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Models used to characterise blockchain features. A systematic literature review and bibliometric analysis

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ABSTRACT

Blockchain has emerged as an innovative technology with potential to transform business management, through operational efficiency improvements. Nevertheless, several performance and vulnerability issues have been identified for the different typologies supporting the wide range of blockchain-based applications currently implemented in different domains.

A variety of analytical and empirical models are being used to evaluate the issues associated with the different blockchain typologies, enabling systematic analyses of the corresponding efficiency impact, and technical or economic threats.

A thorough systematic literature review of these models has been performed, followed by a detailed assessment on the way these models have been employed, and the target parameters and applications evaluated (336 research selected and analysed). We propose a co-classification of these models, allowing us to identify which ones are employed to a greater extent to address the different blockchain issues in scientific research. In a second step, a bibliometric analysis on the selected research is conducted, offering a complementary overview of the status of and trends in blockchain modelling, including the most prolific authors and leading contributing countries to the topic.

The main outcome and contribution of the paper is the provision of a broad overview on how blockchain issues have been analytically tackled, through the synthesis and meta-analysis of the models used in the scientific literature since the inception of blockchain technology. The results have two main direct applications, firstly supporting novel vulnerability and performance analyses of existing blockchain applications by providing historical information on the models used so far, as well as the key parameters and typology of the blockchain-based applications evaluated. Secondly, in the implementation of new applications, by allowing the recognition of key issues identified that are associated with the different blockchain typologies and to determine the most suitable models to analyse the weaknesses and risks of the alternative designs under evaluation for these new implementations.

1. Introduction

Since the inception of blockchain in 2009 by Bitcoin (Nakamoto, 2008),[1] the number of applications relying upon this technology has experienced steady growth (Casino et al., 2019a). Beyond cryptocurrencies,[2] the use of blockchain has now extended to diverse business areas, with specific application in accounting (Dai and Vasarhelyi, 2017; Schmitz and Leoni, 2019), finance (Eyal, 2017; Guo, Y. & Liang, 2016; Treleaven et al., 2017), healthcare (Hölbl et al., 2018; Kuo et al., 2017), insurance (Kar and Navin, 2020) and logistics and the supply chain (Chod et al., 2020; Gonczol et al., 2020; Pournader et al., 2020; Saberi et al., 2019); its disruptive potential for business value creation has been assessed from different perspectives (Angelis & da Silva, 2019; Chin et al., 2022; Chong et al., 2019; Schlecht et al., 2021; Toufaily et al., 2021). This growth and expansion into unpredicted business areas just a few years ago is supported by a wide range of alternative blockchain

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[1] White paper issued in October 2008, describing the Bitcoin blockchain protocol. The "*Genesis block*" was launched on 3 January 2009, and the first Open Source client released one week later.

[2] There are currently more than 22.000 cryptocurrencies, with a market capitalisation of over $\$811{\cdot}10^{12}$. Source: https://coinmarketcap.com (access 20/12/2022).

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typologies (Wang, W. et al., 2019; Zheng et al., 2018a).

In this context of increasing the interests at stake and diversity of blockchain implementations, a number of possible attacks and efficiency issues have been identified so far, not just specifically affecting Bitcoin (Conti et al., 2018a), as the pioneer blockchain application, but also other implementations (Li, X. et al., 2020; Sengupta et al., 2020). A variety of models have been used in scientific research to tackle these issues, as set out in this paper. In this way, based on theoretical formulations and mathematical frameworks previously developed within appropriate research fields, the application of models enables precise analyses of the weaknesses and potential threats detected, as well as assessments of the efficiency for different blockchain implementations.

Several surveys have recently been performed focussed on blockchain performances and vulnerabilities (Agrawal et al., 2020; Cheng et al., 2021; Kushwaha et al., 2022; Zamani et al., 2020), whereas some others describe specific models used to characterise these issues (Fan, C. et al., 2020; Kang et al., 2020; Smetanin et al., 2020). Nevertheless, no previous research to date, to the best of the authors' knowledge, conducts a comprehensive Systematic Literature Review (SLR) on the models used to characterise blockchain performances and vulnerabilities, allowing recognition of how they have been applied to address the different issues for the different blockchain typologies. This research aims to cover this gap, by performing a thorough selection and review of the related scientific literature. The review is conducted following methodological standards, by applying a defined and replicable procedure which aims to reduce bias via thorough literature searches (Vrontis and Christofi, 2021). Taking into account the high number of studies extracted from the literature review, we propose an inclusive co-classification of the relevant models, allowing patterns of use in the assessment of the different performances and vulnerability issues to be identified. Finally, the bibliometric analysis performed on the selected research provides valuable insight into aspects such as how this research has evolved over time, the most prolific authors and the leading contributing countries to the topic.

Regarding the terminology used in the paper, it should be noted that the term *blockchain* is commonly used interchangeably in scientific literature with Distributed Ledger Technology (DLT) (Bencic and Zarko, 2018; Geissler et al., 2019a,b; Lange et al., 2019). In fact, blockchain can be considered a type of DLT, for which transactions are grouped together and validated in blocks. Nevertheless, other forms of DLTs are possible; typically, Direct Acyclic Graph can record transactions on a distributed ledger in tree structures, branching out from one transaction to another. In this paper, the term *blockchain* is used as a broad catch-all term for implementation of Distributed Ledgers.

The remainder of the paper is organised as follows: In section 2, we describe the research methodology followed in this study. In section 3, the rationale behind the categorisation of models is introduced and the five high-level categories are identified, along with the corresponding subcategories. In section 4, we present a comprehensive summary of the way the different models have been applied to characterise blockchain features, grouped into different performances and vulnerabilities, and specifying the target blockchain application and typology. In section 5, the results of the bibliometric analysis performed on the selected research are set out. In Section 6, we discuss the theoretical contributions, the implications in practice and the limitations of the study and suggest different research propositions. Finally, in Section 7 we present the main conclusions.

2. Review methodology

The systematic review methodology refers to the application of regular methods to identify and select relevant research, and to extract and critically analyse findings and data from the chosen research (Christofi et al., 2017). In line with best practices (Kraus et al., 2020; Tranfield et al., 2003), the SLR and the subsequent bibliometric analysis were conducted on the same sample of papers. Additionally, the proposed structure and the way results are presented is consistent with other prior SLRs both related to blockchain (Taylor et al., 2020; Le and Hsu, 2021) or to other disciplines (Christofi et al., 2021; Makrides et al., 2021).

The process carried out throughout the literature review and presented in this section sticks to the methodology by (Briner and Denyer, 2012), providing the means to reproduce the scientific study. Accordingly, the next steps have been considered.

1. Formulate the research questions and boundaries of the SLR.
2. Determine the data sources able to answer the questions.
3. Search the literature to identify the relevant studies.
4. Analyse the retrieved studies for further screening and selection/exclusion in the qualitative analysis.
5. Assess the quality of the studies, extract and synthesise the data.
6. Report the results.

The research aims to provide a useful guideline for scholars and practitioners interested in the specialised analysis of particular blockchain features, in its different implementations, offering information about the models applied so far. The overall view and trends presented can open new lines of research and cooperation opportunities between scholars, also providing ideas for future blockchain research.

2.1. Formulation of research questions

The following research questions (RQ) are worth answering, in line with the objectives of the research.

RQ1: Which are the main models used to characterise blockchain vulnerabilities and performance?
RQ2: How can these models be categorised?
RQ3: What are the target blockchain parameters evaluated by these models?
RQ4: What are the temporal trends of the research on blockchain modelling?
RQ5: Which countries and authors are the main contributors to the research topic?

2.2. Data sources, data acquisition process, selection and assessment

The main sources used to obtain professional and scientific literature have been Web of Science Core Collection[3] (WoS) and Scopus.[4] An iterative process, adapted from the PRISMA statement (Moher et al., 2009), has been followed, as detailed below.

The searches in WoS and Scopus focused on topics, including title, abstract, author and keywords; the timespan covered the period starting in 2009 (when Bitcoin was launched) up to 2021. A large number of results have been retrieved when using a generic query string (i.e. *blockchain models*), particularly due to the growing interest in blockchain in the last 3-4 years; however, the majority of the retrieved papers do not fit the objective of the research. More focused searches, using terms related to constituent elements, performance or blockchain properties (i.e. *blockchain model mining pools, blockchain model transaction confirmation time, blockchain model price prediction*), allowed us to identify a number of models (i.e. Agent-Based, Queueing, Neural Network), to refine the queries and to identify high-level model

[3] WoS database covers 1,9 billion cited references since 1900, with 85,9 million records from more than 21.000 scholarly journals published worldwide. Source: https://clarivate.com/webofsciencegroup/solutions/web-of-science-core-collection/(access: 20/12/2022).

[4] Scopus database covers 1,7 billion cited references since 1970, with over 25,100 titles from more than 5000 publishers. Source: https://www.scopus.com/home.uri - > Content coverage Guide (access 20/12/2022).

typologies (i.e. Markov Chain, Machine Learning); nevertheless most of the results from these new searches are to be discarded, as again they do not describe models characterising blockchain features. Next, another round of searches has been performed, with more specific terms (i.e. *Markov Chain blockchain, transaction graph blockchain, Bitcoin price prediction Machine Learning, Game theoretic blockchain*); the resulting papers have been filtered after a review of the abstracts.

The preselected papers have been fully reviewed for assessment and classification. The cited references in these papers have been considered as an additional source of valid references; those fitting the goals of the research have been checked.

Finally, the reporting analysis has been performed with the set of selected papers, focusing on answering the research questions formulated in the preceding paragraph. For the selected papers, the corresponding ISI and RIS[5] records (respectively from WoS and Scopus) have been generated. These records include the relevant fields of the corresponding references and have been used as an input to the different bibliometric tools.

3. Models used to characterise blockchain and its categorisation

The literature review yields a large volume of research related to the performances and vulnerabilities of blockchain technology (detailed in section 5), which shows the increasing interest over time in this topic, particularly in the last five years, as revealed by the bibliometric analysis results also included hereinbelow. In order to structure our analysis, we proposed a co-classification of models, intended to recognise patterns in the way they are applied in the assessment of the identified blockchain performance and vulnerability issues.

Of course, the proposed categorisation is influenced by the author's subjective evaluations, which is maybe one of the main limitations of this study. In order to deal with this issue, the categorisations proposed by other surveys on the models used to analyse blockchain features have been considered. In particular, mention should be made of: (Fan, C. et al., 2020), which concentrates on blockchain performance evaluation studies, classifies the approaches into empirical evaluation and analytical modelling (Markov chains, queueing models and Stochastic Petri Nets). (Kang et al., 2020), which focuses on stochastic models for evaluation of performance and security in blockchain networks and prediction of cryptocurrency price, classifying them into queueing models, Markov processes, Markov Decision Processes and Hidden Markov Processes (Smetanin et al., 2020). examine analytical and simulation approaches, split into queueing models, Markov processes, Markov Decision Processes and Random Walks, and emulation tools, analysing how they have been used to evaluate blockchain performances.

Additional models have been identified as a result of the current SLR, taking into account the different objectives compared with the specific motivations covered by previous studies. Therefore, the categorisation considered in the present paper enlarges the previous typologies, also dealing with empirical and analytical models. In summary, they have been classified into five high-level categories, as shown in Fig. 1 below and further explained in the following sections.

It should be noted that, in some cases, there is a close relationship between different models or the difference between them is fine, considering their underlying stochastic nature. For instance, although they are integrated into different categories, Hidden Markov models are a particular case of Bayesian Network (Ghahramani, 2001); furthermore, their hidden states are usually inferred through diverse Machine Learning algorithms. On the other hand, some research papers deal with different model typologies (Hashish et al., 2019; Mizerka et al., 2020). In these cases, the inclusion into one or another typology has been performed at the discretion of the authors, depending upon the predominant characteristics of the proposed models, but also taking into account the models directly mentioned by the respective research authors.

It should also be mentioned that, although the terms model, technique and algorithm involve non-negligible nuances (beyond the scope of this paper), they are also often used interchangeably associated with Machine Learning. Throughout this paper, the term Machine Learning models is primarily used.

3.1. Markov Chain models

A Markov Chain is a particular case of a stochastic process. Namely, a stochastic process with a discrete State Space, referred to as chains, that satisfies Markov property.[7] This property may be defined as the system being memoryless, in other words, that its future state only depends on the current state. Considering that the State Space of a Markov Chain is composed of the set of discrete possible values $X(t)$, with $\{X(t), t \in T\}$,[8] it can be expressed as follows:

$$\forall t_1 < \ldots < t_n \in T, P\left(X(t_n) = x_n \mid X(t_1) = x_1, \ldots, X(t_{n-1}) = x_{n-1}\right) = P\left(X(t_n) = x_n \middle| X(t_{n-1}) = x_{n-1}\right) \tag{1}$$

The analysis of blockchain parameters through Markov Chain models relies on the characterisation of the State Space and the Transition Probability Matrix, which integrates the probabilities of transition between the different states. The assumption of hypotheses, typically regarding homogeneity[9] or reachability between the states (i.e. transience or ergodicity), allows us to categorise the corresponding stochastic process, thus leveraging the theory developed within specific fields of expertise.

