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A SYSTEMATIC LITERATURE REVIEW OF PREDICTORS OF SOCIAL MEDIA POPULARITY

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ABSTRACT

A growing area of research has examined the individual behaviors and social antecedents that enable and constrain the popularity of social media users. This systematic review gathers and summarizes 68 naturalistic studies that measure popularity based on users' reach (e.g., followers, fans and subscribers) or engagement (e.g., likes, comments and shares) on multiple platforms. It draws on Barnlund's (2008) transactional model of communication to organize the literature and provides a roadmap for future research by identifying areas of the research that are characterized by consensus and disagreement. It also reveals a gap in the literature. Previous research focuses on communication strategies that maximize reach and engagement and provides less evidence of social structural influences on popularity. More research is needed to understand how the social, economic, and cultural characteristics of users affect their success.

Keywords: Influencer marketing, social media influencers, popularity, engagement, social status

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1 INTRODUCTION

Popular social media users are having a growing impact on consumer behavior, public information campaigns, political debate, voting behavior, and crisis management (Stephen & Galak, 2012; Shaozhi, 2020; Sundermann & Raabe, 2019). For this reason, many scholars have investigated the origins of popularity on platforms like Instagram, YouTube and Twitter.[1] The academic literature on this topic, however, remains fragmented and concentrated in disciplinary silos. Researchers in the fields of business, marketing and advertising are interested in how companies can use their own accounts or collaborate with other users to increase brand value and revenue (e.g., Kwok & Yu, 2013). Political scientists, sociologists and economists are naturally more intrigued by the political, social and economic effects of popular users (e.g., Choi, 2014). Representing a third group, scholars of computer science are focused on the role of influential users in the process of information diffusion in social networks (e.g., Meng et al., 2018).

The aim of this article is to review and organize this sprawling literature, identify areas of consensus and disagreement, and encourage interdisciplinary cooperation and synthesis. The article begins by outlining the procedures used to locate studies for a structured literature review. In the next section, Barnlund's (2008) transactional model of communication will be discussed in order to organize and visualize the predictors of social media popularity and based on this model online interactions will be reviewed. In the third and fourth sections, the findings will be summarized and the parts of the transactional model that have received the most and least attention and consensus from scholars will be identified. In the final section, suggestions for future research have been emphasized.

2 METHOD

Following Sundermann and Raabe's (2019) approach to conducting structured literature reviews, the search for articles was carried out in two stages. First, a list of relevant literature was constructed based on electronic database searches of a university library's "Communication Source" (a merger of high-quality EBSCO databases, Communication and Mass Media Complete and Communication Abstracts), Jstor and Google Scholar. The keywords "influencer marketing," "social media influencer" and "influencer communication" were used to search each database. After exhausting these one-term searches, dual-word searches were utilized with the term "social media" and each of the following: "followers," "engagement," "popularity," and "content analysis." Backward searches of all related sources cited in original articles were carried out, as well as forward searches using Google Scholar to identify later studies that referred to original articles.

[1] The company name "Twitter" will be used in this study, as it may be more familiar to most readers and all the studies reviewed for this article were published prior to Twitter's name change. It should be noted, however, that the owner of Twitter, Elon Musk, formally changed Twitter's legal name to X Corp in April 2023.

These procedures would produce a massive number of articles, most of which predate the rise of social media and pertain to the decades-old literature on social influence and persuasion. Strategic criteria were required to narrow the scope of this review to a feasible number of articles. For this reason, only studies based on quantitative, naturalistic observations of users on Facebook, YouTube, Twitter, Sina Weibo, or Instagram were included in the sample. This excluded three important areas of the literature. First, studies of popular people who engage their audiences through blogs and other websites were not considered. Also excluded was a vast portion of influencer marketing research that utilizes experiments and surveys. While providing valuable findings, experimental and survey-based studies typically focus on a range of dependent variables, such as source credibility, that are conceptually different from this study's operational definition of popularity, which is rooted in naturalistic behaviors, such as likes, shares and follows. Finally, studies based on qualitative research designs were not selected. Qualitative methods like digital ethnography are useful for understanding communities and real-life social interactions online, but their findings are difficult to compare to the bulk of research based on quantitative analysis. All studies in this review utilized some form of quantitative content analysis based on manual methods (coding by humans) or automated methods (using computer software to assist in the coding process).

Four additional inclusion criteria were as follows: 1) a measure of popularity based on users' *reach* (e.g., followers, fans and subscribers) or *engagement* (e.g., likes, comments and shares) on Facebook, YouTube, Twitter, Sina Weibo, or Instagram, 2) analysis of at least one predictor of popularity, 3) written in English, and 4) published in a peer-reviewed journal or conference proceeding. The selection procedure produced 68 articles, from which 88 distinct predictors of popularity were identified. Any significant statistical measure indicating a relationship between two or more variables was considered a predictor. As shown in Tables 1 and 2 in the appendix, for each predictor, the type of user, the social media platform, the measure of popularity, and a citation to the respective study were noted. By accounting for user and channel types, this review evaluates the literature's degree of consensus on the various predictors of popularity, as well as assesses each predictor's consistency across different types of users and platforms.

The following types of social media users were found in this review: Business organizations, celebrities, governments, ordinary people, original social media influencers (SMIs), and universities. Original SMIs are defined as people who became well-known via social media, whereas celebrities are famous for their work outside social media (Piehler et al., 2021). This review identified studies of original SMIs working in multiple industries, including alcoholic beverages, automotive, banking, beauty and cosmetics, environmental sustainability, fashion, fitness, news, politics, public health, health care, science, sports, travel and video games.

3 A FRAMEWORK FOR ORGANIZING RESEARCH ON SOCIAL MEDIA POPULARITY

Two prior literature reviews were organized around Lasswell's transmission model (Sundermann & Raabe, 2019), or a revised version of it (Hudders, De Jans, & De Veirman 2021). Laswell's model is typically used to explain one-way, asymmetric flows of communication. It assumes that the effects of messages are determined by characteristics of sources, messages, channels and receivers. Positioning the source as the primary agent, the transmission model has been applied in several studies of persuasion, advertising, and organizational communication (Sundermann & Raabe, 2019). While the transmission model accounts for key components of the communication process, other frameworks may be more appropriate for organizing the literature around social media interactions.

