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Information diffusion in referral networks: an empirical investigation of the crypto asset landscape

Srinidhi Vasudevan[1] · **Anna Piazza**[1] · **Stefano Ghinoi**[1,2,3,4]

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Abstract

In the last decades, crypto assets have become particularly popular in financial markets. However, public awareness of the crypto asset landscape is rather limited, and usually associated with sensationalized media coverage of a handful of cryptocurrencies. Moreover, while users of crypto assets primarily collect information on Internet, there is a limited understanding of the relational (online) structures supporting the diffusion of information about these financial products. Therefore, the aim of this study is to uncover the structure of online information referral networks dedicated to crypto assets. By adopting a multi-method approach consisting of web scraping, web analytics, and social network analysis, we use data from the top 200 crypto assets by market capitalization to identify pivotal websites and the overall connectedness of the information referral networks. Our results show that social media and news channel sites play a key role in the information diffusion process, while market and trading sites signal innovation adoption. Overall, cryptocurrencies' websites do not seem key in the referral network, as opposed to social media websites which, however, cannot be considered mature hubs because of their low connectivity.

Keywords Web mining · Social network analysis · Web analytics · Diffusion · Crypto asset adoption · Blockchain

✉ Srinidhi Vasudevan
srinidhi.vasudevan@greenwich.ac.uk

Anna Piazza
anna.piazza@greenwich.ac.uk

Stefano Ghinoi
stefano.ghinoi@unimore.it; s.ghinoi@greenwich.ac.uk

1 School of Business, Operations and Strategy, University of Greenwich, London, UK

2 Dipartimento di Comunicazione ed Economia, University of Studi Modena e Reggio Emilia, Modena, Italy

3 Department of Economics and Management, University of Helsinki, Helsinki, Finland

4 Trieste Laboratory on Quantitative Sustainability, Trieste, Trieste, Italy

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1 Introduction

Over the last 2 decades, a new phenomenon has revolutionized financial markets: the introduction of digital currencies adopting blockchain technology (Griffin and Sharms 2020; Nakamoto 2008). Blockchains provide an immutable system which forms the backbone of crypto assets: transactions cannot be deleted or altered, and this enables transaction histories to be stored and transmitted globally through peer-to-peer computers (Koroma et al. 2022). However, public understanding of crypto assets, and the full scope of the crypto asset landscape, remains nascent at best or ill-informed at worst. Recent studies have shown that this limited understanding is linked to sensationalized media coverage of a handful of cryptocurrencies during events of high crypto-market volatility (Olney 2022). Researchers looked at specific groups and interactions in the community of media-sensationalized currencies such as Bitcoin (Hedman et al. 2021) or Ethereum (Bizzi and Labban 2019) to test public engagement, finding that cryptocurrencies' performance is strongly influenced by the media narrative, which tend to be rather sensationalistic and not always objective. Despite the growth of cryptocurrencies' market capitalization—which reached over 3 trillion USD in 2022 (Forbes 2022)—the main information sources leading to such upsurge of crypto assets remains unclear (Antonakakis et al. 2019).

In contrast to other financial assets, the decentralized nature of crypto assets results in lack of formal control; this leads to self-regulating behaviors where social interactions determine the dynamics of the crypto assets landscape (Chiu 2021). This is why recent studies have started to look at the crypto asset landscape as a socio-technical ecosystem, emphasizing that individuals do not act in isolation, but they interact with technologies to the extent that they influence each other (e.g. Shin and Rice 2022). Online websites become key in the spread of information, and in the crypto asset landscape they become particularly relevant since users' activities are mediated by IT tools. This online space can offer novel insights about the influence process related to innovation; however, existing research so far has not investigated in depth the (online) relational aspect characterizing the crypto asset landscape.

We assume that individuals are embedded in complex relational patterns, and they rely on information shared via networks of social interactions (Yi et al. 2020). This idea is the central feature of the innovation diffusion network perspective, where innovation is spread through the social networks of those who are perceived as the most influential and trustworthy sources of information (Valente 2012; Valente and Rogers 1995). However, research also shows that innovation diffusion may vary according to the context (Arieli et al. 2020) and social awareness (Müller and Peres 2019), which may lead to social behaviors that are not linear by nature but depend on the network features of the social system. This paper goes beyond the literature that looks at crypto assets as socio-economic artifacts (Li et al. 2019; Shin and Rice 2022), their geographic dispersion (Park and Park 2020), and their financial determinants (Feyen et al. 2022), and aims to investigate the importance of online interactions in supporting awareness of crypto assets and their diffusion. By using a multi-method approach based on web scraping, web analytics, and social network analysis (SNA), we identify and map a referral network whereby hyperlink referrals are seen as footprints of user behavior. As such, we describe how networks support the adoption of innovation propagated across web hyperlinks. As a result, we identify the most influential websites in disseminating information within the referral network and uncover their connection patterns. Specifically, we describe the impact of the information referral networks as channels for spreading the diffusion process by analyzing the most central or pivotal websites in the network and showcase how popular websites drive the herd behavior in adoption of crypto assets. The primary research question that this study seeks to address is the following: how does network position in the information referral network is affected by, and affects, (crypto asset) information diffusion? In this vein, we seek to unveil the role of (online) relationships and understanding their influence on the crypto asset landscape.