Specific implementations of Markov Chains are usually visualised through diagrams, with circles representing the states and directed arcs the transitions among them. These circles and arcs may represent diverse concepts, depending on the specific characterisation performed. By way of example, Fig. 2 shows three graphical representations of Markov Chain models used for the analysis of different blockchain issues.

[5] Standardised plain text formats proposed by the Institute for Scientific Information (original developer of WoS, currently maintained by Clarivate Analytics) and Research Information System (Scopus).

[6] Some models can be seen from various perspectives, thus fitting into different categories/subclasses (i.e. Bayesian Networks, ranked as graph-based model or Machine Learning, as well as Decision Trees).

[7] The most widely recognised definition of a Markov Chain, which involves discrete State Spaces with either discrete or continuous time, is considered in this paper.

[8] Stochastic processes fulfilling the Markov property are called Markov processes, regardless of the nature of the State Space.

[9] A Markov Chain is said to be homogeneous if the probability of transition from any i to any j state is the same regardless of the step of the process.

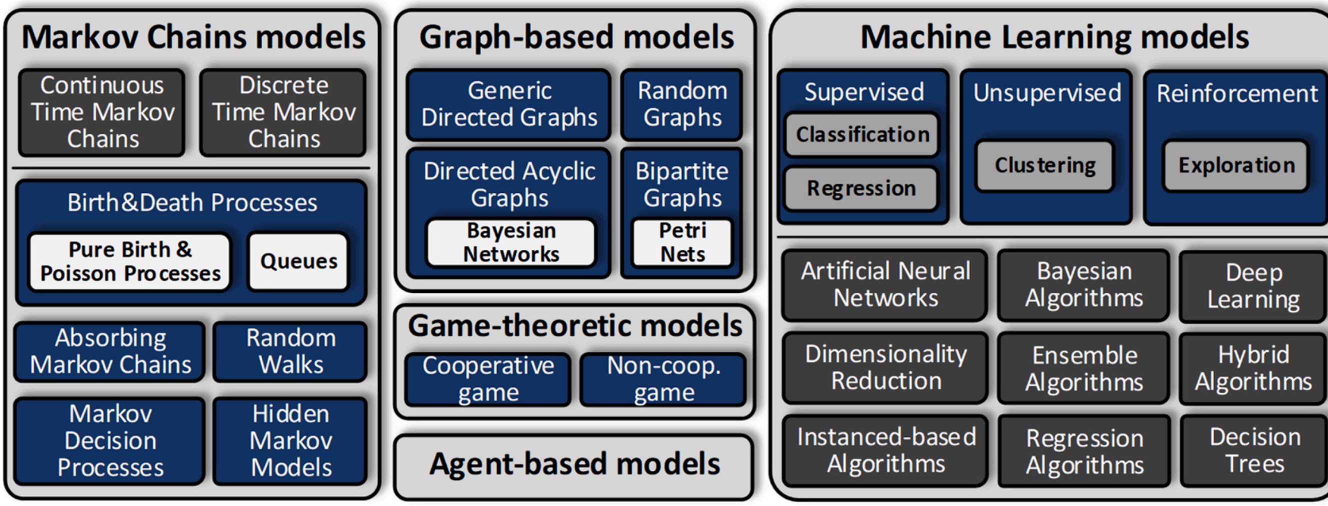
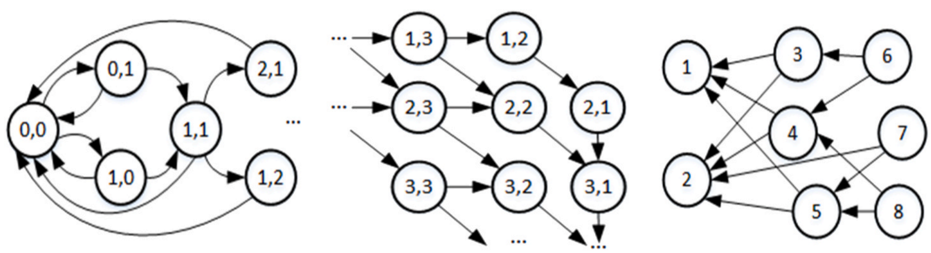


Fig. 1. Classification of models considered in this paper.[6].



(a) (b) (c)

Fig. 2. Different implementations of the Markov Chain in blockchain research.

- Fig. 2 (a): two-dimensional states, representing the difference in blocks perceived by a pool of miners and the rest of the community, whereas the transitions represent the discovery of new blocks and communication to the community. Target: detection of block-hiding behaviour under selfish-mine strategy (Göbel et al., 2016).
- Fig. 2 (b): two-dimensional states are again considered, representing the number of tips and cumulative weight of transactions. The transitions represent the validation by new incoming transactions. Target: analysis of consensus process on DAG (Directed Acyclic Graph)-based ledgers under load regimes (Li, Y. et al., 2020b).
- Fig. 2 (c): the states symbolise transactions, whereas the transitions represent the validation between them (a simple instance of Tangle is shown in this graph). Target: analysis of Biased Random Walk tip selection algorithm on IOTA-Tangle (Cullen et al., 2020).

3.1.1. Sub-categorisation

Depending on the character of time (T in the expression (1)), a first division of Markov Chains into CTMC (Continuous Time Markov Chain) and DTMC (Discrete Time Markov Chain) can be considered. Both types of chains have been used in blockchain research. By way of example.

1) CTMC: CTMC models have been proposed to analyse Hyperledger Fabric performance (Jiang, L. et al., 2020), or to characterise the state of mining pools in the evaluation of the selfish-mine strategy (Göbel et al., 2016; Yang, R. et al., 2020), which was predicted by (Eyal and Sirer, 2014) and further studied by (Javier and Fralix, 2020)).

2) DTMC: DTMC models have been used to model the consensus process of a Directed Acyclic Graph-based blockchain (Li, Y. et al., 2020b), to derive the average confirmation time of transactions and related transaction fees (Qi et al., 2020), to evaluate a variety of proof-based consensus protocols (Yu, G. et al., 2020), and to analyse the impact of network propagation delay on blockchain throughput (Ling et al., 2020). On the other hand (Eyal and Sirer, 2014), use a state machine representing a Markov Chain with transitions at pre-defined frequencies to capture Bitcoin mining behaviour.

Regardless of the nature of time, the following subclasses of Markov Chains have been more specifically used in the analysis of blockchain parameters.

1) Birth-Death Markov Chains (BDMC): for which the transitions can only be to an adjacent state (from $X(t_n) = i$ towards $X(t_{n+1}) = i\text{-}1$ or $X(t_{n+1}) = i + 1$). These chains are commonly used to model Markovian queues[10], with many samples in the frame of blockchain (Fan, J. et al., 2020; Fralix, 2020; Frolkova and Mandjes, 2019; Jiang, L. et al., 2020; Kasahara and Kawahara, 2019; Kawase and Kasahara, 2020; ; Lian, W. et al., 2020; Li, J. et al., 2020Ma, Z. et al., 2020; Memon et al., 2019; Misic et al., 2020; Park et al., 2020).

2) Pure Birth Processes (arrival processes or renewal processes): can be seen as a subclass of birth-death processes, with i.i.d. intervals between arrivals (no departures are possible) according to a general

[10] Queueing Theory represents a specific discipline within Markov Chain theory. Many types of queues have been studied, identified by standard Kendall's notation.

distribution (Cao, B. et al., 2019); model the cumulative weight of transactions under a DAG consensus process as pure birth processes.
3) Poisson Processes (PP): In turn, a special case of pure birth processes, where the interarrival time is exponentially distributed with a constant rate. In blockchain, the arrival of transactions and generation of blocks are commonly considered to be homogeneous Poisson processes; this premise has been questioned in (Bowden et al., 2020) (homogeneity linked to the mining difficulty), hence a nonhomogeneous Poisson arrival assumption has been considered in further research (Fralix, 2020; Goffard, 2019).
4) Absorbing Markov Chains (AMC): in which it is impossible to leave a set of states, which are reachable from any other state after a number of steps. This has been used to model the communication between nodes in blockchain (Huang, D. et al., 2020) or the validation of transactions in DAG-based ledgers (Cullen et al., 2020; Staupe, 2017).
5) Markov Decision Processes (MDP): can be seen as a Markov Chain augmented with actions and rewards (Carlsten et al., 2016). uses a MDP-like approach to analyse Bitcoin instability with only transaction fees as rewards for miners (Nayak et al., 2016), to model Bitcoin mining attacks and (Niu et al., 2020; Sai et al., 2019; Sapirshtein et al., 2016; Zur et al., 2020) to investigate the selfish mining strategy.
6) Hidden Markov Models (HMM): able to capture the evolution of observable events that depend on unobservable states, which form a Markov Chain. These kinds of models have been applied to analyse traceability in permissioned blockchain (Mitani and Otsuka, 2020), predicting Bitcoin prices (Giudici and Abu Hashish, 2020; Hashish et al., 2019) and to evaluate the performance of concrete blockchain implementations (Liu, H. et al., 2020).
7) Random Walks (RW): describe paths consisting of a succession of random steps on a mathematical space. They have been considered for research validation of transactions in DAG-based ledgers (Cullen et al., 2020)[11], (Ferraro et al., 2019; Kusmierz et al., 2019; Son et al., 2020), price evolution of cryptocurrencies (Aggarwal, 2019) and for assessing the fraud risk for double-spending attacks (Goffard, 2019).

Table 1 below summarises the main characteristics of the Markov chain models used in the most relevant research papers identified, and the target features under analysis.

3.2. Graph-based models

In graph theory, a graph can be seen as a set of nodes and edges connecting pairs of these nodes. In the case of a directed graph, each edge has an orientation, linking two nodes asymmetrically. In this way, a directed graph can be formally defined[12] as an ordered pair of elements G = {V, E} where.

- *V* is a set of nodes (also called vertices).
- *E is a set of edges (also called arcs).*
- $\varphi: E \rightarrow \{(x,y) \mid (x,y) \in V^2\}$, is an incidence function mapping every edge to an ordered pair of nodes.

Graphs have the ability to naturally represent dense relationships between a set of elements, making the use of the mathematical research developed in graph theory possible, with significant growth after its beginnings in recreational maths problems.[13] Different graph structures

[11] The process is both a (Biased) Random Walk and an Absorbing Markov Chain.
[12] Directed graphs defined in this way can have loops and multiple edges.
[13] The history of graph theory can be specifically traced to the paper written by the mathematician Leonhard Euler on the Königsberg bridge problem, published in 1736.

Table 1
Details of relevant research papers using Markov Chain models.

Model type	References	Model details	Analysis details[a] V	P	Main target parameters and applications
Generic Markov Chain	Göbel et al. (2016)	2 dimensional CTMC	✓		States of belief of pools in selfish mining. BTC (Bitcoin)
	(Yang, R. et al., 2020), (Javier and Fralix, 2020)	3-2 dimensional CTMC	✓		Behaviour of miners in selfish mining. BTC and ETH (Ethereum)
	Eyal and Sirer (2014)	State-machine (DTMC)	✓		Behaviour of miners in selfish mining. BTC
	(Li, Y. et al., 2020a), (Cao, B. et al., 2019)	2 dimensional DTMC	✓	✓	Confirmation delay and cumulative weight of DAG consensus process
	Yu, G. et al. (2020)	DTMC-like ∞ dimensional	✓	✓	Resources of different proof-based (PoX) consensus protocols. Generic blockchain
	(Ling et al., 2020)	4 states DTMC (rounds)		✓	Impact of network propagation on blockchain throughput. Generic blockchain
Birth-Death Markov Chain. Queues[b]	Jiang, L. et al. (2020)	M/M/c & M/M/1/q queues		✓	Throughput, rejection probability and delay of transaction flow. HLF (HyperLedger Fabric)
	Qi et al. (2020)	Vacation queue with batch & gated service (DTMC)		✓	Average response time of transactions under light-load traffic. BTC-like blockchain
	(Fan, J. et al., 2020), (Ma, Z. et al., 2020)	M/M/1 vacation queue & 4-2-dimens. Quasi BDMC		✓	Stationary distribution, average number of transactions and related confirmation time. BTC-like blockchain
	Fralix (2020)	G/M/∞ and M_t/G/∞		✓	Time-dependent behaviour for different queueing systems. BTC
	Frolkova and Mandjes (2019)	G/M/∞		✓	Transactions queue-length under FIFO-/LIFO-batch departures. BTC
	(Kasahara and Kawahara, 2019), (Kawase and Kasahara, 2020)	$M/G^b/1$		✓	Transaction-confirmation time vs. transaction fees. BTC
	(Li, J. et al., 2020)	M/M/n		✓	Transaction-confirmation

(continued on next page)

Table 1 (*continued*)

