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To blockchain or not to blockchain, these are the questions

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To blockchain or not to blockchain, these are the questions: A structured analysis of blockchain decision schemes

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ABSTRACT

Blockchain technology has garnered significant attention in recent years, prompting researchers, entrepreneurs, and businesses to seek viable ways to validate the application of blockchain within their specific use cases. Blockchain decision schemes (BDSs) can assist in this decision-making process, offering a potentially more cost-effective alternative to domain experts.

Flow chart blockchain decision schemes (FC-BDSs) constitute 77.5% of all BDSs, and this paper systematically reviews these by standardising and aggregating the most prominent schemes into an open-source package. Central to our approach is the definition of an FC-BDS as a directed acyclic graph (DAG). Upon this mathematical foundation, we engage in a meticulous exploration and analysis of various elements within FC-BDSs.

We present an in-depth analysis of the structure of FC-BDSs, exploring features such as vertex count, question categorisation, and outcome distribution. Notably, the majority of FC-BDS questions ask about data and participation (34.1%) above other domains such as security (18.6%) and performance (10.8%). Observations regarding outcomes shows an overall balance in suggesting the usage or avoidance of blockchains; however, there is a discrepancy between the average questions required to reach these outcomes, revealing potential biases within schemes.

Further analysis using similarity metrics (based on both structural and semantic features) identifies significant overlaps between FC-BDSs, with some schemes showing over 90% similarity. These observations could be attributed to a more informal publishing routine for FC-BDSs, and help trace the evolution of FC-BDSs over time.

The insights drawn from this research provide valuable insights into the broader BDSs landscape, and stand to make significant strides towards the standardisation of FC-BDSs, thereby promoting a more coherent and effective utilisation of these decision-making tools in the realm of blockchain technology application.

1. Introduction

1.1. Background

Blockchain technology has gained significant attention in recent years, showing promise in various industries through its potential to improve transparency, security, and efficiency. Fig. 1 depicts the frequency of Google searches for the term "blockchain" from January 2009 (the Bitcoin genesis block) to July 2023. Although prominent spikes of interest are observed during the late 2017, 2021, and 2022 periods, a decline in interest can be discerned after 2022. However, a steady level of interest in the term continues to persist. In light of this interest, businesses, entrepreneurs, and other potential blockchain users face the decision whether or not to adopt this technology for their specific use cases. To aid in this decision-making process, numerous BDSs have been developed to provide a structured and comprehensive approach to making a selection.

BDSs exist to help potential blockchain users objectively evaluate the appropriateness and feasibility of implementing blockchain technology within their domain. They reduce costs and reliance on domain-specific experts by offering an easily applicable method to make informed decisions. By using a BDS, users can efficiently determine whether it is advantageous to proceed with blockchain-based solutions or seek alternative options.

There are three general categories of BDS in existence:

- artificial intelligence blockchain decision schemes (AI-BDSs);
- FC-BDSs;
- scored blockchain decision schemes (S-BDSs).

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Acronyms

AI	artificial intelligence
AI-BDS	artificial intelligence blockchain decision scheme
BDS	blockchain decision scheme
CSV	comma-separated values
DAG	directed acyclic graph
DSA	domain score array
FC-BDS	flow chart blockchain decision scheme
GenAI	generative artificial intelligence
ISA	individual score array
KDE	kernel density estimate
MoBS	Model of Blockchain Suitability
NLP	natural language processing
S-BDS	scored blockchain decision scheme

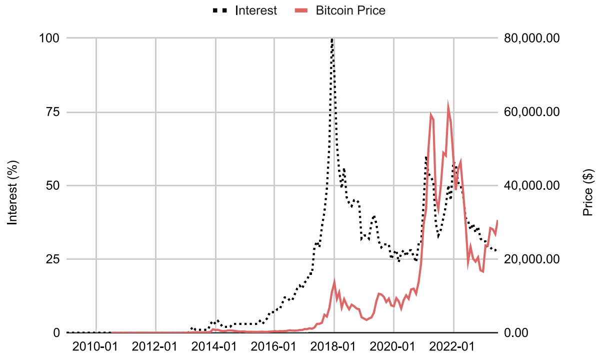

Fig. 1. Interest in the term “blockchain” on Google Search alongside the price of Bitcoin.

FC-BDSs are typically presented as flowcharts, while S-BDSs, often formulated as questionnaires, return a score providing user feedback. AI-BDSs, on the other hand, leverage artificial intelligence (AI) techniques to determine the appropriateness of blockchain usage.

Table 1 catalogues all relevant BDSs that currently exist in the field. The inception of interest in BDSs can be traced back to November 2015 [1], and since then, the number of BDSs has grown steadily. Fig. 2 depicts this growth and presents a chronological representation of the increase in the number of BDSs.

Fig. 2(a) provides a breakdown of BDS quantities by type over time, with AI-BDSs, FC-BDSs, and S-BDSs distinctly charted. It is evident from this representation that FC-BDSs constitute the majority of all BDSs (77.5%), followed by S-BDSs (20%), and AI-BDSs comprising the smallest group (2.5%). We observe the most notable surge in growth occurring in 2017, a period marked by an intensified wave of interest in blockchain technology due to the sharp rise in the price of Bitcoin.

Fig. 2(b), on the other hand, represents a separated count of published[1] versus unpublished BDSs over the same period. It is clear that the majority of early BDSs were unpublished, likely due to an initial spike in interest and the necessity for efficient turnarounds. However, over time, the balance between unpublished and published BDSs has levelled out to almost equal proportions; 47.5% remain unpublished while 52.5% have been published. This evolution may be associated with the considerable time required to carry out peer review processes and other official publication procedures.

Table 1
A list of prominent BDSs, illustrating unpublished and published schemes.

Model	Type	Reference	Date
Greenspan	S	[1]	11-2015
Lewis	FC	[2]	01-2016
Birch	FC	[3]	06-2016
Gardner	FC	[4]	07-2016
PwC	S	[5]	07-2016
IBM	FC	[4]	08-2016
Meunier	S	[4]	08-2016
Nandwani	FC	[6]	08-2016
Suichies	FC	[7]	09-2016
Quindazzi	FC	[8]	10-2016
Verslype	FC	[9]	01-2017
Lin (Social)	FC	[10]	07-2017
Lin (Technical)	FC	[10]	07-2017
Mueller	FC	[11]	07-2017
Maull	FC	[12]	09-2017
Peck	FC	[13]	10-2017
Broadcom	FC	[14]	11-2017
Hyperledger	FC	[15]	11-2017
Lixar	FC	[16]	11-2017
Lo	FC	[17]	11-2017
VerifiedICOs	FC	[18]	11-2017
Klein	S	[19]	02-2018
Pahl	FC	[20]	03-2018
BestofICOs	FC	[21]	04-2018
Mulligan	FC	[22]	04-2018
Lapointe	S	[23]	06-2018
Wüst	FC	[24]	06-2018
Chowdhury	FC	[25]	09-2018
Koens	FC	[26]	09-2018
Casino	S	[27]	03-2019
Pedersen	FC	[28]	06-2019
Yaga	FC	[29]	06-2019
Gourisetti	S	[30]	09-2019
CompTIA	FC	[31]	11-2019
Schletz	FC	[32]	05-2020
Preece	S	[33]	09-2020
Abdo	AI	[34]	10-2020
El Madhoun	FC	[35]	11-2020
Hassija	FC	[36]	07-2021
Chand	FC	[37]	02-2022

1.1.1. *Artificial Intelligence Blockchain Decision Schemes*

Currently, only one AI-BDSs exists. Abdo and Zeadally [34] identify a fundamental limitation in existing schemes, stating that "all existing schemes share a main drawback that the user is limited to a predefined set of answers without having the capacity to fine-grain his preferences in addition to per scheme-specific drawbacks". In response to these drawbacks, their paper proposes the introduction of a neural network-based decision scheme. This innovative approach offers users an advanced decision-support tool, enabling them to detail proportional weights between characteristics. This innovation unlocks potential to resolve the drawbacks inherent to other existing schemes.

