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Weak ties, strong facts: how influencers amplify public health communication on X (formerly Twitter)

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Abstract

Purpose: Social conformity theory emphasizes normative pressure as a drive of collective behavior. However, how these dynamics operate within weak-tie networks on social media remains underexplored. Platform-specific affordances such as X's (formerly Twitter) network structures may reshape these dynamics in public health communication. Using COVID-19 vaccine-related discussions on X (formerly Twitter), this study investigates how networked influence reconfigures the informational and normative social influence during health crises.
Design/methodology/approach: Integrating computational methods, Latent Dirichlet Allocation (LDA) topic modeling, sentiment analysis, and network analysis, this study analyzes 5.5 million tweets about COVID-19 vaccines, collected worldwide via the Twitter Academic API between November 3, 2021, and May 5, 2022, to examine how user roles (influencers vs. general users), tie strength, and content type (factual vs. opinion-based) shape retweet patterns. Latent Dirichlet Allocation (LDA) was applied to uncover thematic structures in vaccine-related discussions, while TextBlob sentiment analysis quantified the subjectivity of tweets to differentiate factual from opinion-based content. Network analysis using iGraph identified influencers based on degree and betweenness centrality, enabling the classification of "authoritarians," "accelerators," and "connectors."
Findings: Weak-tie connections drive information diffusion, with general users' factual tweets shared more frequently than influencers'. Normative social influence from accelerators, connectors, or authoritarian accounts is constrained by X's character limits and decentralized network structure. Opinion-based content, regardless of author status, receives fewer retweets, indicating users prioritize accuracy over subjective narratives.

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Practical implications: Public health campaigns should prioritize concise, evidence-based messaging tailored to X's decentralized networks. Leveraging general users as "fact-checking" nodes and minimizing opinion-laden content can amplify reach. Strategies to counter misinformation must account for platform-specific limitations on normative influence.
Social implications: The findings underscore how digital platforms democratize health communication by empowering non-expert users to shape discourse, while challenging top-down public health messaging. This duality highlights opportunities to bridge information gaps in underserved communities through weak-tie networks.
Originality/value: The first study to dissect social conformity mechanisms on X through a tripartite computational lens, revealing how platform affordances disrupt traditional hierarchies of influence. It redefines "influencer" roles in public health contexts, demonstrating that weak ties and factual content supersede normative pressure in driving engagement.

Keywords: large-scale data; X/Twitter; informational social influence; normative social influence; social conformity; public health communication

1 Introduction

Vaccine hesitancy, defined as the "delay in acceptance or refusal of vaccines despite availability" (MacDonald 2015, 4163), remains a persistent public health challenge worldwide (Dodd et al. 2021; Kreps et al. 2020; Webb Hooper et al. 2021). Social media has become a primary source of health information and a critical channel for disseminating prevention guidelines (Neely et al. 2021). Among these platforms, Twitter (now X) stands out as a major conduit for individuals to access and interact with weak ties, acquaintances, colleagues, and distant peers, while sharing opinions and experiences about vaccines (Valenzuela et al. 2018). These weak-tie interactions often provide novel information not readily available through strong ties, such as family and close friends (Krämer et al. 2021; Valenzuela et al. 2018). Although weak ties are typically perceived as offering less emotional and informational support compared to strong ties (Krämer et al. 2021; Putnam 2000), research by Bakshy et al. (2012), Gray et al. (2013) and Ellison et al. (2014) suggests weak ties can be particularly effective in facilitating informational support. This contrast raises important questions about how influence operates in large, loosely connected online networks.

Social conformity, a process by which individuals adjust their beliefs or behaviors to align with group norms (Asch 1951; Deutsch and Gerard 1955), provides a theoretical lens for examining these dynamics. Traditional conformity research has focused on the role of strong ties groups, where norms are reinforced through close, repeated interactions. However, digital platforms like X (formerly Twitter) amplify weak-tie communications through open networks, algorithmic amplification, and rapid information flows (Granovetter 1973; Krämer et al. 2021; Valenzuela et al. 2018). This structural environment may alter the way normative and informational influence shape public attitudes, particularly in relation to vaccine hesitancy (Dodd et al. 2021; Kreps et al. 2020; Webb Hooper et al. 2021).

Despite this insight, our understanding of the normative influence of weak ties remains limited. This study has two primary aims. First, at a general level, it seeks to advance understanding of how weak-tie digital networks reconfigure the mechanisms of social conformity, contributing to broader theories of online influence. Second, at a specific level, it uses vaccine hesitancy as a case study to investigate how normative and informational influences operate in weakly connected online ecosystems. By focusing on weak-tie ecosystems on Twitter during a period when vaccine debates were highly visible, this study provides empirical insights into how digital social influence contributes to the diffusion of health-related norms and behaviors.

2 Literature review

2.1 Weak ties and network centrality in social networks

In social networks, weak ties, defined as social contacts with looser connections (Kadushin 2012), serve as bridges connecting separate clusters of actors, enabling novel information to spread across communities (Granovetter 1973), and underpinning bridging social capital in social networks (Putnam 2000). Network centrality metrics formalize these roles: out-degree centrality (the number of outgoing connections a node has) reflects a user's broadcast capacity, while betweenness centrality (how often a node lies on shortest paths between others) identifies its role as a bridge between groups (J. Zhang and Luo 2017). For example, a user with high out-degree (an "accelerator") can share content to many contacts, and one with high betweenness (a "bridger" or "connector") links otherwise disconnected audiences. Empirical studies confirm that high-degree nodes tend to be influential in information diffusion: one analysis of Twitter data found users with high degree centrality were more likely to spread information widely (Gupta et al. 2023; Hansen et al. 2020). In public health contexts, these weak-tie bridge roles can overcome echo chambers by carrying messages across social divides (Cava et al. 2023; Valenzuela et al. 2018).

During the COVID-19 pandemic, studies of vaccine discourse illustrate these network dynamics. For example, one multilayer Twitter network analysis found distinct pro- and anti-vaccine communities with very different structures: anti-vaccination users had much denser, more cohesive ego-networks than pro-vaccine users (Bonifazi et al. 2022). Similarly, a study of COVID-19 vaccine discussions on Weibo (a Twitter-like platform in China) found low overall echo-chamber effects: identified opinion leaders and "structural hole spanners" (bridging nodes) acted as bridgers connecting diverse vaccine topics and attitudes (Wang et al. 2022). These users linked disparate groups of users and vaccine viewpoints, exemplifying the Granovetter (1973) hypothesis that weak ties facilitate novel information flow. In line with this, research on Japanese Twitter data showed that a user's community membership strongly predicted their opinion shift: users embedded in a pro-vaccine community were significantly more likely to adopt pro-vaccine stances over time, and similarly for anti-vaccine communities (Q. Wu et al. 2025).

This study integrates these frameworks to examine the role of weak-tie networks in shaping health communication dynamics on Twitter. Using public health discourse –vaccine-related discussions during the COVID-19 crises, this research explores how weak-tie power, which is measured through network centrality metrics, shapes the mechanisms of informational and normative social influence in health-related information dissemination.