Barnlund's (2008) transactional model was used for this review because it includes most of the components of the transmission model, but also theorizes communication as a back-and-forth, continuous process as opposed to a linear one. Barnlund defined communication has a dynamic exchange, a progression of information flows where communicators cocreate meaning by encoding and decoding messages. Communication occurs when communicators turn thoughts into messages (encoding) and messages into thoughts (decoding). Through this process, people make sense of information by attending to the content of messages, characteristics of the source, and cues in the environment continuously and simultaneously.

Barnlund's assumptions about how this happens were informed by the work of Erving Goffman (1973). Goffman theorized communicators as goal-directed impression managers. They are self-aware and pursue their goals with a sensitivity to their surroundings and the perceptions of their audience (Barnlund, 2008). Given that communicators create and interpret messages as if they were the other communicator, the act of encoding and decoding messages is always socially situated, interactive, non-linear, and interdependent.

Goffman's theory of social interaction has been criticized for neglecting the differential power and status of communicators, and the broader social context that enables and constrains the outcomes of interactions (Gouldner, 1970). Yet, Barnlund's transactional model does include the psychological, relational, cultural, and social contexts that shape the communication process (Barnlund, 1968, 7). The co-created meanings of two or more communicators influence, and are influenced by, the communicators' cognitive and emotional experiences (psychological), the history of their interactions (relational), their shared or unshared values and beliefs (cultural), and the rules, norms and social structures that govern communication (social). In summary, Barnlund's model was chosen for this review because it is more appropriate for theorizing the back-and-forth communication of social media than Laswell's model, while also accounting for social-structural constraints on the communication process.

Barnlund's transactional model was originally intended to theorize face-to-face conversations, but some scholars have applied it to interpersonal computer-mediated communication (Eysenbach, 2018). To account for interactions between social media users, the diverse characteristics of social media platforms (channels) must be added to the model. Technical differences between platforms like Twitter and Instagram directly affect outcomes of communication; each platform also fosters a unique psychological, relational, cultural, and social context. As illustrated in Figure 1, a transactional model adopted for social media interactions posits that the mutual effects of user communications, including changes in users' popularity, depend on the characteristics of communicators and their messages, the channels through which they create and interpret messages, and the contexts of communication. Although the act of clicking a like button may seem simple, perhaps trivial, its causes and contingencies, as illustrated in Figure 1, may be varied and complex.

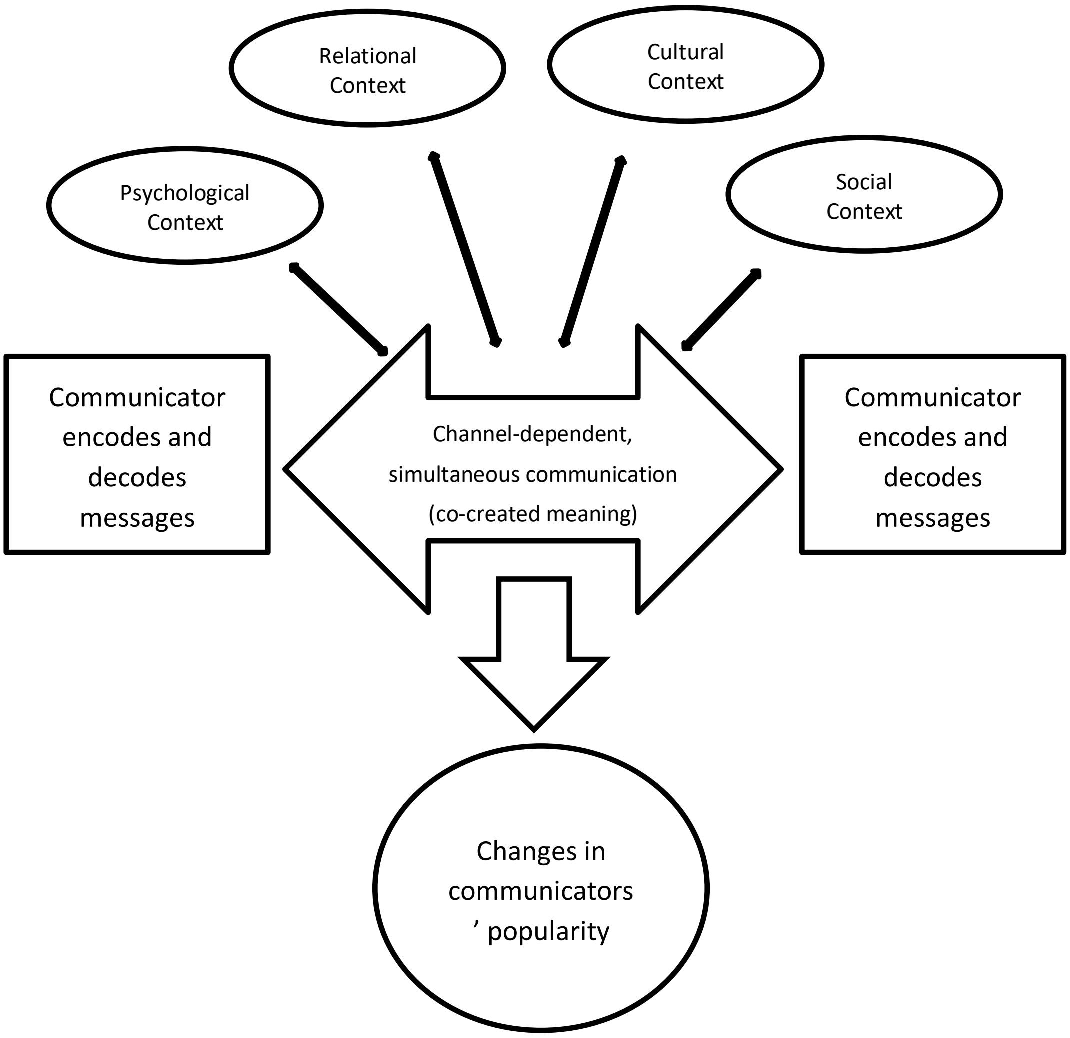

Figure 1. Framework for Organizing Research on Social Media Popularity

4 RESULTS I: SOCIAL MEDIA BEHAVIORS AS PREDICTORS OF POPULARITY

Among the 68 studies in the sample, 54 examined the relationship between a social media behavior and popularity. The behaviors were grouped in seven categories and labeled as follows: 1) frequency and timing, 2) originality, 3) vividness, 4) interactivity, 5) emotion, 6) information, and 7) self-orientation. These labels were established inductively with the goal of matching the labels to the conceptualizations used in the studies under review. For the sake of organization, however, the categories included studies with related but distinct concepts and labels. For instance, the category "originality" encompassed studies on the effects of posting *organic* and *unique* content. Likewise, not all studies in the "vividness" category employed the term vividness or conceptualized this characteristic of content in the same way.

