Blockchain: Research and Applications 4 (2023) 100150

Contents lists available at ScienceDirect

Blockchain: Research and Applications

journal homepage: www.journals.elsevier.com/blockchain-research-and-applications

Research Article

Assessing the impact of network factors and Twitter data on Ethereum's popularity

Sarah Bouraga

Namur Digital Institute (NADI), University of Namur, Belgium

ARTICLE INFO

Keywords:
Blockchain technology
Ethereum
Twitter data
Platform's popularity

ABSTRACT

In March 2021, we witnessed a surge in Bitcoin price. The cause seemed to be a tweet by Elon Musk. Are other blockchains as sensitive to social media as Bitcoin? And more precisely, could Ethereum's popularity be explained using social media data?

This work aims to explore the determinants of Ethereum's popularity. We use both data from Etherscan to retrieve the relevant historic Ethereum factors and Twitter data. Our sample consists of data ranging from 2015 to 2022. We use Ordinary Least Squares to assess the relationship between these factors (Ethereum characteristics and Twitter data) and Ethereum's popularity.

Our findings show that Ethereum's popularity—translated here by the number of daily new addresses—is related to the following elements: the Ether (ETH) price, the transaction fees, and the polarity of tweets related to Ethereum.

The results could have multiple practical implications for both researchers and practitioners. First of all, we believe that it will enable readers to better understand the technology of Ethereum and its stake. Secondly, it will help the community identify pointers for anticipating or explaining the popularity of existing or future platforms. And finally, the results could help in understanding the factors facilitating the design of future platforms.

1. Introduction

On March 24, 2021, Elon Musk announced on Twitter that people could, from then on, buy a Tesla with Bitcoin. It followed that the Bitcoin price skyrocketed. A few weeks later, on May 13, the entrepreneur went back on his decision. What happened next? The Bitcoin price and other cryptocurrencies, such as Ether, dived. This leads to the following question: What if blockchain popularity could be explained using social media data?

Blockchain has been a hot topic for several consecutive years. The technology can be defined as a decentralized public ledger for storing transactions [1]. We have witnessed an evolution of the technology from a platform allowing only cryptocurrency transactions (such as Bitcoin [2]) to a platform allowing both the transfer of cryptocurrency and the development of Decentralized Applications (DApps). Drawing on Bitcoin, Ethereum [3] was the first blockchain that enabled its users to design and deploy smart contracts and DApps. This evolution led to an increase in the number of opportunities and challenges for the adoption of blockchain technology.

Blockchain is an important topic because it is expected to change many industries and create new business models [4,5]. More specifically, studying blockchain technology is relevant for three main reasons [6]. Firstly, blockchain can help the design of innovative marketplaces presenting various benefits such as increased competition and lower barriers to entry. Secondly, blockchain adoption can reduce the cost of various activities by reducing the number of necessary intermediaries. Finally, new challenges related to the technology also arise and need to be addressed.

The aim and corresponding contribution of this paper is to explore the determinants of Ethereum's popularity. Popularity can be defined as "the state or condition of being liked, admired, or supported by many people"[1]. Given this definition, we translate Ethereum's popularity by the number of daily new addresses. The latter indeed becomes a measure of user support. By analyzing data related to the Ethereum network and Twitter data, we find that Ethereum's popularity is related to the following elements: the Ether (ETH) price, the transaction fees, and the

E-mail address: sarah.bouraga@unamur.be.

[1] Oxford Dictionary of English.

https://doi.org/10.1016/j.bcra.2023.100150
Received 18 May 2022; Received in revised form 25 May 2023; Accepted 27 June 2023

polarity of tweets related to Ethereum. Technology adoption has been widely studied in the literature (the interested reader is invited to consult) [7–9]. However, we believe that our work differs from other surveys as follows:

- **Focus.** We focus on a new type of technology—blockchain technology—with its own peculiarities (detailed in Section 2).
- **Methodology.** We choose to use two types of data: (i) data about the Ethereum network and (ii) social media data.

More specifically, on the one hand, as demonstrated by the number of articles addressing a specific technology (e.g., IoT [10], Business Intelligence [11], Artificial Intelligence [12], etc.), we believe it makes sense to dedicate a study to a specific technology—in our case, blockchain technology. Especially when this technology has the potential to disrupt existing industries and business models [13]. On the other hand, many studies investigating the adoption of a new technology approach the problem using a quantitative methodology based on a questionnaire. We wanted here to address both the technology itself (with data about the Ethereum network) and the opinion of Ethereum (potential) users (with social media data). Therefore, this paper differentiates itself from existing studies.

Understanding some of the determinants of Ethereum's popularity has multiple practical implications for both researchers and practitioners. First of all, we believe that it will enable readers to better understand the technology of Ethereum and its stake. Secondly, it could be a stepping stone for the community to understand and potentially anticipate the popularity of existing platforms. And finally, the results could help in understanding the factors facilitating the design of future platforms.

The remainder of this paper is organized as follows. The related work is presented in Section 2 and is composed of (i) a general background on blockchain and Ethereum in Section 2.1, and (ii) a literature review on Ethereum in Section 2.2. Next, we present our research objectives, methodology, and hypotheses development in Section 3. Section 4 introduces the data collection process and some exploratory data analysis. Section 5 details the results of our predictive model. Finally, Section 6 and Section 7 discuss and conclude this paper, respectively.

2. Related work

2.1. Background

The Bitcoin network, introduced in 2008, allows peers to transfer any amount of Bitcoin (BTC) in a transaction without the need for a trusted or central authority [2]. Blockchain is the underlying technology of Bitcoin. It can be defined as:

> "A blockchain is a distributed ledger that is structured into a linked list of blocks. Each block contains an ordered set of transactions. Typical solutions use cryptographic hashes to secure the link from a block to its predecessor."[1]

The technology offers multiple benefits, including decentralization, transparency, immutability, security, and privacy [14].

Over the years, blockchain technology has evolved to fit various needs, leading to the emergence of three types of blockchains [1,15,16]: (i) Public blockchains, which are open to everyone (e.g., Bitcoin and Ethereum); (ii) Private blockchains, which are typically used by a single organization; and finally (iii) Consortium blockchains, which are specialized private blockchains (e.g., Hyperledger) used by industry consortia [17,18].

As mentioned in the definition above, a block is composed of transactions, and each block is validated and then securely linked to the previous one—hence forming a chain of blocks. This process of validation and linkage is called the mining process. It is carried out by the nodes composing the network and it can be both time- and energy-consuming [1]. For that reason, public blockchains need to establish an incentive for nodes to participate in the validation of blocks and to incur the related costs.

On Ethereum, this incentive is composed of a constant amount of ETH and transaction fees. Firstly, the node that mines the next block gets a fixed amount of ETH for the time and computer effort put into the validation of the block. Secondly, the node also gets the transaction fee for each transaction composing the block. This fee is based on the concept of gas. The gas represents the computational steps needed to process the transaction. The fee for a given transaction equals $GasPrice \times GasUsed$. The miner will get the transaction fee for all transactions in the block [1, 19].