Based on the literature review, it was hypothesized that weak ties (e.g., acquaintances, colleagues, or distant connections) enable more efficient information diffusion and bridging across communities compared to strong ties (e.g., family, close friends). Specifically, users with high out-degree centrality (accelerators or amplifiers) and high betweenness centrality (bridgers) are theorized to leverage weak-tie networks to accelerate the spread of information and connect fragmented subgroups, thereby overcoming echo chambers and expanding the reach of critical messaging (Rodrigues 2019). High out-degree centrality reflects a user's capacity to amplify reach and distribute information widely, which aligns with the characteristics of weak ties as bridges for information (Granovetter 1973). This bridging function exemplifies weak-tie power, enabling novel information to traverse disconnected networks, which is consistent with Granovetter's (1973) theory. Therefore, the following hypotheses were proposed:

H1: *Tweets by Twitter users with greater weak-tie power (as measured by network centrality) were retweeted more frequently than tweets by Twitter users with smaller weak-tie power.*

H1a: *Tweets by Twitter users with greater accelerating weak-tie power were retweeted more frequently than tweets by Twitter users with smaller weak-tie accelerating power.*

H1b: *Tweets by Twitter users with greater bridging weak-tie power were retweeted more frequently than tweets by Twitter users with smaller weak-tie bridging power.*

2.2 Social influence and conformity on social media

Conformity theory, proposed by Solomon Asch based on a series of conformity experiments (Asch 1951, 1955), refers to individuals yielding their beliefs and behaviors to a group due to two different types of pressures (Crutchfield 1955). Normative social influence involves conforming to fit in and gain social acceptance (Sherif 1936; Sumner 1906) while informational social influence involves conforming because others are presumed to have accurate information (Festinger et al. 1950; Hardin and Higgins 1996).

On social media, these social pressures are made explicit through visible cues. In normative social influence, users retweet or like content to enhance their social image or avoid rejection by their peers (Ajzen and Fishbein 1980), aiming to mitigate risks tied to deviating from perceived majority behaviors (Latané and Wolf 1981). For instance, trending hashtags and high retweet counts signal majority norms, nudging users to adopt prevailing opinions or behaviors. This process amplifies specific narratives, reinforces (or challenges) existing social norms, as well as lays the foundation for the formation of new ones (Young and Jordan 2013). The visibility of these norms creates a feedback loop that further drives their adoption (Khasawneh et al. 2021; McGraw 2020; Samet 2020). Consequently, widely shared content, even if unverified, gains perceived validity through sheer exposure, as users interpret popularity as a proxy for credibility (H. Lee and Oh 2017). This dynamic extends to information-sharing behaviors (Yoo et al. 2014). In informational influence, users share what they perceive as credible or useful information, often relying on informational cues from perceived experts, opinion leaders, or popular figures (Cialdini and Goldstein 2004; Sherif 1936).

Research shows that on Twitter, many users primarily use the platform to see "what others are saying", indicating the importance of observing social norms (McClain et al. 2021, 9). As a result, tweets with higher retweet volumes are perceived as more influential, reinforcing their propagation (Kapidzic et al. 2022). In light of previous literature on social conformity, and informational and social normative influence, the following hypothesis was proposed:

H2: *Tweets emphasizing informational content (perceived credibility) will be more likely to be retweeted than opinion-based content (alignment with dominant norms).*

Social conformity theory emphasizes the role of group identity and social comparison in shaping influence. Individuals tend to conform to peers they perceive as similar (Deutsch and Gerard 1955), seeking validation by aligning their opinions or behaviors with those of others (Festinger et al. 1950; Hardin and Higgins 1996). On Twitter, these mechanisms operate at scale: the platform facilitates collaborative information-seeking and norm negotiation, particularly in health-related contexts where users collectively construct shared understandings (Samet 2020). During public health crises, hashtags like #PublicHealth aggregate discussions at unprecedented scales, amplifying both evidence-based guidance and contested narratives. Such dynamics highlight the interplay of informational (evidence-driven) and normative (approval-seeking) social forces in shaping health-related perceptions (McGraw 2020). However, Twitter's structural features – its character limits, open networks, and immediacy – tend to privilege concise, factual content over nuanced opinions, suggesting that informational influence may dominate in health contexts. At the same time, opinion-driven tweets may align more closely with normative pressures, appealing to users' desire to fit in with group norms rather than to verify facts. Therefore, extending H2 and informed by conformity theory, the utility of Twitter, and the usage patterns of U.S. adult users, the following hypotheses were formulated:

H2a: *Tweets emphasizing informational content will exert stronger informational social influence and will be retweeted more frequently than opinion-based tweets.*

H2b: *Tweets emphasizing opinion-based content will exert stronger normative social influence and be retweeted less frequently than informational tweets.*

2.3 Influencers and networked social influence

Social media influencers, distinct from traditional opinion leaders who derive authority from institutional credentials (Rogers and Cartano 1962), leverage platform-specific strategies like curated self-presentation and parasocial engagement to shape public discourse (Archer et al. 2021; Kamiński et al. 2021). In the context of health topics, influencers range from medically trained communicators to celebrities discussing health. Those who incorporate factual, evidence-based messaging can exert strong informational influence, while those acting as "curators" of norms may reinforce social norms around behaviors by weaving health into personal narratives (Thorson and Wells 2016). Bridging scientific information and public audiences, influencers shape perceptions of both credibility and acceptability through the reinforcement of communal values (Pöyry et al. 2022).

Network centrality further amplifies influencers' impact. They often occupy the high-centrality roles: an influencer with many followers (high out-degree) or one who bridges multiple interest groups (high betweenness) can disseminate content widely across the network (Rodrigues 2019). Because of these positions, influencers are likely to amplify both types of social influence, as they control information flow and decision-making in fragmented networks (Hanneman and Riddle 2005; J. Lee et al. 2013). Research has shown that users with many outgoing links indeed have more power to spread information (Mochalova and Nanopoulos 2013), and highly connected "third-party" accounts can connect disparate Twitter communities (Enke and Borchers 2019). Retweets, often interpreted as signals of credibility, reflect this dynamic, where users disproportionately share concise, factual content over opinion-based narratives (Saito et al. 2015).

Given the substantial body of previous literature highlighting the powerful impact of influencers in disseminating (or promoting) scientific information on social media, it was posited that influencers possess stronger weak-tie power capabilities, and consequently, exert a heightened degree of social influence upon other Twitter users. Considering their unique capacity to merge informational authority with networked reach, the following hypotheses were formulated:

H3: *Influencers' tweets characterized by greater informational content and weak-tie bridging power, will be retweeted more frequently than those by regular users.*

Zhang et al. (2017) demonstrated that a small fraction of highly engaged users, with a significant "user engine" value, can wield substantial influence on Twitter. Four categories of Twitter users were identified: information creators (professional or non-professional mass media accounts), information promoters (famous or vital individuals), information supporters (ordinary users whose values of user engine are large and focus on the event all the time), and information consumers (passive users who consume and retweet messages). Wu (2024) classified Twitter influencers as "initiators" who create original tweets; "accelerators" who provide "ignition power" through likes, retweets, and comments (based on degree of centrality); and "connectors" who serve as connective communicative tissues (based on betweenness centrality). While informational influence is widespread, Promoters (Accelerators and Bridgers or Connectors) uniquely shape normative dynamics by curating and legitimizing health-related norms through networked visibility. Their structural positions – bridging fragmented audiences or amplifying content to broad networks – enable them to reinforce scientific consensus or challenge misinformation (Saito et al. 2015; Nisbet and Kotcher 2009). Connectors, in particular, leverage weak-tie power to disseminate norms across disconnected communities, aligning with Granovetter's (1973) theory of weak ties as conduits for novel information.