Model type	References	Model details	Analysis details[a] V	P	Main target parameters and applications
					time vs. transaction fees and its equilibrium. BTC
	Lian, W. et al. (2020)	M/M/N/m vs. FCFS		✓	Efficient throughput, delay, and channel utilization for stock trading. Generic blockchain
	Memon et al. (2019)	M/M/1 memory pool and M/M/c mining pool.		✓	Number of transactions per block, throughput, mempool size, transactions waiting time. BTC and ETH.
	Misic et al. (2020)	M/G/1 (+Jackson network)		✓	Transaction & block rates, forking probabilities, network partition sizes. BTC
	Park et al. (2020)	$M^n/M^n/1$		✓	Nb. of customers, transaction-confirmation time and block throughput. ETH
Pure Birth Processes and Poisson Processes	(Li, Y. et al., 2020a), (Cao, B. et al., 2019)	DTMC Pure birth Process		✓	Cumulative weight and transaction confirmation delay vs network load. DAG-based blockchain
	Bowden et al. (2020)	(Non-homogeneous) PP		✓	Block throughput (vs. mining difficulty). BTC
	Goffard (2019)	Renewal & Poisson Process	✓		Length of honest and malicious blockchain (number of blocks). BTC-like blockchain
Absorbing Markov Chains	Huang, D. et al. (2020)	DTMC 2 dimensions AMC.		✓	Network split probability for Raft consensus protocol. Private blockchain
	(Cullen et al., 2020), (Staupe, 2017)	CTMC 1 dimension AMC.	✓		Tip selection algorithm, analysis of resistance to parasite chain attacks. DAG-based blockchain
Markov Decision Processes (DTMC)	Carlsten et al. (2016)	~MDP (continuous states)	✓		Miners behaviour under transaction-fee regime (block reward drop to 0). BTC
	Nayak et al. (2016)	3-dim. states (delta blocks, forks, known fork)	✓		Miners behaviour vs mining and network attacks (reward = block reward). BTC
	Niu et al. (2020)	4-dim. states (public/secret chains, fork-block status)	✓		Selfish mining strategies in BTC-NG (version aiming high throughput).
	(Sai et al., 2019; Sapirshtein et al., 2016)	3-dim. states (public/secret chains, fork status)	✓		Miners behaviour and profits under selfish-mining strategies (different incentive conditions). BTC
	Zur et al. (2020)	2-dim. states (public/secret chains), generalized	✓		Miners behaviour and profits under selfish-mining strategies (incentive block reward, average reward criterion). BTC/ETH
Hidden Markov Model	Mitani and Otsuka (2020)	Hidden: users & amounts	✓		Privacy of participants and traded amounts in permissioned blockchain. Permissioned blockchain
	Hashish et al. (2019)	Hidden: Bitcoin prices		✓	Price evolution (grouped into clusters). Hybrid model HMM-LSTM. BTC
	(Liu, H. et al., 2020)	Hidden: Info authenticity	✓		Authenticity of information managed in blockchain. HLF
Random Walk	Cullen et al. (2020)	Biased RW (BRW) and first-order BRW	✓	✓	Tip selection algorithm (BRW original in Iota), cumulative weight of transactions. DAG-based blockchain
	Ferraro et al. (2019)	Unbiased/biased RW	✓	✓	Tip selection algorithm, analysis of cumulative weight of transactions. DAG-based blockchain
	Kusmierz et al. (2019)	Biased RW (age)	✓	✓	Tip selection algorithm, ensuring validation in finite time while preserving essential features of original tip selection algorithm. DAG based blockchain
	Son et al. (2020)	RW with Bayesian inference	✓	✓	Tip selection algorithm, considering Bayesian inference (≥2nd selections) to increase volatility of cumulative

(*continued on next page*)

Table 1 (*continued*)

Model type	References	Model details	Analysis details[a]		
			V	P	Main target parameters and applications
					wight of tips. DAG-based blockchain
	Aggarwal (2019)	RW H_0 hypothesis & tests		✓	Price evolution for assessment on market efficiency. BTC
	Goffard (2019)	RW with i.i.d. steps	✓		Length difference between honest and double-spending chains. BTC

[a] V= Vulnerabilities, P= Performances.
[b] Standard Kendall's notation is used to describe the queueing models.
Source: Prepared by the authors.

are used to model pairwise relations between objects, allowing to lay out these relations into data structures for further computerised management. This is particularly interesting when dealing with huge amount of elements, as it is usually the case with blockchain applications. Fig. 3 below illustrates some kinds of graphs (there are many others: regular graphs, complete graphs, cycle graphs, chordal graphs, trees, etc …).

3.2.1. Sub-categorisation

The following types of graphs have been particularly used to model different relationships established in blockchain applications.

1) Directed graphs: suitable to represent data relationships between transactions, blocks, addresses and inputs/outputs in blockchain. In this regard, different research studies propose the translation of blockchain data structures into directed graph models (Akcora et al., 2018b; Alqassem et al., 2018; Chen, T. et al., 2020; Guo, D. et al., 2019; McGinn et al., 2018; Meiklejohn et al., 2013; Mizerka et al., 2020; Ober et al., 2013; Reid and Harrigan, 2013; Ron and Shamir, 2013; Sompolinsky and Zohar, 2015; Tsoulias et al., 2020). The study of their dynamic evolution and revealed patterns typically provide relevant insights on anonymity, integrity, performance and the security of the corresponding applications.

2) Directed Acyclic Graphs (DAGs): A Directed Acyclic Graph is a particular case of directed graphs, specifically a directed graph that has no cycles, meaning that no node can reach itself via a nontrivial path (Fig. 3 (d)). These graphs have the ability to reproduce certain desirable behaviour in blockchain, for instance, the transmission of transactions and blocks between nodes.

Taking advantage of the intrinsic characteristics of this kind of graph, some blockchain applications use DAG-based protocols to validate their transactions (i.e. Byteball, Dagcoin, Hedera Hashgraph, IOTA) or blocks (ie. Conflux, Ghost, Nano, Phantom, Spectre), which are directly linked to one another following DAGs structures (Lewenberg et al., 2015b), rather than forming a single sequence of blocks[14]. Alternative DAG-based blockchain protocols have been proposed and evaluated (Cui et al., 2019; Xiang et al., 2019), namely CoDAG and JointGraph. Besides, modifications to the attachment mechanism of Iota-Tangle have been suggested (Ferraro et al., 2019; Son et al., 2020), ensuring that all transactions are validated in finite time and enabling faster computation times. Finally, alternative DAG proposed by (Nguyen et al., 2020) identify risks in blockchain-integrated container shipping systems.

Bayesian Networks, a probabilistic subclass of DAG models, whereby nodes represent a random variable and each edge the associated conditional probability, have also been used in blockchain analysis. In this way (Lu et al., 2019), construct a Bayesian-based transaction network graph to provide a quantitative anonymity assessment in blockchain.

3) Bipartite graphs: graphs whose nodes are split into two disjointed and independent sets; the edges link nodes from the two sets but no nodes within them. Petri Nets, a kind of bipartite graph, and some extensions, such as Colored Petri Nets or Generalized Stochastic Petri Nets, have been used to analyse anonymity in Bitcoin (Pinna et al., 2018), to perform risk modelling of blockchain ecosystem (Kabashkin, 2017), to explore the smart-contracts process in Ethereum (Duo et al., 2020; Hu et al., 2019) or the performance on a Hyperledger-based system (Yuan, P. et al., 2020). Other bipartite graphs are proposed (Jourdan et al., 2019) to model address-transaction data structures.

4) Random graphs: are obtained by randomly adding edges between a predefined set of nodes; the theory of random graphs is sustained both by graph and probability theory. An analytical model based on a subclass of random graphs is proposed by (Shahsavari et al., 2019), namely the Erdös-Renyi random graph, to evaluate the traffic in the Bitcoin network.

It should be mentioned that the rise in blockchain modelling through graphs and the huge amount of data to be managed explain the development of specific tools able to recover and display data from blockchain applications for efficient graph analysis (Di Battista et al., 2015; Dubey et al., 2016; McGinn et al., 2016; Molina-Solana et al., 2017; Xia et al., 2020).

3.3. Machine Learning models

Machine Learning is a subfield of Artificial Intelligence, offering models with the ability to automatically learn and improve their accuracy from data collected during past interactions, without being explicitly programmed. Basically, this kind of model is developed in four steps.

1. Gathering and preparation of a training data set.
2. Selecting the right algorithm to run the training data set.
3. Training the algorithm through an iterative process.
4. Performance measurement and data analysis.

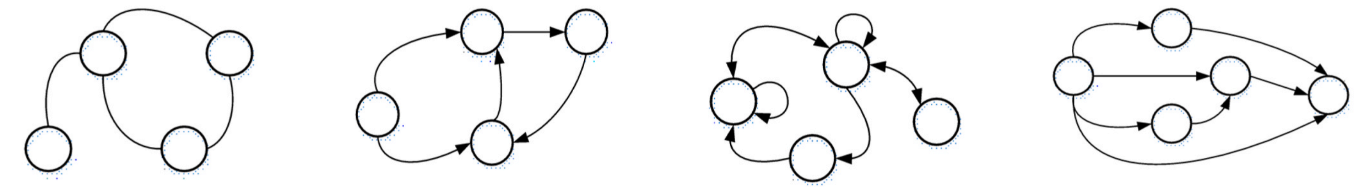
3.3.1. Sub-categorisation

Machine Learning models can be categorised into three main subclasses (Bengio et al., 2013; Lee, J. H. et al., 2018; Qiu et al., 2016; Schmidhuber, 2015): supervised, unsupervised and reinforcement learning[15], depending on how algorithms are trained, respectively using labelled data, unlabelled data or interacting with the environment. These high-level categories deal with different types of problems, respectively, classification and regression, clustering and exploitation (Fig. 4 (a)). Some algorithms can learn through different training approaches, like Artificial Neural Network, so they fit into multiple categories.

An alternative taxonomy groups the algorithms by similarity in terms of function. Fig. 4 (b) illustrates this categorisation, including those algorithms, among the wide range of Machine Learning algorithms,

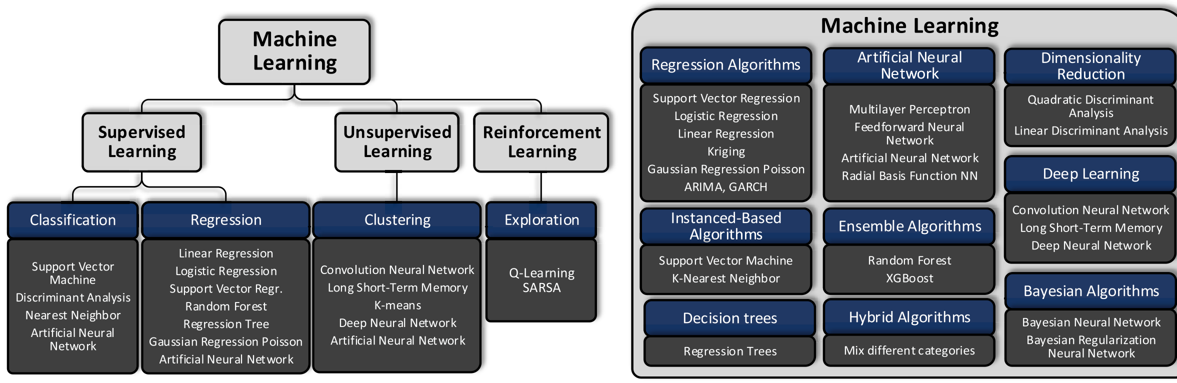
[14] These applications achieve higher rates of transactions per second and lower validation costs with respect to blockchain applications implementing other consensus algorithms, whereas they present some disadvantages, like higher susceptibility to attacks, particularly for low transaction volumes.

[15] Semi-supervised learning approaches can also be considered. Reinforcement learning methods most recently incorporated to this categorisation vs. previously established supervised and unsupervised learning.



(a) Undirected graph (b) Generic directed graph (c) Directed multigraph with loops (d) Directed Acyclic Graph

Fig. 3. Different kinds of graphs.



(a) (b)

Fig. 4. Machine Learning models. Categorisation depending on the algorithm training method (a) or function (b).

identified in blockchain research.

The key focus of Machine Learning models when applied to blockchain is to forecast the price evolution of different blockchain-based cryptocurrencies. The most relevant research is summarised in Table 3.

3.4. Game-theoretic models

Game-theoretic models extend Markov Decision Processes by considering competition between several rational decision-makers (Neyman and Sorin, 2003), to predict their actions in an interactive situation. This kind of models have been widely applied to examine different aspects of the blockchain mining process, they can be also sub-categorised into cooperative and non-cooperative.

1) Cooperative games: applied to analyse the decision-making process of miners (Biais et al., 2019; Koutsoupias et al., 2019; Kroll et al., 2013; Lewenberg et al., 2015a) or the arrangement of attacks against blockchain (Wu et al., 2020).

2) Non-cooperative games: to alternatively formulate the mining strategies in a blockchain network in a competitive way (Ewerhart, 2020; Kim, 2018; Li, W. et al., 2020; Liu, X. et al., 2018), to consider the computation costs of miners (Manshaei et al., 2018), to evaluate the ranking process of transactions (Li, J. et al., 2019a), to analyse the emergence of transaction fees (Easley et al., 2019), to assess the incentives to generate forks (Cheng and Lin, 2019) or the motivations for triggering different attacks (Johnson et al., 2014; Wang, Y. et al., 2019).

Both cooperative and non-cooperative approaches are combined in some research, as is the case of (Bataineh et al., 2020; Singh et al., 2020; Taghizadeh et al., 2020; Tang et al., 2020) aiming to review the monetary reward of miners and computational resources devoted to the mining activities.

