceutical companies working toward developing a COVID-19 vaccine generated during the first wave of the pandemic in the United States and to obtain the frequency distribution of the tweet categories. We also extracted the user engagement associated with each tweet category, identified the three tweet categories that elicited the most user responses and juxtaposed them with the three tweet categories that had

Table 5. Company-Specific Ranking of Tweet Categories According to Their Mean Number of Retweets Generated per Day.

Company	Rank 1 (*M* Retweets)	Rank 2 (*M* Retweets)	Rank 3 (*M* Retweets)
Inovio	Corporate branding, technical, COVID-19 related (104.00)	Corporate branding, nontechnical, COVID-19 related (95.88)	Product branding, technical, COVID-19 related (73.55)
Novavax	No branding, technical, COVID-19 related (362.63)	No branding, nontechnical, unrelated to COVID-19 (22.75)	Product branding, nontechnical, unrelated to COVID-19 (16.33)
Moderna	Product branding, technical, COVID-19 related (298.25)	Product branding, nontechnical, COVID-19 related (53.00)	Corporate branding, technical, COVID-19 related (22.00)
J&J	Product branding, nontechnical, COVID-19 related (224.92)	Product branding, technical, COVID-19 related (64.00)	Corporate branding, nontechnical, COVID-19 related (32.96)

the highest frequency of occurrence. The findings suggest that the level of user engagement elicited by the four companies in our study during the pandemic had a nuanced association with the number of Twitter users who followed their Twitter accounts.

Our analysis of RQ1 offers insight into the four companies' Twitter communication strategies. First, the fact that nearly three fourths of the overall number of tweets shared information related to COVID-19 indicates that these companies were generating content that explicitly considered the atmosphere of uncertainty and stress caused by the pandemic. Not only did they often embed COVID-19-related information while performing corporate or product branding, but they also sometimes (in about a fourth of their tweets) disseminated pandemic-related information without explicitly performing any corporate or product branding, indicating a bona fide attempt to offer such information to people who were eager for it during a public health crisis. While previous studies have demonstrated that government or nonprofit organizations actively use social media to disseminate information to the public during an emergency, our findings revealed that for-profit entities also take on these social responsibilities, and design their Twitter communication strategies to complement the communication efforts of traditional agencies.

We also observed that the two most frequently occurring tweet categories disseminated some form of technical information. Previous studies (Lee et al., 2020; Zhang et al., 2020) have also reported that corporate organizations based on science or technology regularly used Twitter to perform technical communication. Clearly, despite its microblogging nature, Twitter has turned out to be a viable platform to share complex scientific information.

Our examination of brand orientation reveals that the tweets appeared to be rather evenly distributed across the aspects of this attribute. This finding agrees with those of Zhang et al. (2020) and Lee et al. (2020) in the contexts of large IT companies and a DTC genetic-testing company, respectively.

In sum, our analysis of RQ1 showed that the companies were generating Twitter content that performed corporate branding and product branding in a balanced way. We also observed a balanced approach toward generating tweets that contained scientific or technical information. This balanced approach, at a univariate level, was also noted in previous studies (Lee et al., 2020; Zhang et al., 2020). Our analysis also showed that product-branding tweets predominantly contained scientific or technical information about the product whereas corporate-branding tweets predominantly contained nontechnical information.

The companies actively cited peer-reviewed scientific materials to disseminate their product and public health information. Technical communicators could further streamline such scientific or technical communication and design knowledge-based communication strategies that offer a thorough understanding of the genesis, diffusion, and impact of health crises and possible routes for mitigating them. Such a technical communication strategy, adapted from uncertainty reduction theory (Berger & Calabrese, 1974), has been championed in the context of COVID-19 (Grace & Tham, 2020). Our findings offer further empirical support to the framework proposed by Grace and Tham (2020) in that technical communication undertaken by for-profit entities can play an integral part in managing uncertainty during public crises.