Even though informational influence is common among social media influencers, information creators (initiators) and information promoters (accelerators and connectors), may play a crucial role in curating social norms and are more powerful in normative social influence. Specifically, information promoters (or accelerators and connectors) are the most active Twitter users in curating social norms. Therefore, the following hypotheses were proposed:

H3a: *Tweets by information promoters – famous or vital individuals who provide ignition power through likes, retweets, and comments – will exert stronger informational social influence and will be retweeted more than tweets by other Twitter users.*

H4: *Tweets by influencers will contain more opinion-based narratives and exert stronger normative social influence than tweets by regular users.*

H4a: *Tweets of users with greater weak-tie power will exert stronger normative social influence than those of other Twitter users and will be retweeted more (Figure 1).*

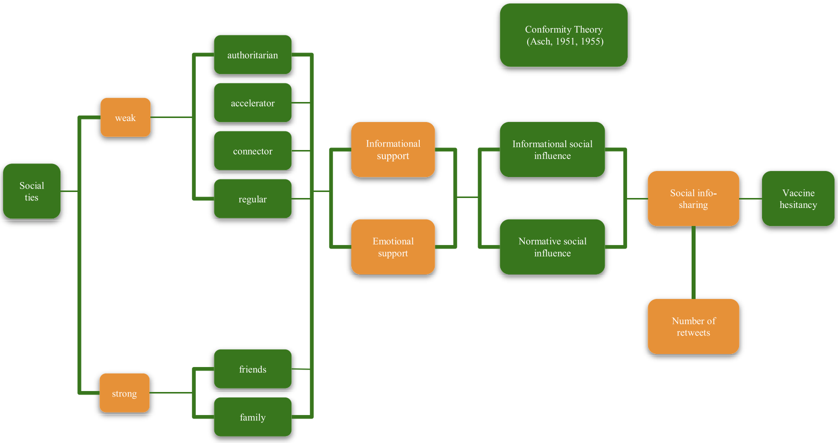

Figure 1: User, tweet type, and social influence on Twitter.

3 Methods

3.1 Data collection

A Python script utilizing the “Requests” library (Reitz et al. 2014) collected a sample of the Twitter stream posts around the COVID-19 vaccine via the Twitter search academic Application Programming Interfaces (API) v2. The Twitter API enabled the extraction of tweets that match search criteria such as keywords, hashtags, locations, and named places, among others. To gather relevant tweets on the public’s attitudes toward the COVID-19 vaccination, hashtags such as “pfizervaccine”, “modernavaccine”, “Johnson&Johnsonvaccine”, and “COVID-19 vaccine” were used as search terms in the crawler. A total of 5,554,372 tweets were collected from November 3, 2021, to May 5, 2022.

For the purpose of this study, the analysis focused exclusively on retweets rather than quote tweets, original tweets, or replies. Retweets provide a direct and quantitative indicator of social influence, as they reflect a user’s decision to endorse, propagate or conform to a message shared by another user. Prior research shows that retweet counts serve as a visible social cue that signals both informational and normative social influence (Kapidzic et al. 2022). Non-English tweets were removed using the Python package “Langdetect” (Rodrigues 2019), resulting in a final sample of 4,625,086 English retweets from users worldwide for analysis. Users’ locations were not filtered, as many did not provide this information.

3.2 Data analysis

First, Latent Dirichlet Allocation (LDA), a three-level hierarchical Bayesian unsupervised machine learning model, was utilized to uncover the hidden thematic structures – main topics – within the sampled tweets discussing COVID-19 vaccines. Each topic was modeled as an infinite mixture of underlying topic probabilities (Blei et al. 2003). The processing involved processing steps such as stop word removal, lemmatization, and tokenization. A dictionary was then created to catalog words frequencies, and text data were converted into a document-term matrix. The LdaModel from the Gensim Python package was selected for accuracy in identifying ten distinct topics (Tijare and Rani 2020).

In the next step, to identify influencers and measure users’ capacity for social influence, network analysis was executed using the igraph library in Python (Hermida 2010; Himelboim 2017; Kolaczyk and Csárdi 2014). Network analysis is a valuable tool for identifying influencers in large, loosely organized groups of users and verifying truthful and reliable information in social network communication (Hermida 2010; Himelboim 2017). For this study, network analysis was executed to measure users' index of influence (degree of centrality and betweenness centrality), which are widely recognized measurements for social networks (J. Zhang and Luo 2017). Degree centrality counts a node's neighbors in a network, to measure individuals' capacity to connect with a network (Gupta et al. 2023; Hansen et al. 2020). No weights were added in the index of influence computation.

The top 1,000 Twitter users with the top in-degree, out-degree, and betweenness centrality were identified as influencers and categorized into three categories: "authoritarians", who received the most attention and gained popularity; "accelerators", who provided accelerating weak-tie power through likes, retweets, and comments (based on the degree of centrality); and "connectors", who acted as connective communicative tissues and provided bridging weak-tie power (based on betweenness centrality) (Nisbet and Kotcher 2009; Saito et al. 2015). The descriptive analysis of the 94 sample prominent influencers revealed that half of the sample are news media users, while public health and government accounts made up 36.17 %, and personal accounts 8.51 %. These influencers were highly connected, averaging 2,506,147 followers and following 3,103 others, which suggests their central role in vaccine-related discussions (Appendix: Tables 1 and 2).

To evaluate the weak-tie power, two centrality metrics, out-degree centrality, and betweenness centrality, were calculated for the 1,728,543 Twitter users, with average values of 3.88 and 641,557.36 respectively. Out-degree centrality captures the extent to which a user actively initiates connections and disseminates information, indicating greater accelerating weak-tie power because such users can rapidly broadcast information to diverse audiences. Betweenness centrality, on the other hand, identifies users who act as bridges between communities, facilitating

Table 1: Influencer Twitter profile (94 users in top 1,000 in-degree, out-degree, and betweenness centrality).

Category	Count	Percentage
1. News media	47	50.00
2. Politicians	1	1.06
3. Public health and government	34	36.17
4. Science communicators	2	2.13
5. Brand influencers and celebrities	1	1.06
6. News media professionals	1	1.06
7. Other	8	8.51
Total	94	

Table 2: Top influencers' Twitter profile.

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
HIREMAIDEA	Direct maid agency NO. 1	https://twitter.com/HIREMAIDEA	7	587	106	Singapore	Jul-18	1,135	2,671	3,733,267,713
hicksyalex	Anti-COVID influencer	https://twitter.com/hicksyalex	5	19,200	30,700	United Kingdom	Jan-21	4,785	1,588	7,319,961,954
NSWHealth	Medical and health	https://twitter.com/NSWHealth	3	312	322,900	Australia	May-09	42,696	1,361	4,277,902,225
Reuters_Health	Sharing health and medical news	https://twitter.com/Reuters_Health	1	75	253,800	None	Mar-09	8,370	1,145	7,386,885,818
Reuters	Top and breaking news	https://twitter.com/Reuters	1	1,198	25,500,000	World	Mar-07	62,791	969	29,700,237,708
inquirerdotnet	Media & News company	https://twitter.com/inquirerdotnet	1	1,772	3,900,000	Makati city	Jul-08	3,857	621	2,703,486,470
TPCHD	We protect and improve the health	https://twitter.com/TPCHD	3	588	6,597	Pierce county, Washington	Dec-11	1,194	596	185,386,189.3
healthgovau	Australian department of health and aged care	https://twitter.com/healthgovau	3	181	126,200	Australia	Mar-10	3,566	589	2,067,085,875
HSELive	What's happening in the health services	https://twitter.com/HSELive	3	485	278,200	Ireland	Aug-09	3,218	583	1,635,358,085
Cnnphilippines (no longer exists)	Media & News company	https://twitter.com/cnnphilippines	1	386	1,900,000	Philippines	Sep-14	2,977	548	1,225,425,281

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
adriandix	Member of the legislative assembly for Vancouver	https://twitter.com/adriandix	2	4,495	58,800	Vancouver	Mar-09	3,830	546	1,594,145,191
WebMD	Health news and information	https://twitter.com/WebMD	3	400	3,000,000	USA	Mar-09	7,363	536	5,015,780,774
globeandmail	Canada's national news organization	https://twitter.com/globeandmail	1	1,015	1,900,000	Canada	Sep-07	4,170	531	1,912,045,651
thehill	Policy and political news	https://twitter.com/thehill	1	346	4,300,000	Washington, DC	Mar-07	22,802	530	9,776,397,098
WashTimes	News	https://twitter.com/WashTimes	1	1,878	47,000	Washington, DC	May-08	5,587	509	1,862,873,467
NJDeptofHealth	New Jersey department of health	https://twitter.com/NJDeptofHealth	3	803	42,900	New Jersey	Feb-11	1,910	506	1,717,124,629
realTuckFrumper	News center for the left	https://twitter.com/realTuckFrumper	1	148,800	310,500	None	Jul-09	6,366	504	2,986,507,809
EpochTimes	Media & News company	https://twitter.com/EpochTimes	1	19	828,700	New York, NY	Apr-09	25,103	503	7,712,967,574
ChannelNewsAsia	Media & News company	https://twitter.com/ChannelNewsAsia	1	179	1,300,000	Singapore	May-09	2,167	493	1,363,744,386
GovCanHealth	Promoting and protecting health and safety	https://twitter.com/GovCanHealth	3	67	455,800	Canada	Apr-09	3,458	487	1,761,420,158