4.1 Frequency and Timing

According to ten studies, the popularity of users was related to how often (frequency) and when (timing) they posted content. For instance, Jensen et al. (2014) analyzed 87 high-profile NCAA football coaches on Twitter and found a significant positive relationship between the coaches' total number of tweets and their followers, "with each additional tweet being worth an additional six followers" (273). As shown in Table 1 in the appendix, four additional articles reported similar results. A study by Hutto et al. (2013) looked at the effect of tweeting many times over a short period of time, known as "bursting." They showed that bursting was associated with higher follower counts. However, the positive effect of bursting may be unique to Twitter and other microblogging sites where multiple interlinked messages or "threads" are common. On Facebook, in contrast, longer time periods between posts were positively related to likes, comments and shares (Banerjee & Chua, 2019; Brech et al., 2017). Finally, pertaining to the best days to interact, two studies found that posting content during weekdays compared to weekends was positively associated with popularity (see Table 1, appendix). These findings were consistent across Facebook and the Chinese microblogging platform Sina Weibo (sometimes referred to as Chinese Twitter).

4.2 Originality

Original content refers to social media posts that occur naturally and without paid promotion (organic), or those which are newly created by the users themselves (unique), as opposed to shared content, such as retweets. Five articles showed that posting organic content was associated with greater engagement, and that posts containing advertisements reduced their popularity (see Table 1, appendix). For instance, in a study of top fitness influencers on Instagram, Neal (2018) found that organic posts received more likes and comments than sponsored ones. As shown in

Table 1 (appendix), similar results were produced by two studies of original SMIs on YouTube ("YouTubers"), one study of Sina Weibo and one Facebook study. Unique content was also associated with popularity. Zou et al. (2021) showed that unique content created by top health influencers on Sina Weibo produced more likes than their shared content. In a longitudinal study of Major League Baseball teams' Twitter accounts, posting unique content predicted increases in followers over time (Watanabe et al., 2015). The positive effects of organic and unique posts were consistent across five social media platforms and two types of users.

4.3 Vividness

Nineteen studies looked at the relationship between the use of various media types and popularity. Social media platforms allow users to post text, images, photos, animations, videos, links and audio recordings. These media are thought to have varying levels of "vividness," which facilitate varying levels of engagement from audiences. Although vividness was measured in different ways, which made it difficult to aggregate findings, there was strong, cross-platform evidence that visual content produced higher levels of engagement than other media types. For example, Cvijikj and Michahelles (2013) coded the vividness of 5,035 company Facebook posts from low to high as follows: 1) text only, 2) photos, 3) links and 4) videos. According to Cvijikj and Michahelles, posts with higher levels of vividness received more likes and shares and longer interaction durations from followers. Luarn et al. (2015) used a similar measure of vividness and produced matching results. As shown in Table 1 in the appendix, three studies combined videos with other types of theoretically vivid media and confirmed the positive relationship between vividness and engagement rates; four studies identified videos alone and an additional four studies measured photos/images alone as positive predictors of engagement.

Some evidence questioned the assumption that videos, which have the highest level of vividness per some scholars, represented the most popular type of media. In a study of company Facebook pages, Dae-Hee et al. (2015) found that posts with photos received significantly more likes, comments and shares than posts with videos. Still, both videos and photos have greater vividness than text-only posts, which further supports the general assumption that posting images is positively associated with popularity. This finding held in studies of two types of users (businesses and ordinary people) and all three platforms that allow for high and low vividness, including Facebook, Twitter and Sina Weibo (note that Instagram and YouTube are specifically designed for sharing photos and videos). Only one study stood in contradiction: Kwok and Yu (2013) found that text-based posts on company Facebook pages generated more engagement than other media types, including videos and photos.

The evidence was intriguingly mixed on the effects of posting URLs on microblogging platforms. As shown in Table 1 in the appendix, four studies based on Twitter samples showed that including URLs in tweets was a positive predictor of retweets; however, three studies drawing on data from Sina Weibo revealed the opposite relationship. These contradictory findings suggest the need for cross-cultural research that compares the effects of posting links on the US-based Twitter versus the China-based Sina Weibo.

4.4 Interactivity

Certain types of social media content are designed to encourage users to react. Twenty-five articles explored the effects of interactive strategies on engagement and reach. These studies involved eight variables, including the use of 1) contests and incentives, 2) questions and polls, 3) platform optimization, 4) profile completeness, 5) responding to followers' replies, 6) tagging, 7) hashtags, and 8) following back. Like the case of vividness, interactivity was operationalized in different ways. Some studies used a scale of interactivity, classifying posts from low to high, while others employed a dichotomous measure and classified certain behaviors as interactive or not. Despite differences in operational definitions, the first five interactivity variables listed above were consistently and positively related to popularity (see Table 1, appendix). Much of this research analyzed company Facebook pages, but the positive effects facilitating interactions by asking questions, taking polls, and replying to the comments were similar for ordinary people on Twitter and original SMIs on YouTube.

More intriguing were the three variables that generated empirical controversy. The first variable involved tagging—that is, including the handle of another account within the body of a message, presumably for the sake of generating interaction with that user. Six studies based on data from multiple platforms (Twitter, Sina Weibo, Facebook) found a positive relationship between tagging and popularity, but two studies, both based on Twitter, found the opposite relationship (see Table 1, appendix). Second, the use of hashtags was examined in eight studies of microblogging websites. As seen in Table 1 in the appendix, four of them revealed a positive relationship between hashtag use and retweets; one suggested that limiting hashtags to two or fewer per post predicted increases in Twitter followers over time; and three studies found a negative association between hashtag use and popularity on Sina Weibo and Twitter. Third, while Hutto et al. (2013) found that following many other accounts was a positive predictor of having followers, two competing studies showed that following fewer other accounts was positively associated with retweets and likes (Zhang & Peng 2015; Valsesia et al. 2020). Studies of tagging, hashtag use, and following back represent a contested area of the literature.