2.2. Literature review

Researchers studying Ethereum focused mainly on smart contracts and gas consumption. Regarding smart contracts, examples include tools such as Smart Check or Oyente. The former detects code issues in Solidity and aims to mitigate the hacking of flawed smart contracts [20]. The latter aims to detect security issues in contracts [21]. Another tool is MadMax [22], which can be used to detect gas-focused vulnerabilities by analyzing smart contracts. Finally, other authors analyzed ways to optimize the efficiency of smart contracts, i.e., to reduce Ethereum transaction costs [23]. Oliva et al. [24] conducted an exploratory study of smart contracts. The authors' main findings are: (i) the activity is focused on a very small subset of smart contracts (specifically, only 0.05%), (ii) the smart contracts fall in token-centric categories (e.g., Initial Coin Offerings (ICO)), and (iii) the code complexity is small. Hartel et al. [25] studied the success of smart contracts on Ethereum. Specifically, based on the New Product Development theory, they posited that (i) the number of transactions per unit of time is a representative proxy for sales, (ii) the amount of ether sent to a contract per unit of time is decisive for profit, and (iii) the number of different addresses interacting with a contract per unit of time is indicative of the market share. The results showed that the listed contracts are more successful than the unlisted contracts.

As far as the issue of gas consumption is concerned, multiple works addressed this issue with regard to Denial-of-Service (DoS) attacks. Examples include (i) the introduction of the gas sustainability concept, which would ensure that Ethereum never runs out of gas [26]; (ii) an adaptive gas cost mechanism [27]; and (iii) approaches to compute the worst-case gas consumption [28].

Another topic that has been thoroughly researched is the ICO and specifically the factor of its success. These factors are (i) inspiring idea that will sell, efficient building of a community of supporters, effective marketing, professional team, and clarity of problem and solution [29]; (ii) the founders disclose more information to investors, have a higher quality rating by cryptocurrency experts, have a pre-ICO GitHub repository, organize a presale, refrain from offering bonus schemes, have shorter planned token sale durations, and have a larger project team [30]; and (iii) a higher search volume, positive sentiment, and the increased use of emotive language on Twitter [31,32]. Belitski and Boreiko [33] showed that (i) registering ICO and publishing the project's code on GitHub, (ii) obtaining Venture Capital (VC) or business angel financing before the campaign or during the presale, and (iii) publishing the whitepaper before the campaign's start can help predict the amount raised, the number of investors, hard cap achievement, and token ranking. Finally, other authors focused on the distinction between legit ICO projects and scams. They discovered that (i) the presence of a website and a Twitter account, (ii) the number of people involved in the projects, and (iii) the positive sentiments shared on Telegram are all good signs for ICO projects [34]. The Ether price has also been studied. Poongodi et al. [35] predicted the Ether price using linear regression and support vector machine with an accuracy of 85.46% and 96.06%, respectively.

Finally, more general papers are also available. In Ref. [36], the authors conducted an open discussion regarding the business value, experience reports, success factors, and technical challenges of blockchain. As far as the success factors were concerned, the authors gave examples of successful projects deployed on the blockchain. A blockchain value propositions pyramid was also proposed in Ref. [37], and the authors discussed how this pyramid can fit within the evolution of digital platforms and the collaborative economy. Multiple authors proposed surveys about blockchain research. Sanka et al. [38] proposed the state of the art of blockchain technology, including its recent developments, and its adoptions with an emphasis on areas different from cryptocurrencies. Uddin et al. [39] focused on blockchain adoption in the IoT by presenting the state of the art, the challenges, and future research directions. Berdik et al. [40] proposed a survey of the use of blockchain as a tool for application within information systems. The main findings are (i) blockchain structure and (ii) the availability of blockchain through public and open-source code, as well as libraries, are crucial for the widespread adoption of the technology.

In this paper, we build on the existing literature and aim to provide a new contribution. Specifically, we add to the collection of empirical papers from a multi-perspective framework: theoretically, empirically, and methodologically.

- **Theoretically.** Firstly, this paper summarizes the current Ethereum literature and integrates other theories (innovation, social media analysis) to provide a comprehensive study of Ethereum's popularity. Contrary to existing research, we do not focus on a specific aspect of Ethereum, such as smart contracts, gas consumption, or ICOs. Instead, we aim to assess the bigger picture, namely Ethereum's popularity. We believe that this is related to blockchain's business value but addresses the problem from another angle. Also, the scope of the current study pertains to Ethereum without specifying a particular domain. This also differs from current studies that focus on blockchain technology (and do not consider the potential differences between platforms) and/or focus on a particular domain.
- **Empirically.** Next, this paper explores Ethereum's entire lifetime—starting from its genesis to today—and confronts Ethereum data with the platform's popularity on the Internet over this timeline.
- **Methodologically.** We apply a quantitative approach to address the topic at hand. Grounding our hypotheses in the literature (in Section 3.3), we then apply an econometric modeling approach to address the research question. We evaluate various models using two types of data, namely, Ethereum network data and social media data.

3. Research objectives, methodology and hypotheses development

3.1. Research objectives

As mentioned earlier, the goal of this paper is to explore the determinants of Ethereum's popularity. Specifically, our research question (RQ) is:

- **RQ.** Which technological and social factors are linked to the popularity of Ethereum?

Here, we define the popularity of Ethereum as the number of newly created Ethereum addresses.

While technology adoption has been thoroughly studied in the literature, we believe that this current work is relevant for two main reasons: (i) **Focus**. We focus on a new type of technology—blockchain technology—with its own peculiarities (detailed in Section 2), and (ii) **Methodology**. We choose to use two types of data: data about the Ethereum network and social media data. Both characteristics make this article different from the existing works.

3.2. Methodology

In order to address the research question, we applied the following methodology:

1. **Hypotheses Development** (Section 3.3). Based on the literature, we identify potential determinants of Ethereum's popularity. We motivate and explain the selection of candidate determinants and formulate our corresponding hypotheses.
2. **Data Collection** (Section 4.1). We collect the necessary data, namely Ethereum network data and social media data, and explain the process for both types of data.
3. **Predictive Modeling** (Section 5). Using our data, we test and evaluate various models. We finally discuss the results.

3.3. Hypotheses development

A rich body of knowledge on innovation adoption exists in the literature. More particularly, predictors of Information Technology (IT)-based innovation have been extensively studied, both on the individual and organizational levels. Prominent theoretical models include the Technology Acceptance Model (TAM) [7], the TAM2 [8], and the Unified Theory of Acceptance and Use of Technology (UTAUT) [9]. The research shows that the best predictors of IT innovation adoption—at the individual level—include Perceived Usefulness, Top Management Support, Computer Experience, Behavioral Intention, and User Support [41]. Other authors contributed to this line of research. Arts et al. [42] further analyzed the predictors of intention and actual adoption behavior. Fan and Suh [43] proposed a model explaining the reasons why users switch to a disruptive technology. Their findings show that customer expectation of IT innovation has a stronger effect than their dissatisfaction regarding the incumbent IT. The timing of the adoption has also been researched in Ref. [44], and the results showed significant differences between early and late adopting groups in organizations. Also, Basole et al. [45] used text analytics to identify salient factors determining IT innovation adoption by enterprises.

Finally, multiple authors have studied the adoption of specific innovations, for instance, digital television [46], mobile banking [47,48], smart technologies in the retail sector [49], internet computing in organizations [50,51], applications for medical education [52], and radio frequency identification (RFID) [53]. These works show that it is relevant to analyze or focus on a particular innovation. In this work, we focus on Ethereum. Given the peculiarity of blockchain architecture, we believe it is relevant to attempt to identify salient factors related to its appeal.

Firstly, blockchain users are sensitive to security [54]. It has been recognized as a benefit of blockchain technology in various sectors, such as healthcare [55], the freight logistics industry [56], and supply chain management [57]. Furthermore, security is one of the properties characterizing the technology. For a blockchain based on the Proof-of-Work consensus, as is still the case for Ethereum, the security is dependent on the amount of processing power that is dedicated to the validation of transactions and blocks [58]. This leads to our first hypothesis:

- **H1**: Ethereum processing power can help predict Ethereum's popularity.