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
Scdhec (No longer active)	Public health and environmental protection	https://twitter.com/scdhec	3	0	17	Columbia, S.C.	Oct-10	3,527	462	1,800,231,341
ABSCBNNews	Media & News company	https://twitter.com/ABSCBNNews	1	1,089	10,000,000	Manila, Philippines	Aug-08	2,301	450	584,712,086.1
IMHO__2017	Personal account	https://twitter.com/IMHO__2017	7	2,085	1,240	London	Apr-09	912	437	739,046,887.8
ONThealth	Ontario's ministry of health	https://twitter.com/ONThealth	3	577	123,200	Ontario, Canada	Feb-11	946	437	584,802,911.2
MassDPH	Massachusetts department of public health	https://twitter.com/MassDPH	3	324	68,200	Boston, MA	Mar-09	1,896	433	1,945,684,282
InfoPEI	Prince Edward Island	https://twitter.com/InfoPEI	7	4,411	38,000	PEI	Mar-11	1,121	423	508,936,155
CDCofBC	Centre for disease control	https://twitter.com/CDCofBC	3	855	41,800	Vancouver	May-10	2,712	422	1,064,259,262
NHSLanarkshire	News and health information from NHS	https://twitter.com/NHSLanarkshire	3	1,418	30,500	Lanarkshire	Mar-10	1,786	416	1,634,099,620
USBornNRaised	Personal account	https://twitter.com/USBornNRaised	1	9,527	65,300	USA	Apr-09	2,793	412	1,050,207,974
Brienico (no longer active)	Personal account	https://twitter.com/brienico	7	1,150	4,913	None	Nov-14	4,584	405	1,932,018,532
gmanews			1	678	6,800,000	Philippines	May-09	2,884	385	1,463,458,377

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
	Integrated news in the Philippines	https://twitter.com/gmanews								
FOX13News	Fox Tampa Bay	https://twitter.com/FOX13News	1	4,352	437,500	Tampa, FL	Aug-08	922	383	349,075,695.4
SharylAttkisson	Investigative journalist	https://twitter.com/SharylAttkisson	6	8,486	580,700	Washington, DC	Oct-10	39,122	375	4,846,603,522
ABC	Media & News company	https://twitter.com/ABC	1	424	17,900,000	None	Apr-09	24,817	375	7,328,874,031
SaskHealth	Saskatchewan health authority	https://twitter.com/SaskHealth	3	179	34,600	Saskatchewan, Canada	Apr-10	2,492	369	1,380,336,761
KCPubHealth	Public health - Seattle & King county	https://twitter.com/KCPubHealth	3	939	40,200	Seattle & King county, WA	May-10	4,071	367	432,334,480.6
nshealth	Nova Scotia's department of health and wellness	https://twitter.com/nshealth	3	428	32,100	Nova Scotia, Canada	Feb-12	1,044	367	225,200,295.4
bhrenton	Researching vaccine rollout, access and equity	https://twitter.com/bhrenton	4	6,239	15,800	Providence, RI	Nov-12	1,620	363	707,814,148.5
StLCountyDOH	Progressive public health department	https://twitter.com/StLCountyDOH	3	912	4,959	Berkeley, Missouri	Sep-09	948	357	538,707,645.1
KFF	Nonprofit organization	https://twitter.com/KFF	3	27	108,800	San Francisco| Washington DC	Oct-09	3,123	356	1,399,361,412
rapplerdotcom			1	415	3,700,000	Philippines	Jul-11	1,952	352	720,217,862.7

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
	Digital Media company	https://twitter.com/rapplerdotcom								
htTweets	Media company	https://twitter.com/htTweets	1	124	8,600,000	India	Apr-09	1,057	346	450,390,132.8
STForeignDesk	News	https://twitter.com/STForeignDesk	1	147	617,000	Singapore	Jan-13	1,121	345	558,718,401
manilabulletin	News	https://twitter.com/manilabulletin	1	199	1,100,000	Manila, Philippines	Jul-08	1,792	342	860,824,198.5
FOX10Phoenix	Fox News Phoenix	https://twitter.com/FOX10Phoenix	1	1,885	37,1000	Phoenix, AZ	Jan-09	1,255	336	667,244,989.6
CTVNews	News	https://twitter.com/CTVNews	1	30	2,400,000	None	Oct-10	11,259	334	6,633,642,999
FOXLA	FOX 11 Los Angeles	https://twitter.com/FOXLA	1	14,400	426,400	Los Angeles, CA	Oct-07	2,367	326	769,019,627.1
business	Media & News company	https://twitter.com/business	1	101	9,700,000	New York and the world	Apr-09	11,537	322	3,421,614,846
WSJ	The wall street journal	https://twitter.com/WSJ	1	1,063	20,800,000	New York, NY	Apr-07	13,248	322	4,908,362,124
latimes	Los Angeles times	https://twitter.com/latimes	1	6,365	3,800,000	El Segundo, CA	Oct-08	4,425	312	1,362,838,732
MOH_TT	Medical and health	https://twitter.com/MOH_TT	3	120	41,500	Trinidad and Tobago	Apr-09	2,683	307	1,182,472,207
statnews			3	4,790	159,800	None	Jul-15	2,567	307	564,752,603.8

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
	Medical and health	https://twitter.com/statnews								
WADeptHealth	Washington state department of health	https://twitter.com/WADeptHealth	3	1,027	1,025,920	Olympia, WA	Jul-09	4,517	305	1,250,949,240
Fraserhealth	Health care and wellness	https://twitter.com/Fraserhealth	3	907	27,700	Surrey, British Columbia	Nov-08	886	296	255,647,075.5
fox5dc	Fox News DC	https://twitter.com/fox5dc	1	5,744	348,200	DC	Feb-08	1,581	293	814,018,613.1
NRPublicHealth	Health care and wellness	https://twitter.com/NRPublicHealth	3	757	115,000	Niagara region	Jul-14	1,070	291	276,169,899.7
Nowthisnews (no longer active)	News and media	https://twitter.com/nowthisnews	1	1,295	2,600,000	New York, NY	Jul-12	12,669	289	3,938,132,414
PHLPublicHealth	The public's health in Philadelphia	https://twitter.com/PHLPublicHealth	3	593	35,700	Philadelphia, PA	Feb-12	1,049	286	781,792,453.8
ctvottawa	News Ottawa	https://twitter.com/ctvottawa	1	394	294,400	Ottawa, Ontario	Feb-09	1,595	282	777,656,421.1
TorontoStar	News and media	https://twitter.com/TorontoStar	1	286	1,200,000	Toronto	Jan-08	6,148	275	1,566,468,776
AustinISD	News and media	https://twitter.com/AustinISD	1	1,463	45,600	Austin, TX	Agu-09	965	275	380,047,758.2
newsmax	News and media		1	795	3,400,000	USA	Feb-09	39,770	269	10,204,294,119