3.5. Agent-based models

In these models, the system is shaped as a set of autonomous entities, aiming to capture the behaviour of individuals within a specific environment (Abar et al., 2017). Agent-based models are used for the simulation of transactions in the IOTA-Tangle (Ferraro et al., 2019), analysing the economy of the mining process (Cocco and Marchesi, 2016; Cocco et al., 2019b), cryptocurrency markets (Cocco et al., 2017; Lee, K. et al., 2018; Luther, 2016) or the overall blockchain system (Kaligotla and Macal, 2018; Rosa et al., 2019).

3.6. Other models

Besides the previous ones, some other models have also been proposed in scientific literature to assess certain blockchain features, but they are intentionally excluded considering that they are only used occasionally or that they focus on a very precise topic.

That is the case of Random Oracle models, implemented through a theoretical black box, that responds to queries with random values chosen from their output domain (Koblitz and Menezes, 2015). Random Oracle models are used to check cryptographic security of signatures or computational puzzles (Kiffer et al., 2018; Li, C. et al., 2021; Pass et al., 2017), as part of the consensus protocols (Ling et al., 2020). proposes the broadcasting of random oracles generated by satellites, in order to improve blockchain performance.

On the other hand, Vector Autoregressive models have been used to forecast cryptocurrency price evolutions (Giudici and Abu-Hashish, 2019; Yang, S. Y. & Kim, 2015) and to analyse how transactions are

Table 2
Details of relevant research using Graph-based models.

Model type	References	Model details[a]	Analysis details[b] V	P	Main target parameters and applications
Generic Directed Graph	Akcora et al. (2018b)	User Network graph		✓	Bitcoin price and volatility prediction.
	Mizerka et al. (2020)	User Network graph		✓	Behaviour of major Bitcoin users, link with Bitcoin price
	Alqassem et al. (2018)	User Network graph		✓	Evolution of statistical properties of BTC transaction graph's vs. other social networks. Use of graph growth metrics
	McGinn et al. (2018)	Nodes: blocks, transactions, inputs & outputs, addresses. Edges: relationships	✓	✓	Detection of users and mining activity, money creation review & defence against DoS (Denial of Service) attacks. BTC
	Meiklejohn et al. (2013)	Both Transaction and User Network graph	✓	✓	Rise of services, suitability to hide illicit transactions. BTC
	Ober et al. (2013)	User Network graph	✓		Topology of BTC transaction graph and implication for anonymity
	Reid and Harrigan (2013)	Both Transaction Network graph (DAG) and User Network graph.	✓		Anonymity, possibility to associate public addresses to external user identities. BTC
	Ron and Shamir (2013)	User Network graph	✓	✓	Behaviour of users, and their financial balance. Statistical and privacy properties of the transaction graph. BTC
	Sompolinsky and Zohar (2015)	Nodes: miners. Edges = broadcast of generated blocks (with delay)	✓		Alternative block adoption algorithm, allowing to increase throughput and to minimize double-spend attacks. BTC
	(Chen, T. et al., 2020)	Money Flow Graph (User Network graph) Smart Contract Creation Graph Smart Contract Invocation Graph	✓	✓	Graph analysis to extract behaviour and security insights. BTC Weighted (Money Flow and Contract Invocation) and unweighted (Contract Creation) directed graphs.
	Guo, D. et al. (2019)	User Network graph (Directed weighted, directed unweighted and undirected unweighted graphs)		✓	Statistical properties of transactions features (ie. volume, graph structure). ETH
Directed Acyclic Graph	Lewenberg et al. (2015b)	Nodes: blocks (including off-chain blocks). Edges: validation between blocks		✓	DAG-based protocol (blocks), allowing to increase throughput, and a better payoff for miners (DAG vs. linear chain structure)
	Cui et al. (2019)	Nodes: blocks Edges: validation between blocks		✓	DAG based protocol (blocks), having the transactions approved within a deterministic period
	Xiang et al. (2019)	Nodes: transactions (packed into events) Edges: validation in DAG structure		✓	Analysis of throughput and latency in Jointgraph DAG blockchain application vs. Hashgraph
	Nguyen et al. (2020)	User Network graph	✓		Risk analysis using network topological metrics. DAG-based blockchain
	Lu et al. (2019)	Bayesian Network	✓		Anonymity assessment. BTC
Bipartite graphs – Petri nets	(Pinna et al., 2018)	User Network graph	✓		Disposable addresses in Bitcoin, times they are used for input/output, and link to anonymity
	Kabashkin (2017)	Evaluation Petri-Nets	✓		Risk modelling of blockchain ecosystem. BTC-like blockchain applications
	Hu et al. (2019)	Business Process Modelling Notation extended to Petri Nets		✓	Reduction of gas cost in smart contract deployment. ETH
	Duo et al. (2020)	Colored Petri Nets	✓		Analysis of security vulnerabilities during smart contract execution. ETH
	Yuan, P. et al. (2020)	Generalized Stochastic Petri Nets		✓	Analysis of performance of HLF (latency and throughput)
Random Graphs	Shahsavari et al. (2019)	Nodes: P2P network nodes. Edges: connectivity between nodes		✓	Block dissemination over the network. Overall performance (propagation delay, and traffic overhead). BTC

[a] User Network graph: Nodes = addresses/accounts, Edges = transactions. Transaction Network graph: Nodes = transactions, Edges = inputs/outputs.
[b] V= Vulnerabilities, P= Performance.
Source: Prepared by the authors.

prioritised and the associated fees (Huang, Z. et al., 2017). Models based on partial differential equations are also applied to the analysis of cryptocurrency prices (Wang and Wang, 2020) and the confirmation time of transactions and blocks (Gatabazi et al., 2019). Linear regressions are used to evaluate the miners' return (Cole and Cheng, 2018), models based on large deviation theory to study the formation of forks (Wang, S. et al., 2019) or based on discrete-event simulation to analyse the behaviour of miners and mining-pool managers (Li, K. et al., 2021).

4. Summary of results

This section provides a summary of the results obtained. Blockchain performance and vulnerability issues are presented linked to the references selected in the literature review. The references are arranged according to the associated blockchain typologies under evaluation in each case, also including the model category and subcategory.

The references considered in the previous sections are included along with additional references, providing a comprehensive overview on the models used and the way they have been applied.

It can be seen that a variety of models are usually employed to evaluate each of the topics. At the same time, there is a certain degree of specialisation. In this way, the withholding strategies are mostly analysed through generic Markov Chains, transaction confirmation time and mempool size through a Birth-Death Markov Chain, the allocation of addresses and anonymity through Graph-based models, the formation of mining pools through Game-theoretic models, the efficiency and miners' welfare though Agent-based models and the price evolution of cryptocurrencies through Machine Learning models.

The use of a model to a larger extent for the analysis of a specific topic does not mean it cannot be applied to another one.

5. Bibliometric analysis

5.1. Tools and data arrangement

Several tools have been used in the bibliometric analysis, depending on their ability to fulfil the requirements of the analysis, in order to obtain a comprehensive overview.

- VoSViewer (v. 1.6.15) for geographical distribution by country and keyword co-occurrence network.
- SciMAT (v. 1.1.04) for temporal analysis.

Table 3
Details of relevant research using Machine Learning models.

Functional groups of algorithms	Classific.	Regression	Clustering	References	Algorithms	Blockchain-based cryptocurrencies[a]
Artificial Neural Network	✓	✓	✓	(Alonso-Monsalve et al., 2020; Uras et al., 2020)	Multi Layer Perceptron (MLP)	BTC, DSH, ETH, LTC, XMR, XRP
				(Nguyen and Le, 2019; Lahmiri and Bekiros, 2020)	Feedforward Neural Network (FFNN)	BTC
				(Akyildirim et al., 2020; Mallqui and Fernandes, 2019; Mudassir et al., 2020; Nakano et al., 2018)	(General) Artificial Neural Network (ANN)	BCH, BTC, DSH, EOS, ETC, ETH, IOT, LTC, OMG, XRP, ZEC
				(Alonso-Monsalve et al., 2020; Lahmiri & Bekiros, 2019, 2020)	Radial Basis Function NN (RBFNN)	BTC, DSH, ETH, LTC, XMR, XRP
Dimensionality Reduction	✓			(Chen, Z. et al., 2020b)	Quadratic Discriminant Analysis (QDA)	BTC
				(Chen, Z. et al., 2020b)	Linear Discriminant Analysis (LDA)	BTC
Ensemble Algorithms		✓		(Akyildirim et al., 2020; Chen, Z. et al., 2020b; Valencia et al., 2019)	Random Forest (RF)	BCH, BTC, DSH, EOS, ETC, ETH, IOT, LTC, OMG, XRP, ZEC
				(Alessandretti et al., 2018; Chen, Z. et al., 2020b)	Gradient Boosting	BTC, ETH, XRP
Decision Trees		✓		Lahmiri and Bekiros (2020)	Regression Trees (RT)	BTC
Regression Algorithms		✓		(Nguyen and Le, 2019; Jang and Lee, 2018; Lahmiri and Bekiros, 2020)	Support Vector Regression (SVR)	BTC
				(Akyildirim et al., 2020; Chen, Z. et al., 2020b)	Logistic Regression	BCH, BTC, DSH, EOS, ETC, ETH, IOT, LTC, OMG, XRP, ZEC
				(Poongodi et al., 2020; Uras et al., 2020)	Linear Regression	BTC, ETH, LTC
				Khedmati et al. (2020)	(Ordinary) Kriging	BTC
				Lahmiri and Bekiros (2020)	Gaussian Regression Poisson (GRP)	BTC
				(Nguyen and Le, 2019; Khedmati et al., 2020)	Autoregressive Integrated Moving Average (ARIMA)	BTC
Deep Learning			✓	(Alonso-Monsalve et al., 2020; Ji et al., 2019; Khedmati et al., 2020)	Convolution Neural Network (CNN)	BTC, DSH, ETH, LTC, XMR, XRP
				(Alessandretti et al., 2018; Chen, Z. et al., 2020b; Nguyen and Le, 2019; Hashish et al., 2019; Ji et al., 2019; Lahmiri and Bekiros, 2019; Mudassir et al., 2020; Uras et al., 2020)	Long Short-Term Memory (LSTM)	BTC, ETH, LTC, XRP
				Ji et al. (2019)	Deep (Residual) Neural Network	BTC
				Valencia et al. (2019)	Neural Network (NN)	BTC, ETH, LTC, XRP
Instance-based	✓			(Akyildirim et al., 2020; Chen, Z. et al., 2020b; Mallqui and Fernandes, 2019; Mudassir et al., 2020; Poongodi et al., 2020; Valencia et al., 2019)	Support Vector Machine (SVM)	BCH, BTC, DSH, EOS, ETC, ETH, IOT, LTC, OMG, XRP, ZEC
				Lahmiri and Bekiros (2020)	K-Nearest Neighbour (KNN)	BTC
Bayesian Algorithms	✓	✓		Jang and Lee (2018)	Bayesian Neural Network (BNN)	BTC
				Lahmiri and Bekiros (2020)	Bayesian Regularization NN (BRNN)	BTC
Hybrid Algorithms	✓	✓	✓	(Alonso-Monsalve et al., 2020; Altan et al., 2019; Nguyen and Le, 2019; Hashish et al., 2019; Kristjanpoller and Minutolo, 2018; Mallqui and Fernandes, 2019)	CNN-LSTM; ANN-GARCH[b]; LSTM-EWT[c]; LSTM-HMM; RNN – K Means; ARIMA-ML	BTC, DSH, ETH, LTC, XMR, XRP

[a] Standard abbreviations: BCH = Bitcoin Cash, BTC = Bitcoin, DSH Dash, EOS = EOS.IO, ETC = Ethereum Classic, ETH = Ethereum, HLF Hyperledger Fabric, IOT = IOTA, LTC = Litecoin, OMG = OmiseGO, XMR = Monero, XRP = Ripple, ZEC = ZCash.
[b] GARCH: Generalized AutoRegressive Conditional Heteroskedasticity.
[c] EWT: Empirical Wavelet Transform.
Source: Prepared by the authors.

- Citespace (v. 6.1.R2) for the analysis of authorship, sources and categories. Also, for conversion of RIS to ISI format, thus allowing joint management of data recovered from WoS and Scopus.

Additionally, a manual adjustment has been performed in the ISI&-RIS files, in order to homogenise the information (ie. the labels "*Peoples R China*"/"*China*" or "*England*"/"*United Kingdom*", although not equivalent, are normalised to the second terms).

5.2. Geographical distribution

Table 5 details the top eleven[16] most prolific countries in number of research papers, according to the author's associated institutions, and the corresponding citation ranking for these countries. The last row in these tables gathers the data for those countries not included in the respective top eleven positions, thus allowing the percentage of total

[16] Other prolific countries are Israel and Japan ranked *ex aequo* in eleventh position with ten research papers.

Table 4
Models used to characterise blockchain features.