The paper is organized as follows. First, we review the technical features of crypto assets, and we introduce the relational perspective used for understanding innovation diffusion. Second, we describe the data collection process and the method of analysis. Third, we present the results of our analysis, focusing on the key nodes (i.e. websites) that are supporting the spread of information related to crypto assets. Finally, we discuss the practical implications of our analysis—how crypto asset developers should use central websites to reach a broader audience.

2 Theoretical framework

2.1 Understanding crypto assets

Crypto assets are digital assets that use digitalization technologies such as Public Key Infrastructure (PKI), cryptographic techniques, and Distributed Ledger Technology (DLT)—which rely on the blockchain technology. While initially designed with the purpose of transaction storage, it has since been used for implementing several decentralized applications like asset tracking (Rosenfeld 2012), smart contracts (Drummer and Neumann 2020; Mohanta et al. 2018), and distributed databases (McConaghy et al. 2016), to name a few. While there is currently no standard taxonomy provided for crypto assets, there are international standards in place for blockchains and DLT created by the International Organization for Standardization (ISO).[1] Crypto assets can be classified into 3 main categories. The first includes payment or exchange tokens commonly referred to as cryptocurrencies: peer-to-peer (P2P) alternatives to legal tender issued by governments based on PKI and cryptographic mechanisms, which are used as a general medium of exchange with the ability to convert it to a legal tender (Hays and Kirilenko 2019). The second category is decentralized finance (DeFi), which relies on the use of smart contracts—self-executing agreements between a seller and a buyer stored in a decentralized and distributed blockchain network (Bartoletti and Pompianu 2017). The third category of assets are Non-Fungible Tokens (NFTs) and Collectibles commonly referred to as Play to Earn (PTE) tokens. In the cryptocurrency markets, ubiquitous speculation exists with games that are offered in the blockchain environment (Gandal et al. 2018); PTEs are part of collective initiatives and are provided in the form of puzzles, avatars, or NFTs that can be used in the game.

[1] The different types of crypto assets are provided in the guidance document ISO/TR 23455:2019. Another work on this topic has been published under the title ISO/TS 23258 "Blockchain and distributed ledger technologies — Taxonomy and Ontology".

2.2 The social aspect of the crypto landscape: from a socio-technical to a relational ecosystem

A major line of contemporary blockchain research describes the crypto asset landscape as a socio-technical ecosystem that encourages interactions among participants (Park and Park 2020). Here, the socio-technical component of the crypto landscape underlines the link between social factors and technological factors in understanding the ecosystem (Gandal et al. 2018): social factors are strictly related to individuals' behavior and attitude, while technological factors are associated with the characteristics of technology (Bostrom and Heinen 1977). Individuals and technologies interact to the extent that individuals use and apply technologies. As such, a crypto asset "is seen as a network with a socio-technical structure since the systems are composed of technical infrastructure and the social relations between users of the crypto ecosystem" (Park and Park 2020). A relational framework therefore explains the interaction between social and technological factors as it highlights the importance of interactions among participants: participants are embedded in a network of social relationships through which tangible and intangible resources are exchanged. If the socio-technical framework characterizes crypto assets and their link to legal and ethical aspects (Dowling 2022), the relational framework can be identified by both structures (in terms of social relations) and processes (or mechanisms, which generate these structures). As such, adopting crypto assets into the social structure is the result of interactions among key players (such as users, group of users, community of practices, stakeholders and market) who are social innovators to the extent they impact and change these social interactions. Thus, the social agency is not only an attribute of participants, but also an attribute to the system and distributed across the network of relations within the crypto landscape. Adopting crypto assets is therefore established through the joint actions of multipoint contacts within this ecosystem. Specifically, interactions between innovators provide the relational infrastructure to support a range of social processes, including the adoption and diffusion of innovation (Sousa et al. 2022). These social processes represent the actual mechanisms through which the adoption of crypto assets operate among individuals. For this reason, the relational nature of the crypto asset ecosystem may be explained with innovation diffusion theories.

2.3 Innovation diffusion and networking

Innovation diffusion theories not only explain the velocity of innovation adoption, but also why some innovations become de facto widely adopted while others might not take off at all. According to Rogers (2003), diffusion is "the process by which an innovation is communicated through certain channels over time among the members of a social system"; the importance of individuals in this process is evident, but at the same time the vehicle of diffusion and the presence of a structured social systems are key for the success of an innovation's diffusion.