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
		https://twitter.com/newsmax								
Smackenziekerr	Personal account	https://twitter.com/Smackenziekerr	4	4,962	7,937	None	Apr-20	1,873	269	503,858,424.2
PublicHealthSD	Public health	https://twitter.com/PublicHealthSD	3	1,316	5,703	Sudbury, Ontario, Canada	Oct-11	1,228	268	380,974,108.3
Forbes	News and media	https://twitter.com/Forbes	1	4,645	20,700,000	New York, NY	Nov-09	4,940	266	1,256,992,053
cityofhamilton	City of Hamilton communications account	https://twitter.com/cityofhamilton	3	43	108,700	Hamilton, Ontario, Canada	Jun-09	2,372	264	1,329,939,511
dcexaminer	News and media	https://twitter.com/dcexaminer	1	455	36,400	Washington, DC	Jan-09	2,139	264	1,200,033,769
PDChina	The largest newspaper in China	https://twitter.com/PDChina	1	3,907	6,500,000	Beijing, China	May-11	3,433	263	820,713,392.6
StateDept	U.S. department of state	https://twitter.com/StateDept	3	429	6,500,000	Washington, DC	Oct-07	16,663	263	5,012,534,041
NEWS1130	News and media	https://twitter.com/NEWS1130	1	1,546	28,200	Vancouver, British Columbia	Jan-09	1,415	261	321,455,298.4
AHS_media	Alberta health services	https://twitter.com/AHS_media	3	680	75,700	Alberta	Apr-11	3,294	258	1,376,838,510

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
CBSNews	News and media	https://twitter.com/CBSNews	1	625	8,900,000	New York, NY	Jun-08	13,587	258	4,267,977,493
WCVB	Boston's news leader	https://twitter.com/WCVB	1	964	392,800	Boston, MA	Feb-09	1,230	255	483,886,487
ChinaDaily	News and analysis from China	https://twitter.com/ChinaDaily	1	162	4,100,000	Beijing, China	Nov-09	1,668	255	277,637,965.7
UPI	News and media	https://twitter.com/UPI	1	639	51,500	Washington, DC	Oct-08	1,416	254	149,638,058
PharmacyNS	Pharmacy association of Nova Scotia	https://twitter.com/PharmacyNS	3	957	1,811	Nova Scotia	Jan-10	1,561	253	867,891,845.3
RCDHealthUnit	Health news and information	https://twitter.com/RCDHealthUnit	3	155	2,226	Renfrew county and district	Mar-18	1,184	252	509,027,994.4
DeanParise	Personal account	https://twitter.com/DeanParise	7	1	0	None	Oct-22	1,145	250	454,887,926.3
Expecte02304588	Personal account	https://twitter.com/Expecte02304588	7	177	9,761	None	Oct-21	1,569	249	1,101,765,889
CNN	Media & News company	https://twitter.com/CNN	1	1,049	63,600,000	None	Feb-07	39,647	245	5,975,419,356
CTVToronto	Media & News company	https://twitter.com/CTVToronto	1	48	743,900	Toronto, Ontario	Nov-08	2,734	240	803,340,172.6
Ptbohealth	Healthcare center	https://twitter.com/Ptbohealth	3	2,489	6,432		Nov-09	1,653	239	952,304,241.9

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
						Peterborough, Ontario, Canada				
OttawaHealth	Health news and information	https://twitter.com/OttawaHealth	3	680	144,500	Ottawa, Ontario	Oct-09	10,614	237	2,713,315,957
FOX5Vegas	Media & News company	https://twitter.com/FOX5Vegas	1	342	362,800	Las Vegas, NV	Feb-09	1,254	237	506,653,035.9
PBNS_India (no longer active)	Digital news service of India's public broadcaster	https://twitter.com/PBNS_India	1	60	211,900	None	Apr-19	1,188	236	316,417,671.7
ACTHealth	Health news and information	https://twitter.com/ACTHealth	3	1,428	29,500	Canberra, Australia	Jul-11	1,693	234	349,693,312.6
GlobalNational	Media & News company	https://twitter.com/GlobalNational	1	410	307,200	None	Nov-08	1,150	233	339,718,254.8
WAPFLondon	Food account	https://twitter.com/WAPFLondon	7	269	20,400	None	Nov-10	3,929	230	419,420,026.1
KFLAPH	Public health agency for Kingston	https://twitter.com/KFLAPH	3	432	21,400	Kingston, Ontario	Apr-09	3,348	229	1,292,753,114
Jerusalem_Post	Media & News company		1	882	840,500	Israel	Jan-09	2,019	228	1,231,026,464

Table 2: (continued)

Username	Identity	Twitter profile link	Type of influencer	Following	Followers	Registered location	Registration time	InDegree centrality	OutDegree centrality	Betweenness centrality
		https://twitter.com/Jerusalem_Post								
BMore_Healthy	Health department	https://twitter.com/BMore_Healthy	3	1,902	19,400	Baltimore, MD	Oct-09	1,376	214	741,183,650.1
HHSGov	Media & News company	https://twitter.com/HHSGov	1	29	1,600,000	Washington, DC	Jun-09	8,071	213	1,433,838,148
CTVCalgary	Media & News company	https://twitter.com/CTVCalgary	1	431	243,900	Calgary, Alberta, Canada	Feb-09	1,359	208	435,685,148.4
Tanfox13	Personal account	https://twitter.com/Tanfox13	7	1,898	3,149	Democrat-run shithole, USA	Sep-2009	1,145	307	739,486,403.9

Type of influencer categories: 1. News media; 2. Politicians; 3. Public health and government; 4. Science communicators; 5. Brand influencers and celebrities; 6. News media professionals; 7. Other.

communication and information exchange across different groups. This bridging role enables novel information to flow across network clusters and overcome echo chambers (Granovetter 1973). Together, these metrics provide a robust measure of weak-tie power in social networks and these values served as criteria for evaluating ties or connections between users. Among these users, 320,374 (19 %) had above-average out-degree centrality, indicating significant accelerating weak-tie power, while 1,408,169 (81 %) had below-average values. Additionally, 54,254 (3 %) users had above-average betweenness centrality, signifying strong bridging weak-tie power, whereas 1,674,289 (97 %) had below-average values.

Finally, sentiment analysis using Natural Language Processing (NLP) was executed through crowd coding, a method shown to be as reliable as trained coders but more cost-effective, transparent, and replicable (van Atteveldt et al. 2021). This analysis determined the prevalence of informational versus opinion-based content in each tweet by evaluating the text of all tweets.

Sentiment analysis of all tweets was performed using the TextBlob Python library, which offers a standardized API for various NLP tasks, including tagging, classification, and sentiment analysis (Loria 2021). TextBlob utilizes a Naïve Bayes classifier trained with unigram features (Araque et al. 2017; Loria 2021), to calculate sentiment scores, specifically the subjectivity score, using the pattern library (Giatsoglou et al. 2017). Subjectivity quantifies the amount of personal opinion and factual information contained in the text. The subjectivity score ranges from 0 to 1, where 0 denotes high objectivity and 1 denotes high subjectivity. The higher subjectivity means that the text contains personal opinion rather than factual information. For example, both ‘great’ and ‘not great’ have a subjectivity score of 0.75. This score reflects the balance of personal opinion (expressing of opinions, feelings, or subjective judgments) versus factual information in a tweet, with higher values indicating greater subjectivity (opinions) and lower values indicating greater objectivity (factual information) (Shah 2020).

To evaluate the reliability of TextBlob’s sentiment scoring, an intercoder reliability test was conducted using the Pattern sentiment library (Rodríguez López and de Jesús Hoyos Rivera 2019) as an independent automated coder. A random 10 % sample of the dataset (n = 462,288 tweets) was analyzed separately with Pattern, and the sentiment outputs (polarity and subjectivity) from the two tools were compared. The agreement between TextBlob and Pattern was assessed using Cronbach’s alpha, yielding α = 0.70 for both polarity and subjectivity. These values demonstrate a high level of consistency between the two sentiment analysis tools, supporting the robustness of TextBlob’s measures for large-scale analysis.