Feature		Blockchain typology[a]	Model category/ subcategory		References
Vulnerabilities	Selfish-mining and other withholding strategies	Linear, public, permissionless (ie. BTC, ETH)	Markov Chain	Generic	(Bai, Q. et al., 2019; Cheremushkin, 2020; Eyal and Sirer, 2014; Göbel et al., 2016; Javier and Fralix, 2020; Kang et al., 2021; Li, Q. et al., 2021; Li, T. et al., 2021; Ma & Li, 2021; Motlagh et al., 2021a; Motlagh et al., 2021b; Niu and Feng, 2019; Wang, H. et al., 2021; Wang, Z. et al., 2019; Yang, R. et al., 2020; Yang, R. et al., 2021; Zhou et al., 2021a; Zhou et al., 2021b; Zhou et al., 2022)
				MDP	(Gervais et al., 2016; Nayak et al., 2016; Niu et al., 2020; Sapirshtein et al., 2016; Wang, Y. et al., 2020; Zur et al., 2020)
			Game		(Li, W. et al., 2020; Yu, L. et al., 2020)
	Denial of Service attacks	Linear, public, permissionless (ie. BTC)	Markov Chain	Generic	Bordel et al. (2021)
			Graph	Directed	McGinn et al. (2018)
			Game		(Johnson et al., 2014; Laszka et al., 2015; Wu et al., 2020; Zheng et al., 2019)
			Agent-based		Rosa et al. (2019)
	Double-spending and bribery attacks	Linear, public, Permissionless (ie. BTC, Proof of Stake)	Markov Chain	Generic	Kaidalov et al. (2018)
				MDP	(Gervais et al., 2016; Sun, H. et al., 2020; Zheng, J. et al., 2021)
				RW	Goffard (2019)
			Game		(Kroll et al., 2013; Winzer et al., 2019)
			Agent-based		Platt and McBurney (2021)
		Linear Permissioned	Markov Chain	BDMC	Altarawneh et al. (2021)
			Agent-based		Chen, S. et al., (2021)
		Tree-chain, public, permissionless. (ie. IOT)	Markov Chain	Generic	Bramas (2020)
				AMC	Staupe (2017)
	Other users & miners (dishonest) behaviour	Linear, public, permissionless (ie. BTC, ETH, VANETs)	Markov Chain	HMM	(Liu, H. et al., 2020; Liu et al., 2021)
			Graph	Directed	(Maesa et al., 2016; Maesa et al., 2017; Phetsouvanh et al., 2021)
			Game		(Kiayias et al., 2016; Nojoumian et al., 2019)
			Machine Learning		Rakkini and Geetha (2021)
		Linear Permissioned(HLF)	Machine Learning		Maskey et al. (2021)
		Tree-chain, public, permissionless. (ie. IOT)	Markov Chain	Generic	Mirsky et al. (2020)
Vulnerabilities	Formation of forks (under different reward regimes)	Linear, public, permissionless (ie. BTC)	Game		(Arenas et al., 2020; Biais et al., 2019; Chen, C. et al., 2021; Cheng and Lin, 2019; Ewerhart, 2020; Koutsoupias et al., 2019; Liao and Katz, 2017)
	Risks identification	Linear, public, permissionless (ie. BTC, ETH)	Graph based	Petri Net:	(Kabashkin, 2017; Shahriar et al., 2020)
				DAG, Directed	(Agarwal et al., 2021; Nguyen et al., 2020; Ofori-Boateng et al., 2021; Poursafaei et al., 2021; Tharani et al., 2021)
	Stability and security	Linear, public, permissionless (ie. BTC, ETH)	Markov Chain	MDP	(Carlsten et al., 2016; Sai et al., 2019; Zhang, R. & Preneel, 2019)
				BDMC-Queues	(Huberman et al., 2017; Li, Q. et al., 2019)
			Graph	Directed	Essaid et al. (2020)
			Game		(Kim, 2021)
			Machine Learning		(Nguyen et al., 2021; Tanwar et al., 2020)
		Tree-chain, public, permissionless. (ie. IOT)	Markov Chain	AMC	Cullen et al. (2020)
				RW	(Ferraro et al., 2019; Kusmierz et al., 2019)
			Graph	DAG	Prostov et al. (2021)
			Machine Learning		(Serrano, 2021; Waheed et al., 2021)
	Consistency and reliability	Linear, public, permissionless (ie. BTC, ETH)	Graph	DAG	Cachin et al. (2020)
			Game		Di et al. (2020)
		Tree-chain, public, permissionless. (ie. IOT)	Markov Chain	Generic	(Kiffer et al., 2018; Liu, Y. et al., 2018)

(continued on next page)

Table 4 (*continued*)

Feature		Blockchain typology[a]	Model category/ subcategory		References
			Graph	Petri Nets	Baouya et al. (2020)
		Linear, private, permissioned (ie. ETCoin, proprietary app.)	Markov Chain	Queues	Meng et al. (2021)
			Graph	Directed graphs	(Choubey et al., 2019; Melo et al., 2021b)
			Game		Bai, Y. et al. (2021)
	Centralization trends and mining-pools composition	Linear, public, permissionless (ie. BTC, ETH)	Markov Chain	AMC	Karakostas and Kiayias (2021)
			Game		(Chen, Z. et al., 2020a; Di et al., 2020; Lewenberg et al., 2015a; Liu, X. et al., 2018; Wang, Y. et al., 2019; Zolotavkin et al., 2019)
Performances	Scalability and analysis of consensus protocols	Linear, public, permissionless (ie. BTC and alternatives)	Markov Chain	Generic	(Bespalov et al., 2021; Pal and Kant, 2021; Pass et al., 2017; Putra Hastono and Kusuma, 2021; Wang, X. et al., 2021; Yu, G. et al., 2020; Zheng, K. et al., 2018)
				MDP	(Liu, X. et al., 2019; Niu et al., 2020)
			Graph	Directed	(Anada et al., 2019; Sompolinsky and Zohar, 2015)
				DAG	Tsoulias et al. (2020)
			Game		Burmaka et al. (2021)
		Tree-chain, public, permissionless. (ie. IOT)	Markov Chain	Generic	(Qushtom et al., 2021; Son et al., 2020; Wang, X. et al., 2019)
			Graph	DAG	(Boyen et al., 2018; Chen, W. et al., 2021; Cui et al., 2019; Halgamuge, 2021; Kan et al., 2018; Tian et al., 2020; Xiang et al., 2019)
			Game		Lewenberg et al. (2015a)
	Allocation of addresses and anonymity	Linear, public, permissionless (ie. BTC, ETH, EOS)	Markov Chain	HMM	(Mitani and Otsuka, 2020; Oakley et al., 2018)
			Graph	Directed	(Chan and Olmsted, 2017; Drobnic et al., 2019; Feld et al., 2016; Fleder et al., 2015; Gaihre et al., 2018; Lu et al., 2019; Lv et al., 2020; Meiklejohn et al., 2013; Muzammal et al., 2019; Ober et al., 2013; Turner and Irwin, 2018; Zhao, C. & Guan, 2015; Zhao, Y. et al., 2020)
				DAG	Reid and Harrigan (2013)
				Petri Nets	(Pinna, A., 2016; Pinna et al., 2018)
				Bipartite	Jourdan et al. (2019)
	Throughput of transactions and blocks, mempool size	Linear, public, permissionless (ie. BTC, B-RAN)	Markov Chain	Generic	Kaidalov et al. (2018)
				BDMC-Queues	(Bowden et al., 2020; Fan, J. et al., 2020; Fralix, 2020; Frolkova and Mandjes, 2019; Geissler et al., 2019; Kasahara, 2021; Kawase, Y. & Kasahara, 2017; Kawase and Kasahara, 2018; Kawase and Kasahara, 2020; Ke and Park, 2021;Li, Q. et al., 2019; Ling et al., 2021b; Ma, Z. et al., 2020; Memon et al., 2018; Memon et al., 2019; Park et al., 2020; Santhi and Lawanya Shri, 2020; Seol et al., 2020; Srivastava, 2019; Varma and Maguluri, 2021; Wang, J. et al., 2021; Wang, M. et al., 2021; Wilhelmi and Giupponi, 2021)
				MDP	(Gervais et al., 2016; Yuan, S. et al., 2021)
			Game		Ling et al. (2021a)
		Tree-chain, public, permissionless. (ie. IOT)	Markov Chain	Generic	(Li, Y. et al., 2021; Li et al., 2020b)
				BDMC-Queues	Cao, B. et al. (2019)
		Linear, private, permissioned (ie. HLF)	Markov Chain	BDMC-Queues	(Jiang, L. et al., 2020; Su Wai et al., 2020)
			Graph	Petri Nets	Yuan, P. et al. (2020)
			Game		Song et al. (2021)
	Prioritization of transactions, and associated fees	Linear, public, permissionless (ie. BTC)	Markov Chain	BDMC-Queues	(Huberman et al., 2017; Kasahara and Kawahara, 2019; Li, J. et al., 2018; Li, J. et al., 2019a; Li, J. et al., 2020; Qi et al., 2020; Ricci et al., 2019)
			Graph	Directed	(Li, J. et al., 2019b)
			Game		(Huberman et al., 2017; Jiang, S. & Wu, 2019; Li, J. et al., 2018; Yan et al., 2020)
	Network topology and synchronization	Linear, public, permissionless (ie. BTC)	Markov Chain	Generic	(Danzi et al., 2018; Ling et al., 2020; Papadis et al., 2018; Pass et al., 2017)
				BDMC-Queues	Misic et al. (2020)
			Graph	Directed	(Chen, T. et al., 2020; Essaid et al., 2020; Guo, D. et al., 2019; Ron and Shamir, 2013)
Performances				DAG	Pontiveros et al. (2019)
				Random	Shahsavari et al. (2019)
			Graph		King (2021)

(*continued on next page*)

Table 4 (*continued*)

Feature	Blockchain typology[a]	Model category/ subcategory		References
	Tree-chain, public, permissionless. (ie. IOT)		Random DAG	
	Linear, private, permissioned (ie. HLF)	Markov Chain	BDMC-Queues	Krieger et al. (2019)
			AMC	Huang, D. et al. (2020)
	Linear, public, permissionless (Alternatives to BTC)	Graph	Petri Net	(Zheng, K. et al., 2018)
Efficiency, miners' welfare optimization and acceptance	Linear, public, Permissionless (ie. BTC, ETH, Ripple, …)	Markov Chain	BDMC-Queues, DTMC	(Fang, M. & Liu, 2020; Lian, W. et al., 2020; Zhao, W. et al., 2021; Zheng, K. et al., 2021)
			MDP	(Al-Marridi et al., 2021; Wang, T. et al., 2021; Ye et al., 2021)
		Graph	Directed	(Alqassem et al., 2018; Bataineh et al., 2020; Casale-Brunet et al., 2021; Chai et al., 2021; McGinn et al., 2018; Pierro, 2021)
		Game		(Altman et al., 2019; Bataineh et al., 2020; Chen and Wang, 2020; Kim, 2018; Kim, Sungwook, 2019; Lajeunesse and Scolnik, 2021; Liu, W. et al., 2020; Manshaei et al., 2018; Singh et al., 2020; Taghizadeh et al., 2020; Tang et al., 2017; Tang et al., 2020; Toda et al., 2021; Yang et al., 2017)
		Agent based		(Cocco and Marchesi, 2016; Cocco et al., 2019a; Kaligotla and Macal, 2018; Luther, 2016)
		Machine Learning		(Kamble et al., 2021; Polemis and Tsionas, 2021; Tsai et al., 2021)
	Linear, private, permissioned (ie. HLF, Health Federated, …)	Markov Chain	CTMC	(Melo et al., 2021a)
		Graph	Directed	Cao, M. et al. (2021)
		Game		(Doan et al., 2021; Fan, Y. et al., 2021; Pan et al., 2021; Zhong et al., 2021)
		Agent based		(Mai et al., 2021; Polap et al., 2021; Yao et al., 2021; Zhao, N. et al., 2019)
	Tree-chain, public, permissionless (IoT)	Machine Learning		(Chen, G. et al., 2021)
Smarts contracts management and usability	Linear, public, permissionless (ie. ETH)	Markov Chain	Generic	Mavridou and Laszka (2018)
		Graph	Petri Nets	(Duo et al., 2020; García-Bañuelos et al., 2017; Hu et al., 2019; Liu and Liu, 2019; Zupan et al., 2020)
		Game		De Giovanni (2020)
Price evolution	Linear, public, permissionless (ie. BCH, BTC, DSH, EOS, ETC, ETH, IOT, LTC, OMG, XMR, XRP, ZEC)	Markov Chain	HMC, Generic	(Figa-Talamanca et al., 2021; Giudici and Abu Hashish, 2020; Kim et al., 2021; Koutmos and Payne, 2021; Lian, Y. & Chen, 2021)
			RW	Aggarwal (2019)
		Graph	Directed	(Abay et al., 2019; Akcora et al., 2018a; Akcora et al., 2018b; Baumann et al., 2014; Li, Y. et al., 2020a; Mizerka et al., 2020; Motamed and Bahrak, 2019; Partida et al., 2021)
		Agent-based		(Cocco et al., 2017; Cocco et al., 2019b; Ha and Lee, 2020; Lee, K. et al., 2018)
		Machine Learning		(Aggarwal, 2019; Akyildirim et al., 2020; Alessandretti et al., 2018; Alonso-Monsalve et al., 2020; Altan et al., 2019; Barnwal et al., 2019; Borges and Neves, 2020; Cai et al., 2021; Cavalli and Amoretti, 2021; ; Chevallier et al., 2021Chen, Z. et al., 2020b; Chowdhury et al., 2020; Cocco et al., 2021; Cross et al., 2021; Dutta et al., 2020; Dyhrberg, 2016; Fang, F. et al., 2021; Felizardo et al., 2019; Gidea et al., 2020; Gunay et al., 2021; Guo, H. et al., 2021; Hashish et al., 2019; Jang and Lee, 2018; Jay et al., 2020; Ji et al., 2019; Khedmati et al., 2020; Kim et al., 2021; Kim et al., 2021; Kristjanpoller and Minutolo, 2018; Kurbucz, 2019; Lahmiri and Bekiros, 2019; Lahmiri and Bekiros, 2020; Lahmiri and Bekiros, 2021; Livieris et al., 2020; Livieris et al., 2021; Maciel, 2021; Mallqui and Fernandes, 2019; Meegan et al., 2021; Metawa et al., 2021; Mostafa et al., 2021; Mudassir et al., 2020; Munim et al., 2019; Nakano et al., 2018; Othman et al., 2020; Peng et al., 2018; Phaladisailoed & Numnonda, 2018; Nguyen and Le, 2019; Poongodi et al., 2020; Poyser, 2019; Radityo et al., 2017; Saad et al., 2020; Salman and Ibrahim, 2020; Shah & Kang Zhang, 2014; Shahzad et al., 2021; Sin and Wang, 2017; Siu and Elliott, 2021; Smuts, 2019; Sun, X. et al., 2020; Sutiksno et al., 2018; Tan et al., 2021; Uras et al., 2020;