The notion of using generative artificial intelligence (GenAI) in decision-making processes poses tremendous potential. Yet, to date, this concept has not been exhaustively explored. The ongoing lack of in-depth scrutiny in this area presents numerous untapped opportunities for innovation and refinement within the domain of BDSs. Our investigations and insights concerning the application of GenAI and its role in shaping future BDSs decision-making processes will be further elaborated in Section 7.2 of this paper.

1.1.2. *Flow chart blockchain decision schemes*

Among BDSs, FC-BDSs stand out as the predominant category due to their intuitive visual representation and step-by-step nature, which simplifies the decision-making process for users.

What is notable about many of these FC-BDSs is their unconventional publication platforms. Instead of traditional academic journals,

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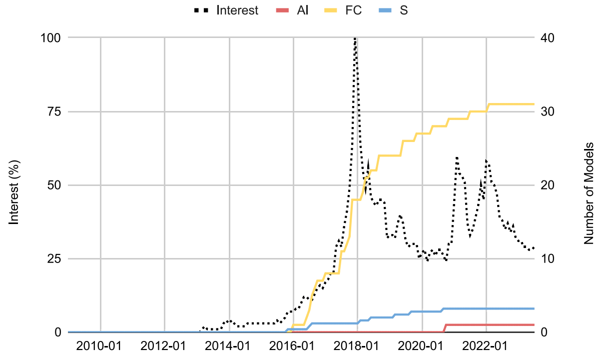
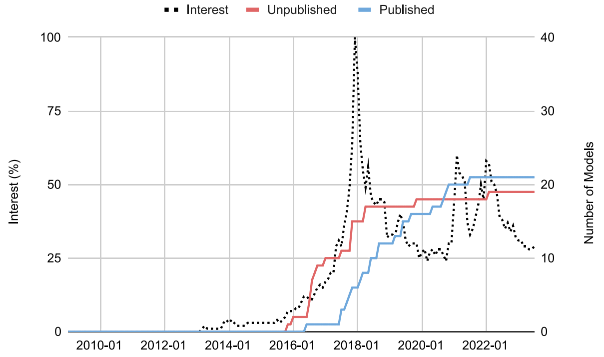
[1] We define published as a BDSs that has undergone a form of peer review.



(a) Number of BDSs per type over time.



(b) Number of published and unpublished BDSs over time.

Fig. 2. Number of BDSs over time.

they primarily feature on websites [2,9,14–16,21,31,37,38], social media platforms such as LinkedIn [6] and X (formerly Twitter) [8,39], and blogging platforms like Medium [4,7,11,18]. Birch et al. [3] is credited with the pioneering academic publication of an FC-BDS.

Among the academic contributions, the work by Wust and Gervais [24] is one of the most frequently cited. Their paper – suitably titled "Do You Need a Blockchain" – traverses into a deep exploration of the necessity of blockchain. They analyse the properties of different blockchain types (i.e., permissioned and permissionless), contrasting these with centrally managed databases. With three use cases including supply chain management, interbank and international payments, and decentralised autonomous organisations, they argue the need and type of blockchain appropriate for specific applications.

It is vital to note that some FC-BDSs bear striking similarities to others, either by republication, minor amendment, or in possibly in certain instances, plagiarism. This aspect will be further examined in Section 6 of this paper, where we explore scheme similarities.

1.1.3. Scored Blockchain Decision Schemes

One of the most comprehensive collections of BDSs is curated by Meunier [4]. While simultaneously maintaining an up-to-date Medium article with an array of FC-BDSs, Meunier also contributes their own S-BDS to the field, condensing their own findings of analysing FC-BDSs into a single scheme. This scheme is towards the more simplistic end of S-BDSs, asking users to tick checkboxes, and tallying the results. A higher score indicates a higher likelihood that blockchain is a useful technology for the use case.

Preece [33] identifies potential biases inherent in FC-BDSs stemming from their structural and flow characteristics. To counteract these biases, Preece [33] introduces the Model of Blockchain Suitability (MoBS). This model prompts the user with ten questions, each presenting a set of optional answers. Upon the user's input, MoBS compiles two different score arrays. The first one, the individual score array (ISA), generates three scores out of 100, representing a percentage indicative of the suitability of private blockchain, public blockchain, and alternative technologies relative to the user's specific response. The second, the domain score array (DSA), offers three similar scores that reflect how well-suited the three options are within the larger domain under consideration.

In a separate development, Gourisetti et al. [30] puts forth a S-BDS that is systematically compartmentalised into five domains, 18 subdomains, and approximately 100 controls. This comprehensive S-BDS is engineered to digest elaborate user requirements and to execute a weighted evaluation rooted in mathematical constructs, thus ascertaining the most fitting combination of blockchain for a given application. In addition to detailing the core logical structure of the S-BDS, the paper demonstrates the effectiveness of the S-BDS by elucidating its operation through two practical use cases.

1.1.4. Previous analysis

Koens and Poll [26] offers a comprehensive analysis of both FC-BDSs and S-BDSs. Their methodology evaluates the number of end states and the outcomes suggested by different FC-BDSs (i.e. use blockchain, avoid blockchain, or utilise specific technologies within these categories). Furthermore, they highlight inconsistencies among various schemes and propose a new scheme based on their findings. Our methodological framework draws inspiration from this approach, with the addition of a focus on structures and semantics from a computational perspective.

1.2. Aims and objectives

As previously identified, FC-BDSs make up the majority of schemes. Despite the abundance of FC-BDSs available, there remains a noticeable lack of an aggregated source that compiles these models in a single and easily accessible location. This paper addresses this gap by introducing an open-source Python package that consolidates various FC-BDSs into a single cohesive resource. Additionally, this article includes a comparative analysis of FC-BDSs to evaluate their robustness and relative effectiveness. By unifying various FC-BDSs models in one place and performing a thorough evaluation of their performance, this article offers a valuable resource to researchers and organisations looking at blockchain technology and BDSs. The integration of AI-BDSs and S-BDSs is beyond the scope of this paper, and remains a potential area of future research.