4.5 Emotion

Twenty-five articles examined the relationship between expressing emotion and popularity. The bulk of evidence, drawn from studies of multiple platforms and user types, showed that expressing various types of emotion in posts was positively associated with engagement and follower counts. Consistent results were found in research rooted in diverse methodological frameworks and based on various operational definitions of emotion. Four studies identified emotional content, without specifying its valence, as a positive predictor of multiple popularity metrics (see Table 1, appendix). Nine studies found that the use of positive sentiment, feeling or emotion was a predictor of popularity (see Table 1, appendix). Content coded as entertaining or interesting was also linked to engagement. For instance, investigating brand marketing on Facebook, three studies revealed an association between entertaining content and more likes, comments and shares; another study identified a link between posting interesting tweets and being retweeted (see Table 1, appendix). Expressing negative sentiment, feeling or emotion was also a positive predictor of popularity, according to nine studies (see Table 1, appendix). Negative or critical content appeared to be especially engaging to audiences in the context of news topics and political debate. In addition, Naveed et al. (2011) found that using negative emoticons encouraged retweets, and Kivran-Swaine and Naaman (2011) demonstrated a positive association between expressing sadness on Twitter and follower counts.

A small minority of studies offered caveats or findings that conflicted with the majority view. For example, although certain types of controversial messaging generated engagement, using negative emotional language that stigmatized groups was shown to diminish retweets and likes on Twitter (Schwartz & Grimm, 2017; Jain et al., 2020). As shown in Table 1 in the appendix, research on the effects of fear appeals produced mixed results.

4.6 Information

Thirteen articles considered the informational appeal of social media messages. Content coded as informative was shown to increase engagement in four studies (see Table 1, appendix). Yesiloglu and Waskiw (2021) found that providing information in a conversational tone increased the number of comments on Instagram. Beauty influencers on YouTube received more comments when posting information-rich product reviews compared to four other video types (Delbaere et al., 2021). YouTubers in the automotive sector who used more "concreate language" tended to have more views and subscribers than those who used less concrete language (Lee & Theokary, 2021), while the use of tentative words like "maybe" and "perhaps" on Twitter was negatively associated with retweets (Kim et al., 2016). The presence of longer, more complex words was correlated with an uptake in follower counts on Twitter (Hutto et al., 2013). The total number of words in posts was positively related to retweeting on Sina Weibo (Zhang & Peng, 2015) but negatively related to engagement indicators on Facebook (Banerjee & Chua, 2019). Focusing Twitter content on a narrow coherent set of topics attracted more followers over time (Wang & Kraut, 2012) and more retweets (Cha et al., 2010), suggesting that practical information, tailored to a specific audience, tends to boost the popularity of users.

4.7 Self-orientation

Seven studies examined the link between various forms of self-orientation and popularity. Lee and Theokary (2021) found that the use of self-referential pronouns was positively associated with increases in views and subscribers on YouTube. Thoughtful discussions centered on the YouTuber's personal experiences with a product ("reflective theme") were more engaging than five other video themes (Lim et al., 2021). Including a human face in Instagram posts increased the number of comments (Yesiloglu & Waskiw, 2021). However, the effectiveness of centering the self in social media posts may only hold for original SMIs. Four studies of ordinary people and business organizations found that placing an emphasis on the account holder diminished reach and engagement. For the average person on Twitter, using self-referential pronouns was negatively associated with follower counts (Hutto et al., 2013). Tweets about one's self tended to generate fewer retweets than posting content that addressed broader public interests (Naveed et al., 2011). In the case of company Facebook pages, self-oriented content involved references to a corporation, brand or product rather than a person, and was shown to diminish likes, comments and shares (Dae-Hee et al., 2015; Swani et al., 2017).

5 RESULTS II: CHARACTERISTICS OF USERS AS PREDICTORS OF POPULARITY

While most studies focused on the behaviors of users, 31 of the 68 studies in the sample looked at how the users' social characteristics predicted their reach and engagement. The predictors were categorized as 1) popularity, 2) organizational resources and status, 3) individual status, and 4) geography. These categories were established inductively and labeled based on the language used in the corresponding studies, though some conceptual differences exist among the studies in each category.

5.1 Popularity

One of the strongest and most consistent predictors of social media popularity was popularity itself, a conclusion drawn in thirteen studies. Much of this research conceptualized popularity as reach, and showed that users with more followers, fans or subscribers generated more engagement than those with fewer followers (see

Table 2, appendix). Rodríguez-Vidal et al. (2020) found that having more influential followers (those with many followers themselves) was positively associated with having more followers in general. As shown in Table 2 in the appendix, six studies of Twitter demonstrated that being retweeted in the past was a strong predictor of being retweeted in the future. Research showing the cumulative advantage of being popular covered three user types and four social media platforms.

5.2 Organizational Resources and Status

Six articles examined the economic resources and status characteristics of organizations as predictors of popularity. Sports teams with higher operating incomes (Scelles et al., 2017) and teams that hired advertising agencies to manage their social media accounts had more fans and followers on Facebook and Twitter than teams with fewer resources (Hopkins, 2013). Six related variables—appearing on national television, employing players with large social media followings, having high attendance turnouts at games, playing in older stadiums, being a historically newer team within a league, and winning games—were also strong positive predictors of the reach of professional sports teams on Facebook and Twitter (see Table 2, appendix). A study of university Facebook pages showed that schools that enrolled more students and achieved higher prestige rankings generated more engagement and reach than schools with fewer students and lower prestige rankings (Brech et al., 2017).

5.3 Individual Status

Eleven studies focused on the status characteristics of individual account holders. The variables considered were verification status, occupational status, level of experience, age and race. Having a "verified badge" on Twitter increased the likelihood of retweets in three studies, but one study of Sina Weibo found that verified status was negatively related to retweets (see Table 2, appendix). The authors of the latter study argued that most verified accounts were controlled by the Chinese government and perceived by many people as propaganda, which made them less likely to be retweeted.

Five articles looked at occupational status. Celebrities tended to have more followers than original SMIs on Instagram (Zeren & Gökdağlı, 2020). In the context of Covid-related crisis communication, celebrity and original SMIs produced greater engagement rates on Instagram than politicians, public health officials, science communicators and accounts representing news organizations (MacKay et al., 2022). The public health establishment and other institutional users were also retweeted less frequently than other types of users in the discussion of the opioid crisis (Jain et al., 2020). In the context of natural disasters, however, institutional users, such as emergency-related agencies, were retweeted more often than other types of users (Liu et al. 2012). Jensen et al. (2014) found that the most influential factor explaining the popularity of big-time college football coaches on Twitter was their university's prestige and the long-term success of its football program.