On Ethereum, the processing power is represented by the so-called Hash Rate, which can be defined as “An estimate of how many hashes are being generated by Ethereum miners trying to solve the current Ethereum block or any given block” [59].

Next, transaction fees could also play a role in Ethereum's popularity. Firstly, transaction fees act as incentives for miners and thereby ensure the security and decentralization of the blockchain. On the one hand, it is in the miners' best interest to validate the correct transactions (and blocks), since the validation would lead to getting the reward; furthermore, if a malicious miner tampers with the blockchain, this tampering would be visible to everyone. These two elements contribute to the security of the blockchain. On the other hand, decentralization is ensured by attracting miners with appealing transaction fees [58]. Transaction costs are also one of the factors differentiating centralized and decentralized systems [60]. It thus makes sense to incorporate this variable in a model assessing the popularity of the specific blockchain technology. This discussion leads to the following hypothesis:

- **H2**: Network transaction fees can help predict Ethereum's popularity.

Thirdly, in Ref. [61], the author examined the relationship between Bitcoin price and search queries on Google Trends and Wikipedia and showed that an increase in the Bitcoin price leads to an increase in the interest of both investors and the general public. Given their similar theoretical foundations, we extend this result to Ethereum by proposing our next hypothesis:

- **H3**: Ether price can help predict Ethereum's popularity.

Finally, according to the UTAUT [9], social influence has an influence on the behavioral intention to use an IT product. Furthermore, when it comes to voluntary contexts, the social influence construct builds on two specific mechanisms, namely internalization and identification. Drawing on that result, the authors in Ref. [62], who studied the determinant of the Bitcoin exchange rates, posited that the overall public recognition affects the value of the Bitcoin system. Again, we expand this observation to Ethereum, and this leads to our final hypothesis:

- **H4**: Public recognition can help predict Ethereum's popularity.

Here, following Ref. [62], we use Twitter data as a proxy for public recognition. This is also in line with the works of Refs. [31,32]. It is worth noting that social media data have been proven to be useful for prediction. They have been used to predict the future in a wide range of fields [63], for example, crime prediction [64], movie revenues [65], flu prediction [66–68], election prediction [69,70], stock prediction [71], and travel demands [72]. Social media data have also been used to predict aspects related to blockchain. In most cases, they were used to predict cryptocurrency prices. Specifically, Abraham et al. [73] used both Twitter data and Google Trends data to predict Bitcoin and Ether prices. The authors found that tweet volume is a good predictor of price direction. Another example includes [74], where the authors aimed to detect price bubbles using Reddit data.

4. Data collection and exploratory data analysis

4.1. Data collection

The data were collected from two main sources: Etherscan[2] and Twitter. The former provides various types of Ethereum data, categorized into: Market Data, Blockchain Data, Network Data, Top Statistics, Ethereum Name Service Data, and Contract Data. For our purpose here, we collected data about the following: (i) Unique Addresses, (ii) Ethereum Daily Price (USD), (iii) Network transaction fees, and (iv) Hash rate. The data range from July 30, 2015, to August 17, 2022 ($N = 2576$).

Unique Addresses will be used here as the dependent variable. Indeed, an address on Ethereum refers to "an externally owned account or contract that can receive (destination address) or send (source address) transactions on the blockchain" [75]. We consider that the number of unique addresses, and more specifically, the daily increase of unique addresses can constitute an appropriate proxy for Ethereum's popularity. The other data will be used as independent variables in our model.

In order to collect Twitter data, we first needed to get access to the tweets, and then we could collect them. Hence, we first created a Twitter developer account. Following Twitter's instructions, we then created a project, and within that project, we created an app. Finally, we had to generate a token. These steps gave us access to the full-archive search. Afterwards, we could start sending requests to the Twitter API using Python.

We based our research on the keyword "Ethereum". Since the full-archive search's endpoint can deliver up to 500 Tweets per request, we looped through every day from January 1, 2015, to August 14, 2022. This allowed us to collect 1,040,159 tweets. This number encompassed both tweets and retweets; when removing the retweets, we get a dataset of 529,662 tweets ($N = 578{,}065$).

The structures of our two datasets can be found in Tables 1 and 2, with examples of rows for each dataset.

The data collected and used for this paper are available upon request.

4.2. Exploratory data analysis

As mentioned above, Unique Addresses will be the variable we want to predict in this paper. Fig. 1 shows the daily increase in Unique Addresses on Ethereum from 2015 to 2022. We can observe a peak around 2018 and another one at the end of 2020.

Table 3 presents the summary statistics for each variable and Fig. 2 shows the pairwise correlation in our data. The matrix displays a strong positive correlation ($= 0.87$) between the Hash Rate and Ether Prices; while the other pairs show a correlation < 0.50. Given this result, we will remove the variable Hash Rate from our model. By removing the Hash Rate, we still keep a variable covering the security concern of users (i.e., the transaction fees) and we also keep the potential relationship between Ether prices and the users' interest as proposed by Ref. [61].

We used the Python TextBlob library to perform a sentiment analysis. TextBlob allows the processing of textual data by providing a simple API to execute common natural language processing tasks [76]. We kept only the original tweets and discarded the retweets. We applied the sentiment property to obtain the polarity of each tweet. This property returns a polarity score ranging from $[-1.0, 1.0]$ [76]. We then randomly selected 100 labeled tweets and labeled them manually. The author herself, who has been working on blockchain for several years, went through the 100 tweets one by one and labeled them as "Positive", "Neutral", or "Negative". In doing so, we were sure that the labeling of the data was done by someone who knew and understood the domain, the data, and the objective of the study. This manipulation allowed us to control the polarity provided by TextBlob, i.e., to evaluate the sentiment analysis results. Specifically, it allowed us to identify the polarity thresholds to distinguish between positive, neutral, and negative sentiments. Fig. 3 shows the number of tweets by sentiment. We can see that most tweets can be considered "neutral", followed by positive and then negative tweets. From 2021, we can see that the difference between the number of positive tweets and neutral tweets seems to decrease.

Finally, we can also analyze the content of the tweets. Fig. 4 shows Word Clouds for the tweets. Fig. 4a shows the content excluding the following terms: 'http', 'https', 'co', 'ethereum', and 'Ethereum'. We can observe that many words are related to the cryptocurrency semantic

Table 1
Etherscan data—structure and example.

Date	Daily Increase	ETH Prices	Tx Fees	Hash Rate
November 1, 2021	154386.0	4322.79	1752.258702	812768.9228
November 2, 2021	162290.0	4593.15	2062.091832	813533.6271

[2] https://etherscan.io.

Table 2
Twitter data—structure and example.

Date	Tweet
November 2, 2021	@ethereum, #Ethereum is the coin with the best risk-adjusted returns of the past 24 h
November 4, 2021	"Gas fees are insane right now! I guess I'll have to wait till after midnight to save some cash! #Ethereum #GasFees #ETH #NFTs"

domain. Hence, in Fig. 4b, we added the following stopwords: 'bitcoin', 'cryptocurrency', 'crypto', 'btc', and 'eth'. The second figure still shows words related to the cryptocurrency domain (such as "average price", "market cap", and "exchange") but also unveils other words such as "smart contract", "hard fork", and "vitalik buterin".

This exploratory data analysis allows us to draw the following conclusions. Firstly, from the Ethereum network data, we can observe a correlation for some characteristics while others seem to be uncorrelated. Secondly, as far as the Twitter data are concerned, we can notice that the majority of tweets fall into the "neutral" category and that many tweets are related to the cryptocurrency/Decentralized Finance (DeFi) domain.

