Decentralized Opinion Leadership: A Study of Crypto Influencers in the Twitter Discourse on Bitcoin

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Abstract

Based on 115 million Bitcoin-related tweets from 2009 to 2022, we propose an opinion leader index (OLI) for decentralized technologies, such as Bitcoin, and identify the foremost Bitcoin opinion leaders (N=218 BOLs). The OLI consists of a scoring scheme for social media opinion leader classification along six criteria: audience engagement, niche alignment, reputation, audience reach, activity, and consistency. We further classify BOLs into eight archetypes and show that their tweet activity strongly correlates with Bitcoin price performance. Linguistic content analysis reveals that each BOL archetype exhibits a distinct communication style and content focus, with themes ranging from financial and technological aspects to power and politics. Our study advances the field by introducing a classification approach for social media opinion leaders in the context of decentralized technologies. We derive future research avenues for other decentralized contexts across different social media platforms and further measures of opinion leader influence.

Keywords: Opinion leadership, Social media influencer, Bitcoin, Twitter, Linguistic content analysis

1. Introduction

Historically, opinion leaders—that is, individuals of high influence on the decision-making of others—have had a tremendous impact on society by shaping and forming public opinion through interpersonal interactions (Lazarsfeld et al., 1948; Rogers & Cartano, 1962; Weimann, 1991). Extant research investigated opinion leadership in the context of presidential elections (Lazarsfeld et al., 1948), corporate social responsibility (Chu et al., 2020), purchase decision-making (Jia & Liu, 2017), or product launch and adoption strategies (Goldenberg et al., 2006; Parakhonyak & Vikander, 2019). However, the increasing prevalence of social media platforms created new opportunities for information sharing and opinion expression, establishing a new opinion leader type, namely social media influencers (SMIs) (Arora et al., 2019; Vrontis et al., 2021). SMIs rely on their online presence and often specialize in niches such as sports or fashion (Belanche et al., 2021; Kay et al., 2020).

The rise of Bitcoin has also given rise to a specific SMI type, the so-called crypto influencers (i.e., social media opinion leaders of decentralized technologies), that challenge our understanding of SMIs and influencer marketing based on "traditional" (i.e., centralized) companies and brands (Farivar et al., 2021; Mallipeddi et al., 2021). In the context of decentralized technologies (i.e., technologies that enable decentralized business models), new types of opinion leadership emerge, such as those present in the Bitcoin discourse. These Bitcoin opinion leaders (BOLs), such as Michael Saylor, Natalie Brunell, and Elon Musk, have an extraordinary impact on the crypto community (Öztürk & Bilgiç, 2022). Their tweet activity can significantly affect crypto market prices (Öztürk & Bilgiç, 2022; Shahzad et al., 2022) or shape the entire crypto discourse through ideology-driven values rather than purely financial motivations (e.g., as so-called "Bitcoin maximalists" or even Bitcoin critics). Furthermore, in contrast to "traditional" SMIs, crypto opinion leadership bears the phenomenon of pseudonymous accounts, describing highly influential individuals that do not disclose their identity to the community, such as the BOLs "PlanB," "WhalePanda," or "Gigi." Finally, BOLs do not typically collaborate with brands and are not paid by established firms to promote products and services. Thus, as evident, many characteristics of traditional SMIs do not generalize to SMIs of decentralized technologies, necessitating a differentiated view of both groups.

In addition, in the case of decentralized technologies (e.g., Bitcoin), there is no systematic procedure for the identification and classification of opinion leaders, as there is for traditional SMIs (e.g., Arora et al., 2019). Specifically, we lack understanding and knowledge on two aspects regarding opinion leaders of decentralized technologies:

(1) How can we classify social media opinion leaders for decentralized technologies (i.e., BOLs)?

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(2) How do different types of BOLs differ in "how" and "what" they communicate with the public?

To classify BOLs, we develop a scoring scheme-based opinion leader index (OLI), along six criteria derived from a synopsis of the opinion leader and SMI literature: (1) *audience engagement*, (2) *niche alignment*, (3) *reputation*, (4) *audience reach*, (5) *activity*, and (6) *consistency*. Based on new metrics to apply the OLI in the context of Bitcoin, we identify 218 influential accounts from a collected dataset of 115 million tweets on Bitcoin, in the period between 2009-2022, and 24 Bitcoin and crypto influencer lists. To enhance our understanding of the heterogeneity of these 218 BOLs, we also use the OLI to develop a typology of BOLs and apply Linguistic Inquiry and Word Count (LIWC; Tausczik & Pennebaker, 2010) analyses on 545,711 BOL tweets.