(*continued on next page*)

Table 4 (*continued*)

Feature	Blockchain typology[a]	Model category/ subcategory	References
			Uras and Ortu, 2021; Valencia et al., 2019; Velankar et al., 2018; Wu et al., 2018; Wu, 2021; Yiying and Yeze, 2019; Zhang, Z. et al., 2021)

[a] According to the management of transactions.
• Public/private (Federated), if there is an entity or central authority with the ability to decide the rights of the nodes to manage transactions.
• Permissionless/permissioned validation: depending on which nodes (all/authorised) can validate the transactions.
According to the data structure: linear-chain/tree-chain.
Any combination resulting from these features is possible.
Source: Prepared by the authors.

Table 5
Top eleven most prolific countries in research papers on blockchain modelling, and citations.

Country	Research papers							Citations						
	Rank	Markov chain	Machine Learning	Graph based	Game theoretic	Agent-based	Total	Rank	Markov chain	Graph-based	Machine Learning	Game theoretic	Agent-based	Total
China	1	53	10	18	12	0	93	3	115	46	32	75	0	268
USA	2	29	13	15	7	3	67	1	764	96	65	127	49	1.101
Italy	3	5	10	5	1	5	26	7	7	74	22	1	53	157
UK	4	8	7	5	5	0	25	2	5	83	43	166	0	297
Canada	4	10	6	6	3	0	25	6	41	85	21	27	0	174
Australia	6	6	6	6	3	0	21	4	95	23	86	21	0	225
India	7	5	6	3	1	0	15	8	36	39	15	1	0	91
South Korea	7	4	7	1	2	1	15	9	6	75	0	2	0	83
Germany	9	7	2	5	0	0	14	5	63	0	115	0	0	178
France	10	4	5	3	0	1	13	10	5	39	1	24	0	69
Others	–	35	37	21	13	2	108	–	716	746	979	304	0	2.745

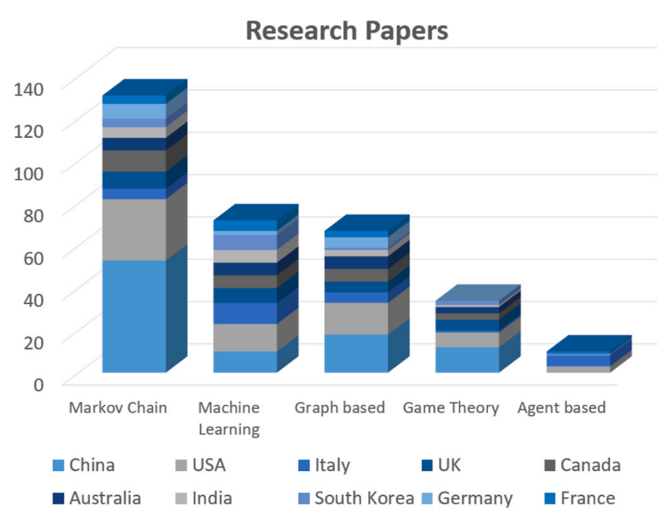


Fig. 5. Research papers by country & typology of models.

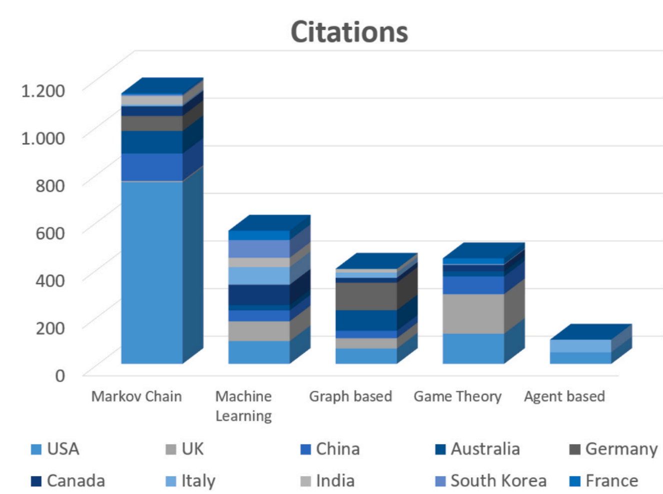


Fig. 6. Citations by country & typology of models.

research papers and citations for each country to be calculated.

China leads the ranking, followed by the USA, together representing 38% of world production; the top eleven countries represent close to 74% of the total.

On the other hand, the USA accounts for 20% of the citations, with substantial contributions from Markov Chain and Game-theoretic models respectively, but also relevant in the rest of the typologies. China is relegated to third position, and the overall contribution from the top eleven countries is reduced by up to 49%.

Figs. 5 and 6 graphically represent the previous results, including share per country and model typology. The relevant weight of the two leading countries in research papers, China and USA, can be seen, as well as the influence of the USA and Israel for citations, as mentioned above.

Markov Chain is the most productive area, involving 39% and 34% of the research papers and citations, followed by Machine Learning models, with 26% and 24% respectively. Behind the two leading models, Graph-based and Game-theoretic models present similar figures; Agent-based models are shown in the last position.

The key results are graphically summarised in Fig. 7, which includes the ranking and percentages of research papers and citations, at a global level, for the top-eleven most prolific countries.

[17] Tool: MapChart.

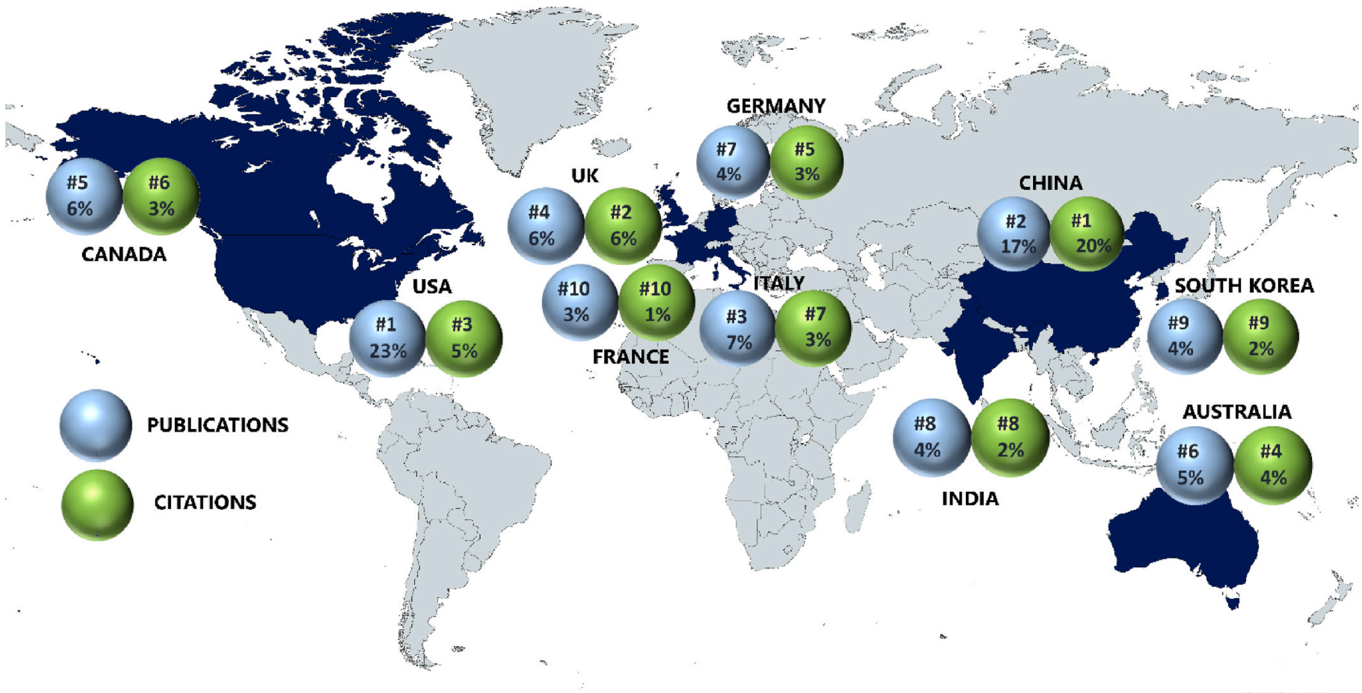


Fig. 7. Research papers and citations geographical distribution. Top eleven countries.[17].

Table 6
Research papers per year and model.

Model	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Markov Chain	0	0	0	4	3	11	21	32	44	**115**
Machine Learning	0	1	0	1	2	11	17	19	31	**82**
Graph-based	3	1	4	4	5	9	17	13	16	**72**
Game-theoretic	0	1	3	1	3	4	14	16	12	**54**
Agent-based	0	0	0	2	1	2	3	1	4	**13**
Subtotal	**3**	**3**	**7**	**12**	**14**	**37**	**72**	**81**	**107**	**336**

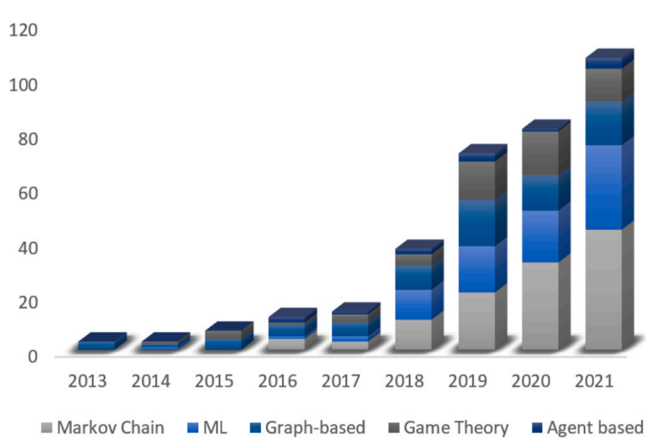


Fig. 8. Research papers per year and model. Period 2013–2021.

5.3. *Temporal analysis*

Of particular interest is the analysis of the temporal evolution of the research identified, both considering the specific progress for the different model typologies and the combined figures. Table 6 below depicts these data, covering the period from 2013, for the earliest research papers identified, until 2021.

The number of research papers has grown significantly since the first ones identified in 2013, and has particularly been intense in the last two years in the Markov Chain and Machine Learning areas (Fig. 8). Fig. 9, through 100% stacked bar charts, allows us to identify the relative weight of the different models per year. Markov Chain models accounted for 41% last year.

A combined geographical-temporal snapshot is provided in Fig. 10, which depicts the time profile of the research papers (all typologies) by country, limited to the top eleven. It can be seen that the average publication dates are quite recent in general, more for China, India, South Korea or Canada than for the USA, Italy, the UK or Australia, whereas those from Germany and Israel are older on average.

The data in Fig. 10 above are coherent with the fact that China is the most prolific country in Markov Chain research papers (Table 5, Fig. 5), which exhibit an increasing weight over time (Table 6, Fig. 8).

5.4. *Main keywords*

Table 7 lists the most used keywords in the selected articles, including both Author Keywords and Keyword-Plus[19] retrieved from VOSviewer, shown in Figs. 11 and 12 (limited number of keywords displayed). Very similar results have been found when using Citespace,

[18] The colour of the circles represents the average year of publication, its size is proportional to the number of research papers from a given country.

[19] Author Keywords are those provided by the authors, whereas Keyword-Plus are those extracted from the titles of the references.