5. Predictive Modeling

In this section, we attempt to predict Ethereum's popularity based on the data introduced in Section 4.2. We start with Model 1 in Section 5.1, where we forecast Ethereum's popularity based solely on the Ethereum network data from Etherscan[3]. Then, we carry out the same exercise using both Ethereum network data and Twitter sentiment analysis: first, using the "TextBlob value" in Section 5.2, and then (ii) using the predicted sentiment category in Section 5.3.

5.1. Model 1—network data

We attempt to predict Ethereum's popularity based solely on the data retrieved from Etherscan. This is translated in the following equation:

$$\begin{aligned}\log(\text{DailyIncrease}) &= \alpha + \beta_1 \log(\text{EtherPrices}) \\ &+\beta_2 \log(\text{TransactionFees}) + \varepsilon\end{aligned} \tag{1}$$

We standardize the data and use the Ordinary Least Squares (OLS) from statsmodel [77] to estimate the models. The results are presented in Table 4. The models satisfy OLS classical assumptions [78,79]:

- **Assumption 1 (A1).** The disturbances have zero mean, i.e., $E(\mu_t) = 0$
- **Assumption 2 (A2).** Homoscedasticity: the disturbances have a constant variance, i.e., $var(u_i) = \sigma^2$
- **Assumption 3 (A3).** The disturbances are not correlated, i.e., $cov(u_i, u_j) = 0$
- **Assumption 4 (A4).** The explanatory variable X is not correlated with the disturbances

Table 3
Summary statistics.

	Increase	ETH Prices	Tx Fees	Hash Rate
Count	2576.0	2576.0	2576.0	2576.0
Mean	79006.46	773.32	1732.57	272699.4
Std	61300.17	1125.72	3634.33	301047.2
Min	0.0	0	0	11.53
25%	16410.75	83.01	109.31	23577.53
50%	80676.5	238.01	471.92	180221.1
75%	111507.0	843.09	1296.95	285484.2
Max	355726.0	4810.97	42763.25	1126674

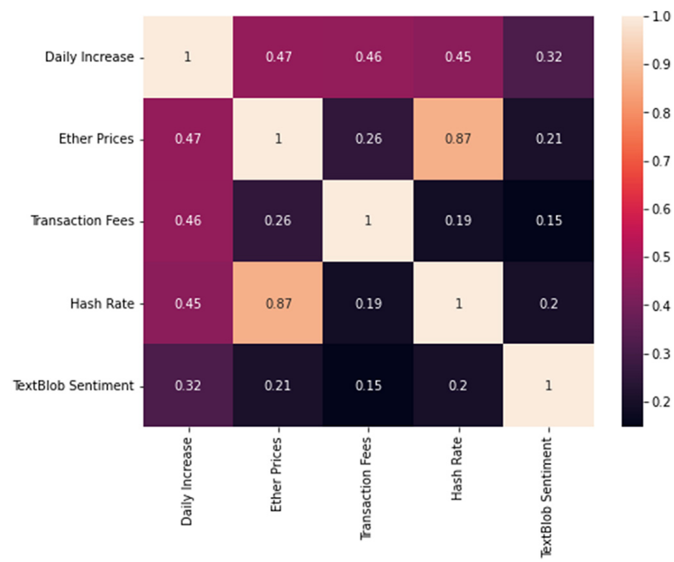


Fig. 2. Correlation matrix.

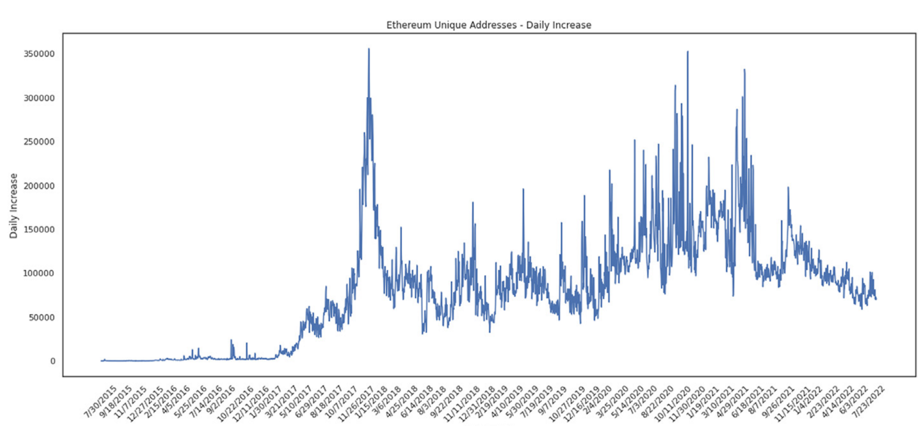


Fig. 1. Ethereum's popularity—unique addresses daily increase evolution.

[3] https://etherscan.io.

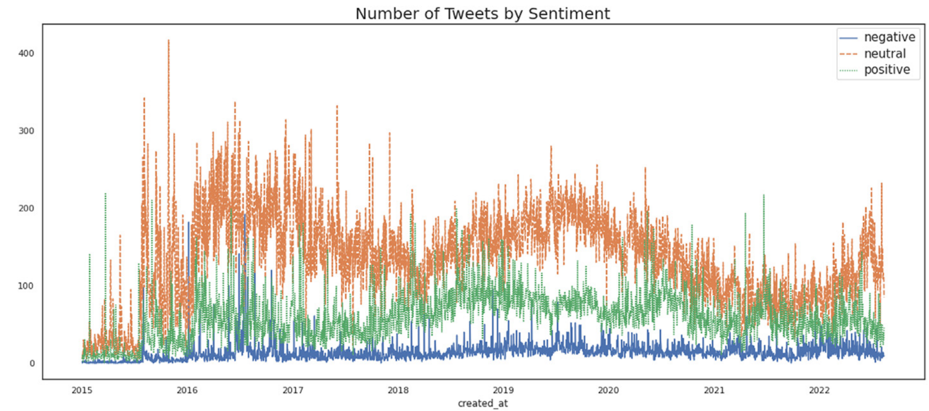
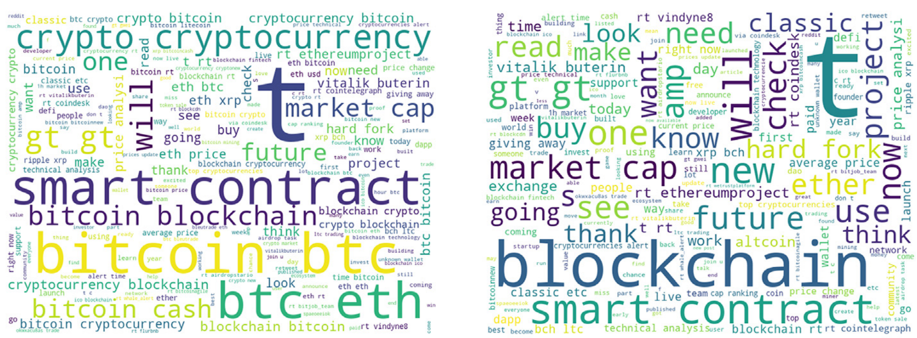


Fig. 3. Number of original tweets by sentiments throughout the years.



(a) (b)

Fig. 4. Two word clouds.

Table 4
Regression results.