Our study contributes to existing social media opinion leadership and blockchain technology research in two ways. First, we contribute to SMI and opinion leadership research (Arora et al., 2019; Casaló et al., 2020) by shifting the focus from traditional influencers, typically sponsored by brands and firms, to independent opinion leaders of technologies that enable decentralized business models such as Bitcoin. These leaders navigate the Bitcoin discourse with diverse agendas and communication patterns, emphasizing the challenges of identifying opinion leaders in such contexts. Hence, the creation and operationalization of an OLI in our work also serves as a foundation for future studies to systematically classify opinion leadership for further decentralized contexts, such as societal movements (e.g., #MeToo, #MarchForOurLives) and political protests (e.g., Arab spring), that go beyond the specific case of decentralized technologies (Tumasjan, 2023a).

Second, we contribute to blockchain technology and Bitcoin research by developing a typology of BOLs and uncovering their distinguishing communication patterns. While prior research has focused on specific BOL communities, such as Bitcoin developers and core members (Kang et al., 2020; Thapa et al., 2021), or YouTube vloggers (Meyer et al., 2023), our investigation extends beyond this BOL understanding by highlighting the heterogeneity across BOL types. Advancing extant research, our work provides a more nuanced understanding of BOLs as significant actors in the blockchain and crypto industry (Tumasjan, 2021) with substantial influence over the Bitcoin and blockchain discourse and cryptocurrency price fluctuations.

2. Theoretical background

The original concept of opinion leadership describes individuals that "exert an unequal amount of influence on the decision of others" (Rogers & Cartano, 1962, p. 435). Opinion leaders possess large social networks, expertise, and deep knowledge in specific domains, making them highly regarded by others (Casaló et al., 2020; Goldenberg et al., 2006; Weimann, 1991). Therefore, these individuals shape the public discourse and can sway their followers' attitudes and behaviors (Katz & Lazarsfeld, 1955; Rogers, 2003). However, with the rise of social media, social interactions increasingly occur in the digital world, amplifying the reach and impact of opinion leaders (Casaló et al., 2020; Goldenberg et al., 2006). Social media thus created a new opinion leader type—the social media influencer (Belanche et al., 2021; Vrontis et al., 2021). The SMI is a person who gained a substantial following on social media platforms and has the power to impact their audience's decisions, attitudes, preferences, and purchasing behavior through their content and online persona (Belanche et al., 2021; Schouten et al., 2020). While opinion leaders and influencers share similarities in their ability to impact people's opinions and behavior, they differ in their primary medium and the nature of their perception. Opinion leaders derive their influence from the expertise and social connections within a specific domain (Casaló et al., 2020; Goldenberg et al., 2006), while influencers primarily rely on their social media presence and personal brand (Belanche et al., 2021; Schouten et al., 2020).

Importantly, many major characteristics of "traditional" SMIs (i.e., persons who collaborate with brands and are paid by firms to promote products or services on social media) do not generalize to influencers of decentralized movements, such as crypto influencers (i.e., social media opinion leaders of decentralized technologies). While crypto influencers share some attributes with traditional influencers, such as a significant follower base (De Veirman et al., 2017), a key difference is that crypto influencers are typically not paid by firms to promote decentralized technologies. While they still may have financial interests by promoting cryptocurrencies (e.g., because they are invested themselves), crypto influencers typically engage in promoting cryptocurrencies for values-based reasons, such as their ideological beliefs, political, and personal values, factors recognized as drivers of Bitcoin use (Lichti & Tumasjan, 2023). For the same reasons, crypto influencers may also engage in constantly criticizing Bitcoin and other cryptocurrencies. As a result, their motivations and the nature of their advocacy markedly differ from those of traditional influencers that advertise brands to make a living.

Existing studies have discerned various factors influencing the sway of opinion leaders, such as online network size (Park & Kaye, 2017), sentiment and engagement (Arora et al., 2019), and author-reader interaction (Li & Du, 2011). However, these factors overlook critical criteria that are crucial for opinion leadership in decentralized contexts, such as niche alignment and temporal consistency along with their corresponding metrics (influencer lists, the duration of tweet activity, and a periodic average h-index). To advance the field, we synthesize existing research on social media influence and SMI identification to create an OLI for decentralized technologies. Drawing on Leung et al. (2022), we derive six index criteria based on a synopsis of the literature on drivers of social media influence and apply these influencer criteria to the context of Bitcoin by operationalizing new criteria metrics. We build on Goldenberg et al. (2006) to cluster the criteria into two overarching characteristics of opinion leaders, namely *expertise* (comprising activity, consistency, and niche alignment) and *social connections* (comprising audience engagement, reputation, audience reach) (see Table 1 in Section 3.2).

(1) Audience engagement. A strongly engaged audience reflects individuals' impact on the resonance of their audience. An engaged audience indicates that the targeted community is interested in the contents and opinions shared, meaning that the community values the individual's opinion. Through engagement, emotional commitment to the contents and opinions of the community increases, which in turn leads to stronger in-group behaviors (Wang, 2017). Higher levels of engagement on digital platforms also increase the reach (e.g., through influential retweets; Gong et al., 2017) and, consequently, the visibility of individuals, making them more influential (Arora et al., 2019; Boyd et al., 2010).