1.3. Paper structure

This paper is divided into seven sections (including this introduction, Section 1):

- Section 2 details our methodology for standardising FC-BDSs into a singular, comprehensive definition (both qualitatively and quantitatively), providing a uniform framework for evaluating and comparing different FC-BDSs;
- Section 3 discusses how we aggregate all FC-BDSs under the aforementioned standardisation into an open-source Python package, enabling simplified accessibility and facilitating a wider usage of these decision schemes within the developer community;
- Section 4 delves into a detailed analysis of the vertices of FC-BDSs, comprehensively discussing the relevance and implications of the outcomes derived from this analysis;
- Section 5 provides a thorough analysis of the paths of FC-BDSs, exploring the relevancy of the results and highlighting the pivotal role of paths within the decision-making process of the FC-BDSs;
- Section 6 offers a comparative study between all the FC-BDSs, shedding light on the similarities and differences between the various schemes, and ultimately contributing to our understanding of the wider landscape of BDSs;

- Section 7 concludes the paper by reviewing the results and discussing their broader implications, and suggesting potential directions for future research, offering a prospectus for continued work in this compelling and rapidly developing area.

2. Standardisation: Defining a Flow Chart Blockchain Decision Scheme

An FC-BDS is an effective visual tool that facilitates decision-making by providing users with a structured, sequential, and logical set of questions to determine the suitability of blockchain for their use case. However, existing FC-BDSs have been developed separately without any standardisation. To proceed with aggregation and analysis, we must agree on a structural definition of a FC-BDS. For the interest of readers of multiple fields who may find interest in this paper, we provide both a qualitative and mathematical definition of FC-BDSs in Sections 2.1 and 2.2 respectively.

2.1. Qualitative definition

Consider Fig. 3. Here we see a toy FC-BDS consisting of a variety of elements: five vertices (three question vertices and two outcome vertices), and six edges. The definitions for these elements are as follows:

Vertex An element within the flow chart that represents a question or outcome. There are two types of vertex: question vertices and outcome vertices.

Question vertex A question presented to the user.

Outcome vertex A vertex that terminates the flow chart and makes a suggestion to the user, either indicating the adoption or rejection of blockchain technology, or, in some cases, specifying which types of blockchain are most suitable for the user's objectives.

Edges A connection between vertices within a FC-BDS, denoting the relationship or transition between question vertices and outcome vertices

At each question vertex, the user must decide which edge more appropriately aligns with their response. Upon making a decision, the user will be instructed to another question vertex to continue the process, or an outcome vertex to finish the process and reach a suggestion from the FC-BDS. By navigating through the vertices via the edges, users can make informed decisions on the appropriate use of blockchain technology within their projects.

2.2. Mathematical definition

An FC-BDS can be mathematically represented as a DAG. A DAG is a graph that has a finite number of vertices and edges, with each edge directed from one vertex to another. The graph must be acyclic, which means that there are no cycles within the graph, ensuring that users eventually reach an outcome. Formally, an FC-BDS is a DAG G such that

$$G = (V, E), \tag{1}$$

where V is the finite set of question vertices $Q = \{q_1, q_2, \dots, q_n\}$ and outcome vertices $O = \{o_1, o_2, \dots, o_n\}$ such that

$$V = (Q, O), \tag{2}$$

and E is a finite set of directed edges such that

$$E = (v_i, v_j) | v_i, v_j \in V \wedge i \neq j. \tag{3}$$

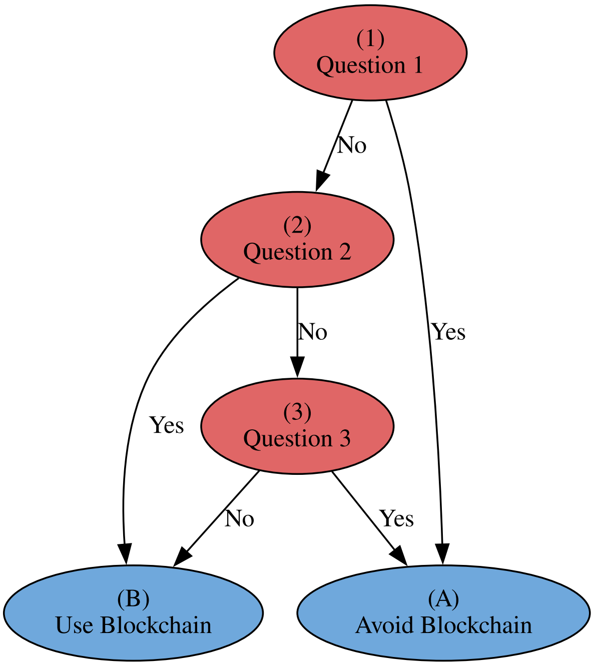


Fig. 3. A toy FC-BDS, with question vertices, outcome vertices, and edges connected them.

3. Aggregation: An open-source package

In order to aggregate the FC-BDSs into a single source for usage and analysis, we built an open-source package in the Python programming language. Section 3.1 offers a concise overview of the Python package architecture. Subsequently, Section 3.2 delves into the construction process of the package from a CSV file and elucidates how question vertices are classified into respective categories. Finally, Section 3.3 provides a summary of the topics covered.

3.1. Architecture

The architecture of the package is simplistic, with two main classes, described as follows:

`FlowChart` Each FC-BDS is an instance of the `FlowChart` class. Within this class, the package creates two representations of the FC-BDS:

Tabular version This representation utilises the Pandas library and stores the FC-BDS data as a `DataFrame`.

Graph version This representation of the FC-BDS is created using the NetworkX library, which stores the FC-BDS as a `DiGraph`.

`FlowChartCollection` This class stores the entire collection of FC-BDS objects, facilitating easier aggregated analysis by providing utility methods for operating on the set of `FlowChart` instances.

3.2. Process

The process of building the package consists of three steps:

1. Ingesting a comma-separated values (CSV) file detailing the structure and content of each FC-BDS.
   Table 2 provides an example CSV construction for the toy example of Fig. 3. Each row of the CSV describes one vertex of a FC-BDS. There are eight columns:

Table 2
An example CSV file, representing the toy FC-BDS in Fig. 3.

Blockchain decision scheme	Vertex type	Vertex ID	Vertex label	Edge A label	Edge A Next Vertex ID	Edge B label	Edge B Next Vertex ID
Toy	Question	1	Question 1	Yes	A	No	2
Toy	Question	2	Question 2	Yes	B	No	3
Toy	Question	3	Question 3	Yes	A	No	B
Toy	Outcome	A	Avoid Blockchain	–	–	–	–
Toy	Outcome	B	Use Blockchain	–	–	–	–

Blockchain Decision Scheme The name of the FC-BDS.

Vertex Type Whether the vertex is a question vertex or an outcome vertex.

Vertex ID The unique identifier for the vertex. Typically, this is a numeric value for a question vertex, and a letter for an outcome vertex.

Vertex Label The label associated with the vertex. Disregarding the toy example, this value is expected to be in the form of a question or statement e.g. “Do you require transparency?”

Edge *x* Label The label of the first edge from the question vertex. This will usually take the value of “yes” or “no”, but may be more verbose depending on the question vertex label.