4 Results

In this section, the results of the thematic analysis were presented, highlighting the top ten common themes identified in the sample tweets. The most popular topics include health and safety concerns, vaccine administration and distribution, media coverage and public perception, data and scientific insights, public figures and authorities, local efforts and community events, legal challenges and rights, social media and public discourse, as well as technology and innovations regarding COVID-19 vaccines (Appendix: Table 3).

In the next step, two negative binomial mixed-effects models were constructed, which took into account the skewed distribution of retweeting, were created to predict the number of retweets a given tweet by (1) tweet content (information vs opinion; positivity vs negativity), (2) user's weak-tie power (accelerating and bridging weak-tie power); (3) user category (influencer vs regular user); and (4) the moderating effects of weak-tie power and user category. Additional covariates such as number of followers, number of followings, and a user's in-degree, out-degree, and betweenness centrality in the discussions regarding COVID-19 vaccines on Twitter were also included.

To test hypothesis 1, Twitter users were categorized into two categories based on their out-degree centrality (accelerating weak-tie power) and betweenness centrality (bridging weak-tie power).

A complex negative binomial regression model was built to test the predictive power of retweets by users with small and big accelerating and bridging weak-tie power. The results (Pseudo R-squ. (CS): 0.77) showed number of followers, number of followings, in-degree centrality, out-degree centrality, and betweenness centrality, number of tweets created of a user did not predict number of retweets. Additionally, ANOVA tests showed significant differences in the retweet count of tweets posted by users with small and big accelerating weak-tie power (F (1, 4,602,103) = 138,668.81, $p < 0.001$); and small and big bridging weak-tie power (F (1, 4,602,103) = 31,238.49, $p < 0.001$). Moreover, big accelerating (out-degree) weak-tie power significantly increase retweet counts, [out-degree weak-tie power, (IRR) = 1.25, 95 % confidence interval (CI): 0.22-(0.23)]; However, big bridging (betweenness) weak-tie power significantly decrease the number of retweet, [betweenness weak-tie power, (IRR) = 0.64, 95 % confidence interval (CI): −0.45-(0.45)] (Tables 4 and 5). Hence, hypothesis 1a was supported, confirming weak ties' role in information diffusion. However, hypothesis 1b was not supported, suggesting connectors prioritize curation over virality. Hypothesis 1 was partially supported by the data.

To test hypothesis 2, tweets were categorized into three categories based on their content: tweets that were dominated by informational, opinioned, and balanced

Table 3: Topic modeling results.

Number	Thematic analysis results	Keywords	Topic	Sample tweets
1	Words: 0.084*"action" + 0.078*"state" + 0.039*"refusing" + 0.035*"thank" + 0.035*"legislation" + 0.033*"rep" + 0.032*"introduced" + 0.032*"drew" + 0.032*"cosponsoring" + 0.027*"parent"	Legislation and political action	Legislative actions and political responses related to COVID-19 vaccines. Discussions revolve around state actions, legislative efforts, and political figures' roles in shaping vaccine policies.	"The bicameral women's health protection act is critical to creating a future where every woman is free to make the personal health decisions that are best for themselves, their lives, and their families, without political interference and congress must pass this legislation."
2	Words: 0.043*"health" + 0.032*"rwmalonemd" + 0.018*"risk" + 0.016*"fda" + 0.015*"dr" + 0.014*"one" + 0.014*"passed" + 0.014*"authority" + 0.014*"keep" + 0.012*"announced"	Health and safety concerns	Health-related aspects of COVID-19 vaccines. Topics include health risks, FDA updates, and concerns about vaccine safety and efficacy, often reflecting public health debates and expert opinions.	"The vaccine isn't providing significant benefit at two doses against the risk of transmission, as compared to someone unvaccinated." Dr. Moore has pointed out the elephant in the room. Now what? #COVID19 #omicron https://t.co/lBeKZnv1Wg
3	Words: 0.054*"dose" + 0.054*"johnson" + 0.054*"amp" + 0.049*"people" + 0.042*"first" + 0.038*"booster" + 0.034*"shot" + 0.028*"received" + 0.022*"month" + 0.021*"electionwiz"	Vaccine administration and distribution	Practical aspects of vaccine deployment. It includes discussions on vaccine doses, distribution logistics, booster shots, and updates on the number of people receiving vaccines, highlighting logistical challenges and progress.	"This newest shipment brings to 8.6 million total number of delivered Pfizer doses, of which 4,681,170 doses were sourced from the COVAX facility. The country has received a total of 64,380,400 COVID-19 vaccine doses from various manufacturers since February. https://t.co/DShsGSFmyS"
4	Words: 0.048*"news" + 0.041*"prevent" + 0.041*"member" + 0.036*"big" + 0.030*"adult" + 0.021*"bird" + 0.021*"time" +	Media coverage and public perception	Media representations and public perceptions of COVID-19 vaccines. Discussions encompass news	1. "First byline since July 2020 and I'm so glad it's to report on children 5–11 likely soon being eligible for the COVID19

Table 3: (continued)

Number	Thematic analysis results	Keywords	Topic	Sample tweets
	0.020*"administered" + 0.020*"back" + 0.020*"fox"		coverage, prevention efforts, and public reactions to vaccination campaigns, shaping public opinion and awareness.	vaccine. This brings so much hope to millions of families. https://t.co/uJPafiMH5N"; 2. "BREAKING: Pfizer says its COVID-19 vaccine works for kids ages 5 to 11; plans to seek authorization for this age group soon. https://t.co/YDoxAlNmab"
5	Words: 0.056*"data" + 0.025*"hr" + 0.024*"release" + 0.024*"repthomasmassie" + 0.023*"please" + 0.019*"hospital" + 0.018*"emergency" + 0.017*"wing" + 0.016*"involved" + .016*"kellyesorelle"	Data and scientific insights	Statistical data and research findings related to COVID-19 vaccines. Topics include data releases, hospitalization rates, and statistical analyses of vaccine efficacy and side effects.	1. "97.3 % of the 87,748 Americans that have died of Covid since the vaccines first became widely available in May have been unvaccinated."; 2. "Novavax on Thursday announced that its COVID-19 vaccine was around 80 % effective among adolescents aged 12–17 years in a phase 3 trial. https://t.co/R8gpKEHVni"
6	Words: 0.063*"fauci" + 0.055*"naturally" + 0.052*"walensky" + 0.033*"biden" + 0.029*"sign" + 0.026*"take" + 0.025*"jeff" + 0.024*"religious" + 0.023*"cdc" + 0.021*"email"	Public figures and authorities	Prominent figures in the COVID-19 vaccination efforts. It includes statements and actions from public figures like Fauci and Walensky, along with governmental responses from figures like President Biden and the CDC.	1. "The CDC recommends getting a flu shot by the end of October. And it's safe to get your flu vaccine and COVID-19 vaccine at the same time! Learn more about this year's flu vaccine at https://t.co/1VYcTnddod https://t.co/EJSSkrvxu7"
7	Words: 0.064*"get" + 0.050*"class" + 0.035*"today" + 0.032*"vaccination" + 0.021*"clinic" + 0.021*"van" + 0.018*"bay" +	Local efforts and community events	Local vaccination efforts and community responses to COVID-19 vaccines. Discussions cover vaccination clinics, events update, community	"Join APH at the delco activity center vaccine tent to receive the COVID-19 vaccine (Moderna or Pfizer) for individuals 12+. Pre-register to save time

Table 3: (continued)