(2) Niche alignment. When individuals are passionate about a certain topic, share similar values, and there is a strong congruence between individual and product, individuals are more likely to influence communities regarding attitudes, purchase and recommendation intentions (Belanche et al., 2021). As a result, they can effectively communicate their stance and convince others of its merits, thus contributing to the formation of public opinion. Put differently, opinion leadership is not only about popularity or reach; it also involves the ability to align with the values and beliefs of a community (Lou & Yuan, 2019).

(3) Reputation. The concept of reputation for opinion leaders dates back to the beginnings of opinion leadership research, defining three attributes for influential individuals, namely "who one is … what one knows … and whom one knows" (Katz, 1957, p. 73). When individuals create a reputation for their expertise, credibility, and social connections, they are more likely to be perceived as trustworthy subsequently driving engagement (e.g., Casaló et al., 2020; De Veirman et al., 2017; Lou & Yuan, 2019). Furthermore, reputation fosters online loyalty (Caruana & Ewing, 2010). As a result, a loyal audience is more likely to share, promote or even advocate an individual's beliefs and opinions.

(4) Audience reach. Having a large audience on social media platforms (e.g., indicated by a large number of followers), in combination with following only a few others, creates the perception of influence (Basyurt et al., 2022). Additionally, the perceived influence eventually enhances engagement with the opinions and topics posted (e.g., likes, retweets, replies). Furthermore, having a large audience while at the same time only following fewer others grants autonomy and subsequently exerts more influence (Valsesia et al., 2020). Therefore, an individual's large audience reach not only showcases their visibility and awareness but also their ability to scale, potentially influencing the formation of trends and opinions (Arora et al., 2019; Boyd et al., 2010).

(5) Activity. The ongoing engagement of an individual with specific topics creates visibility and trustworthiness, as it indicates that the participation in the public discourse is not single-event driven but rather profound and recurrent (Li et al., 2013). Such activity is important with regard to audience retention, as activity creates engagement and consequently reduces the risk of losing audience. Moreover, through repetition of opinion expression, individuals can reinforce the influence on their audience (Casaló et al., 2020).

(6) Consistency. A continuous, active participation shows the individual's ability to cope with the ongoing conversation in a given field. Individuals engaging with certain topics over a long period are more likely to be perceived as opinion leaders due to their long-standing expertise. Furthermore, dealing with a niche topic over a long period can enhance credibility and trustworthiness, thereby leading to more vital opinion leadership (Li et al., 2013).

In summary, while current research offers various approaches and factors to identify social media opinion leaders (e.g., Arora et al., 2019; Li & Du, 2011; Park & Kaye, 2017), these approaches fall short in the context of decentralized applications. They either lack metrics (duration of tweet activity and the periodic average h-index) necessary for a comprehensive coverage of major criteria (i.e., temporal consistency) or do not generalize to the context of decentralized technologies, such as Bitcoin, or societal movements (e.g., #MeToo, #MarchForOurLives) because they do not cover fundamental criteria that are specific to this context (i.e., niche alignment). Therefore, we synthesize the criteria from extant SMI and opinion leader research to create a robust scoring scheme.

3. Methodology

3.1 Data set and pre-processing

For our data collection, we used three different types of sources. First, we collected social media data using Twitter's public API to download 114,969,048 tweets directly related to Bitcoin in the period between 01/01/2009 and 12/31/2022. To retrieve the relevant posts, we used the following keywords, at least one of which must be present in the tweet: Bitcoin, Bitcoins, and #BTC. We excluded retweets from the search and focused on English-language tweets only.

Second, we collected online references of lists identifying (1) Bitcoin maximalists and (2) crypto influencers. To compile a comprehensive list of Bitcoin maximalists and crypto influencers, we conducted an extensive search using Google and terms like "Bitcoin maximalist," "Bitcoin maximalist lists," "crypto influencer," and "crypto influencer lists." To increase reliability, we employed Bing AI for additional sources, yielding three online references for Bitcoin maximalists, such as CryptoSlate's list (cryptoslate.com/people/category/bitcoin-maxis), and 21 online references for crypto influencers, including reputable ones like CoinMarketCap's list of the most influential people (coinmarketcap.com/alexandria/influencers-2020). The two lists were reviewed by three Bitcoin and cryptocurrency experts. No incorrectly assigned persons in the respective list or missing persons were identified by the experts in the process. Our approach was designed for accuracy, reliability, and comprehensiveness, striving to represent an exhaustive list of prominent figures in the Bitcoin, blockchain and cryptocurrency communities.

Third, to compare BOL activity and audience engagement with Bitcoin price movements over time, we collected daily closing price data via the cryptocurrency database CryptoCompare. In total, the initial dataset comprises 115 million tweets on Bitcoin, 24 Bitcoin and crypto influencer lists, and historical Bitcoin price data.