Individuals' behavior in the adoption of innovation can be influenced by a variety of psychological and environmental factors, and usually it follows five different stages: knowledge, persuasion, decision, implementation, and confirmation of the innovation adopted (Rogers 2003). Moreover, adoption decisions can stem from the indirect influence of those who adopted the innovation in the first place (Chao et al. 2020). Social pressures lead to further adoption of the innovation as individuals prefer to conform to social norms, which further reinforce the bandwagon effect (Abrahamson and Bartner 1990).

This effect is usually strengthened by a communication channel that can reduce the amount of time necessary for exchanging information between individuals (Vishwanath and Barnett 2011). Internet is probably the most powerful tool for knowledge and information exchange that has been created in decades, and digital networks have become fundamental in spreading new ideas and innovation (Sproull and Kiesler 1991). Especially when considering novel technologies, internet and IT infrastructures foster the commitment of individuals to social norms and therefore explain the rapid adoption of certain technologies (Sawang et al. 2014).

Nevertheless, without a social system where innovation can be spread this process would be unsuccessful. Ashley (2009) pointed out that it is within social systems that innovation can be spread, and individuals and their relations—as well as organizations and institutions—determine who can be reached by the new information about it. Diffusion processes within social systems can be investigated by adopting the research lens of network theory and using relational approach for empirically evaluating network-related phenomenon. Depending on their structuring, networks can facilitate the access to novel information: relations are created between network actors via physical or online interactions, and the positioning of these actors in the network impact the diffusion process (Burt 1992). A study from Ma et al. (2014) shows that actors' behavior to share news is influenced by the strength of their relationships. Similarly, Zhang and Peng (2015) show centrality of individuals in advertising systems are key in the diffusion process. In this vein, referral networks are extremely important in shaping and driving users' behavior, because it has been demonstrated that individuals make their choices (about a new product and/or innovative system) according to their reference group (Cho et al. 2012)—individuals accessing the same web pages and websites referring to the same set of information from the same group of websites. Therefore, we argue that relational approach can be used for understanding the crypto assets' diffusion process.

3 Research method

3.1 Data collection

We collected and triangulated 3 different sets of data to examine the network position that websites come to occupy within the referral network. Specifically, we used a 3-steps approach to scrape crypto assets data. First, we relied on the coinmarketcap API to obtain the top 200 assets by market capitalization.[2] Coinmarketcap also provides a classification of the assets (Defi, NFT, PTE, currency). For each of the assets, the API provides the official website, the total market capitalization, circulating supply, trading volume as well as the maximum supply if applicable (Coinmarketcap 2021). Following prior research on cryptocurrencies (Drobetz et al. 2019; van Tonder et al. 2019), we use a Web scraping approach from the Coinmarketcap website. This approach was adopted as the API of Coinmarketcap allows us to automate the process of extracting data about the crypto assets

[2] We also triangulate the data obtained from coinmarketcap with the data on coinbase to get the top 200 assets by market capitalization. We find minor discrepancies in the data from coinmarketcap and coinbase in terms of ranking of (some) assets but the top 200 remain the same

such as cryptocurrency name, price, circulating supply, official website of the currency and market capitalization and storing this data in a structured manner as a CSV file (Coinmarketcap 2021).

Some assets have more than one official website listed, in which case all the sites are taken into consideration for the analysis. Second, we used the API from SimilarWeb to scrape web analytics data for the websites of the top 200 crypto assets (by market capitalization) obtained from coinbase and coinmarketcap in September—November 2021. This approach of data triangulation has been holistic, however, there was no analytic data available for 54 websites which resulted in a total of 173 websites. This is not a limitation per se as there were multiple websites for some crypto assets and all categories of the assets have been represented in the sample obtained. Also, this period has been chosen as it is characterized by volatility in the market. Furthermore, there were several major events and developments since the mid of the year. First, on the 7th of September, due to deleveraging, over $320 million leveraged Bitcoin was liquidated leading to a 11% market-wipe out of the Total Value Locked (TVL). Second the Chinese Government announced that all cryptocurrencies were illegal. Third, El Paso accepted crypto currency as the legal tender. Finally, several Tweets of Elon Musk led to fluctuations in the market. For instance, one of his tweets caused a 4% drop in bitcoin prices, pushing it below its 20-day moving average at $33,710 in June 2021; driving down Tesla's (NASDAQ: TSLA) stock quote by a third and Bitcoin (BTC) by more than 40% below its April peak at $64,895.22 (Yahoo News 2021). On the other hand, Dogecoin (rolled out as a joke with little stock value Source in NYTimes, 2021), had a multibillion-dollar valuation (DOGE value as at July 2021: 26.244B), mostly as a result of another tweet from him. Indeed, Nick Spanos, the co-founder of ZAP protocol mentioned that "when Elon Musk tweets any crypto-related content, the market … expects a reaction" (Yahoo News 2021).