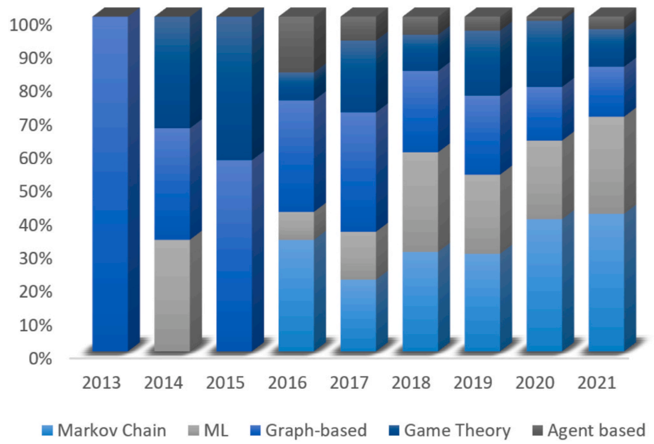


Fig. 9. Percentage of research papers by model in time.

with eight out of the top ten Author Keywords found and ranked almost in the same order. The link strength and centrality[20] figures are also included in this Table 7, respectively from VOSviewer and Citespace, which provide information on the importance of the corresponding nodes in the network.

The two most frequent Author Keywords, by far, are *Bitcoin* and *Blockchain*. It is worth focusing on the links with the other keywords; *Cryptocurrency(ies)* and terms related to the evolution of prices (*Forecasting, Machine Learning, Predictive Model,* ….) are more closely associated with *Bitcoin*; on the other hand, more generic terms such as *Security*, *Analytic Models or Internet of Things*, have a closer, but not exclusive, relationship with *Blockchain*.

Bitcoin and *Blockchain* also lead the ranking of Keyword-Plus. Some other terms, such as *Volatility*, *Economics*, or *Gold* are included in this ranking. Even though they are too general, and therefore not considered by authors to describe an article, they are regularly used in research papers, so identified as Keyword-Plus.

Previous Figs. 11 and 12 merge keywords for the different model typologies. Significant contrasts can be found when looking into the keywords of the specific model. Although *Blockchain* and *Bitcoin* remain at the top of the ranking, the second level keywords are tuned according to the specific model domain; for instance, *Queueing Theory* for Markov Chain models, *Anonymity* for Graph-Based models, *Prediction* for Machine Learning models, *Miner* for Game-Theoretic models or *Autonomous Agents* for Agent-based models. By way of example, Fig. 13 shows the Author Keywords for the research papers on Markov Chain models.

5.5. Authors and related most cited references

We observe a very low authorship concentration in the selected research papers. Just three out of more than seven hundred authors are involved in more than three papers (Marchesi, M.; Cocco, L. and Tonelli, R.), with articles written in the same areas of expertise; and just thirteen of them are involved in more than two papers. Hence, the maximum g-index (Egghe, 2006) computed by Citescape 4[21]. This small concentration degree suggests low productivity in this domain, which is not surprising considering the short period of time under evaluation, as a result of the novelty of blockchain technology. Actually, production is mainly concentrated in the last three years.

A different picture emerges when analysing the most cited authors, summarised in Fig. 14 (2876 different authors are involved) (see Fig. 15).

Nakamoto, via the original Bitcoin whitepaper (Nakamoto, 2008), is cited in a very high percentage of research papers (33%), followed by the authors of some pioneering research exploring different blockchain issues or features. Table 8 below lists the top ten most cited authors and the corresponding main cited reference (among 3971 references) and research topic.

Besides Nakamoto, it can be observed that the main referenced research from the most cited authors, which led the way in different fields, dates back for the most part to an early age of blockchain; namely five out of nine in 2013, two in 2014, one in 2015 and the last one in 2018. The generic fields addressed at that time gave rise to more specific issues, regularly assessed by means of models as shown in Table 4 above.

5.6. Sources and categories of research papers

A high diversity of sources is also observed in the papers involving models for evaluation of blockchain features, which reflects the multidisciplinary nature of this field. Table 9 summarises the main sources identified per model typology.

All the journals in the top ten ranking are integrated in the Science Citation index Expanded (SCIE), few cases of research papers in journals with other indexes have been identified (the occasional case in Social Sciences Citation Index – SSCI). The following figure depicts the categories for all the research papers included in the analysis. They are primarily categorised in *Computer Science* (and its subcategories), followed by *Engineering* and *Telecommunications*. On a third level, *Business & Economics* and *Mathematics* categories can be found.

6. Discussions and research propositions

Beyond the fields in which blockchain has been applied after its initial implementation in the field of cryptocurrencies, presented in section 1, there are still potential applications that can benefit from the use of this technology (Hughes et al., 2019), as in the innovative fields of Big Data (Deepa et al., 2022), Artificial Intelligence (Salah et al., 2019) and the Internet of Things (IoT) (Gadekallu et al., 2022; Novo, 2018; Saxena et al., 2021). On the other hand, different blockchain-based applications continue to emerge across more traditional fields like Energy (Bao et al., 2021; Wang et al., 2022), Finance (Ahluwalia et al., 2020; Kowalski et al., 2021) and Industry (Al-Jaroodi and Mohamed, 2019).

Significant research dealt with blockchain vulnerability and performance issues (Agrawal et al., 2020; Cheng et al., 2021; Conti et al., 2018b; Kushwaha et al., 2022; Li, X. et al., 2020; Sengupta et al., 2020; Zamani et al., 2020), catching up with the expanding trend of blockchain technology and its wide range of implementation alternatives. Prior SLRs pointed out the way ahead to improve blockchain security and performances (Taylor et al., 2020; Le and Hsu, 2021); our research complements them with a different approach focusing on the underlying models used in the scientific literature dealing with these issues and offering a cross-sectional analysis of these models.

Against this background, we now summarise the most relevant contributions, both from a theoretical and practical point of view, and outline the main limitations and research propositions.

6.1. Theoretical contributions

This paper makes original contributions in at least three directions. First, it covers a gap by conducting a SLR of extant research on models used to characterise blockchain performances and vulnerabilities, which have developed in a diverse theoretical and contextual setting. The review allows us to recognise and underline how the different models have been applied for the diverse blockchain-based applications and typologies, while providing information on the target parameters evaluated (Tables 1–3).

[20] Calculated by considering the number of shortest paths from all vertices to all others that pass through the node. This parameter gives an idea of the node influence on the transfer of information through the network.
[21] K = 50, N = 50, N% = 0.10, 1-year slices.

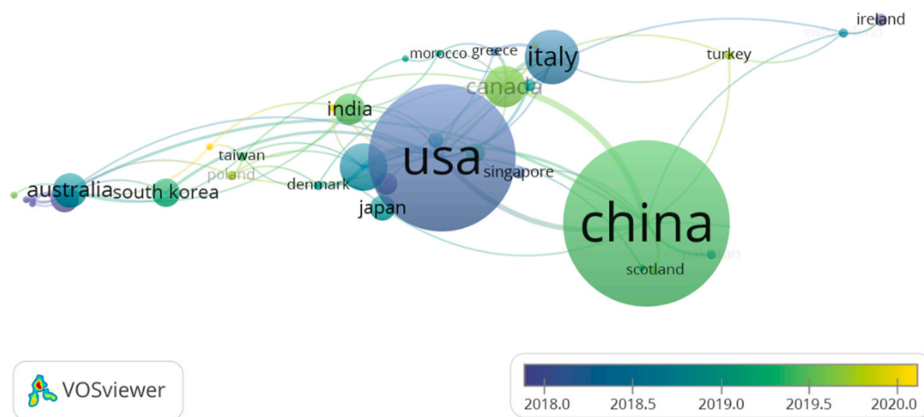


Fig. 10. Time profile of research papers from top ten countries [18].

Table 7
Main keywords.

	#	Keyword	Occurrences	Link strength[a]	Centrality (Citespace)
Author Keywords	1	Blockchain	109	100	0,28
	2	Bitcoin	69	88	0,21
	3	Cryptocurrency(ies)	43	44	0,16
	4	Machine Learning	23	35	0,08
	5	Security	14	28	0,12
	6	Ethereum	13	21	0,09
	7	Deep Learning	12	21	0,09
	8	Selfish mining	12	19	0,01
	9	Forecasting	10	16	0,02
	10	Game theory	9	11	0,01
Keyword Plus	1	Bitcoin	40	47	0,29
	2	Blockchain	34	46	0,22
	3	Internet	11	8	0,07
	4	Volatility	8	16	0,11
	5	Electronic Money	8	17	0,06
	6	Game theory	7	20	0,02
	7	Gold	7	11	0,01
	8	Neural Network	7	8	0,04
	9	Security	7	6	0,02
	10	Economics	6	13	0,01

[a] The link strength represents the number of references an item, or keyword in this case, has in common with others (that is, both items occur at the same time).

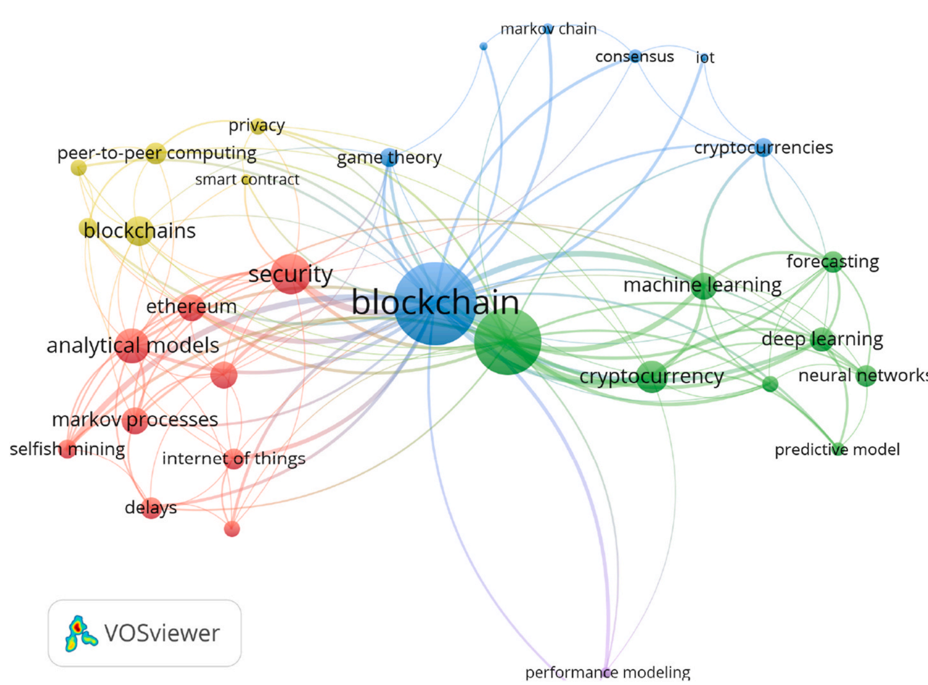


Fig. 11. Co-occurrence author keywords.

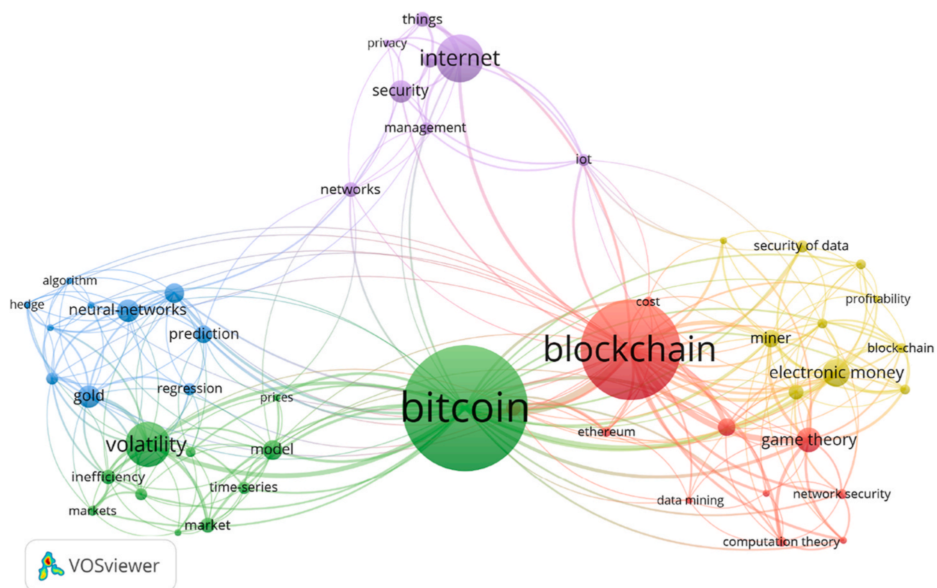


Fig. 12. Co-occurrence keyword-plus.