In the pre-processing of the Twitter dataset, Twitter-specific syntax, such as @mentions and URLs, was removed using regular expression patterns. Newline and carriage return characters were replaced with single newline characters, and HTML entities were converted back to their original characters. Lastly, tweets lacking the search terms (Bitcoin OR Bitcoins OR #BTC) after removing @mentions and URLs were filtered out.

3.2 Identifying Bitcoin opinion leaders

To identify and classify the most influential accounts tweeting about Bitcoin, we build on the above OLI criteria and operationalize them using concrete indicators, as will be described in this section. We operationalize the six criteria of potential opinion leaders in the Bitcoin and crypto space using six indicators (see Table 1). Only if an individual meets the criteria for at least three indicators, are they classified as a BOL. This scoring scheme is used to (1) identify a broad number of BOLs who exert a certain minimum influence and (2) evaluate the extent to which an individual can be characterized as a BOL within the Bitcoin community, contingent upon the number of criteria they satisfy.

Table 1. Bitcoin OLI

Criteria to classify opinion leaders	**Metric to classify a BOL**	**BOL indicator** The individual …
1. *Audience engagement* (e.g., Boyd et al., 2010)	Annual average Hirsch index (h-index) adapted to the number of retweets, follower base	… is in the top 200 based on the average value of the h-indices per year and has at least 10,000 followers
2. *Niche alignment* (e.g., Belanche et al., 2021)	Inclusion in Bitcoin maximalist list	… is listed at least one time as a Bitcoin maximalist
3. *Reputation* (e.g., Casaló et al., 2020)	Inclusion in crypto influencer list	… is listed at least four times as a crypto influencer
4. *Audience reach* (e.g., Basyurt et al., 2022)	Number of Twitter followers	… has at least one million followers
5. *Activity* (e.g., Casaló et al., 2020)	Number of Bitcoin tweets	… has directly tweeted about Bitcoin at least 100 times
6. *Consistency* (e.g., Li et al., 2013)	Duration of tweeting about Bitcoin	… has directly tweeted about Bitcoin for at least three years

Note: Only if an individual meets the criteria for at least three indicators, are they classified as a BOL.

First, following prior research (Grčar et al., 2017; Novak et al., 2018), we adapted the Hirsch index (h-index; Hirsch, 2005) to measure Twitter users' influence by using retweet count as a proxy for citations. This Twitter-based h-index evaluates a user's influence by considering both the quantity and impact of their tweets. We calculated the average value of the h-indices per year, focused on the top 200 users with at least 10,000 followers, and excluded non-personal accounts. This approach ensured (1) long-term engagement of the individual's audience with their tweets, (2) the presence of a substantial audience, and (3) individuals' thoughts representation.

Second, we searched for online references explicitly listing Bitcoin maximalists. Identifying individuals as "Bitcoin maximalists" implies that they are strong advocates for Bitcoin's superiority over other currencies. This criterion acknowledges the importance of shared beliefs and values in opinion leadership.

Third, we searched for online references explicitly listing general crypto influencers. Being featured multiple times in influencer lists indicates that others consistently recognize an individual as a thought leader within the Bitcoin or cryptocurrency space. Three blockchain and cryptocurrency experts validated the resulting Bitcoin maximalist and the general crypto influencer list.

Fourth, we examined whether the individual had at least one million followers. A high follower count is a strong indicator of an individual's reach and potential influence on social media.

Fifth, we counted Bitcoin-related content. Publishing at least 100 tweets about Bitcoin can be considered to indicate an individual's active engagement with the topic and their dedication to sharing knowledge, news, and opinions with their audience.

Sixth, we examined user expertise in terms of temporal consistency. Tweeting about Bitcoin for at least three years indicates that the individual has been consistently involved in the community and has likely developed a deeper understanding of the subject matter.

3.3 Linguistic content analysis

We used linguistic analysis to study BOLs' tweet style (e.g., sentiment) and content (topic-specific words, e.g., related to money), creating a hashtag word cloud and employing the Linguistic Inquiry and Word Count (LIWC) software (Boyd et al., 2022). LIWC is an established linguistic approach that quantifies specific linguistic categories using a predefined dictionary of over 12,000 words and word stems. It computes the relative frequency of words in categories like basic linguistic processes, psychological constructs, and social processes. In addition, LIWC detects subtle language variations, allowing researchers to uncover meaningful associations between language patterns and psychological and social variables. We used LIWC (software version 2022; Boyd et al., 2022) to analyze our text corpus. We pre-processed the data and examined the linguistic patterns to draw inferences about underlying cognitive, emotional, and social processes.

4. Results and analysis

4.1 Sample descriptives

From our initial dataset of 115 million Bitcoin tweets from 7.3 million Twitter accounts and 24 Bitcoin and crypto influencer lists, we classified Twitter users as BOL based on the indicators in Table 1. Our classification approach yielded a sample of 218 Twitter users who met at least three criteria, with a total of 545,711 tweets directly related to Bitcoin. Figure 1 shows that only two (0.9%) individuals (Michael Saylor and Anthony Pompliano) met all six criteria, indicating powerful opinion leadership within the Bitcoin community. 7.3% met five criteria (e.g., Andreas Antonopoulos), 20.6% met four criteria (e.g., Tim Draper), and 71.1% met three criteria (e.g., Elon Musk).