SimilarWeb provides a comprehensive list of engagement metrics for a website including unique users who visited a page, countries where the page has been accessed from, bounce rates, time spent on the site, the sites which have led users to the site in question, and the sites that the current website redirects the users to. User-centric data is collected from a global user panel of 400 million users, website analytics and ISP data to obtain website traffic information. To set up the web mining tool, first, an API key was obtained. Once this was done, there was a 3-step process followed to obtain the necessary information about the websites. First, the end points were constructed by creating a batch API request. Second, this request was sent as an HTTP POST request as a batch. This was particularly useful considering that we could obtain batch jobs and all data from the request can be obtained in one-go as opposed to creating individual requests. Using the website's data allowed us to obtain information pertaining to both traffic and engagement—including global rank, country rank, bounce rate. Next, the referral traffic data was used to obtain information about visitors who visited a website through clicking links from other pages. Finally, the API response was received in JSON format.

Third, we obtained the network data on the referral sites. For every crypto asset, we looked at the top five sites that refer the user to the website of the assets, and also the top five websites visited by the users of the crypto websites. The information referral network includes sites and referred sites that have been created by using SimilarWeb. An adjacency matrix (A) for the directed network is created such that the rows and columns correspond to a website. The value at position (A_{ij}) is 1 if there is a directed tie from website (i) to website (j), and 0 otherwise. The rows in the matrix represent the outgoing ties and the columns represent the incoming ties. The network comprises 2273 nodes (websites) with 2101 ties representing the information referral process.

3.2 Analysis

To investigate the level of diffusion and the most central websites, we employed a combination of web analytics and SNA. Web analytics helps to understand which are the topical trends, how website users behave, the interests of the users and the most popular sites/pages (Jansen 2009). Studies using web analytics concentrate on individuals, websites, and the networks created by online interactions to estimate traffic to websites; interactions are mapped via hyperlinks, which enable individuals to make contacts with "people or groups anywhere in the world" (Park 2003, p. 50). We accounted for 3 different metrics namely web global ranks (calculated using the total unique pageviews and visitors), total visits and average time spent per unique user (SimilarWeb 2021).

Since we can see hyperlinks as connections, it is possible to assume that the hyperlink structure is a communication network among actors operating online (Park 2003). Hence, SNA is then applied for assessing how the diffusion of crypto assets spreads across information channels. SNA is a discipline which focuses on the investigation of social structures by using analytical methods derived from graph theory (Wasserman and Faust 1994); social structures—or social networks—can be found in both physical and digital environments, where networks can be mapped if we have nodes (individuals, organizations, institutions, or other identifiable actors) connected together via a set of relationships. Relationships can be directed or undirected—if there is a flow from one node to the other—and weighted or unweighted—if the relationship has a value, such as a monetary value, or not (Prell 2012). The World Wide Web (WWW) is seen as a medium where information about innovation and innovation itself are connected to individuals; hence, SNA can be used for exploring patterns between individuals and web pages emerging from hyperlinks (Barnett and Park 2014; Can and Alatas 2019) and 'understanding the interplay between computer-mediated social processes' (Park 2003, p. 50). As highlighted before, networks are made by nodes connected via ties/relationships (Wasserman and Faust 1994): in our context, nodes are the web pages, which are connected by the referral relationship; the referral process is based on the idea that when a user leaves a website to go to another a relationship between nodes (websites) is created. The users' behavioral intention can be captured as they knowingly click on hyperlinks that are created by the site editor to move to other pages within the same or different site. This shapes the social structure which results in the formation of the network, as the web does not have an engineered architecture (Rosen et al. 2011). Hyperlink network analysis has become an important research area in SNA, since the seminal works of Park (2003) and Park and Thelwall (2003); in the last 20 years, scholars have used this methodological approach to investigate digital network structures in tourism and hospitality (Ying et al. 2016), politics (Elgin 2015; Lusher and Ackland 2010), and manufacturing (Hyun Kim 2012), using quantitative methods and statistics from SNA.