Four articles showed that users with more years of experience on Twitter tended to have more followers and were more likely to be retweeted than those with fewer years on the platform (see Table 2, appendix). Only one study looked at the effects of race on user popularity. Watanabe et al. (2017) compiled a large sample of Twitter accounts held by active Major League Baseball (MLB) players from the 2014 and 2015 seasons. Hispanic players had significantly fewer followers on Twitter, even when controlling for several other variables, than white players. The study also considered the age of players; older players tended to have more followers than younger ones, but popularity gains declined over time as players aged.

5.4 Geography

Four studies looked at differences in popularity across geographical regions. Most of them compared the reach of users located in areas of varying population sizes. Mainka et al. (2015) examined the social media accounts of several international cities and found a positive relationship between the city's population size and its number of followers, fans and subscribers. Two studies showed that major league sports teams located in highly populated areas had greater reach on Facebook and Twitter than sports teams in less populated areas (see Table 2, appendix). Although the many studies reviewed for this essay originated from several countries, only one study demonstrated that the effects of certain types of social media content on popularity varied across nations and cultures (Khan et al., 2016).

6 DISCUSSION

This study systematically gathered, categorized and evaluated a reasonably large sample of naturalistic studies of social media popularity. The aims were to identify the variables that have generated the most and least interest from scholars and locate areas of the literature marked by consensus and disagreement. An adapted version of Barnlund's (2008) transactional model of communication was used to map this intellectual terrain. In brief, the model assumes that interactions between two or more users are shaped by who they are, how they communicate, and how they interpret each other's messages. This process is further influenced by the technical attributes of the given social media platform and by the psychological, relational, cultural, and social contexts.

Each of the assumptions in Barnlund's model has attracted some scholarly attention, but researchers appear to be more interested in the communication behaviors that maximize popularity than the social structural forces that enable and constrain it. Among the 68 studies in the sample, 80 percent of them contained at least one predictor involving the behaviors of users, such as posting frequently or sharing emotional content; only 46 percent of studies investigated the effects of users' social positions, such as their age or race, on popularity. Among the 87 predictors of popularity identified in this study, 71 percent involved user behaviors; 29 percent involved their social, cultural and economic circumstances. Scholars were most interested in how emotion, interactivity, and vividness affect popularity, and least interested in the influences of geography, originality, and organizational status of users. Research on the effects of users' race, gender, sexuality, and socioeconomic status on their popularity was notably scarce.

The relative disregard for the social origins of popularity echoes Hampton's (2023) claims about the negligible role of sociology in the field of digital media and the need for more sociological theory and research. Social theory may be particularly useful for investigating social antecedents of popularity, such as race, class and gender, but it also may enrich the agency-focused literature on the behaviors of users. For example, many scholars have examined how emotional language can be used to attract and engage followers. Most studies, however, are agency focused and assume that individuals use emotions as a form of strategic communication. While rich in empirical insight, this literature has largely missed the opportunity to demonstrate how emotion work on social media links individual agency to social structure. Decades of sociological research has shown how the ability to manage emotions and use them strategically varies across gender and social class, and that reactions to emotional displays by men and women are likewise socially dependent (Hochschild, 1979, 1983). To the extent that emotional expression regulates the distribution of a socially valued resource – popularity – the use of it by users reproduces the gendered and class structures in which individuals are embedded.

This review also identified areas of the literature characterized by general agreement among scholars and areas where conditional or contradictory findings were common. To briefly summarize the most widely supported claims, users who posted frequently, produced original content and utilized visual images tended to be more popular than users who used alternative strategies. Messages that were overtly interactive, such as posting questions, organizing contests and actively responding to followers, consistently engaged audiences. That both emotional and informative content boosted multiple popularity metrics was also well-established in the literature. In most cases, these predictors of popularity were consistent across different social media platforms and user types.

Though fewer in number, scholars who examined the link between popularity and social position rarely disagreed. As shown in this study, the past popularity of users was a positive predictor of their future popularity. That popularity itself was among the strongest and most consistent predictors of increases in reach and engagement may not be surprising, but it yields important evidence that social media, rather than nurturing equal opportunity, widen social inequality (see Table 2, appendix). Popularity, as argued by sociologists for decades (Merton, 1968), readily accumulates for those who already have it and leads to an ever-increasing gap between the popular and the unpopular. Users who enjoyed other structural advantages—access to economic resources and high social prestige—also tended to generate more reach and engagement than those who lacked these resources (see Table 2, appendix). The geographical context played a role, as users located near highly populated cities tended to be more popular than those in less populated areas. Only one study looked at how the effectiveness of social media strategies depends in part on the users' cultural and national context.

In some cases, the effects of predictors depended on the type of user or channel being studied. Posting several messages over a short period of time was more effective on micro-blogging sites than on Facebook. Including links in posts was associated with more popularity on the US-based Twitter but with less popularity on the China-based Sina Weibo. The posts of verified Twitter users were more likely to be retweeted; yet, this relationship reversed on Sina Weibo, where the posts of verified government agencies may be perceived as less worthy of being shared. Engagement increased with the number of words in posts on Sina Weibo but decreased with word counts on Facebook. Centering the self in posts and expressing personal interpretations of products and events appeared to be an optimal strategy for increasing reach and engagement for original SMIs on Instagram and YouTube, but not for company brands on Facebook.

These conditional effects, rooted in user and channel types, suggest the need for multidisciplinary research and more exploration of the contexts included in Barnlund's model. To account for the full complexity of social media interactions, a research team needs technical knowledge of platform capabilities, cultural knowledge of the values and beliefs associated with communities on each platform, and sociological knowledge of the structures that enable and constrain the various types of users. Given that the three predictors that produced the most disagreement (tagging, hashtags, and following back) involved overtly interactive behaviors, scholars should also attend to the relational context of communication—the personal relationships between users and the development and outcomes of their conversations.

7 LIMITATIONS

The primary weakness of this review is its narrow focus on studies based on naturalistic quantitative content analysis. This sampling criteria excluded survey-based and experimental studies, which have provided a foundation for decades of related research on social influence and persuasion (Gass & Seiter, 2022). Studies based on qualitative research designs were also excluded. Qualitative methods such as digital ethnography capture the naturalistic dimension of social media interactions. Research in this tradition, particularly qualitative studies involving the relational (Abidin, 2015; Mäkinen, 2021), cultural (Raun, 2018), and social contexts (Duffy, 2017) of Barnlund's transactional model, could have provided important empirical and theoretical insight on social media popularity. Although the goals and concepts of related qualitative studies were deemed too difficult to incorporate and compare with the studies reviewed in this article, future reviews of qualitative research on social media popularity are in demand.