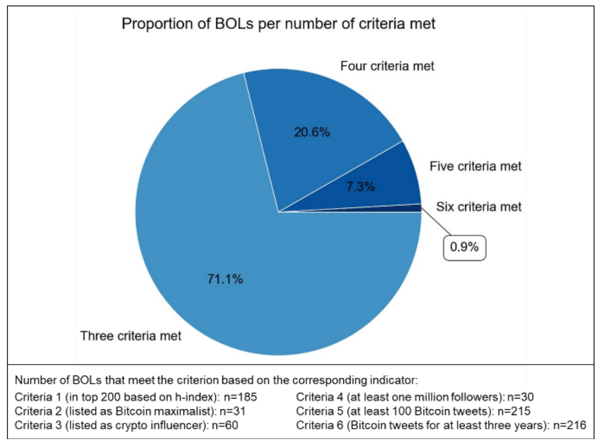

Figure 1. Scoring scheme descriptives

The Twitter user metrics in our sample of 218 BOLs reveal that, on average, users have a substantial following, with an average follower count of 1,093,656. The average number of accounts followed by these users is 3,374. A substantial proportion of the accounts (48.62%) have a "verified" badge, signifying that they were confirmed under the Twitter legacy verification system as active, notable, and authentic. Unlike the new subscription-based verification system that began on April 1, 2023 (Twitter, n.d.), these accounts received their verification without the need for a subscription, indicating the prominence of these opinion leaders as public interest figures. The average age of the user accounts is 9.83 years, suggesting that these BOLs have been active for a considerable time. In terms of tweet metrics, the average values for various engagement measures are as follows: like count (249.84), reply count (27.54), retweet count (35.89), and quote count (3.68). The average hashtag count is 0.82, the mention count is 0.86, and the URL count is 0.56. A noteworthy 37.50% of the tweets in the sample are replies, indicating a high level of engagement and interaction between these BOLs and their audiences. On average, these users have a total tweet count of 48,460, with 2,503 tweets related explicitly to Bitcoin. These numbers translate to a share of 8.96% of their tweets directly referring to Bitcoin. Similar numbers can be found in prior influencer studies (e.g., Arora et al., 2019).

To gain an initial understanding of BOL content around Bitcoin, we generated a hashtag word cloud (top 100 excluding the tags "Bitcoin" and "BTC") of all BOL tweets with the most popular topics discussed within the BOL community (see Figure 2). As evident, the opinion leaders in the Bitcoin and crypto community are discussing a wide range of topics, from the broader concepts of crypto and blockchain technology (#blockchain, #Ethereum, #fintech), specific cryptocurrencies (#XRP, #litecoin, #dogecoin), investment and trading (#gold, #payments), to specific technological developments in the crypto world and regional discussions (#LightningNetwork, #ElSalvador).

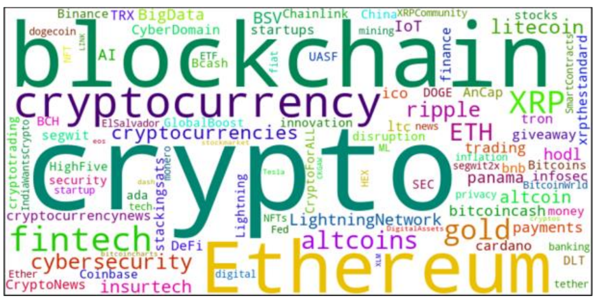

Figure 2. Hashtag word cloud of BOL tweets

4.2 A typology of BOLs

To accurately represent the entire spectrum of BOLs, individuals were categorized into the following BOL archetypes based on the criteria to classify opinion leaders (see Table 1): (1) *Engagement Gurus* (EM; individual is in the top 50 based on the h-index; e.g., Carl Runefelt; n=50), (2) *Bitcoin Maximalists* (BM; individual is listed as a Bitcoin maximalist; e.g., Tone Vays; n=31), (3) *Crypto All-Stars* (CA; individual is listed as a crypto influencer; e.g., Vitalik Buterin; n=60), (4) *Millionaire Magnets* (MM; individual has at least one million followers; e.g., Elon Musk; n=30), (5) *Bitcoin Conversationalists* (BC; individual has directly tweeted about Bitcoin at least 3000 times; e.g., Randy Hilarski; n=71), (6) *Persistent Pundits* (PP; individual has directly tweeted about Bitcoin for at least nine years; e.g., Jeff Garzik; n=84), (7) *Confrontational Conversationalists* (CC; individual is mainly critical of Bitcoin, e.g., Peter Schiff; n=12), and (8) *Incognito Influencers* (II; individual with limited personal disclosure and deliberate concealment of their true identity; e.g., PlanB; n=33). We added CC and II to account for the fact that BOLs—in contrast to traditional SMIs—may also be critical of Bitcoin and cryptocurrencies (CC) or have a significant presence in the crypto community while maintaining a carefully concealed identity (II). These archetypes highlight the broad spectrum of opinion leaders in the Bitcoin and crypto space, ranging from those with exceptional audience engagement to individuals known for their consistent or critical perspectives on digital currency.