In order to assess the diffusion of innovation in our information referral network, we estimated a set of network statistics, similar to what has been done in previous studies on online networks (e.g. Barnett and Park 2005). We concentrate on one network-level measure called degree assortativity, and 3 node-level measures, namely in-degree, out-degree, and betweenness centrality. Degree assortativity is the Pearson correlation of the degree of single nodes in the network, and it shows the extent to which nodes with similar degrees are connected to each other; when its value is high, it means that nodes with higher degrees will be connected to each other (Newman 2002). This is captured by measuring for each node i in the network with j neighbours the average degree of its neighbors ($k_{\eta n}(k_i)$, and is given by the formula:

$$k_{\eta n}\left(k_i\right) = \frac{1}{k_i}\sum_{j=1}^{N} A_{ij}k_j \tag{1}$$

Once the average degree is measured, the conditional probability (Eq. 2) P(k′lk) is used for quantifying the degree correlations (Pearson correlation coefficient given by r—Eq. 3) inspecting the dependence of knn(k)- which denotes the average degree of degree-k nodes on k. Thus,

$$k_{\eta n}(k) = P\sum_{k\prime} k' P(k'|k) \tag{2}$$

$$r = \sum_{jk} \frac{jk(e_{st} - q_j q_k)}{\sigma^2} \tag{3}$$

Centrality measures allow us to explore users' capability to spread information according with the positions that they come to occupy within the network (Wasserman and Faust 1994). Specifically, in-degree centrality accounts for the ability of a website to be an influencer based on its number of connections. To calculate the in-degree of a node *i*, the *i*th row is summed and is given by the formula:

$$K_i^{in} = \sum_j a_{ij} \tag{4}$$

Influential websites may be seen as opinion leaders since these sites can shape users' behaviors and decisions. When websites funnel connections to other sites, they basically spread information in the network by connecting to other sites. This networking behavior is captured by the out-degree centrality which is an estimate of the number of connections from one node to others (Wasserman and Faust 1994). To calculate the out-degree of a node *i*, the *i*th column is summed and is given by the formula:

$$K_i^{out} = \sum_j a_{ji} \tag{5}$$

Finally, websites may play a role of information bridge by connecting different sites within the network. This is captured by the betweenness centrality which accounts for the number of times that one node is in the shortest path between other nodes in the network (Rosen et al. 2011) denoted by the formula:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{6}$$

Hubs characterized by nodes with high betweenness centrality are vital for disseminating information in the network, and their presence usually leads to a higher diffusion rate [46] given by the formula:

$$P_{kk^1} = \frac{kk'}{2L} \tag{7}$$

where L refers to the total number of links.

Table 1 Descriptive statistics

Statistic	Web Global rank	Average visit time	Total visits
Minimum	1,152,412	00:00:41	44,000
Maximum	216	00:27:44	165,700,000
Average	227,721.52	00:03:20	3,272,284
Std. Dev	241,998.72	00:02:52	17,770,560
Median	155,697	00:02:34	335,100

Table 2 Web analytics results

Web global rank		Average visit time		Total visits	
Crypto asset	Type	Crypto asset	Type	Crypto asset	Type
Binance Coin	Currency	Splintershards	PTE	TerraUSD	Currency
Waves	Currency	Dark Energy Crystals	PTE	yearn.finance	Defi Token
Axie Infinity	PTE	Axie Infinity	PTE	Huobi Token	Defi Token
FTX Token	Defi token	Alien Worlds	PTE	Alpha Finance Lab	Defi Token
Splintershards	PTE	Binance Coin	Currency	Seedify.fund	PTE
Uniswap	Defi token	WAX	Defi Token	The Sandbox	PTE
Crypto.com Coin	Defi token	X World Games	PTE	Atari Token	Defi Token
WAX	Defi token	Bitcoin Cash	Currency	NEM	Currency
Helium	Currency	Avalanche	Defi token	Polygon	Currency
Rarible	Defi token	Aavegotchi	Defi token	Pancake Swap	Defi Token

4 Results

For the top 200 crypto assets based on market capitalization, a total of 227 websites were identified; no analytic data was available for 54 websites, which resulted in the analysis of 173 crypto assets. Table 1 provides some descriptive statistics.[3]

The top 10 crypto assets based on Web Global Rank, average time visit, and total visits—as listed in coinmarketcap by using data from the web scraping process—are provided in Table 2.

We look at measures of engagement and user attention by analyzing the Web Global Rank, average visit time and total visits, since these metrics are considered the most important indicators for user activity (SimilarWeb 2021). Currency websites such as Binance Coin and Waves have a higher global rank followed by Axie Infinity, which is a PTE. This shows that traffic (determined by unique views globally) to these websites are higher compared the much-sensationalized cryptocurrencies such as Bitcoin or Ethereum. The top asset types by average visits are PTE, and with the exception of Binance Coin and Bitcoin Cash most of the currencies have a lower average visit duration next to NFTs. While it is possible to argue that higher average visit could also be associated with complex sites,

[3] Some crypto assets have more than one official registered web address; hence, the number of websites is higher than the number of crypto assets.