Edge *x* Next Vertex ID The vertex ID of the vertex that leads to this edge.

We note that although most vertices have two edges, some FC-BDSs offer vertices that have three edges. As such, there is the possibility to have columns for up to three *Edge Label* and *Edge Next Vertex ID*.

2. Classifying the question vertices labels into attributes.
   Each question vertex contains a label that represents the question or statement that the user needs to respond to. For this analysis, we sought to classify the labels according to the five domains proposed by Gourisetti et al. [30], which Table 3 describes. There are 92 pre-classified questions from Gourisetti et al. [30].
   To achieve this classification, we leverage the power of natural language processing (NLP) using the `SentenceTransformer` class from the HuggingFace library. The process is as follows:
   (a) Encode both the question vertices labels and the questions from Gourisetti et al. [30]. `SentenceTransformer`, based on the `bert-base-nli-mean-tokens` model, was used to generate embeddings for both the question vertex labels and the Gourisetti et al. [30] questions.
   (b) Compute a similarity matrix between each question vertex and each Gourisetti et al. [30] question. The `cosine_similarity` function from the sklearn library was then applied to compute the similarity between the generated embeddings, returning a score between 0 and 1, where 1 is identical.
   (c) Per question vertex, extract the domain of the Gourisetti et al. [30] question with the greatest similarity.
3. Constructing the `FlowChart` instances.

3.3. Summary

This Python package provides both tabular and graphical representations of each FC-BDS, allowing users to access, interact with, and analyse the models in a streamlined and standardised manner. Its open-source nature encourages continuous development and improvement, fostering a collaborative environment for researchers and businesses alike. By simplifying the analysis and implementation of FC-BDSs, this package effectively guides users in making informed decisions regarding the adoption and selection of suitable blockchain technologies, serving as a valuable resource for businesses and researchers aiming to leverage and build upon existing models and streamline decision-making processes.

Table 3
The attributes and domains from Gourisetti et al. [30].

Domain	Attributes	Questions
Data and Participation	Data Attributes	5
	Authority Nodes	2
	Readers and Writers	5
	Reader and Writer Characteristics	5
		17
Performance and Efficiency	System Performance	5
	Expandability Attributes	5
	Market Design	5
		15
Security	Governance	3
	Security Activities	6
	Access Control	4
		13
Technical Attributes	Codebase and Networks	8
	Smart Contracts	3
	Transaction Constraints	5
	Transaction Processes	6
	Miners and Consensus	13
		35
Trust Parameters	Visibility	4
	Integrity	3
	Validation	5
		12
		92

4. Vertex analysis

This section offers an in-depth analysis of the vertices found within the FC-BDSs, examining various aspects of their structure and composition. Section 4.1 delves into vertex counts by exploring the number of question vertices and outcome vertices present in each model and using box plots to display the median and percentiles, providing information on their distribution. In Section 4.2, the focus shifts to the composition of the domain of the question vertex, assessing how the question vertices in each model are classified according to the domains outlined in Table 3, and presenting an aggregated view of all the models combined for a comprehensive perspective. Section 4.3 introduces a word cloud as a text visualisation tool to illustrate the terms found most frequently within the question vertex labels, helping to understand the major themes and concerns that influence blockchain decision-making processes. Finally, Section 4.4 summarises the findings.

4.1. Vertex counts

The vertex count $|V|$ is the total number of vertices in the FC-BDS. Fig. 4 presents a count plot for both question vertices and outcome

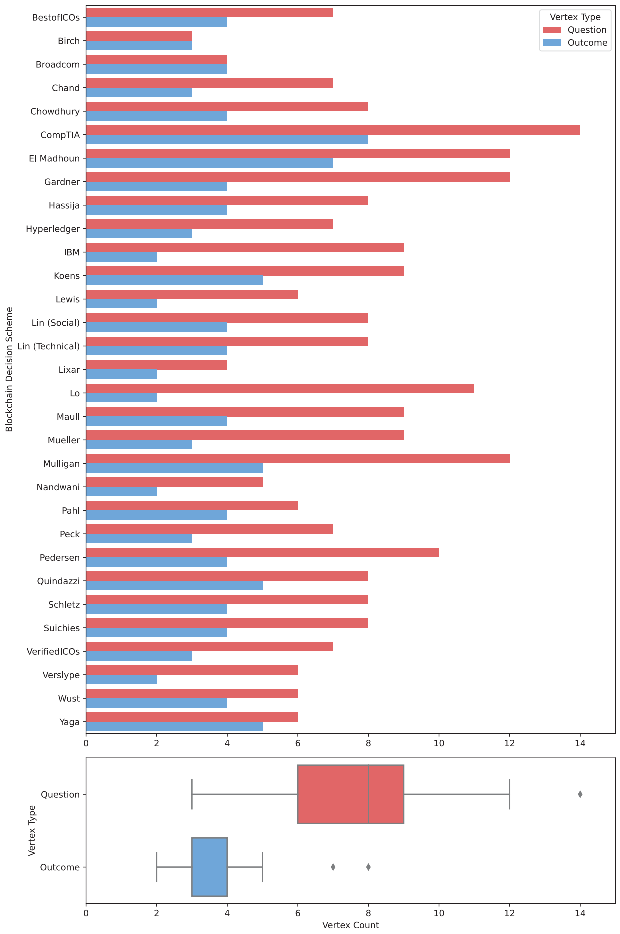


Fig. 4. Count plot for question vertices and outcome vertices against all FC-BDSs.

vertices across all FC-BDSs, illustrating that every model possesses a larger or equal number of question vertices to outcome vertices, as anticipated. Fig. 4 also provides two box plots that aggregates this data for all models, categorising them by question vertices and outcome vertices. This data reveals that the average number of question and outcomes vertices is eight and four respectively, indicating a range of questions and potential outcomes beyond just binary options like “avoid blockchain” and “use blockchain”. These diverse outcomes and their implications are further explored in Section 5.

4.2. Question vertex domain composition

Fig. 5 displays a bar plot of the question vertex domain composition per FC-BDS. The pie plot complements this by aggregating question vertices from all models to showcase the overall composition. The data reveals that the *Data and Participation* category constitutes more than a third of all question vertices, followed by *Technical Attributes*, *Security*, *Performance and Efficiency*, and *Trust Parameters*. These results imply that the most critical factors in blockchain decision-making processes gravitate around *Data and Participation*, as well as *Technical Attributes*, emphasising the importance of these domains when designing and evaluating FC-BDS models. This information also signifies potential areas of focus for future research and development in blockchain technology to address users’ priorities and concerns effectively.

4.3. Question vertex label wordcloud

Fig. 6 presents a word cloud containing the cleaned text (with stopwords removed) from the labels of all question vertices, offering a visual representation of their most frequently occurring words. The term “need” stands out as the most prominent, followed by other notable keywords such as “blockchain”, “transaction”, “data”, and “public”. These findings imply that the decision-making processes in the context of blockchain technology revolve around the identification of specific needs, types of data and transactions, and whether or not to utilise public blockchains. Consequently, this highlights the importance of understanding the specific requirements, data handling, and privacy preferences of users when designing and evaluating blockchain decision models or when implementing blockchain-based systems.