Number	Thematic analysis results	Keywords	Topic	Sample tweets
	0.016*“government” + 0.015*“care” + 0.015*“feeling”		involvement, and government support for local initiatives.	on-site: https://t.co/AVhWdhK3fS Walk-ups are welcome! 📍4601 Pecan Brook Dr, Austin, TX 78724 📅 Tuesday–Friday ⏰ 9am–12pm https://t.co/GJoOlCd0nG
8	Words: 0.139*“mandate” + 0.062*“child” + 0.059*“federal” + 0.049*“breaking” + 0.045*“say” + 0.042*“year” + 0.026*“vaccinated” + 0.025*“old” + 0.024*“show” + 0.021*“safe”	Legal challenges and rights	Legal aspects and challenges related to COVID-19 vaccines. It includes discussions on vaccine mandates, federal regulations, and debates over individual rights and public health measures.	“The sister-in-law of MAGA GOPThe sister-in-law of MAGA GOP Georgia Gov. Brian Kemp died of COVID-19 days ago. In completely unrelated news, Kemp pledged to fight President Biden’s new COVID-19 vaccine orders until his dying breath. Clearly he doesn’t care about his own families dying breath.Georgia Gov. Brian Kemp died of COVID-19 days ago.”
9	Words: 0.077*“immune” + 0.063*“suit” + 0.060*“lodge” + 0.048*“employee” + 0.027*“chuckcallesto” + 0.024*“system” + 0.024*“court” + 0.023*“Tennessee” + 0.021*“lawsuit” + 0.018*“filed”	Social media and public discourse	Social media discussions and public discourse surrounding COVID-19 vaccines. It includes the dissemination of information and opinions across social platforms such as lawsuits filed against mandates, legal immunity for vaccine manufacturers, employee rights, and court decisions impacting vaccination policies.	1. “I am sorry for tweeting so late. Thank you for sharing this vital information with me. I am not planning to take the Covid-19 vaccine! I do take vitamins. It’s my body and my choice. Our freedoms come from God, not Beijing Biden, Fauci, nor Francis Collins!”; 2. “Court papers have been filed on behalf of hundreds of Los Angeles fire department firefighters who want a judge to set aside the city’s COVID-19

Table 3: (continued)

Number	Thematic analysis results	Keywords	Topic	Sample tweets
				vaccine requirement. https://t.co/nSbYNmOxWh"
10	Words: 0.184*"rt" + 0.142*"vaccine" + 0.142*"covid" + 0.074*"http" + 0.063*"co" + 0.020*"pfizer" + 0.012*"new" + 0.012*"worker" + 0.010*"moderna" + 0.009*"age"	Technology and innovations	This theme underscores how technological innovation has played a pivotal role in the global response to COVID-19, from vaccine development (Pfizer, Moderna), distribution strategies, to implications for different age groups, thereby shaping the landscape of public health interventions and global healthcare responses.	1. "Interested in innovation in COVID-19 vaccines? 💉 WTO staff released a working paper with a statistical analysis of 74 patent families. The analysis is based on #VaxPaL, a vaccines database developed by @MedsPatentPool. 💻 Download here: https://t.co/W6Qna33Rzi https://t.co/VM1tO6BR9s"; 2. "Pfizer is now saying that their COVID-19 vaccine is safe for children 5–11 years old and will seek emergency FDA authorization. In England, studies found that COVID-19 caused 25 deaths in people under 18 between March 2020 and February 2021.";

Table 4: Complex model: negative binomial regression on number of retweets.

	(Pseudo R-squ. (CS): 0.77		
	b(SE)	**IRR[95 % CI]**	***p*-Value**
(Intercept)	5.76(0.00)	317.42[5.76, 5.76]	<0.001***
Individual level predictors			
User predictors			
Followers count	0.00(0.00)	1.00[−0.00, 0.00]	0.267
Following count	0.00(0.00)	1.00[0.00, 0.00]	<0.001***
Tweet count	0.00(0.02)	1.00[0.00, 0.00]	<0.001***
In-degree centrality	−0.00(0.00)	1.00[−0.00, 0.00]	<0.001***
Out-degree centrality	0.00(0.00)	1.00[0.00, 0.00]	<0.001***
Betweenness centrality	−0.00(0.00)	1.00[−0.45, −0.45]	<0.001***
Accelerating weak-tie power	0.22(0.00)	1.25[0.22, 0.23]	<0.001***
Bridging weak-tie power	−0.45(0.00)	0.64[−0.45, −0.45]	<0.001***
Influencer	3.12(0.00)	22.73[3.12, 3.13]	<0.001***
Content predictors			
Information vs opinion	−0.16(0.00)	0.85[−0.16, −0.16]	<0.001***
Polarity	0.18(0.00)	1.19[0.18, 0.18]	<0.001***
Group level predictors			
Weak-tie power	−0.23(0.00)	0.80[−0.23, −0.23]	<0.001***
Influencer	3.12(0.00)	0.99[−0.01, −0.01]	<0.001***
Moderating effects			
Followers count and influencer	0.00(0.00)	1.00[0.00, 0.00]	<0.001***
Following count and influencer	0.00(0.00)	1.00[0.00, 0.00]	<0.001***
Tweet count and influencer	−0.00(0.00)	1.00[−0.00, −0.00]	<0.001***
In-degree centrality and influencer	0.00(0.00)	1.00[0.00, 0.00]	<0.001***
Out-degree centrality and influencer	−0.00(0.00)	1.00[−0.00, −0.00]	<0.001***
Betweenness centrality and influencer	0.00(0.00)	1.08[0.07, 0.08]	<0.001***
Information vs. opinion and influencer	0.01(0.00)	1.01[0.00, 0.01]	<0.001***
Polarity and influencer	−0.06(0.00)	0.94[−0.06, −0.06]	<0.001***

**$p < 0.05$, ***$p < 0.001$.

content. The ANOVA test indicated that there were significant differences in tweet content (information and opinions) among the three aforementioned tweet types, (F (2, 4,602,102) = 10,013.93, $p < 0.001$). The complex model indicated tweets with more informational content received more retweets than tweets contain more opinions, showed an Incidence Rate Ratios (IRR) of 0.85 [information versus opinion,

Table 5: Simple model: negative binomial regression on number of retweets.

	(Pseudo R-squ. (CS): 0.77		
	b(SE)	**IRR[95% CI]**	***p* value**
(Intercept)	5.77(0.00)	319.41[5.76, 5.77]	<.001***
Individual level predictors			
User predictors			
User category	1.27(0.00)	2.19[0.78, 0.79]	<.001***
Content predictors			
Information vs opinion	−0.16(0.00)	0.85[−0.16, −0.16]	<.001***
Polarity	0.18(0.00)	1.19[0.17, 0.18]	<.001***
Group level predictors			
Weak-tie power	−0.26(0.00)	0.77[−0.27, −0.26]	<.001***
Influencer	−0.70(0.01)	0.50[−0.71, −0.69]	<.001***
Moderating effects			
Accelerating weak-tie power and influencer	−1.10(0.00)	0.33[−1.12, −1.12]	<.001***
Bridging weak-tie power and influencer	0.47(0.00)	1.23[0.20, 0.21]	<.001***
Information vs opinion and influencer	0.01(0.00)	1.01[0.00, 0.01]	<.001***
Polarity and influencer	−0.07(0.00)	0.93[−0.07, −0.07]	<.001***

$^{**}p < .05$, $^{***}p < .001$.

(IRR) = 0.85, 95 % confidence interval (CI): −0.16-(-0.16)]. Therefore, the data supported hypothesis 2 (See Tables 4 and 5).

To test hypothesis 3 and hypothesis 4, Twitter users were categorized based on the degree of centrality into four categories: general users, authoritarians, accelerators, and connectors.