Myers et al. (2008) have shown that when web interfaces are complex, this leads to individuals bouncing off. Similarly, there are no NFTs in the top-10 by total visits, while DeFi tokens overall have higher total visits than other crypto asset types—even if the top website per total visits refers to TerraUSD, a cryptocurrency.

Figure 1 illustrates the information diffusion process across websites, i.e.; how users obtain information and where they are bounced off—after viewing one page—when they leave a website. The dots represent the websites. The size of each dot is proportional to the number of websites receiving connections (the "indegree" of the information referral networks). Coinmarketcap; GitHub; Medium; Coinbase; and Coingecko are the most popular websites, i.e., they are influential as they shape users' behaviors. The lines represent the referral process.

The network density (proportion of the total network ties over the total number of possible ties) is 0.001 and the average degree (average number of connections a node has in a network) is 0.927; both these statistics are particularly low, which indicate an environment characterized by lower diffusion of information and therefore innovation (Myers et al. 2008). While too much density can be an issue in terms of innovation diffusion, because of the risk of redundancy and tendency towards imitation, it is also true that a moderate

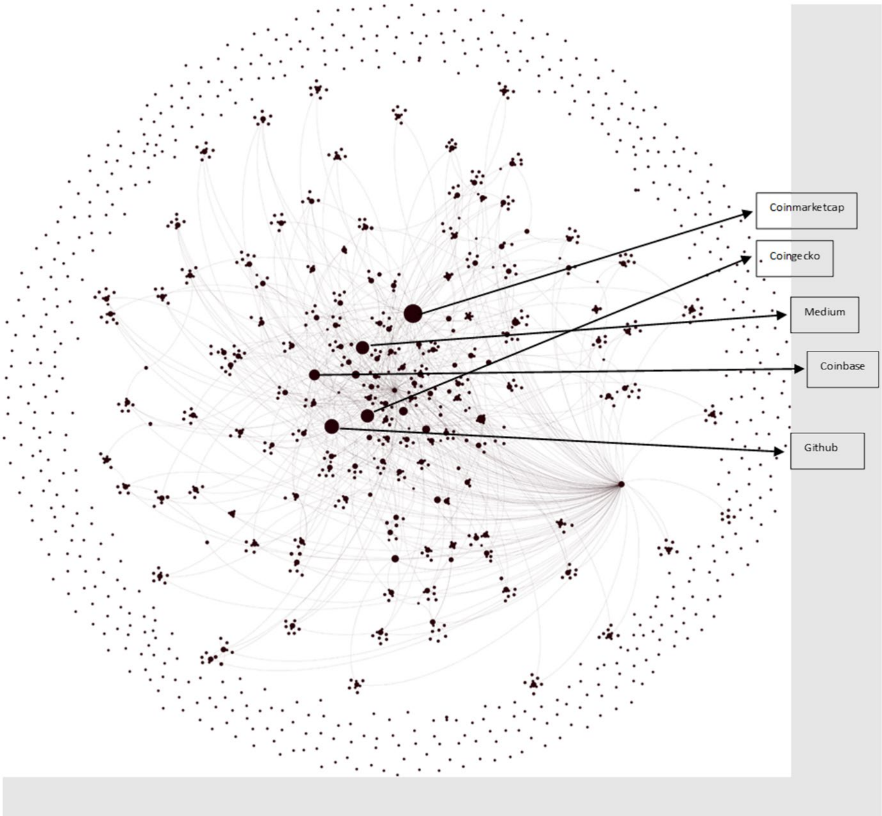

Fig. 1 Information Referral network. The dots represent the website, and the lines represent the referral process —when a user leaves a website to go to another. The size of the node is proportional to the number of incoming connections

level of density is needed to increase the likelihood of being exposed to novel ideas (Shaw-Ching Liu et al. 2005). Similarly, a low level of average degree centrality indicates that we are observing a network characterized by several peripheral actors: this is not favoring innovation diffusion, since peripheral actors are not able to influence other nodes and spread innovative ideas.

The score for degree assortativity is 0.019, which is considered almost null (i.e. there is almost no relationship between nodes with similar degrees); this may indicate that there is no redundancy in the network. If we look at the node-level, we see that certain websites are more prone to attract users and send them to the market sites. Social media websites (such as YouTube, Twitter (now X), LinkedIn, and GitHub—which can be considered a social media platform for developers) and informational sites (etherscan.io, which is a blockchain explorer for Ethereum network, or medium.com, which is a publishing platform) can thus be good information sources to observe users' actions before making choices about adopting crypto assets (Tandon et al. 2021). From our analysis, we see that users move from sites social media websites to crypto assets' website, and from there they reach the market sites as indicated by the scores for out-degree centrality in Table 3. Websites with higher in-degree centrality act as the initiators of the diffusion process, while websites with higher out-degree centrality enable individuals to conform to (online) social norms via the adoption of crypto assets—because these are the market sites where individuals can purchase assets. Finally, nodes with high betweenness centrality are seen as those influencing the flow of information in the network as they act as bridges to connect to the official websites of the crypto asset.