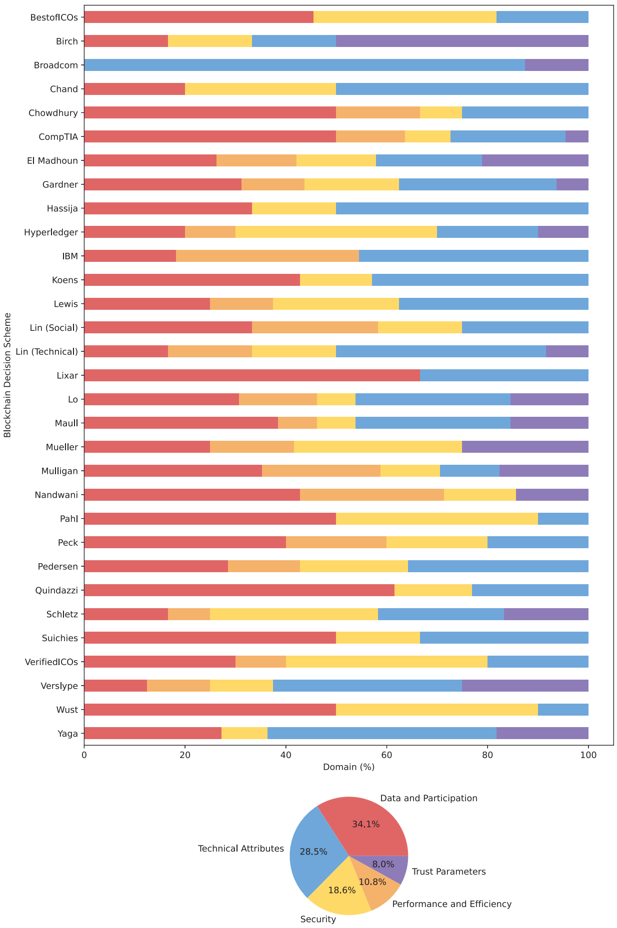


Fig. 5. Bar plot of question vertex domain composition (Data and Participation, Performance and Efficiency, Security, Technical Attributes, and Trust Parameters) per FC-BDS.

Fig. 6. Wordcloud of all question vertex label text.

4.4. Summary

In this section, we have presented an exhaustive examination of the vertices, incorporating both the question and outcome aspects. Our analysis covered multiple dimensions including vertex counts, the composition of question vertex categories, and a presentation of these findings through a wordcloud. These results offer significant value in gaining insights into the major themes encompassing the queries posed in each FC-BDS. This reflective understanding allows us to discern what exactly these FC-BDSs are prompting from their users, thereby further enhancing our understanding of their functionalities and applications.

5. Path analysis

This section presents an in-depth path analysis of the FC-BDSs. These schemes, when represented as DAGs, define a path p as a series of question vertices culminating into an outcome vertex such that

$$p_{i,j} = \{q_1, q_2, \dots, q_n, o_i\}, \tag{4}$$

where i is a FC-BDS and j is a unique path within that FC-BDS. In total, a single scheme will have n paths such that

$$P_i = \{p_{i,1}, p_{i,2}, \dots, p_{i,n}\}, \tag{5}$$

Qualitatively speaking, a path reflects a particular chain of questions leading to a specific outcome.

Ensuring an exhaustive exploration of the decision space, we undertake extensive evaluation of every possible path $P = \{P_1, P_2, \dots, P_n\}$ that can potentially exist across all FC-BDSs. Section 5.1 delves into the counts of paths for each model, followed by Section 5.2 which examines the average path lengths for each model. Section 5.3 further investigates the outcomes of paths and the composition of different outcomes per model. Lastly, Section 5.4 rounds up with a comprehensive summary of the findings.

5.1. Path counts

Path count $|P_i|$ refers to the total number of possible paths for a BDS i. Fig. 7 illustrates a count plot of path counts for each FC-BDS, paired with a box plot to aggregate these path counts across all schemes. It clearly indicates that the majority of FC-BDSs tend to offer between seven and 15 paths, with an average of nine possible paths. However, there is notable variation, with certain FC-BDSs like the CompTIA model with as many as 42 possible paths.

The proliferation of potential paths in an FC-BDS is a signifier of its complexity. Here, complexity is not about the vertex count $|V|$, but rather how the vertices interconnect to form different decision trails. This complexity underpins a level of choice for the users; FC-BDSs with a higher number of paths are, in essence, extending a richer palette of decision-making avenues for users, as opposed to rushing them towards predetermined outcome vertices.

5.2. Path lengths

Another crucial aspect that supports our understanding of FC-BDSs is the path length $|p_{i,j}|$. The length of a path is determined by the number of vertices it incorporates. Having calculated all possible paths, Fig. 8 features a box plot for each FC-BDS, conveying the average length of their possible paths. An aggregated box plot is also included to provide an overarching view of path lengths across all models.

The visualisation recognises a noticeable variability across different models. Some FC-BDSs manifest significantly longer average path lengths compared to others. Longer paths imply a more elaborate user-engagement process and provide a more detailed decision-making framework. In contrast, shorter paths, while time-efficient, may lack the comprehensive data gathering necessary for sound decision-making.

The longest paths observed stretch to a length of 13 vertices, providing a minutely detailed decision route. However, the average path length across all FC-BDSs constitutes around seven vertices, striking a balance between robust data gathering and user time commitment.

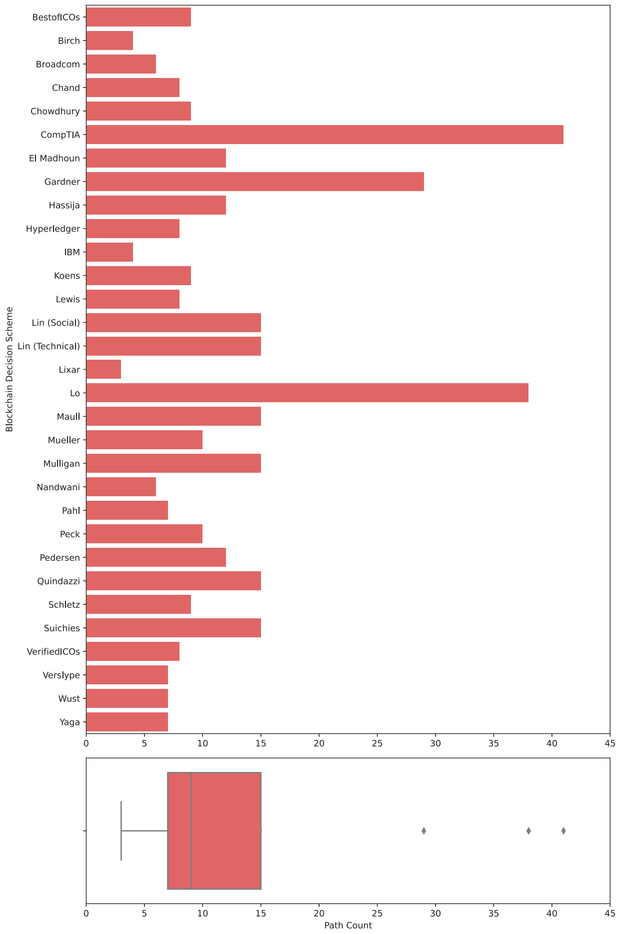


Fig. 7. Count plot of possible paths per FC-BDS.