	Model 1 Network		Model 2 Sentiment		Model 3 Predicted Sentiment		Model 4 Sentiment		Model 5 Predicted Sentiment	
	Coef.	**Std Err.**	**Coef.**	**Std Err.**	**Coef.**	**Std Err.**	**Coef.**	**Std Err.**	**Coef.**	**Std Err.**
Intercept	0.0	0.010	0.0	0.010	0.0	0.008	0.0	0.009	0.0	0.210
Tx Fees	0.3307***	0.018	0.3269***	0.018	0.3308***	0.016	0.1329***	0.019	0.1982***	0.015
ETH Prices	0.6306***	0.020	0.6308***	0.020	0.6544***	0.015	0.8213***	0.019	0.6913***	0.031
Sentiment			0.0137	0.008			0.0224*	0.008		
Positive					0.0881***	0.007			0.0881***	0.009
Neutral					0.1503***	0.008			0.0553***	0.008
Negative					0.0300***	0.007			0.0672***	0.008
R^2	0.861		0.861		0.902		0.895		0.908	
Adjusted R^2	0.861		0.861		0.902		0.895		0.908	

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Models 2 and 3 consider data without Retweets; Models 4 and 5 consider data with Retweets.

- **Assumption 5 (A5).** The disturbances are normally distributed $N(0, \sigma^2)$
- **Assumption 6 (A6).** No perfect multicollinearity
- **Assumption 7 (A7).** Correct functional form

We use OLS to estimate the models, using heteroscedasticity and autocorrelation consistent (HAC) estimates of the covariance matrix to address **(A2)** and **(A3)**. We added an intercept which ensures $E(\mu_t) = 0$ **(A1)**. In order to address **A4**, we also estimated Eq. (1) by the generalized method of moments. Specifically, we worried about the endogeneity of Transaction Fees. We used as instruments the variable Difficulty. Indeed, the difficulty is defined as "A network-wide setting that controls how much computation is required to produce a proof-of-work" [75]. We can expect that the difficulty will have an influence on the transaction fees. However, the Hausman test did not signal any endogeneity. Hence, we decided we could keep OLS estimates [78].

By using the Central Limit Theorem, we can also state that our sample size ($n = 2576$) [80] allows us to satisfy **(A5)**, i.e., the disturbances are normally distributed. Also, with a condition number inferior to 10, the OLS results did not show any trace of multicollinearity **(A6)** [81]. Finally, using a log ensures the linearity of the parameters, as proven by the plotting of the residuals of Model 1 in Section 5.1 against the predicted values in Fig. 5 [82], hence satisfying **(A7)**.

5.2. *Model 2—tweet sentiment—sentiment value*

We augment our model in Section 5.1 with the Twitter data, more specifically, with the sentiment analysis. Therefore, we add the so-called TextBlob value to our model. The goal is to evaluate the following equation:

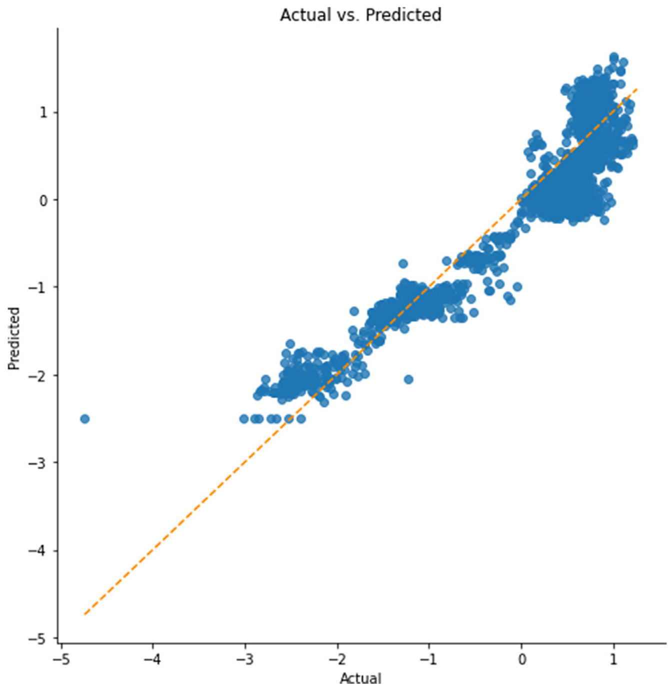


Fig. 5. Linearity assumption check.

$$\log(\text{DailyIncrease}) = \alpha + \beta_1 \log(\text{EtherPrices}) + \beta_2 \log(\text{TransactionFees}) + \beta_4 \log(\text{SentimentValue}) + \varepsilon \quad (2)$$

5.3. Model 3—tweet sentiment—sentiment category

Finally, we first use the TextBlob value to create a categorical column displaying the sentiment of the tweet, and we turn that column into dummy variables. The goal is to evaluate the following equation:

$$\log(\text{DailyIncrease}) = \alpha + \beta_1 \log(\text{EtherPrices}) + \beta_2 \log(\text{TransactionFees}) + \beta_4 \log(\text{Positive}) + \beta_5 \log(\text{Neutral}) + \beta_6 \log(\text{Negative}) + \varepsilon \quad (3)$$

In Table 4, we can observe that all sentiment categories are significant and have a positive sign.

6. Discussion

The coefficients resulting from the regression in Sections 5.1 to 5.3 are reported in Table 4.

If we focus on Model 1, we can state that the coefficients are all significant, validating the set of hypotheses in Section 3.3, except for H1. Indeed, given the high correlation between Hash Rate and Ether Prices, we decided not to include the former in our model.

Firstly, the Ether Prices have a positive effect on Ethereum's popularity. Secondly, the Transaction Fees also have a positive effect on Ethereum's popularity. The transaction fee represents the cost associated with a transaction. It might thus seem surprising that it has a positive effect on Ethereum's popularity. However, we should recall that transaction fees can also relate to the security of the network as well as the inner workings of Ethereum. Indeed, it works as incentive for miners to join and process the transactions and blocks: the higher the incentives, the more secure the network.

When adding the sentiment value to the equation, we obtain a significant coefficient for the variable only for the data including the retweets. Hence, we turn to the categories of sentiment instead, which are significant for both sets of data.

When analyzing the model in Section 5.3, we can observe that all coefficients are significant and have the expected sign, except for the Negative Sentiment. First of all, the Positive and Neutral Sentiment categories have a positive sign, indicating that an increase in the number of Positive or Neutral tweets is associated with an increase in Ethereum addresses. A more surprising result relates to the Negative Sentiment category, which also has a positive sign. This result seems to indicate that it does not matter how people talk (or tweet) about Ethereum; what matters is that they *do* talk (or tweet).

6.1. Theoretical and practical implications

We believe that these results can have multiple implications, both theoretical and practical. Table 5 sums up the validation of hypotheses for each model.

First of all, the findings allow us to advance the theory on Ethereum—and by extension blockchain—popularity. As mentioned earlier, blockchain is expected to change many industries in the future, and given its peculiarities, we believe it is relevant to assess the factors linked to its popularity. This study contributes to the body of knowledge regarding technology advancement. Specifically, we showed that some of the relevant factors linked to Ethereum's popularity are the transaction fees, the Ether price, and the tweet sentiment.

As far as the practical implications are concerned, we trust that this study can help readers better understand Ethereum—its technology and its stake. Using our model, readers can see that four factors seem to play a role in the Ethereum appeal. Ethereum users seem to be sensitive to the security of the network. This is translated by the transaction fees. Also, the positive sign for the transaction fees can be interpreted as the fact that between the cost of using the platform and ensuring its security, Ethereum users choose security. Readers can also observe that—as expected—the Ether price seems to play a role: the higher the price, the higher the number of new users. These various elements can help readers better understand the Ethereum platform and how its different characteristics interact with one another.

Secondly, it will help the community identify pointers for the anticipation or explanation of the popularity of existing or future platforms. With our model, one can identify the factors to monitor in order to recognize a future increase in platform adoption. For instance, the tweet volume is definitely an aspect that should be controlled for prediction. This is relevant so that the platforms can address any scalability challenges [83].