Given the practical need to identify a manageable portion of the literature, similar review articles have selected studies based on whether they included a certain type of social media user, such as original SMIs, or focused on articles that examined research questions typically covered by particular academic disciplines, such as business and marketing (Hudders, De Jans, & De Veirman, 2021; Sundermann & Raabe, 2019; Vrontis et al., 2021). This review's selection criteria were intended to provide a unique, interdisciplinary pool of studies that include a similar measure of popularity and share an interest in predicting the reach and engagement of a wide range of social media users. As the global population of active social media accounts continues to rise, popular users, from celebrities and original SMIs to businesses and governments, will likely shape important social, economic, and cultural outcomes. For this reason, research on the origins of social media popularity should interest scholars from a wide range of disciplines.

Identified by Ye et al. (2021) as a "future direction in influencer marketing research" (172), naturalistic research also has some advantages over other methods. In contrast to experimental research, naturalistic inquires tap into the interactions and relationships between influencers and followers. These relationships develop over time through multiple interactions and are difficult to replicate with mock influencers, experimental stimuli or cross-sectional survey designs (Delbaere et al. 2021). Experiments and surveys openly elicit responses from subjects, which threatens the validity of findings, whereas content-based indicators are unobtrusive and measure popularity based on observations of real-life behaviors. Mixed-method research combining qualitative and quantitative content analysis may be a particularly useful approach to studying the back-and-forth communication and relational context of social media.

8 CONCLUSION

Based on the 68 studies reviewed here, research on social media popularity has coalesced around four specialized areas. Business scholars are primarily focused on predicting customer engagement on company Facebook pages. Another group examines the impact of original SMIs on specific industries such as fashion and fitness and gravitate toward the study of interactions on Instagram and YouTube. Drawing primarily on automated coding procedures and natural language processing, a third group of scholars concentrates on message diffusion (retweets) on microblogging websites. And a fourth group looks at the effects of popular users on a range of social issues, political controversies and public health concerns. Though conceptualized in different ways – as a form of social currency, social capital or popularity – the reach and engagement of users have origins and consequences that are captivating researchers from multiple academic disciplines.

Scholars have made broad strides in identifying the communication strategies and types of social media content that maximize popularity, but social structural influences have received far less attention. While the status characteristics of users, such as their race, gender, socio-economic status, age, culture and national origin, likely affect how audiences and sponsors react to them, relatively few studies in the naturalistic tradition have investigated the social origins of internet fame (Hampton, 2023). Given that much of the research reviewed here has been carried out in disciplinary silos among scholars with similar academic backgrounds, future studies may benefit from assembling multidisciplinary teams to study social media popularity.

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10 APPENDIX

Table 1. Positive Behavioral Predictors of Social Media Popularity

Predictors	User Types	Platforms	Measures of Popularity	References
Frequency and Timing				
Posting more often	Original SMIs	Twitter	Followers	Jensen et al. 2014
	Business orgs	Twitter	Followers	Watanabe et al. 2015
	Business orgs	Twitter	Followers	Hopkins 2013
	Original SMIs	Sina Weibo	Followers, likes, retweets	Wang et al. 2020
	Business orgs	Twitter	Followers	Ashley & Tuten 2015
Posting many times over a short period	Ordinary people	Twitter	Followers	Hutto et al. 2013
Longer time intervals between posts	Business orgs	Facebook	Likes, comments, shares	Banerjee & Chua 2019
	Universities	Facebook	Likes, shares, comments, fans	Brech et al. 2017
Posting on weekdays compared to weekends	Business orgs	Facebook	Comments	Pletikosa et al. 2013
	Business orgs	Sina Weibo	Retweets	Zhang & Peng 2015
Originality				
Posting organic content compared to sponsored content	Original SMIs	Instagram	Likes, comments	Neal 2018
	Original SMIs	YouTube	Comments	Costello & Urbanska 2021
	Original SMIs	YouTube	Engagement rates	Lim et al. 2021
	Business orgs	Sina Weibo	Retweets	Zhang & Peng 2015
	Business orgs	Facebook	Likes, comments	Kwok & Yu 2013
Posting unique content compared to sharing others' content	Business orgs.	Twitter	Followers	Watanabe et al. 2015
	Original SMIs	Sina Weibo	Likes	Zou et al. 2021
Vividness				
Posting media with higher levels of vividness	Business orgs	Facebook	Likes, shares, comments	Luarn et al. 2015

	Business orgs	Facebook	Likes, shares, interaction duration	Cvijikj & Michahelles 2013
	Ordinary people	Sina Weibo	Retweet	Liu et al. 2012
	Business orgs	Facebook	Likes, shares, comments	Khan et al. 2016
	Business orgs	Facebook	Likes, shares, comments	Coursaris et al. 2016
Posting videos	Ordinary people	Twitter	Retweets	Jain et al. 2020
	Business orgs	Facebook	Likes, shares, comments	Banerjee & Chua 2019
	Business orgs	Facebook	Likes	Cvijikj et al. 2011
	Business orgs	Facebook	Likes	De Vries et al. 2012
Posting photos	Business orgs	Facebook	Likes, shares, comments	Banerjee & Chua 2019
	Business orgs	Facebook	Interaction duration	Cvijikj et al. 2011
	Business orgs	Facebook	Likes, comments, interaction duration	Cvijikij & Michahelles 2011
	Ordinary people	Twitter	Retweets	Meng et al. 2018
Posting photos compared to videos	Business orgs	Facebook	Likes, shares, comments	Dae-Hee et al. 2015
Posting text compared to other media types	Business orgs	Facebook	Likes, comments	Kwok & Yu 2013
Posting URLs	Ordinary people	Twitter	Retweets	Shi et al. 2018
	Ordinary people	Twitter	Retweets	Tsugawa et al. 2017
	Ordinary people	Twitter	Retweets	Naveed et al. 2011
	Ordinary people	Twitter	Retweets	Suh et al. 2010
Avoiding URLs	Business orgs	Sina Weibo	Retweets	Zhang & Peng 2015
	Ordinary people	Sina Weibo	Retweets	Liu et al. 2012
	Ordinary people	Sina Weibo	Comments	Wang et al. 2019
Interactivity				
Posting content with higher levels of interactivity	Business orgs	Facebook	Likes, shares, comments	Luarn et al. 2015
	Business orgs	Facebook	Likes, shares, comments	Khan et al. 2016