In analyzing the user engagement (RQ2), we observed that tweets disseminating vaccine-related information garnered the most retweets and favorites. Also, the user engagement with this tweet category significantly differed from the user engagement with tweets that did not offer any COVID-19-related information. Evidently, Twitter users were actively seeking information about the COVID-19 vaccine that these companies were developing. This corroborated the RISP model's prediction that individuals seek information from multiple channels during unexpected pandemics (Wang & Ahern, 2015).

In ranking the tweet categories according to their occurrence and user engagement, we found a general agreement between these two ranking schemes in the top-three tweet categories. But a closer inspection revealed a potential information gap. Although tweets sharing any information about COVID-19 vaccines generated a high level of user engagement, the companies predominantly used scientific or technical jargon when they tweeted vaccine-related information. Perhaps the complex, cutting-edge technology that led to the development of these vaccines had prompted the companies to embed technical information in their product-branding tweets. But the fact that users also appreciated nontechnical information about these prophylactics indicated that there is a market for nontechnical messages that convey important information about technologically advanced products. Again, technical communicators could play an integral role in providing such information by breaking down complex scientific information into compact, lucid nontechnical messages that the general population could easily understand. This strategy could contribute toward increasing user engagement with the social media contents generated by science or technology-based companies.

An interesting finding emerged when we assessed the bandwagon effect (RQ3). Previous studies have reported a significant positive association between user engagement with a tweet (in terms of both retweets and favorites) and the number of followers associated with the source's Twitter account (Flanagin & Metzger, 2013; Liu et al., 2017). But our study found a potential bandwagon effect in the retweets dimension only. The size of the follower base had limited impact on the favorites dimension of user engagement. Recall that, retweeting, which measures the viral reach of a tweet, is the least cognitively demanding interactive behavior in Twitter (Alhabash & McAlister, 2015) and our finding that retweet count showed a significant bandwagon effect corroborates Sundar's (2008) argument that this effect can considerably reduce the cognitive resources people need for information processing. The fact that the least cognitively demanding user-engagement dimension exhibited a pronounced bandwagon effect indicates that a considerable proportion of Twitter users were simply following others' opinions perhaps without fully processing the information presented in the original tweet.

Further investigation suggested that tweets disseminating scientific or technical information about COVID-19 were in the top-three most frequently occurring types of tweets both in the overall and in the company-specific rankings. Because processing technical information likely demands a greater cognitive investment, the fact that the least cognitively demanding user-engagement dimension showed higher engagement with cognitively demanding content offers further support to Sundar's (2008) argument that Twitter users rely on others' opinions in order to process information presented in the original messages.

Next, when we ranked the tweet categories in terms of favorite count, two of the top-three categories consisted of messages related to COVID-19 that did not contain any scientific or technical information. This absence of the bandwagon effect in the favorites dimension suggests that users were willing to allocate more cognitive resources to messages that did not demand a high level of cognitive effort and that when Twitter users put forth a greater cognitive effort to process information, they are unwilling to simply follow others' opinions. Further, we can argue that because favoriting a tweet indicates users' affective response to the original message (Alhabash & McAlister, 2015) and because during public crises, people actively seek crisis-related information to assuage their uncertainty about the situation, tweets serving that purpose would elicit positive feelings—favorites—from users.

In sum, this study finds evidence that U.S. companies engaged in developing COVID-19 vaccines effectively integrated scientific and technical communication in their overall Twitter communication strategies during the first wave of the pandemic in the United States. We also uncovered a potentially disturbing relationship between retweeting behavior and technical content of the tweets in which a considerable number of users seemed to simply rely on the opinions of others to decide whether to retweet an original message instead of processing the technical information themselves.

Implications for Practitioners

The implications of our findings should be useful to both biotechnology and pharmaceutical companies and technical communicators. From a corporate perspective, these findings imply that it could be beneficial for companies that are developing a social media communication strategy to track user engagement with different types of messages and then generate content in a way that closely matches with users' information-seeking behavior. In other words, the most-frequently occurring message categories should closely match the message categories that generated the most user engagement. Any discrepancy in that matching potentially indicates an information gap that companies should strive to close.