Finally, the results could offer some pointers regarding the requirements for a new platform. Specifically, the results show that Ethereum users do value security, as proven by the validation of **H2**. When designing a new platform, this should definitely be a priority concern. A presence on social media—and more generally public recognition—can also determine the popularity of a new platform.

6.2. Limitations

This study suffers from two main limitations. Firstly, we do not claim to have identified all the determinants of Ethereum's popularity. However, we believe that we have identified some relevant factors playing a role in the Ethereum appeal. While we tested for the endogeneity of a

Table 5
Results—summary.

	Model 1	Model 2	Model 3	Model 4	Model 5
H1—Processing Power	×	×	×	×	×
H2—Transaction Fee	✓	✓	✓	✓	✓
H3—Ether Price	✓	✓	✓	✓	✓
H4—Public Recognition	∅	×	✓	✓	✓

Models 2 and 3 consider data without Retweets.
Models 4 and 5 consider data with Retweets.

variable (Transaction Fees), we cannot be certain that we accounted for all other potential endogeneity sources. For example, other potential determinants, such as malicious attacks on Ethereum could definitely impair Ethereum's popularity. Second of all, we did not extract every single tweet related to Ethereum. As mentioned before, we collected about 500 tweets per day for the whole Ethereum lifeline. And even though we do not have an exhaustive tweet collection, we are convinced that the dataset we managed to build offers a reliable view of the "Twitterverse".

7. Conclusions

"There's no such thing as bad publicity". This proverb seems to apply here too.

In this paper, we aimed to assess whether we could use various types of data to explain parts of Ethereum's popularity, i.e., to identify pointers for the explanation of its popularity. To achieve that goal, we first summarized and integrated existing literature about Ethereum, innovation, and social media analysis, in which we grounded our hypotheses. Afterwards, we collected both Ethereum network data and Twitter data, and we finally used them in a multiple regression model. The results showed that four variables can help explain Ethereum's appeal: (i) the Ether (ETH) price, (ii) the transaction fees, and (iii) the sentiment of tweets related to Ethereum. The results also showed that the negative tweets do not seem to hurt Ethereum's popularity, leading us to claim that the (in)famous proverb applies here too. This work can serve various purposes, as explained in the discussion section. And more generally, it can contribute to the study of Ethereum—or blockchain—adoption.

Research data for this article

The data collected and used for this paper are available upon request.

Authorship contribution

Sarah Bouraga: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing—original draft, Writing—review & editing, Visualization, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] X. Xu, I. Weber, M. Staples, Architecture for Blockchain Applications, Springer, Cham, 2019. https://doi.org/10.1007/978-3-030-03035-3.
[2] S. Nakamoto, Bitcoin: A Peer-To-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf, 2008 (Accessed: 15 May 2022).
[3] V. Buterin, A next-generation smart contract and decentralized application platform. https://ethereum.org/669c9e2e2027310b6b3cdce6e1c52962/Ethereum_Whitepaper_-_Buterin_2014.pdf. 2014. (Accessed: 15 May 2022).
[4] D. Tapscott, A. Tapscott, Blockchain Revolution: How the Technology behind Bitcoin Is Changing Money, Business, and the World, Penguin, New York, NY, 2016.
[5] M. Swan, Blockchain: Blueprint for a New Economy, O'Reilly Media, Inc.", Sebastopol, CA, 2015.
[6] C. Catalini, J.S. Gans, Some Simple Economics of the Blockchain, Technical Report, National Bureau of Economic Research, 2016. https://www.nber.org/system/files/working_papers/w22952/w22952.pdf.
[7] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. 13 (3) (1989) 319–340, https://doi.org/10.2307/249008.
[8] V. Venkatesh, F.D. Davis, A theoretical extension of the technology acceptance model: four longitudinal field studies, Manag. Sci. 46 (2000) 186–204, https://doi.org/10.1287/mnsc.46.2.186.11926.
[9] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, MIS Q. 27 (3) (2003) 425–478, https://doi.org/10.2307/30036540.
[10] M. Carcary, G. Maccani, E. Doherty, G. Conway, Exploring the determinants of iot adoption: findings from a systematic literature review, In: J. Zdravkovic, J. Grabis, S. Nurcan, et al. (Eds.). Perspectives in Business Informatics Research. Springer, Cham. 2018, pp. 113–125, https://doi.org/10.1007/978-3-319-99951-7_8.
[11] N. Ain, G. Vaia, W.H. DeLone, M. Waheed, Two decades of research on business intelligence system adoption, utilization and success–a systematic literature review, Decis. Support Syst. 125 (2019) 113113, https://doi.org/10.1016/j.dss.2019.113113.
[12] J. Jöhnk, M. Weißert, K. Wyrtki, Ready or not, ai comes—an interview study of organizational ai readiness factors, Bus. Inf. Syst. Eng. 63 (2021) 5–20, https://doi.org/10.1007/s12599-020-00676-7.
[13] Y. Chen, C. Bellavitis, Blockchain disruption and decentralized finance: the rise of decentralized business models, J. Bus. Ventur. Insights 13 (2020) e00151, https://doi.org/10.1016/j.jbvi.2019.e00151.
[14] C.T. Nguyen, D.T. Hoang, D.N. Nguyen, D. Niyato, H.T. Nguyen, E. Dutkiewicz, Proof-of-stake consensus mechanisms for future blockchain networks: fundamentals, applications and opportunities, IEEE Access 7 (2019) 85727–85745, https://doi.org/10.1109/ACCESS.2019.2925010.
[15] Z. Zheng, S. Xie, H.-N. Dai, X. Chen, H. Wang, Blockchain challenges and opportunities: a survey, Int. J. Web Grid Serv. 14 (2018) 352–375, https://doi.org/10.1504/IJWGS.2018.095647.
[16] O. Delgado-Mohatar, J. Fierrez, R. Tolosana, R. Vera-Rodriguez, Blockchain and biometrics: a first look into opportunities and challenges, In: J. Prieto, A. Das, S. Ferretti (Eds.). Springer, Cham. 2020. pp. 169–177, https://doi.org/10.1007/978-3-030-23813-1_21.
[17] C. Cachin, Architecture of the hyperledger blockchain fabric. https://theblockchaintest.com/uploads/resources/IBM%20Research%20-%20Architecture%20of%20the%20Hyperledger%20Blockchain%20Fabric%20-%202016%20-%20July.pdf, 2016 (Accessed: 15 May 2022).
[18] J. Sousa, A. Bessani, M. Vukolic, A byzantine fault-tolerant ordering service for the hyperledger fabric blockchain platform, In: 48th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN), IEEE, 2018, pp. 51–58, https://doi.org/10.1109/DSN.2018.00018.
[19] G. Wood, Ethereum: a secure decentralised generalised transaction ledger, Ethereum project yellow paper 151 (2014) 1–32.
[20] S. Tikhomirov, E. Voskresenskaya, I. Ivanitskiy, R. Takhaviev, E. Marchenko, Y. Alexandrov, Smartcheck: static analysis of Ethereum smart contracts, In: Proceedings of the 1st International Workshop on Emerging Trends in Software Engineering for Blockchain, ACM, 2018, pp. 9–16, https://doi.org/10.1145/3194113.3194115.
[21] L. Luu, D.-H. Chu, H. Olickel, P. Saxena, A. Hobor, Making smart contracts smarter, In: Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, ACM, 2016, pp. 254–269, https://doi.org/10.1145/2976749.2978309.
[22] N. Grech, M. Kong, A. Jurisevic, L. Brent, B. Scholz, Y. Smaragdakis, Madmax: surviving out-of-gas conditions in Ethereum smart contracts, Proceedings of the ACM on Programming Languages 2 (2018) 116, https://doi.org/10.1145/3276486.
[23] T. Hukkinen, J. Mattila, K. Smolander, T. Seppala, T. Goodden, Skimping on gas–reducing Ethereum transaction costs in a blockchain electricity market application, In: Proceedings of the 52nd Hawaii International Conference on System Sciences, 2019, pp. 6875–6884.
[24] G.A. Oliva, A.E. Hassan, Z.M.J. Jiang, An exploratory study of smart contracts in the Ethereum blockchain platform, Empir. Software Eng. 25 (2020) 1864–1904, https://doi.org/10.1007/s10664-019-09796-5.
[25] P. Hartel, I. Homoliak, D. Reijsbergen, An empirical study into the success of listed smart contracts in Ethereum, IEEE Access 7 (2019) 177539–177555, https://doi.org/10.1109/ACCESS.2019.2957284.
[26] F. Zhang, E. Cecchetti, K. Croman, A. Juels, E. Shi, Town crier: an authenticated data feed for smart contracts, In: Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, ACM, 2016, pp. 270–282, https://doi.org/10.1145/2976749.2978326.
[27] T. Chen, X. Li, Y. Wang, J. Chen, Z. Li, X. Luo, M.H. Au, X. Zhang, An adaptive gas cost mechanism for Ethereum to defend against under-priced dos attacks, In: International Conference on Information Security Practice and Experience, Springer, 2017, pp. 3–24, https://doi.org/10.1007/978-3-319-72359-4_1.
[28] M. Marescotti, M. Blicha, A.E. Hyvärinen, S. Asadi, N. Sharygina, Computing exact worst-case gas consumption for smart contracts, In: T. Margaria, B. Steffen (Eds.). Leveraging Applications of Formal Methods, Verification and Validation. Industrial Practice. Springer, Cham. 2018. pp. 450–465, https://doi.org/10.1007/978-3-030-03427-6_33.
[29] A. Panin, K.-K. Kemell, V. Hara, Initial Coin Offering (ICO) as a fundraising strategy: a multiple case study on success factors, In: S. Hyrynsalmi, M. Suoranta, A. Nguyen-Duc, et al. (Eds.). Software Business. Springer, Cham. 2019. pp. 237–251, https://doi.org/10.1007/978-3-030-33742-1_19.
[30] P. Roosenboom, T. van der Kolk, A. de Jong, What determines success in initial coin offerings? Ventur. Cap. 22 (2020) 161–183, https://doi.org/10.1080/13691066.2020.1741127.
[31] S. Albrecht, B. Lutz, D. Neumann, How sentiment impacts the success of blockchain startups – an analysis of social media data and initial coin offerings, In: 52nd Annual Hawaii International Conference on System Sciences, HICSS 2019, IEEE Computer Society, 2019. pp. 4545–4554.
[32] S. Albrecht, B. Lutz, D. Neumann, The behavior of blockchain ventures on twitter as a determinant for funding success, Electron. Mark. 30 (2020) 241–257, https://doi.org/10.1007/s12525-019-00371-w.
[33] M. Belitski, D. Boreiko, Success factors of initial coin offerings, J. Technol. Tran. 47 (2022) 1690–1706, https://doi.org/10.1007/s10961-021-09894-x.