5.3. Path outcomes

Taking the previously discussed path metrics into account, a new proposition emerges: given a specific FC-BDS, which outcome vertex does each path lead to? In other words, which decision – whether to use or avoid blockchain technology – does a particular path suggest?

Fig. 9 delivers deeper insights into this question by introducing a violin plot for each FC-BDS. This plot showcases two distinct bands: the upper band represents a kernel density estimate (KDE) of path lengths for paths concluding in an *avoid blockchain* verdict, and the lower band illustrates the same for paths suggesting to *use blockchain*. An aggregated violin plot is also rendered to provide a comprehensive overview.

These visualisations collectively reveal an interesting trend: paths leading to the avoid blockchain outcome are, in general, shorter than paths that advise using blockchain; an average length of approximately four and eight respectively. This discrepancy is substantial, introducing a subtle bias towards outcomes suggesting to avoid blockchain technology, primarily because users tend to reach these conclusions faster. However, it also raises a counterpoint that longer paths indicating the usage of blockchain represent more question vertices, thus, conducting more extensive fact-finding before recommending blockchain.

Furthering this analysis, Fig. 10 presents a normalised bar plot showcasing the outcome distribution for each model. This chart breaks down the outcomes into the two major categories as before; *avoiding blockchain* and *using blockchain*, further subdivided into more specific verdicts such as which type of blockchain to use. Interestingly, the majority of FC-BDSs lean towards recommending avoidance of blockchain

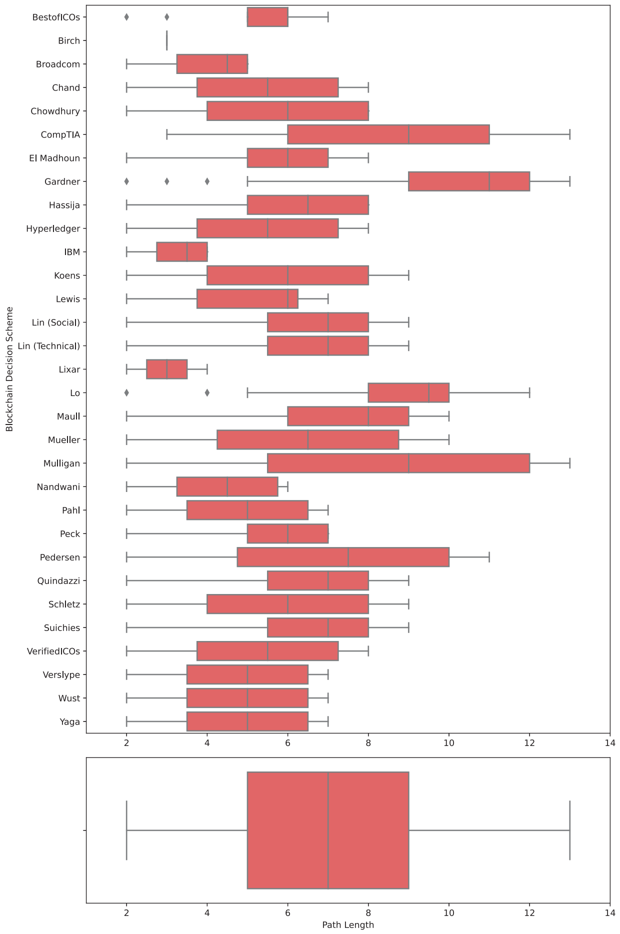


Fig. 8. Box plots of path lengths for each FC-BDS.

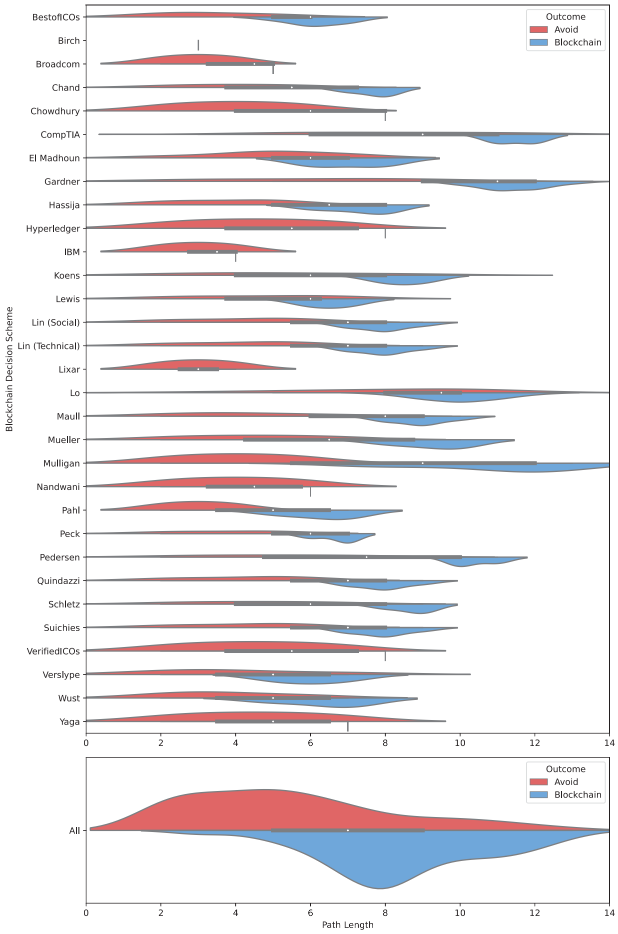


Fig. 9. Violin plots of path lengths per FC-BDS for outcomes that suggesting avoiding blockchain and using blockchain.

technology. However, the difference between advising the use or avoidance of blockchain is minimal, reflecting a subtle equilibrium in the decision-making landscape of these schemes.

5.4. *Summary*

This section has provided an in-depth analysis of the paths within FC-BDSs. Our findings indicate that most FC-BDSs typically possess around nine paths at an average length of seven vertices. However, there is considerable variation in this aspect, with some models featuring as few as three paths while others extend up to as many as 42. A noteworthy observation is that paths leading to an outcome that suggests avoiding blockchain are, on average, shorter than those paths advising the use of blockchain. This implies that FC-BDSs typically require a more detailed review and consideration when advocating for blockchain usage, underscoring the importance of thorough analysis in such decisions.

6. Model comparison

In this section, we examine the shared characteristics amongst different FC-BDSs. For this comparative analysis, we employ two distinct measures of similarity: structural similarity and semantic similarity. Structural similarity, explained in Section 6.1 concentrates on the underlying architecture of the DAGs that constitutes each BDS, using factors such as the number of vertices, edges, and paths. Semantic similarity, on the other hand, evaluates resemblance based on the text of question vertices. This measure assesses how closely the nature of the questions encapsulated within the vertices resembles across the different schemes. This is explained in greater detail in Section 6.2. By synergistically combining these two strands of similarity metrics, Section 6.3 constructs a comprehensive measure of general similarity. This integrated measure affords a holistic perspective, contributing to an inclusive understanding of the commonalities between various FC-BDSs. Section 6.4 provides a summary of the similarity findings.