5 Discussion

Our analysis provides novel insights on the crypto asset landscape, and the diffusion process of information related to crypto assets. Two main findings emerge from this research: first, websites of the much-sensationalized cryptocurrencies are not key in information diffusion; second, social media websites are seen as enablers of the diffusion process—but

Table 3 Centrality measures at node-level

In-degree		Out-degree		Betweenness	
Site	Score	Site	Score	Site	Score
github.com	0.0335	coinmarketcap.com	0.1533	coinmarketcap.com	0.0891
medium.com	0.0257	coingecko.com	0.1198	medium.com	0.0756
t.me	0.0232	coinbase.com	0.0296	github.com	0.0718
discord.com	0.0219	medium.com	0.0283	coingecko.com	0.0553
etherscan.io	0.0180	github.com	0.0244	umaproject.org	0.0348
binance.com	0.0128	etherscan.io	0.0180	raydium.io	0.0295
youtube.com	0.0128	binance.com	0.0154	etherscan.io	0.0272
Twitter (now X).com	0.0116	dappradar.com	0.0128	oceanprotocol.com	0.0220
linkedin.com	0.0116	bakeryswap.org	0.0090	superfarm.com	0.0206
play.google.com	0.0103	polygon.technology	0.0090	coinmarketcap.com	0.0891

they actually cannot be considered mature hubs for supporting this process because of their low connectivity.

Regarding our first finding, this may be perceived quite surprising. However, it is also true that market-related information about crypto assets is often conveyed by other media—especially news media specialized in finance such as CNBC and Forbes. Major events related to crypto assets have a positive or negative impact on their returns (Hashemi Joo et al. 2020), and the larger the media coverage the higher the impact—which is something that a single website cannot do. Official websites like Bitcoin.com can promote or recommend specific financial products, such as open-source wallets, but previous studies found that professional investors sometimes prefer to collect first-hand information via Twitter (now X) (Shen et al. 2019). In this vein, our study complements the analysis of Park and Park (2020), which focused on the websites of top 50 cryptocurrencies and found that, among these websites, those related to the much-sensationalized cryptocurrencies (by the news channels between September and November 2021) are central in the network. However, since they did not concentrate on other crypto assets or media websites, we argue that websites of popular cryptocurrencies are key only when considering this specific asset—the cryptocurrency. Eryiğit and Eryiğit (2021) pointed out that social media play a relevant role in the diffusion process; their work specifically focused on Bitcoin, but their findings support the idea that word of mouth is particularly effective—and social media strengthen this process. As highlighted by Yang et al. (2019), self-media users are important sources of diffusion. Compared to official media users, those users creating their own contents on platforms such as Weibo—the microblogging platform examined by these scholars—are more effective in spreading information and ideas compared to those who refer to traditional media or official sources of information. Our results are aligned with this finding: social media platforms are powerful tools for information diffusion, and within these platforms unofficial content creators (e.g. YouTubers) are capable of reaching a larger audience as opposed to official sources (e.g. Bitcoin.com).

The above discussion relates to our second finding: social media websites play a relevant role in the diffusion process. This confirms what has been reported by Moser and Brauneis (2023): there is a world of professional (but also non-professional) financial advisors that are sharing contents using social media such as YouTube or Twitter (now X), and their channels are rather popular among investors. This finding needs to be interpreted in light of the relational approach we used for understanding innovation diffusion. Interactions between different players can be detected all around the globe: the World Wide Web enables individuals with different expertise to share information via different channels and potentially reaching everyone in the world –with an Internet connection. In a way, the diffusion of crypto assets is supported by the presence of social innovators who communicate using different social media channels. van der Linden and van Beers (2017) found that some social innovators tend to promote crypto assets in their geographical environment, because of personal interests; however, crypto assets are global by definition, and therefore we also have social innovators who aim to be disruptive—in their approach to innovation—and influence as many individuals as possible globally. Hence, the adoption of this particular type of innovation follows social processes that have been observed also in other contexts. However, we discovered that social media websites are not providing the boost that is needed for initializing a robust diffusion process. Low levels of degree assortativity and connectivity in networks indicate potential issues in knowledge diffusion. As highlighted by Müller and Peres (2019), high assortativity is important because relevant actors/nodes in the networks can be strongly interconnected and reaching them can effectively boost the diffusion process. If such actors are missing in the network, this may hinder the diffusion process. Low assortativity per se is not a structural problem, from a network perspective, but there should be at least a set of nodes with high betweenness centrality—i.e. nodes that act as brokers in the network and support interconnectivity—in order to facilitate knowledge diffusion. In general, technological networks are considered to be disassortative and particularly sensitive to disruptions such as the removal of key nodes (Newman 2002); in this context, it is confirmed that the overall referral network is not dense, and we are missing relevant nodes capable of supporting the diffusion of information related to crypto assets. These nodes (social media websites) have potential, but we are just observing the first stages of such a process.