[34] P. Cerchiello, P. Tasca, A.M. Toma, ICO success drivers: a textual and statistical analysis, J. Altern. Investments 21 (2019) 13–25, https://doi.org/10.3905/jai.2019.21.4.013.
[35] M. Poongodi, A. Sharma, V. Vijayakumar, V. Bhardwaj, A.P. Sharma, R. Iqbal, R. Kumar, Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system, Comput. Electr. Eng. 81 (2020) 106527, https://doi.org/10.1016/j.compeleceng.2019.106527.
[36] C. Pautasso, O. Zimmermann, L. Zhu, T. Bocek, X. Larrucea, Unchain or block the hype?: decision drivers, success factors, and perspectives for blockchain adoption, IEEE Software 37 (2020) 97–103, https://doi.org/10.1109/MS.2020.2999989.
[37] A. Zutshi, A. Grilo, T. Nodehi, The value proposition of blockchain technologies and its impact on digital platforms, Comput. Ind. Eng. 155 (2021) 107187, https://doi.org/10.1016/j.cie.2021.107187.
[38] A.I. Sanka, M. Irfan, I. Huang, R.C. Cheung, A survey of breakthrough in blockchain technology: adoptions, applications, challenges and future research, Comput. Commun. 169 (2021) 179–201, https://doi.org/10.1016/j.comcom.2020.12.028.
[39] M.A. Uddin, A. Stranieri, I. Gondal, V. Balasubramanian, A Survey on the Adoption of Blockchain in Iot: Challenges and Solutions, Blockchain Res. Appl. 2 (2) (2021) 100006, https://doi.org/10.1016/j.bcra.2021.100006.
[40] D. Berdik, S. Otoum, N. Schmidt, D. Porter, Y. Jararweh, A survey on blockchain for information systems management and security, Inf. Process. Manag. 58 (2021) 102397, https://doi.org/10.1016/j.ipm.2020.102397.
[41] A. Jeyaraj, J.W. Rottman, M.C. Lacity, A review of the predictors, linkages, and biases in it innovation adoption research, J. Inf. Technol. 21 (2006) 1–23, https://doi.org/10.1057/palgrave.jit.2000056.
[42] J.W. Arts, R.T. Frambach, T.H. Bijmolt, Generalizations on consumer innovation adoption: a meta-analysis on drivers of intention and behavior, Int. J. Res. Market. 28 (2011) 134–144, https://doi.org/10.1016/j.ijresmar.2010.11.002.
[43] L. Fan, Y.-H. Suh, Why do users switch to a disruptive technology? an empirical study based on expectation-disconfirmation theory, Inf. Manag. 51 (2014) 240–248, https://doi.org/10.1016/j.im.2013.12.004.
[44] J.L. Carlo, J. Gaskin, K. Lyytinen, G.M. Rose, Early vs. late adoption of radical information technology innovations across software development organizations: an extension of the disruptive information technology innovation model, Inf. Syst. J. 24 (2014) 537–569, https://doi.org/10.1111/isj.12039.
[45] R.C. Basole, C.D. Seuss, W.B. Rouse, IT innovation adoption by enterprises: knowledge discovery through text analytics, Decis. Support Syst. 54 (2013) 1044–1054, https://doi.org/10.1016/j.dss.2012.10.029.
[46] D.J. Atkin, K. Neuendorf, L.W. Jeffres, P. Skalski, Predictors of audience interest in adopting digital television, J. Media Econ. 16 (2003) 159–173, https://doi.org/10.1207/S15327736ME1603_2.
[47] I. Brown, Z. Cajee, D. Davies, S. Stroebel, Cell phone banking: predictors of adoption in South Africa—an exploratory study, Int. J. Inf. Manag. 23 (2003) 381–394, https://doi.org/10.1016/S0268-4012(03)00065-3.
[48] H. Karjaluoto, J. Püschel, J.A. Mazzon, J.M.C. Hernandez, Mobile banking: proposition of an integrated adoption intention framework, Int. J. Bank Market. 28 (5) (2010) 389–409, https://doi.org/10.1108/02652321011064908.
[49] S.K. Roy, M. Balaji, A. Quazi, M. Quaddus, Predictors of customer acceptance of and resistance to smart technologies in the retail sector, J. Retailing Consum. Serv. 42 (2018) 147–160, https://doi.org/10.1016/j.jretconser.2018.02.005.
[50] K. Lyytinen, G.M. Rose, Disruptive information system innovation: the case of internet computing, Inf. Syst. J. 13 (2003) 301–330, https://doi.org/10.1046/j.1365-2575.2003.00155.x.
[51] K. Lyytinen, G.M. Rose, The disruptive nature of information technology innovations: the case of internet computing in systems development organizations, MIS Q. 27 (4) (2003) 557–596, https://doi.org/10.2307/30036549.
[52] M. Sandholzer, T. Deutsch, T. Frese, A. Winter, Predictors of students' self-reported adoption of a smartphone application for medical education in general practice, BMC Med. Educ. 15 (2015) 91, https://doi.org/10.1186/s12909-015-0377-3.
[53] A. Sharma, A. Citurs, Radio frquency identification (rfid) adoption drivers: a radical innovation adoption perspective, AMCIS 2005 Proceedings (2005) 211.
[54] X. Li, P. Jiang, T. Chen, X. Luo, Q. Wen, A survey on the security of blockchain systems, Future Generat. Comput. Syst. 107 (2020) 841–853, https://doi.org/10.1016/j.future.2017.08.020.
[55] S. Balasubramanian, V. Shukla, J.S. Sethi, N. Islam, R. Saloum, A readiness assessment framework for blockchain adoption: a healthcare case study, Technol. Forecast. Soc. Change 165 (2021) 120536, https://doi.org/10.1016/j.techfore.2020.120536.
[56] I.J. Orji, S. Kusi-Sarpong, S. Huang, D. Vazquez-Brust, Evaluating the factors that influence blockchain adoption in the freight logistics industry, Transport. Res. E Logist. Transport. Rev. 141 (2020) 102025, https://doi.org/10.1016/j.tre.2020.102025.