6.1. *Structural similarity*

Seven distinct metrics have been used to ascertain the structural similarity amongst various FC-BDSs. These metrics include:

- question vertices count;
- outcome vertices count;
- outcome vertices (avoid blockchain) count;
- outcome vertices (use blockchain) count;
- paths count;
- paths average length;
- paths standard deviation.

Each of these metrics is encoded for every FC-BDS. Based on these encodings, we then derive a similarity matrix by computing the cosine similarity for each pair of FC-BDSs. The cosine similarity C between scheme A and scheme B is computed as

$$C(A,B) = 100 \times \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}, \tag{6}$$

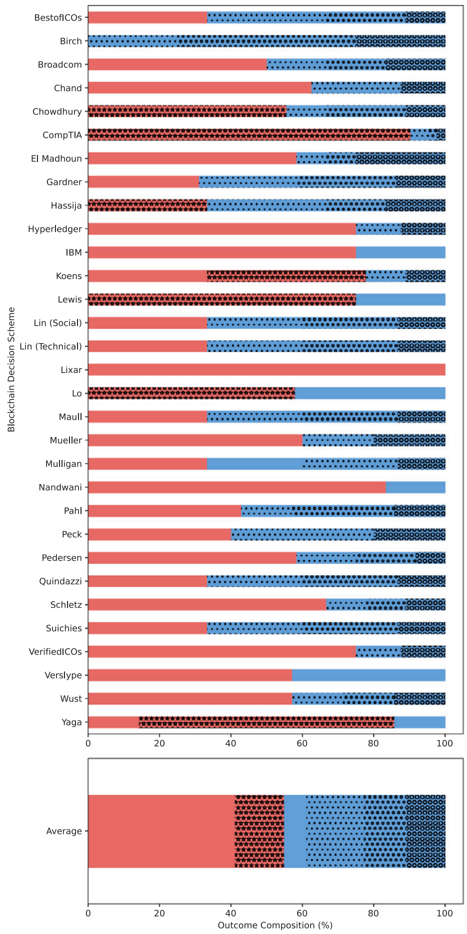


Fig. 10. Normalised bar plot of outcome composition per FC-BDS.

where i is one of the aforementioned metrics, yielding a value between 0 and 100, where 0 denotes no similarity and 100 suggests identical structures.

Fig. 11 presents the structural similarity matrix for the FC-BDSs. Upon reviewing this matrix, we observe several instances of identical similarity (with a value of 100). This pattern suggests that many FC-BDSs may either be exact replicas or models inspired by pre-existing ones, hence absolute structural parallelism.

6.2. Semantic similarity

Much like the process employed for deriving structural similarity, semantic similarity also leverages cosine similarity to yield a value between 0% and 100%. However, the computation differs in the type of input being compared. For semantic similarity, we replace the seven structural metrics i with the NLP encodings that were calculated as part of the question vertex classification process (detailed in Section 3.2). These encodings capture the linguistic context and meaning embedded within the vertices of each model.

Fig. 12 represents these comparisons with the semantic similarity matrix. Upon reviewing this matrix, it is observed that, unlike the structural similarity results, there are no pairings that yield an identical score of 100%. This outcome is predictable, as semantic similarities can be more nuanced and harder to replicate exactly.

That said, there still exists a notable amount of semantic similarity amongst certain FC-BDSs. For instance, the models developed by Hyperledger and VerifiedICOs display a high degree of similarity, highlighting the potential of shared decision-making principles and language between them.

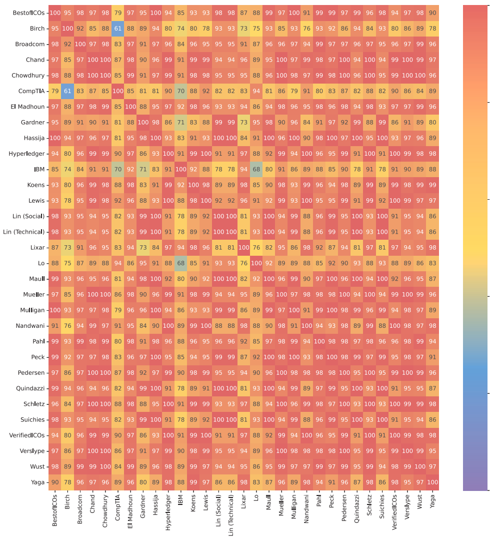


Fig. 11. The structural similarity matrix.

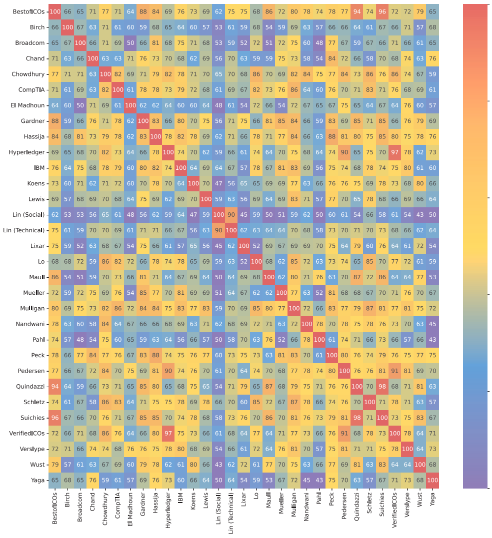


Fig. 12. The semantic similarity matrix.

6.3. General similarity

Promoting a more comprehensive understanding of resemblances among FC-BDSs, the general similarity measure is formulated by combining the previously computed structural similarity and semantic similarity matrices. The union of these matrices is achieved by computing the average value for each corresponding model pair across both matrices, such that

$$C_{\text{general}} = \frac{C_{\text{semantic}} + C_{\text{structural}}}{2}. \tag{7}$$

This method of integrating similarity measures results in a more granular analysis of the correlations among the various models.

Fig. 13 presents the culmination of these integrations in the form of a general similarity matrix. Upon analysis, we observe that certain FC-BDSs bear substantial resemblance to others, quite possibly indicating that they are imitations or adaptations of prior models. This is particularly evident for pairs yielding a similarity score of 90% or above, suggesting nearly identical structural and semantic properties.

Table 4 presents the top ten general similarity scores between FC-BDSs. Notably, Maull et al. [12] appears twice in the top two entries,

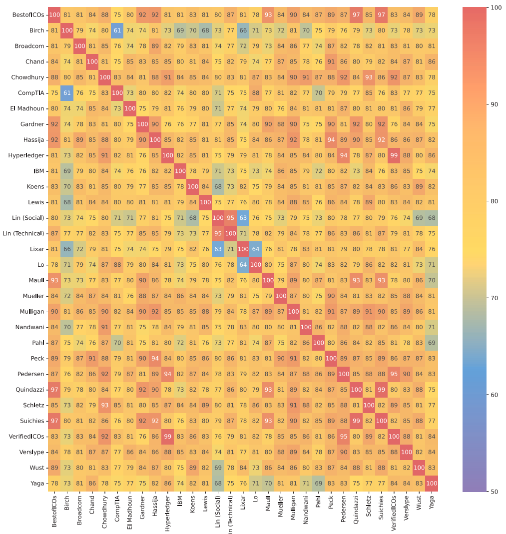


Fig. 13. The general similarity matrix.