From a technical communicators' perspective, these findings imply that during public health crises, technical communicators can play a vital role in corporate settings by using social media platforms to explain complex scientific facts about disease propagation, therapeutic measures, and population immunity. This can assuage the public's tendency to seek multiple channels of information during health crises and help shape the organizations' identities as authorities in their specialized scientific fields. The fact that non-technical messages, specifically those focusing on pandemic-related therapeutic measures, occurred relatively less frequently despite garnering some of the highest levels of user engagement indicates an area in which technical communicators could make substantial contributions toward satisfying the demand for relevant nontechnical information.

For instance, J&J produced an eight-episode video series, *The Road to a Vaccine*, which was shared on Twitter from April 14, 2020, through June 2, 2020 (Johnson & Johnson, 2020b). In this series, the host interviewed several individuals and groups who were at the forefront of combating the pandemic. Guests who were technical experts (e.g., scientists and doctors) attempted to explain complex scientific information whereas guests who were not technical experts (e.g., a youth advocate, a leader of a social organization) explained the observed impact of the pandemic on society. This series offered a good example of using non-technical information to contextualize complex scientific information about the virology, pathology, and epidemiology of COVID-19.[2] Companies can benefit from such a user-centric content-generation strategy that could lead to higher user engagement and enhance company visibility.

Limitations and Future Directions

We conducted this study during a period of unique public health crisis, so the results must be interpreted with caution after the crisis has subsided. Also, we analyzed only a single social media platform. All the companies studied here use various platforms (both social media and traditional channels) for communication purposes, so the results of this study may not cross over to other communication platforms.

We gave equal weight to our two metrics for measuring user engagement; however, as Alhabash and McAlister (2015) suggested, favoriting and retweeting require different levels of cognitive abilities, so user engagement should be weighted accordingly. In other words, appropriately weighting user engagement can produce a scalar user-engagement index, so instead of crafting messages targeting individual dimensions of user engagement, companies could frame messages to maximize that index.

Because we conducted this study during the first wave of the spread of COVID-19 in the United States, the study offered a baseline both in terms of content generated and user engagement elicited in Twitter by four U.S. companies engaged in developing a COVID-19 vaccine. Subsequent longitudinal studies could be conducted to compare how the frequency of (and user engagement with) various types of tweets changed during various epochs of the pandemic.

Appendix

Company Profiles

Johnson & Johnson (@JNJNews) is a highly diversified company, more than a century old, that develops medical devices, pharmaceuticals, and consumer health care products. It is the one of the largest pharmaceutical companies in terms of revenue generation (Teramae et al., 2020). In its annual report for fiscal year 2019, it reported that "advertising expenses worldwide, which comprised television, radio, print media and Internet advertising, were $2.2 billion, $2.6 billion and $2.5 billion in 2019, 2018 and 2017, respectively" (Johnson & Johnson, 2020a, p. 46).

Moderna (@moderna_tx) is a biotech company founded in 2010. It exclusively focuses on the mRNA-based drug development with no commercially available product thus far. In its 2019 annual report, Moderna (2020) did not disclose any advertising expenses.

Inovio Pharmaceuticals (@InovioPharma) is a biotech company founded in 1983. It focuses on developing synthetic DNA-based vaccines for cancers and other infectious diseases including HIV, Ebola, Zika, MERS, and Lassa Fever (Inovio, 2020). The only commercially available product that Inovio has so far is an electrical impulse-based injection device called Cellectra. In its 2019 annual report, Inovio did not disclose any advertising expenses (United States Securities and Exchange Commission, 2019).

Novavax (@Novavax), founded in 1987, is a biotech company. It focuses on developing recombinant nanoparticle-based vaccines for infectious diseases, including seasonal Flu, SARS, MERS and Ebola. So far, Novavax does not have any commercially available product. In its 2019 annual report, Novavax (2020) did not disclose any advertising expenses).

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Notes

1. The second wave of COVID-19 spread began around the second week of June 2020 (The New York Times, 2021).
2. The series is currently in its second season, perhaps underscoring its popularity.

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