A comparison of the strength of opinion leadership among these archetypes, as measured by the average number of BOL criteria met per person, shows that BMs (4.25) most strongly qualify as BOLs, followed by CAs (4.07) and MMs (4.03). CCs (3.00) and IIs (3.09) least strongly qualify as BOLs (see Figure 3).

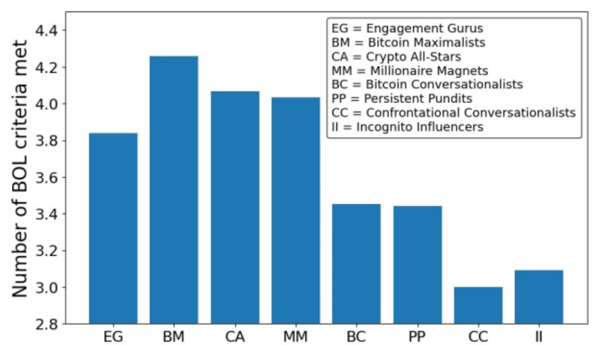

Figure 3. BOL criteria met per archetype

To understand how often BOL archetypes engage in Twitter discussions about Bitcoin versus Bitcoin price trends, Figure 4 shows how the number of tweets develops over time across the eight different BOL archetypes compared to the Bitcoin price. The plots indicate that BOL tweet activity is strongly related to Bitcoin price performance across all archetypes. More precisely, there are positive Pearson correlations between the number of tweets per month for each BOL archetype and the Bitcoin price, with the correlation being strongest for MM (r=0.90), followed by EG (r=0.86), BM (r=0.84), BC (r=0.84), II (r=0.81), CA (r=0.72), CC (r=0.71), and weakest for PP (r=0.59).

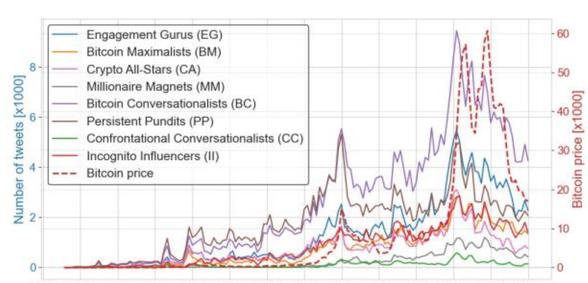

Figure 4. BOL archetype tweet count vs. Bitcoin price over time (monthly)

To understand how the BOL archetypes differ in terms of audience engagement, apart from our conceptualization of the h-index, we compare Twitter engagement metrics (i.e., likes, retweets, replies, quotes) across the different BOL archetypes (see Table 2 and Figure 5). Table 2 shows that MM have the highest average number of all four engagement metrics per tweet, while BC have the lowest engagement metrics in comparison to the other archetypes. Interestingly, II have moderately high engagement metrics despite their high level of anonymity. This finding highlights that individuals with concealed identities can achieve a significant presence and impact within the crypto community.

Table 2. Engagement metrics across BOL archetypes

Engagement metric per tweet (average)	BOL archetype							
	EG	**BM**	**CA**	**MM**	**BC**	**PP**	**CC**	**II**
#likes	441.9	224.1	300.9	828.9	64.2	136.2	167.5	166.5
#retweets	62.1	30.9	40.6	136.7	8.8	25.4	25.3	33.3
#replies	51.8	17.4	28.3	119.3	6.1	15.3	15.4	24.4
#quotes	5.9	4.8	5.9	15.0	0.8	3.1	2.7	2.4

Figure 5 shows how the "likes" engagement metric develops over time across the eight BOL archetypes compared to the Bitcoin price. Similar to BOL tweet activity (see Figure 4), this plot indicates that BOLs' audience engagement—as reflected in likes and mirrored in the other metrics of retweets, replies, and quotes (not shown here for space considerations)—is related to Bitcoin price performance across all archetypes. Specifically, there is a positive Pearson correlation between the number of likes per month for each BOL archetype and the Bitcoin price, with a notably strong correlation for likes of BC tweets (r=0.95), followed by PP (r=0.94), EG (r=0.94), CA (r=0.93), BM (r=0.92), MM (r=0.92), II (r=0.92), and weakest for CC tweets (r=0.87). Notably, similar trends were observed for all engagement metrics, even though the correlations were slightly weaker, with the weakest being for retweets of II tweets (r=0.69).