Posting contests or other incentive-driven calls to action	Business orgs	Facebook	Likes	De Vries et al. 2012
	Business orgs	Facebook	Comments	Cvijikj & Michahelles 2013
	Business orgs	Facebook	Likes	Luarn et al. 2015
	Business orgs	Facebook	Fans	Ashley & Tuten 2015
	Business orgs	Twitter	Followers	Ashley & Tuten 2015
Posting questions	Business orgs	Facebook	Comments	De Vries et al. 2012
	Business orgs	Facebook	Comments	Cvijikj et al. 2011
	Ordinary people	Twitter	Retweets	Naveed et al. 2011
	Original SMIs	YouTube	Views, subscribers	Lee & Theokary 2021
	Business orgs	Facebook	Comments	Cvijikij & Michahelles 2011
Optimizing platform's technical capacities for interacting with followers	Business orgs	Facebook	Followers	Hopkins 2013
Completing profile information	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Ordinary people	Facebook	Fans	Lampe et al. 2007
Reacting to comments	Business orgs	Twitter	Followers	Hopkins 2013
Tagging (@s)	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Business orgs	Sina Weibo	Retweets	Zhang & Peng 2015
	Ordinary people	Sina Weibo	Retweets	Liu et al. 2012
	Business orgs	Facebook	Likes, shares, comments	Banerjee & Chua 2019
	Ordinary people	Sina Weibo	Retweets, comments	Wang et al. 2019
	Ordinary people	Twitter	Retweets	Nesi et al. 2018
Avoiding tagging (@s)	Ordinary people	Twitter	Retweets	Shi et al. 2018
	Ordinary people	Twitter	Retweets	Naveed et al. 2011
Using hashtags	Ordinary people	Twitter	Retweets	Shi et al. 2018
	Ordinary people	Twitter	Retweets	Tsugawa et al. 2017

	Ordinary people	Twitter	Retweets	Naveed et al. 2011
	Ordinary people	Twitter	Retweets	Suh et al. 2010
Using two or fewer hashtags	Ordinary people	Twitter	Followers	García et al. 2016
Avoiding hashtags	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Original SMIs	Sina Weibo	Likes	Zou et al. 2021
	Ordinary people	Sina Weibo	Comments	Wang et al. 2019
Following more accounts	Ordinary people	Twitter	Followers	Hutto et al. 2013
Following fewer accounts	Business orgs.	Sina Weibo	Retweet	Zhang & Peng 2015
	Original SMIs	Twitter	Likes, retweets	Valsesia et al. 2020
Having more followers per followee	Ordinary people	Twitter	Followers	Hutto et al. 2013
Emotion				
Expressing emotion	Business orgs.	Facebook	Likes, shares, comments	Coursaris et al. 2016
	Original SMIs	Instagram	Comments	Yesiloglu & Waskiw 2021
	Ordinary people	Twitter	Retweets	Stieglitz & Dang-Xuan 2013
	Business orgs.	Facebook	Engagement rates	Huertas & Marine-Roig 2016
Avoiding emotional appeals	Business orgs.	Chinese micro-blogging site	Retweeting	Zhang & Peng 2015
Avoiding the use of exclamation points	Ordinary people	Twitter	Retweets	Naveed et al. 2011
Expressing positive sentiment, feeling or emotion	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Ordinary people	Twitter	Retweets	Bakshy et al. 2011
	Ordinary people	Twitter	Retweets	Kim et al. 2016
	Ordinary people	Twitter	Retweets	Naveed et al. 2011
	Ordinary people	Twitter	Retweets	Gruzd et al. 2011
	Ordinary people	Twitter	Retweets	Ferrara & Yang 2015

Expressing positive sentiment in non-news-related content	Ordinary people	Twitter	Retweets	Hansen et al. 2011
Expressing joy	Ordinary people	Twitter	Followers	Kivran-Swaine & Naaman 2011
Expressing hope	Ordinary people	Sina Weibo	Retweets, comments	Wang et al. 2019
Avoiding negative sentiment	Ordinary people	Twitter	Followers	Hutto et al. 2013
Posting entertaining content	Business orgs.	Facebook	Likes, comments	Khan et al. 2016
	Business orgs.	Facebook	Comments, shares	Luarn et al. 2015
	Business orgs.	Facebook	Likes, shares, comments	Cvijikj & Michahelles 2013
Posting interesting content	Ordinary people	Twitter	Retweets	Bakshy et al. 2011
Expressing negative sentiment, feeling or emotion	Ordinary people	Twitter	Retweets	Stieglitz & Dang-Xuan 2013
	Ordinary people	Twitter	Retweets	Meng et al. 2018
	Ordinary people	Twitter	Retweets	Naveed et al. 2011
	Ordinary people	Twitter	Retweets	Tsugawa et al. 2017
Expressing negative sentiment or critiques in news related content or political discussions	Ordinary people	Twitter	Retweets	Hansen et al. 2011
	Ordinary people	Twitter	Retweets	Choi 2014
	Celebrities	Twitter	Likes, retweets, comments	Pérez 2020
	Ordinary people	YouTube	Likes	Briones et al. 2012
Using negative emoticons	Ordinary people	Twitter	Retweets	Naveed et al. 2011
Avoiding positive emoticon	Ordinary people	Twitter	Retweets	Naveed et al. 2011
Expressing sadness	Ordinary people	Twitter	Followers	Kivran-Swaine & Naaman 2011
Avoiding language that may stigmatize others	Ordinary people	Twitter	Retweets, likes	Schwartz & Grimm 2017
	Ordinary people	Twitter	Retweets	Jain et al. 2020
Using fear appeals	Original SMIs	Sina Weibo	Likes	Zou et al. 2021