6 Contribution to research and practice

This study provides an empirical analysis of the referral (online) network describing the diffusion process of information related to crypto assets. Our results show that the most central websites in this network are market sites, which indicates that adopters are exposed to information by chance and through ill-defined exploration. Specifically, crypto market information websites and trading websites provide up to date information and re-direct potential users towards other specialistic websites. Overall, we conclude that the adoption of these assets is at its very beginning. Low assortativity and average degree indicate that crypto assets are in their awareness stage, where the public attention to the existence of these assets is beginning to expand. Awareness can be enhanced when there are information flows about the innovative product (De Bruyn and Lilien 2008), and in the crypto assets landscape this is achieved by mass social communications, news outlets, and word-of-mouth communications; this is confirmed by the higher prominence of websites such as YouTube, LinkedIn, and Medium.

This study provides several contributions to research and practice. From a research perspective, we advance our understanding of how information about crypto assets is shared online, and how the diffusion process is currently structured in this context. By using a relational approach, we mapped the key global websites which contribute to the diffusion process, and we analyzed their referral network using advanced analytical network techniques. In this vein, our methodological approach is innovative because it combines web scraping, web analytics, and SNA to empirically detect initiators and influencers. Second, our study does not limit to cryptocurrency websites only (Park and Park 2020) or cryptocurrency users only (Bharadwaj and Deka 2021), but it explores the entire crypto assets world—and thus it offers a broader overview of the phenomenon. In terms of business implications, there are two main aspects emerging from this work. First, the aforementioned importance of social media channels is something that organizations offering crypto assets might want to capitalize. This does not mean that such organizations are not aware of the potentials of YouTube or LinkedIn: as described by Hua et al. (2022), cryptocurrencies are often used for donations to YouTube content creators, and a variety of contents about crypto assets can be found in social media channels.[4] However, this has not been done systematically, or establishing formal partnerships between organizations offering crypto-related products and social media platforms. What has been observed in recent studies (e.g.

[4] Ethereum has even introduced the concept of decentralized social network, a blockchain-based system for social interactions and the sharing of contents (see here: https://ethereum.org/en/social-networks/).

Moser and Brauneis 2023) is that professional financial advisors—which can be called ‘crypto-influencer’—are using social media for promoting crypto assets, but they mainly operate in a clickbait-shaped environment where organizations such as Ethereum are not directly involved in the creation of their contents. The second main practice-related contribution relates to something that is, in a way, diametrically opposed to what highlighted before, i.e. the importance of keeping blockchain-based solutions decentralized. Decentralisation is the foundation of crypto assets: the same concept of blockchain is based on this idea. Our analysis shows that websites of the much-sensationalized cryptocurrencies are not as powerful—in terms of information diffusion—as other websites. At the same time, social media platforms such as Facebook have started introducing their own cryptocurrency (Diem) using a permissioned and private blockchain, which is in contradiction with the whole idea of distributed ledger technology (Ferrari 2020). This should emphasize the value of using online and offline advertising systems for raising awareness among global customers, especially for those players who are well-recognized and capitalized—such as Bitcoin and Ethereum.

7 Limitations and directions for future research

Our findings produce novel insights on the role of social interactions explaining how global (online) network structures influence the adoption of crypto assets. While this study is able to expand previous research on crypto assets web dynamics (Park and Park 2020; Sakas et al. 2022), our results are limited by the following constraints. First, we were able to collect web analytics data and map the referral network by using the free version of SimilarWeb. Because of that, we constrained our data collection capacity to no more than five websites that are referred by and referred to. While this does not account for 100% of the referrals, our network still accounts for over 75% of them. Further research can concentrate on using other tools, such as Google Analytics, to collect web analytics data and compare advantages and disadvantages of using different algorithms for the data collection. Second, our study focuses on the most central website and the structure of the referral network, since this is strictly connected to our research objective. We believe that future research should look more in depth into the causal relationship between network centrality and web analytic measures, to test for social influence processes linked to adoption technology. Finally, our study relies on cross-sectional data reflecting individuals' choices. This has an impact on the possibility to disentangle any sub-process, for instance social selection and social influence, related to innovation adoption. Since it has been recognized that individuals' choices change over time and only longitudinal research design support this type of analysis, future studies are encouraged to implement a longitudinal research design to investigate how networks evolve in the crypto asset landscape.

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Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

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