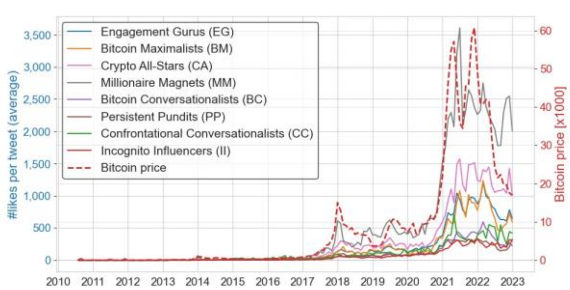

Figure 5. BOL archetype tweet likes vs. Bitcoin price over time (monthly)

4.3 Linguistic content analysis

To identify the mechanisms BOLs use to influence their audience, we studied how BOL archetypes differ in their tweet style and content using several LIWC categories (i.e., *analytical thinking*, *clout*, *emotional tone*, *cognition*, and *social processes* reflecting tweet style; *money*, *technology*, *future focus*, *power*, *politics*, *risk*, and *reward* reflecting tweet content) that are particularly relevant in the context of Bitcoin and cryptocurrencies (Tables 3 and 4). Analytical thinking is crucial given cryptocurrencies' complex, technical nature, and the necessity to analyze and interpret market data and regulatory updates. Clout, emotional tone, cognition, and social processes are also crucial as cryptocurrency conversations often involve high-status (clout) influencers, such as Elon Musk, and discussions are often emotionally charged (emotional tone) due to the volatility of crypto markets (Ahn & Kim, 2023). Understanding cognition and social processes helps evaluate the level of cognitive engagement and social dynamics involved in these discussions. Regarding content, categories like money, technology, future focus, power, politics, risk, and reward echo main themes typically found in crypto discourse. Money and technology are central aspects of cryptocurrencies, being digital assets built on blockchain technology. The future focus reflects the speculative and forward-looking nature of the crypto market. Power and politics often come into play due to the decentralized nature of cryptocurrencies and their potential to disrupt traditional financial systems (Golumbia, 2016). Finally, the highly volatile nature of cryptocurrencies brings discussions around risk and reward to the forefront as participants weigh potential gains against potential losses. These categories thus encapsulate the key aspects of the Bitcoin and cryptocurrency discourse.

Table 3. LIWC metrics on communication styles across different BOL archetypes

LIWC metric per BOL archetype (average)	BOL archetype							
	EG	**BM**	**CA**	**MM**	**BC**	**PP**	**CC**	**II**
Analytical thinking	62.70	54.50	59.74	64.48	57.16	66.64	62.28	61.90
Clout	42.66	42.63	39.22	48.07	41.75	42.12	36.88	44.86
Emotional tone	39.74	42.33	42.31	38.61	38.39	39.94	34.66	37.16
Cognition	10.36	12.86	11.91	8.73	12.53	10.28	12.30	8.88
Social processes	7.37	9.31	7.77	8.20	8.21	7.26	6.46	6.65

Regarding the style dimension (Table 3), *analytical thinking* is highest in PP, indicating their content is logical, analytical, and complex, while BM score lowest, suggesting a less formal communication style. MM exhibits the highest *clout*, indicative of confidence and assertiveness. BM and CA show the most positive sentiment (i.e., *emotional tone*), while CC have the most negative. BM and BC score the highest in *cognition*, indicating more cognitive engagement and complexity, while MM and II use simpler communication. BM also score highest in *social processes*, suggesting community-focused discourse, while CC and II score lowest, indicating a focus on individual perspectives or technical aspects.

Table 4. LIWC metrics on communication content across different BOL archetypes

LIWC metric per BOL archetype (average)	BOL archetype							
	EG	**BM**	**CA**	**MM**	**BC**	**PP**	**CC**	**II**
Money	11.52	9.87	9.85	12.35	10.83	11.69	9.87	11.76
Technology	8.75	7.61	7.67	10.25	9.03	9.56	6.59	9.13
Future focus	1.79	1.43	1.48	1.97	1.60	1.47	2.04	2.03
Power	1.58	1.64	1.58	1.42	1.69	1.41	1.53	1.07
Politics	0.50	0.50	0.43	0.48	0.54	0.48	0.42	0.27
Risk	0.40	0.39	0.37	0.46	0.40	0.37	0.39	0.22
Reward	0.30	0.30	0.26	0.33	0.30	0.25	0.21	0.26

Regarding the content dimension (Table 4), MM score highest in *money*-related and *technology*-related words, while other archetypes have a broader focus. CC and II have the highest *future focus*. BC and BM score highest in *power*-related words, while II score lowest. BC use *politics*-related words the most, while II use them the least. The MM archetype has the highest score on both *risk* and *reward*-related words, while II score lowest on risk and CC score lowest on rewards.

Our findings show a nuanced picture of how Bitcoin social media opinion leaders markedly differ in their communication style and content. Specifically, each BOL archetype has a unique communication approach, ranging from the versatile EG to the community-oriented BM, the optimistic CA, the confident MM, the politics-oriented BC, the analytical PP, the critical CC, and the future-focused II. By recognizing the unique communication tendencies and thematic foci of each archetype, we can better understand how these leaders distinguish themselves in their use of language to influence public conversations and emotions regarding Bitcoin and other decentralized business models. Moreover, understanding these communication patterns lays the groundwork for future research on opinion leadership and social influence in the area of decentralized technologies.