[57] Y. Wang, J.H. Han, P. Beynon-Davies, Understanding blockchain technology for future supply chains: a systematic literature review and research agenda, Supply Chain Manag.: Int. 24 (1) (2018) 62–84, https://doi.org/10.1108/SCM-03-2018-0148.
[58] C. Catalini, J.S. Gans, Some simple economics of the blockchain, Commun. ACM 63 (2020) 80–90, https://doi.org/10.1145/3359552.
[59] Ethereum.org, Ethereum Developers, 2021. https://ethereum.org/en/developers/docs/data-and-analytics/block-explorers/#network (Accessed: 15 May 2022).
[60] J. Pereira, M.M. Tavalaei, H. Ozalp, Blockchain-based platforms: decentralized infrastructures and its boundary conditions, Technol. Forecast. Soc. Change 146 (2019) 94–102, https://doi.org/10.1016/j.techfore.2019.04.030.
[61] L. Kristoufek, Bitcoin meets google trends and wikipedia: quantifying the relationship between phenomena of the internet era, Sci. Rep. 3 (2013) 1–7, https://doi.org/10.1038/srep03415.
[62] X. Li, C.A. Wang, The technology and economic determinants of cryptocurrency exchange rates: the case of bitcoin, Decis. Support Syst. 95 (2017) 49–60, https://doi.org/10.1016/j.dss.2016.12.001.
[63] L. Phillips, C. Dowling, K. Shaffer, N. Hodas, S. Volkova, Using Social Media to Predict the Future: a Systematic Literature Review, 2017 06134 arXiv preprint arXiv:1706.
[64] X. Wang, M.S. Gerber, D.E. Brown, Automatic crime prediction using events extracted from twitter posts, In: S.J. Yang, A.M. Greenberg, M. Endsley (Eds.). Social Computing, Behavioral - Cultural Modeling and Prediction. Springer, Berlin, Heidelberg. 2012. pp. 231–238, https://doi.org/10.1007/978-3-642-29047-3_28.
[65] S. Asur, B.A. Huberman, Predicting the future with social media, In: IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology IEEE, 2010, pp. 492–499, https://doi.org/10.1109/WI-IAT.2010.63.
[66] J. Ritterman, M. Osborne, E. Klein, Using prediction markets and twitter to predict a swine flu pandemic, 1st international workshop on mining social media 9 (2009) 9–17.
[67] H. Achrekar, A. Gandhe, R. Lazarus, S.-H. Yu, B. Liu, Predicting flu trends using twitter data, In: IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPS), IEEE, 2011, pp. 702–707, https://doi.org/10.1109/INFCOMW.2011.5928903.
[68] H. Achrekar, A. Gandhe, R. Lazarus, S.-H. Yu, B. Liu, Twitter Improves Seasonal Influenza Prediction, Proceedings of the International Conference on Health Informatics, 2012, pp. 61–70, https://doi.org/10.5220/0003780600610070.
[69] P.T. Metaxas, E. Mustafaraj, D. Gayo-Avello, How (not) to predict elections, In: IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing, IEEE, 2011, pp. 165–171, https://doi.org/10.1109/PASSAT/SocialCom.2011.98.
[70] D. Gayo-Avello, A meta-analysis of state-of-the-art electoral prediction from twitter data, Soc. Sci. Comput. Rev. 31 (2013) 649–679, https://doi.org/10.1177/0894439313493979.
[71] A. Mittal, A. Goel, Stock Prediction Using Twitter Sentiment Analysis, Standford University, 2011, p. 15. CS229, http://cs229.stanford.edu/proj2011/GoelMittal-StockMarketPredictionUsingTwitterSentimentAnalysis.pdf, 2012.
[72] J.H. Lee, S. Gao, K.G. Goulias, Can twitter data be used to validate travel demand models, In: 14th International Conference on Travel Behaviour Research, 2015.
[73] J. Abraham, D. Higdon, J. Nelson, J. Ibarra, Cryptocurrency price prediction using tweet volumes and sentiment analysis, SMU Data Science Review 1 (2018) 1.
[74] R.C. Phillips, D. Gorse, Predicting cryptocurrency price bubbles using social media data and epidemic modelling, In: IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, 2017, pp. 1–7, https://doi.org/10.1109/SSCI.2017.8280809.
[75] Ethereum.org, Ethereum Glossary, 2021. https://ethereum.org/en/glossary/. (Accessed: 15 May 2022).
[76] Textblob TextBlob, Simplified Text Processing, 2020. https://textblob.readthedocs.io/en/dev/. (Accessed: 15 May 2022).
[77] S. Seabold, J. Perktold, statsmodels, Econometric and statistical modeling with python, Proceedings of the 9th Python in Science Conference, 2010, pp. 92–96.
[78] B. Baltagi, Econometrics, 5th ed. Springer, Berlin, Heidelberg, 2011, https://doi.org/10.1007/978-3-642-20059-5.
[79] C. Brooks, Introductory Econometrics for Finance, Cambridge university press, Cambridge, 2019, https://doi.org/10.1017/9781108524872.
[80] R.M. Heiberger, R.M. Heiberger, B.H. Burt Holland, Statistical Analysis and Data Display an Intermediate Course with Examples in R, Springer, New York, NY, 2015, https://doi.org/10.1007/978-1-4939-2122-5.
[81] J.H. Kim, Multicollinearity and misleading statistical results, Korean journal of anesthesiology 72 (2019) 558–569, https://doi.org/10.4097/kja.19087.
[82] G. James, D. Witten, T. Hastie, R. Tibshirani, An Introduction to Statistical Learning, Volume 112, Springer, New York, NY, 2013, https://doi.org/10.1007/978-1-4614-7138-7.
[83] G. Kaur, C. Gandhi, Scalability in blockchain: challenges and solutions, In: Handbook of Research on Blockchain Technology, Elsevier, 2020, pp. 373–406, https://doi.org/10.1016/B978-0-12-819816-2.00015-0.