Table 4
Top ten general similarity scores for FC-BDSs.

	Earlier Model	Later Model	Score (%)
1	Quindazzi	Maull	98.74
2	Suichies	Maull	98.69
3	Hyperledger	Pedersen	97.00
4	Peck	Hassija	96.55
5	VerifiedICOs	Pedersen	95.18
6	Lin (Social)	Lin (Technical)	94.90
7	Quindazzi	BestofICOs	94.36
8	Hyperledger	VerifiedICOs	93.93
9	Suichies	BestofICOs	93.43
10	Suichies	Quindazzi	92.85

suggesting significant commonalities with the models of Quindazzi [8] and Suichies [7], as it exhibits similarity scores of 98.74% and 98.69% respectively.

Quindazzi [8] independently confirms their model's basis upon the work of Suichies [7], evidenced by an impressive 92.85% similarity score. However, Maull et al. [12] does not make any specific reference to either Quindazzi [8] or Suichies [7]. According to Maull et al. [12], their model development process was inspired through extensive dialogue with the core developer teams of Bitcoin and Ethereum. This was further supplemented by a comprehensive review of existing technical literature and an analysis of 20 proof-of-concept (PoC) projects spanning over a period of three years.

Another noteworthy observation is that Pedersen et al. [28], with a 97.00% similarity to the Hyperledger [15] model, confirms inspiration directly from the latter. Meanwhile, Hassija et al. [36] – scoring a 96.55% similarity with Peck [13] – references said paper, but fails to explicitly credit the BDS rooted in Peck [13].

Finally, both Hyperledger [15] and VerifiedICOs [18], with a similarity score of 93.93%, denote a strong mutual influence, substantially indicating that they drew significant inspiration from each other in their respective BDS creation processes.

6.4. Summary

This section has undertaken a thorough investigation of two distinctive methods for comparing the similarity among FC-BDSs. The first, structural similarity, implements cosine similarity on seven distinct metrics to determine similarity. The second method, semantic similarity, incorporates the use of cosine similarity applied on language encodings of question vertices.

In addition, we have developed a measure of general similarity that amalgamates insights from the structural and semantic methods. This is accomplished by computing the average of the two aforementioned similarities. A notable outcome of this is that there are several instances where the general similarity scores exceed 90%, indicating a high degree of similarity and suggesting potential duplication amongst certain FC-BDSs.

7. Conclusion

7.1. Summary

This paper has reviewed the current landscape of BDSs. As previously mentioned, BDSs come in one of three main types; AI-BDSs, FC-BDSs, and S-BDSs. Due to their intuitive nature, FC-BDSs constitute the vast majority among these types (77.5%), and our research illuminates the variety present among these FC-BDSs in terms of both their structural and semantic features. A significant range of diversity was observed concerning question vertices, path lengths, and overall decision-making routes.

Our methodology began by establishing a standardised definition of an FC-BDS as a DAG, to ensure consistency and clarity. To aid in this process, we created an open-source Python package that not only streamlines aggregation of these models, but also fosters accessibility and widespread usability for other researchers and businesses.

Further deepening our investigation, we conducted an in-depth analysis of these FC-BDSs based on their vertices and paths. The average number of vertices for a model is 12 (eight question vertices and four outcome vertices), with the majority of question vertices pertaining to Data and Participation attributes. In evaluating possible paths and outcomes within the FC-BDSs, we discovered an imbalance in the recommendations towards avoiding blockchain usage versus employing it. This skewed inclination could potentially introduce bias into the decision-making process of these models. Future FC-BDS developments should address this imbalance to provide a fairer representation of scenarios that adequately require the use of blockchain.

Moreover, using measures of structural and semantic similarity, we performed a comparative analysis comparing these models against each other. This multi-pronged investigation revealed that despite the vast pool of FC-BDSs available, there exist schemes that show high similarities of over 90%. This phenomenon could be attributed to the less formalised nature of FC-BDSs publication, often circumventing the standard of peer review, and instead sourcing inspiration from earlier models to build upon. This can lead to models that resemble their progenitors while only making minor alterations to fit specific needs.

The techniques employed in our research, particularly similarity computations, can serve as powerful tools to detect these prevalent similarities. Furthermore, they could be beneficial in identifying potential instances of plagiarism within the field and preserving the integrity and authenticity of future FC-BDS creations. Overall, our research provides an expansive understanding of FC-BDSs, laying the groundwork for future studies and technological developments within this field.

7.2. Future research

Looking ahead, we envision broadening the horizons of our research by leveraging the comprehensive data collected through our open-source package to automatically generate a novel, unified FC-BDS. This endeavour would involve assimilating the piecemeal insights gathered from all existing models into a single, optimised FC-BDS that best embodies the collective wisdom and efficacy of its precursors.

Furthermore, it is our intention to delve into comparative studies involving FC-BDSs against other types of BDS such as AI-BDSs and S-BDSs. This would enable us to better understand the relative strengths and weaknesses of these various categories of BDS, and potentially identify opportunities for cross-pollination and innovation that could enhance the efficacy of future models.

Moreover, we envision that our package will act as a foundational layer for the development of new software, aimed at making FC-BDSs accessible to the general public. By creating an easily navigable and intuitive interface, this software could empower individuals to understand, interact with, and make informed decisions about blockchain technologies. As we continue to refine and expand the capabilities of our package, our goal remains focused on promoting transparency, enhancing understanding, and fostering a more inclusive dialogue around FC-BDSs.

As we enter the era of GenAI tools, these technologies may potentially transform our reliance on BDSs. Such tools could supplant the need for domain experts, allowing prospective blockchain users to interact directly with AI, and ask as many questions as necessary, providing as much detail as they desire. However, this leap in technology is still unexplored territory. GenAI, unlike existing BDSs, does not offer transparency in how it arrives at a conclusion. This lack of explainability can be seen as a disadvantage compared to BDS, which are notable for presenting logical and traceable decision-making processes. While GenAI promises significant advances, it also raises important considerations about transparency and reliance on algorithms in decision-making processes. We envision that these factors will be scrutinised in future research to supplement developments in BDSs.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Joe Preece reports administrative support, article publishing charges, and equipment, drugs, or supplies were provided by University of Birmingham. Joe Preece reports a relationship with University of Birmingham that includes: employment.

Data availability

Data is available online at https://github.com/joedpreece/blockchain_decision_scheme.

Declaration

During the preparation of this work the authors used Bearly AI in order to draft and improve the language used within the paper. At no point was generative artificial intelligence used to conduct automated research or provide automated insights; all original research was undertaken by the authors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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