Based on the results of the complex model, factors without predicting power were removed, a simplified negative binomial model was constructed (Pseudo R-squ. (CS):0.77). The simple model demonstrated that influencer was a significant predictor of retweets [influencer, (IRR) = 0.50, 95 % confidence interval (CI): −0.71-(-0.69)]. Influencer moderated the effect of subjectivity (information vs opinion) on retweet rate [subjectivity and influencer, (IRR) = 1.01, 95 % confidence interval (CI): 0.00 – (0.01)]. Influencers significantly moderated the effects of accelerating weak-tie power [accelerating weak-tie power and influencer, (IRR) = 0.33, 95 % confidence interval (CI): −1.12-(-1.12)] and bridging weak-tie power on retweet counts [bridging weak-tie power and influencer, (IRR) = 1.23, 95 % confidence interval (CI): 0.20-(0.21)] (Table 5). This demonstrated that while influencers overall suffer a retweet penalty, those with high bridging power received more retweets. This suggests influencers uniquely leverage their position to transform structural brokerage into visibility, likely by connecting polarized communities that regular users cannot bridge effectively.

For H3, the ANOVA test showed significant differences existed between the tweet content (F (3, 4,602,101) = 483.14, $p < 0.001$) and retweet count (F (3, 4,602,101) = 113,789.85, $p < 0.001$) of general users', authoritarians', accelerators', and connectors' tweets. Therefore, hypothesis 3 was supported by the data.

For H4, the ANOVA test indicated significant differences between influencers' and general users' tweets in terms of the tweet content (F (1, 4,602,103) = 1,274.14, $p < 0.001$) and retweet count (F (1, 4,602,103) = 288,687.74, $p < 0.001$). Therefore, hypothesis 4 was supported by the data. This demonstrated influencers amplified informational content more effectively and curate more norms by propagating opinion-based narratives.

5 Discussion

This study illuminates how weak-tie networks and social conformity dynamics shape critical health information diffusion on Twitter during crises. While grounded in COVID-19 vaccine discourse, the mechanisms, particularly the dominance of informational influence over normative pressures, reflect platform-driven dynamics that likely extend to other public health communication crises.

Thematic analysis revealed that weak-tie networks amplify accuracy-seeking conformity while restricting approval-seeking conformity due to low accountability. A pronounced preference for amplifying concise, data-driven content, such as statistical updates on public health initiatives, policy measures, and scientific developments, shared by authoritative entities (e.g., institutions, verified experts) was recognized. In contrast, anecdotal narratives or opinion-based posts from general users were less widely disseminated. This pattern underscores the platform's structural dynamics: its weakly connected network architecture prioritizes rapid, large-scale information diffusion rather than fostering nuanced dialogue. This pattern suggests that users tend to amplify content from authoritative sources, aligning with theories of weak-tie influence, where minimally connected users act as bridges for factual, broadly relevant content. However, normative trust-building was inhibited due to Twitter's character limits. On Twitter, this manifests as a preference for easily shareable, institutionally endorsed messaging that aligns with public information-seeking behaviors during health crises. This also supports Khasawneh et al.'s (2021) findings that weak-tie networks drive the circulation of institutional messaging during crises. Consequently, Twitter functions less as a space for collective norm-building and more as a catalyst for "informational broadcasting," with content design and algorithmic engagement further reinforcing this trend.

5.1 Theoretical implications

This study reinforces Granovetter's (1973) theory of weak ties as conduits for rapid information diffusion. Weak ties, characterized by a loosely connected network structure with minimal social overlap, prioritize content that is factual, concise, and broadly applicable over nuanced debates. This structure inherently favors updates such as vaccine distribution statistics, highlighting the tension between reach (broad dissemination) and depth (in-depth discussion) in digital ecosystems. Contextual trust-building, for which social conformity is relied on, is inhibited within Twitter's virtual communities. This underscores Twitter's role as a megaphone for institutional messaging, amplifying authoritative sources while marginalizing subjective perspectives. These findings extend Granovetter's (1973) framework to health communication on social media, illustrating how weak-tie networks, particularly bridging weak-tie power, facilitate public health messaging during crises while limiting opportunities for norm curation.

The study advances the theoretical understanding of social influence by demonstrating that accelerating and bridging weak-tie power are stronger predictors of retweetability than follower count or tweet volume. This directly challenges Suh et al.'s (2010) study, which emphasizes follower metrics, indicating a positive association between a user's follower and following counts and retweetability. Instead, this current study resonated with Cha et al. (2010) assertion that network structure and tie strength, not the number of followers, drive engagement.

In addition, the findings' alignment with Liu and Zheng's (2024) conclusion that the informative value of content critically shapes parasocial relationships between influencers and followers, highlights a key mechanism driving user engagement on Twitter. Influencers who disseminate evidence-based updates enhance trust and credibility, driving retweetability. This dynamic further distinguishes social media influencers from traditional opinion leaders, as their influence stems not from institutional authority but from digital attributes such as platform-specific social ties and curated relatability (Cheung et al. 2022; Kim and Kim 2022). For instance, influencers leveraging weak-tie connections can transcend traditional hierarchies, embracing Katz's (1957) assertion that influence in fragmented networks depends more on "whom one knows" (weak-tie reach) than "who one is" (institutional authority).

The limited retweetability of opinion-based posts suggests that normative influence (conforming to shared group values) is constrained by the platform's structure. Unlike long-form platforms (e.g., YouTube), where community interaction fosters norm curation, Twitter's design favors central-route processing of factual information (Cho et al. 2024). For instance, connectors drove over half of retweets by disseminating factual updates, while authoritarians (e.g., institutional accounts) had limited reach. This supports Zhang et al.'s (2017) finding that ordinary active users, not traditional elites, often wield the greatest influence in digital networks. As a result, Twitter's network design constraints limit the potential for subjective narratives to shape collective behavior (McClain et al. 2021) and heighten engagement during the COVID-19 pandemic (Samet 2020). The minimal impact of opinion-based content further underscores Twitter's role as a real-time information hub rather than a space for norm formation. This reinforces the idea that follower counts signal popularity but not credibility, reinforcing that conformity on Twitter is driven more by informational influence (adherence to credible sources) than by normative influence (adherence to group values).

5.2 Practical implications

The findings of this study offer actionable strategies for public health communicators. Social conformity models must account for *platform-driven dissociation* of informational and normative influence. Health campaigns on Twitter should prioritize concise, evidence-based data messaging (but not opinions) tailored to the platform's rapid diffusion dynamics. Moreover, the non-significant role of follower count suggests that investing in accounts solely for their large audiences may be inefficient. Instead, strategies should focus on identifying users with high weak-tie bridging or accelerating power, even if they have modest followings. Accelerators, often science communicators or local healthcare workers, can broadcast information to broad audiences, while connectors, such as community leaders, help bridge polarized subgroups, ensuring messages reach ideologically diverse communities. Authoritarians like institutional accounts may rely on their credibility to propagate accurate information, but require collaboration with connectors to penetrate fragmented audiences. Furthermore, public health campaigns should adopt a cross-platform strategy, reserving nuanced, emotion-driven narratives for platforms like YouTube, where long-form content fosters communal validation and norm curation.

5.3 Limitations

While this study provides critical insights into Twitter's role in health communication, several limitations must be acknowledged. First, the exclusion of retweets from suspended or deleted accounts may introduce bias, potentially overrepresenting persistent institutional voices while undercounting transient or dissenting users. Second, reliance on automated natural language processing (NLP) for sentiment analysis risks misclassifying nuanced content. Finally, the dynamics observed may not fully generalize to non-crisis health topics or less polarized issues.

5.4 Future research

Future studies should expand on these findings by exploring how platform-specific affordances shape health communication across diverse contexts. Comparative analyses of weak-tie dynamics on video-centric platforms (e.g., TikTok) versus closed networks (e.g., WhatsApp groups) could reveal how content format and network structure interact to drive engagement. Additionally, investigating the mediating role of issue valence such as contentious topics versus neutral ones, could clarify how controversy amplifies or diminishes weak-tie influence. Longitudinal research tracking shifts in influencer roles during public health crises versus routine advocacy periods would further illuminate the stability of network-driven leadership. Finally, integrating mixed-method approaches (e.g., NLP with qualitative interviews) would deepen understanding of how users interpret and act on health information in fragmented digital ecosystems.

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