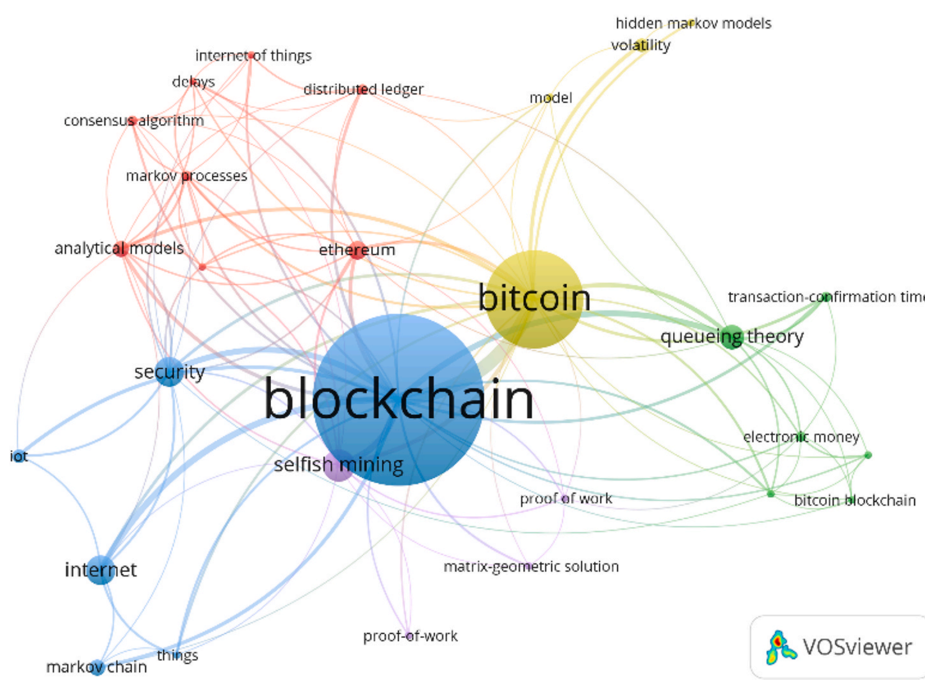


Fig. 13. Co-occurrence Keywords (both Author Keywords and Keyword-Plus) for Markov Chain research papers.

Second, our analysis structures the models used in the selected research proposing an inclusive co-classification, thus allowing us to identify emerging patterns in the application of models across different but interrelated research fields, in line with the suggestions by (Shams et al., 2020). The proposed classification provides valuable information on the most suitable mathematical tools for the analysis of the common performance and vulnerability issues, while structuring the information on how these issues have been previously approached depending on the typology of the host blockchain applications. This information is summarised in Table 4, which links the target appraised topics to the corresponding blockchain typology and distinctive applications, showing the model category and subcategory and listing the set of studies identified in each area. This summary reveals that some kind of models (typically Markov chain mathematical models) are applied transversally whatever the underlying blockchain typology analysed, while some other are mostly used to evaluate specific topics (for instance Machine Learning to assess the price evolution of cryptocurrencies). Overall, this proves to be a useful source of information for future analyses of analogous issues.

Third, the bibliometric analysis provides complementary information on the literature, showing how the volume of research has increased rapidly in recent years in this area and a high degree of multidisciplinary nature and heterogeneity in the way the models have been applied. It should be noted that there has been an evolution of the models used to analysed blockchain vulnerability and performance issues, with certain models becoming more prominent over time, in parallel with the evolution in the way blockchain technology is applied since its inception.

Finally, this study advances our understanding of the complexity of

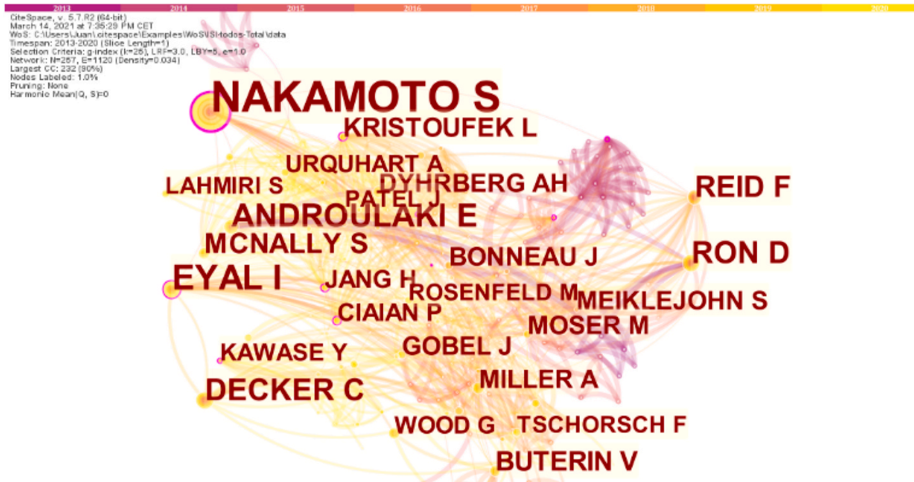


Fig. 14. Co-citation, cited authors.

Fig. 15. Journal's categories.

Table 8
Top ten most cited authors and main cited reference.

Author	Nb. of citations	Main cited reference	Research topic
Nakamoto, S.	104	Nakamoto (2008)	Blockchain white paper
Eyal, I.	48	Eyal and Sirer (2014)	Vulnerability of mining process
Androulaki, E.	28	Androulaki et al. (2013)	Bitcoin users' privacy
Ron, D.	24	Ron and Shamir (2013)	Bitcoin transaction graph
Decker, C.	21	Decker and Wattenhofert (2013)	Information propagation in the Bitcoin network
Reid, F.	20	Reid and Harrigan (2013)	Anonymity in Bitcoin
Kristoufek, I.	19	Kristoufek (2015)	Bitcoin price drivers
Buterin, V.	19	Buterin (2014)	Ethereum white paper
McNally, L.	16	McNally et al. (2018)	Bitcoin price evolution
Meiklejohn, S.	14	Meiklejohn et al. (2013)	Anonymity in Bitcoin

this research domain, in an attempt to enhance our knowledge in a context of fast-growing development of blockchain-based applications. While providing a general overview, it supports further studies focused on characterising specific issues linked to novel blockchain implementations, enabling the selection of endorsed models according to the particularities of the target application.

6.2. Implication for practice

While blockchain technology offers a number of distinct benefits when compared with traditional solutions based on centralised management (Golosova and Romanovs, 2018; Yuan, Y. & Wang, 2018), it exhibits several limitations identified in the literature (Coyne and McMickle, 2017; Hawlitschek et al., 2020; Hughes et al., 2019; Olnes et al., 2017). The consequences of the performance and vulnerability issues have already been significant (Alkhalifah et al., 2019; Baqer et al., 2016; Pierro and Rocha, 2019; Shanaev et al., 2020; Sokolov, 2021; Vasek et al., 2014), and are expected to go hand by hand with the increasing use of blockchain technology in different areas beyond cryptocurrencies, which is also accompanied by the deployment of a variety of blockchain typologies (Wang, W. et al., 2019; Zheng et al., 2018b). In this context the findings of this research have twofold practical implications:

On the one hand, in the design of new blockchain-based applications. The risks and lack of efficiency in novel solutions needs to be assessed before implementation, in order to avoid or minimize the effects of deliberate attacks or accidental stressful situations. In this regard this research provides valuable information on the most appropriate models

Table 9
Top ten sources and related categories of research papers.

Journal	Number of research papers					Journal category and last impact factor (JCR)		
	Markov Chain	Graph-based	Machine Learning	Game-theory	Agent-based	Category		Quartile
IEEE Access	3	1	2	7	1	Computer Science, Information Systems	SCIE	Q1
						Engineering, Electrical & Electronic	SCIE	Q1
						Telecommunications	SCIE	Q2
Lecture notes in computer science	3	3	–	4	–	Computer Science, Theory & Methods	SCIE	Q4
Financial Cryptography and data security	1	2	–	3	–	Not integrated in JCR	–	–
Computers and Security	4	–	–	–	–	Computer Science, Information Systems	SCIE	Q2
Economics Letters	–	2	1	1	–	Economics	SCIE	Q2
Applied Soft Computing	–	–	3	–	–	Computer Science, Artificial Intelligence	SCIE	Q1
						Computer Science, Interdisciplinary apps.	SCIE	Q1
Chaos solitons & fractals	–	–	3	–	–	Physics, multidisciplinary	SCIE	Q1
						Mathematics, Interdisciplinary applications	SCIE	Q1
						Physics, Mathematical	SCIE	Q1
Communications in computer and information science	1	2	–	–	–	Not integrated in JCR	–	–
Expert systems with applications	–	–	3	–	–	Computer Science, Artificial Intelligence	SCIE	Q1
						Operations Research & Management Science	SCIE	Q1
						Engineering, Electrical & Electronic	SCIE	Q1
Physica a-statistical mechanics and its applications	–	–	3	–	–	Physics, Multidisciplinary	SCIE	Q2
Stochastic Models	3	–	–	–	–	Statistics and & Probability	SCIE	Q4

for such assessment, depending on the planned typology and the target parameters of the specific application under evaluation, together with the most common features analysed so far (summarised in section 4).

On the other hand, our study provides information on the underlying models to be used for the measurement of performance metrics through KPIs (Key Performance Indicators) in existing blockchain-based applications, and provides information on the parameters assessed in previous studies through different models, which can help in better defining such KPIs framework. Different examples of KPIs evaluation in blockchain-based applications can be found in the literature (Casino et al., 2019b; Geissler et al., 2019a; Raval et al., 2022). This kind of assessments support the decision making on the evolutions to be implemented, if necessary, to improve robustness or efficiency. In this sense, it is important to note that it is common for blockchain–based applications to evolve in order to circumvent identified problems.[22]

6.3. Limitations and future research directions

Several limitations are acknowledged in this study. First, the paper selection process may have been biased by the authors' subjective evaluations. A second limitation, somehow interrelated to the previous one, is that the source databases for the searches are WoS and Scopus. The fact of having applied best practices in the conduct of the SLR (as detailed in section 2) restricts the effects of these two limitations. On the other hand, both databases are generally accepted as the most comprehensive data sources for journal selection, research evaluation and bibliometric analyses (Pranckute, 2021). Finally, the bibliometric analysis is carried out on the limited set of selected references obtained in the previous literature review, so that any bias in that phase is carried over to this analysis.

At any event, perhaps the main limitation of the study is that the proposed co-classification of models can again be influenced by the author's subjective interpretation. In order to deal with this issue, we have analysed the classifications proposed by other surveys addressing the models used to analyse blockchain features (summarised in the introductory paragraph of section 3). However, it is acknowledged that alternative classifications are possible, and that some research studies are likely to fall into different model typologies (as also detailed in section 3).

Notwithstanding the current limitations, the study presents an innovative framework for guiding both research and practice in the development of blockchain solutions. In particular, we encourage future research in two main directions. First, the specific study of those models more suitable for blockchain typologies specifically applicable to innovative technologies (namely tree-chain), such as IoT. Second, focusing on several uncovered specific parameters and relevant blockchain subdomains, for instance the economic significance of transaction fees and related market structures,[23] or focusing on specific use of blockchain to current topical issues (ie. blockchain has been recently proposed in support of Covid-19 pandemic (Nandi et al., 2021; Xu et al., 2021)).

[22] Some relevant examples:Bitcoin SegWit Protocol 24th August 2017, freeing up space to add more transactions into the blocks. Most recently Taproot Protocol 12th November 2021, aiming to solve problems with privacy and efficiency.- Bitcoin core 0.22, issued in September 2021, includes various bug fixes and performance improvements (source: https://bitcoincore.org/en/releases/22.0/).- Creation of Ethereum Classic (hard fork) 20th July 2016, following a successful cyberattack that stole nearly $50 million worth of Ethereum.

[23] It should be noted that the economic significance of transaction fees has remained rather marginal so far, but it is expected to gain momentum in the near future due to several factors (namely the inflationary policy implemented by many cryptocurrencies, the need to compensate blockchain agents in exchange for providing resources and services, and their weight under high transactions under the throughput regime.

7. Conclusions

Blockchain-based applications have shown their ability to improve the efficiency of managerial and operational processes, being increasingly applied in different areas such as accounting, finance, healthcare, insurance and operations, and attracting interdisciplinary interest from the scientific community. Accordingly, a variety of analytical models are being used to analyse performances and vulnerabilities of different blockchain typologies (public/private, permissionless/permissioned, linear-/tree-chain) with different consensus protocols and reward policies for participants. After thorough search and review of the research papers implementing these models, we propose an inclusive classification into five categories: Markov Chain, Graph-based, Machine Learning, Game-Theoretic and Agent-based models.

Each of the models in these categories have been applied in a heterogeneous way, with numerous variations or subcategories depending on the specific research targets. The overall picture, resulting from cross-checking the main blockchain issues (split into vulnerabilities and performances) and the models identified, shows that a variety of them are normally employed to evaluate each issue. Nonetheless a certain degree of specialisation is observed, meaning that several models have been used to a greater extent than others for the analysis of some specific topic, for instance: generic Markov Chains for withholding strategies, Birth-Death Markov Chains for transaction confirmation times and mempool size, Graph-based models for allocation of addresses and anonymity, Game-theoretic models for creation of mining pools, Agent-based models for miners' welfare optimization and Machine Learning price trends of cryptocurrencies.

The bibliometric analysis conducted to the research papers previously identified and categorised offers a complementary view and valuable information on the status and trends to date. This analysis shows a high concentration in publishing countries, with China and USA leading world production (35% together); the top ten publishing countries also gather high percentages of citations. It is worth noting that the number of research papers has grown significantly in the last five years; this growth has been particularly intense in the Markov Chain field. A high level of multidisciplinary nature is observed, a reflection of the low concentration of authors and sources.

The classification and assessment of models performed in this research provide support for selecting the most suitable ones in future specific analysis for a given feature of interest, or for determining the right blockchain typology to be implemented for a given blockchain application.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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