5. Discussion

5.1 Summary and contributions

This study sought to investigate opinion leadership on social media in the context of decentralized technologies. Whereas social media influencers (SMI) sponsored by firms and brands are the subject of an increasingly emerging research stream (Arora et al., 2019; Casaló et al., 2020), our understanding of the nature of opinion leadership in the context of technologies that enable decentralized business models is limited. To address this gap, we first introduced an approach for identifying and classifying opinion leaders in the area of decentralized technologies using the context of Bitcoin. Our opinion leadership index (OLI) identifies and classifies Bitcoin opinion leaders (BOLs) based on six criteria and corresponding indicators. Second, we identified BOL archetypes and compared their communication patterns.

Our results show that the identified BOLs substantially shape the Bitcoin discourse based on their large follower base, avid audience engagement in terms of likes, retweets, and replies, and their long-term engagement with the topic spanning many years on average. Moreover, BOLs' tweet activity is strongly associated with the Bitcoin price. These results support the notion that our index indeed captures Bitcoin opinion leadership on Twitter. Furthermore, our detailed analysis of BOL sub-groups yields eight BOL archetypes that differ considerably in their communication and audience engagement patterns. Thus, our study reveals the nuanced nature of opinion leadership in the context of decentralized technologies and business models, reflecting a wide range of actors' communication agendas, strategies, and outcomes.

Our research contributes to the literature in two major ways. First, we advance extant SMI and opinion leadership research on social media (Arora et al., 2019; Casaló et al., 2020) by going beyond "traditional" (i.e., brand and firm-sponsored) influencers toward examining opinion leaders of decentralized technologies. In contrast to traditional SMIs paid by firms to promote their brands, opinion leaders in the context of decentralized technologies, such as Bitcoin, shape the respective discourse independently and with a range of different agendas and communication patterns. Consequently, identifying opinion leaders as such poses a challenge due to the heterogeneity of the actors resulting from the decentralized business model nature of the technologies. Thus, our work and the resulting OLI lays the groundwork for future research to investigate opinion leadership, its antecedents, and outcomes in decentralized business models and movements.

Second, we advance blockchain technology and Bitcoin research by developing a typology of BOLs and revealing the archetypes' distinct communication patterns. Whereas prior research has been limited to specific BOL sub-communities, such as Bitcoin developers and core members (Kang et al., 2020; Thapa et al., 2021) or YouTube vloggers (Meyer et al., 2023), our research goes beyond the state of the art by showing the considerable heterogeneity and wide range of different BOL archetypes. We thereby enrich our understanding of BOLs as major actors in the blockchain and crypto industry (Tumasjan, 2021) that not only shape the global Bitcoin and blockchain discourse but also considerably influence Bitcoin and other cryptocurrencies' price development.

5.2 Limitations and future research

Our research has limitations that concurrently offer opportunities for future research. First, we focus on Bitcoin opinion leaders while neglecting opinion leaders in other decentralized contexts related to other blockchain-based business models (e.g., NFTs) or even decentralized societal movements on social media (e.g., #MeToo). While our focus on Bitcoin is based on its widespread attention and embodiment of decentralization principles, future research focusing on these comparison groups is needed to validate if the criteria we have identified are similar in influence scale across different decentralized domains.

Second, our typological approach is exploratory in nature. While an exploratory approach is appropriate for work in nascent research fields such as ours, future work may build on our typology to engage in theorizing and hypothesis-testing research. For instance, examining the impact of different BOL archetypes on Bitcoin's price fluctuations could offer theoretical progression to our observation, i.e., the pronounced correlations between BOLs' tweet activity and Bitcoin's valuation. To refine the understanding of our preliminary observation, future studies might provide insights into how positive or negative sentiments from these leaders might affect the Bitcoin price, while also accounting for external factors (e.g., global economic events, regulatory decisions, technological advancements).

Third, our methodological toolbox to measure the opinion leader criteria, though comprehensive, has not been entirely leveraged. While our OLI encapsulates a diverse spectrum of indicators, future research could bolster our findings. An example trajectory might be integrating eigenvector centrality measures, extending the notion of audience reach beyond our follower count indicator by accounting for the influence of the opinion leader's followers.

Fourth, our work investigates opinion leadership only in the context of Twitter. While Twitter is the most important social media platform for the Bitcoin and cryptocurrency discourse (Öztürk & Bilgiç, 2022), we encourage future research to examine opinion leadership and the generalizability of our approach using other platforms and contexts, such as non-mainstream (e.g., Mastodon), non-US (e.g., Weibo), and non-text-based (e.g., TikTok) social media (Tumasjan, 2023b) to complement our knowledge on opinion leadership that is mainly based on "traditional" social media.

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