	Ordinary people	Sina Weibo	Comments	Wang et al. 2019
Avoiding fear appeals	Ordinary people	Sina Weibo	Retweet	Wang et al. 2019
Information				
Posting informative content	Business orgs.	Facebook	Likes, shares, comments	Khan et al. 2016
	Business orgs.	Facebook	Likes, comments	Cvijikj & Michahelles 2013
	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Business orgs.	Facebook	Likes, shares, comments	Dae-Hee et al. 2015
Posting informative-conversational content	Original SMIs	Instagram	Comments	Yesiloglu & Waskiw 2021
Posting about the functionality of products	Original SMIs	YouTube	Comments	Delbaere et al. 2021
Using functional appeals in B2B messages	Business orgs.	Facebook	Likes	Swani et al. 2017
Focusing content on a single topic	Ordinary people	Twitter	Followers	Wang & Kraut 2012
	Ordinary people	Twitter	Retweets	Cha et al. 2010
Using concrete language	Original SMIs	YouTube	Views, subscribers	Lee & Theokary 2021
Avoiding tentative language	Ordinary people	Twitter	Retweets	Kim et al. 2016
Using longer words	Ordinary people	Twitter	Followers	Hutto et al. 2013
Using more words	Business orgs.	Sina Weibo	Retweeting	Zhang & Peng 2015
Using fewer words	Business orgs.	Facebook	Likes and shares	Banerjee & Chua 2019
Self-orientation				
Using self-referencing pronouns	Original SMIs	YouTube	Views and subscribers	Lee & Theokary 2021
Describing personal experiences with a product	Original SMIs	YouTube	Engagement rates	Lim et al. 2021
Including a human face	Original SMIs	Instagram	Comments	Yesiloglu & Waskiw 2021
Avoiding self-referencing pronouns	Ordinary people	Twitter	Followers	Hutto et al. 2013
Avoiding self-oriented content	Business orgs.	Facebook	Likes, shares, comments	Dae-Hee et al. 2015
Avoiding mentions of corporate brand	Business orgs.	Facebook	Likes	Swani et al. 2017

names in B2C messages				
Posting content addressing broader public interests	Ordinary people	Twitter	Retweets	Naveed et al. 2011

Table 2. Characteristics of Users as Predictors of Popularity

Predictors	User Types	Platforms	Measures of Popularity	References
Popularity				
Having more followers, fans or subscribers	Ordinary people	Twitter	Retweets	Bakshy et al. 2011
	Business orgs.	Sina Weibo	Retweets	Zhang & Peng 2015
	Ordinary people	Sina Weibo	Retweets	Liu et al. 2012
	Ordinary people	Twitter	Retweets	Kim et al. 2016
	Ordinary people	Twitter	Retweets	Pezzoni et al. 2013
	Ordinary people	Twitter	Retweets	Zaman et al 2010
	Ordinary people	Twitter	Retweets	Cha et al. 2010
	Ordinary people	Twitter	Retweets	Tsugawa et al. 2017
	Ordinary people	Twitter	Retweets	Suh et al. 2010
	Ordinary people	Twitter	Retweets	Hong et al. 2010
	Business orgs.	Facebook	Likes, shares, comments	Banerjee & Chua 2019
	Ordinary people	Sina Weibo	Retweets, comments	Wang et al. 2019
	Original SMIs	YouTube	Views, likes, comments	Sui et al. 2022
Being followed by other top influencers	Original SMIs	Twitter	Followers	Rodríguez-Vidal et al. 2020
Having a high retweet rate in the past	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Ordinary people	Twitter	Retweets	Bakshy et al. 2011
	Ordinary people	Twitter	Retweets	Xu et al. 2012
	Ordinary people	Twitter	Retweets	Hong et al. 2011
	Ordinary people	Twitter	Retweets	Luo et al. 2013.
	Ordinary people	Twitter	Retweets	Xu et al. 2012

Organizational Status				
Having high operating income	Business orgs.	Facebook, Twitter	Fans, Followers	Scelles et al. 2017
Hiring an advertising agency to manage platforms	Business orgs.	Facebook, Twitter	Fans, Followers	Hopkins 2013
High sports performance (wins/playoffs/championships)	Business orgs.	Facebook	Fans	Scelles et al. 2017
	Business orgs.	Twitter	Followers	Scelles et al. 2017
	Business orgs.	Twitter	Followers	Watanabe et al. 2015
	Business orgs.	Twitter	Followers	Watanabe et al. 2016
	Business orgs.	Twitter	Followers	Pérez 2013
Appearing on national television	Business orgs.	Twitter	Followers	Watanabe et al. 2015
Employing players with high follower counts	Business orgs.	Twitter	Followers	Watanabe et al. 2015
High attendance at games	Business orgs.	Facebook, Twitter	Fans, Followers	Scelles et al. 2017
Having an older stadium	Business orgs.	Facebook, Twitter	Fans, Followers	Scelles et al. 2017
Being a newer team in the league	Business orgs.	Twitter	Followers	Watanabe et al. 2015
Having more students	Universities	Facebook	Likes, shares, comments, followers, fans	Brech et al. 2017
Having a high prestige ranking	Universities	Facebook	Likes, shares, comments, followers, fans	Brech et al. 2017
Individual Status				
Having a verified account	Business orgs.	Sina Weibo	Retweets	Zhang & Peng 2015
	Ordinary people	Sina Weibo	Retweet	Liu et al. 2012
	Ordinary people	Twitter	Retweet	Xu et al. 2012
Not having a verified account	Ordinary people	Sina Weibo	Retweets, comments	Wang et al. 2019
Being an original SMI or celebrity compared to a business or government	Original SMIs, celebrities, business orgs, governments	Instagram	Engagement rates	MacKay et al. 2022

Being a celebrity compared to an original SMI	Celebrities, original SMIs	Instagram	Followers	Zeren & Gökdağlı 2020
Being an original SMI or media channel compared to a health organization	Original SMIs, business orgs., governments	Twitter	Retweets	Jain et al. 2020
Being a media channel, government or emergency organization compared to other types of users	Business orgs., governments, ordinary people	Sina Weibo	Retweet	Liu et al. 2012
Working for a prestigious university	Celebrities	Twitter	Followers	Jensen et al. 2014
Having a longer account history	Celebrities	Twitter	Followers	Jensen et al. 2014
	Ordinary people	Twitter	Followers	Hutto et al. 2013
	Ordinary people	Twitter	Retweets	Suh et al. 2010
	Ordinary people	Twitter	Retweets	Xu et al. 2012
Being older	Celebrities	Twitter	Followers	Watanabe et al. 2017
Not being Hispanic	Celebrities	Twitter	Followers	Watanabe et al. 2017
Geography				
Located in highly populated area	Governments	Twitter, YouTube, Facebook, Instagram	Followers	Mainka et al. 2015
	Business orgs.	Facebook, Twitter	Followers	Scelles et al. 2017
	Business orgs.	Twitter	Followers	Watanabe et al. 2016
Depends on national context (Australia, UK, USA).	Business orgs.	Facebook	Likes, comments and shares	Khan et al. 2016