

Evolution of ESG-focused DLT Research: An NLP Analysis of the Literature

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ABSTRACT

As Distributed Ledger Technologies (DLTs) rapidly evolve, their impacts extend beyond technology, influencing environmental and societal aspects. This evolution has increased publications, making manual literature analysis increasingly challenging. We address this with a Natural Language Processing (NLP)-based systematic literature review method to explore the intersection of Distributed Ledger Technology (DLT) with its Environmental, Social, and Governance (ESG) aspects. Our approach involves building and refining a directed citation network from 107 seed papers to a corpus of 24,539 publications and fine-tuning a transformer-based language model for Named Entity Recognition (NER) on DLT and ESG domains. Applying this model, we distilled the corpus to 505 key publications, enabling an inaugural literature review and temporal graph analysis of DLT's evolution in ESG contexts. Our contribution include an adaptable and scalable NLP-driven systematic literature review methodology and a unique NER dataset of 54,808 entities, tailored for DLT and ESG research. Our inaugural literature review demonstrates their applicability and effectiveness in analyzing DLT's evolution and impacts, proving invaluable for stakeholders in the DLT domain.

1 INTRODUCTION

Emerging technologies have seen increasing scrutiny in terms of energy consumption and broader ecological impacts, encompassing vital resources like water, precious metals, and synthetic compounds [73, 91]. This shift towards environmental consciousness emphasizes the need to evaluate technological advancements through their ecological footprint, including DLT. DLT promises record immutability and decentralization but faces challenges like high energy consumption in certain consensus algorithms, such as Bitcoin's Proof of Work (PoW) [71], aimed to effectively prevent attackers from pretending to be many users simultaneously to increase their weight in the network, known as Sybil attacks. While DLT offers breakthroughs in security and immutability, understanding and analyzing its multifaceted implications, ever-evolving applications, and continuously growing body of research demands a sophisticated and nuanced approach.

In this context, NLP, a sub-field of Artificial Intelligence (AI)¹ and linguistics², emerges as a facilitator to examine the growing

number of publications in DLT, from academic articles to whitepapers. NLP focuses on certain human-related language tasks such as Question Answering (QA) and NER, among others³. In this paper, we use NER to identify entities representing specific DLT technologies (e.g., PoW, Proof of Stake (PoS), etc.) and some of their ESG implications ("energy consumption", "computational power", etc.) within the corpus of our dataset to illuminate gradual shifts in research emphasis of these DLT technologies.

Unlike previous systematic literature reviews that rely on citation measures and analysis of abstracts and keywords, our approach examines the text of the body of the publications. This enables us to detect thematic shifts in key areas of research and industry publications (e.g., whitepapers) for technologies within the DLT field by mapping the publications' tokens to the technology components of the hierarchical taxonomy of DLT from [101], which we extended to include ESG implications of DLT. We demonstrate the generalizability and transferability of our methodology by successfully applying some biomedical field precedents from using ontologies, or hierarchical taxonomies, for creating NER datasets until using these datasets for NLP-driven literature mining/review [5, 18, 48, 64, 69, 92].

Our research has the following contributions:

- A curated NER dataset composed of 54,808 named entities for twelve DLT's taxonomy categories in the context of ESG. To the best of our knowledge, this is the first NER dataset explicitly designed for DLT.⁴
- A methodology and framework for executing a NLP-driven systematic literature review at the intersection of domains, in this case, DLT and ESG research.⁵
- Conducting what we believe is the first NLP-driven systematic literature for the DLT field that places a special emphasis on ESG aspects.

Additionally, our work represents a step for future research directions to improve further automated systematic literature review processes at scale, capable of capturing the intrinsic dependencies and evolution of concepts related to the intersection of fields.

2 RELATED WORK

Previous literature reviews have extensively explored blockchain applications in various sectors [17, 117]. These reviews, however,

¹https://cso.kmi.open.ac.uk/topics/artificial_intelligence from [82]

²<https://cso.kmi.open.ac.uk/topics/linguistics> from [82]

³https://cso.kmi.open.ac.uk/topics/natural_language_processing from [82]

⁴The dataset will be made available

⁵The code will be made available

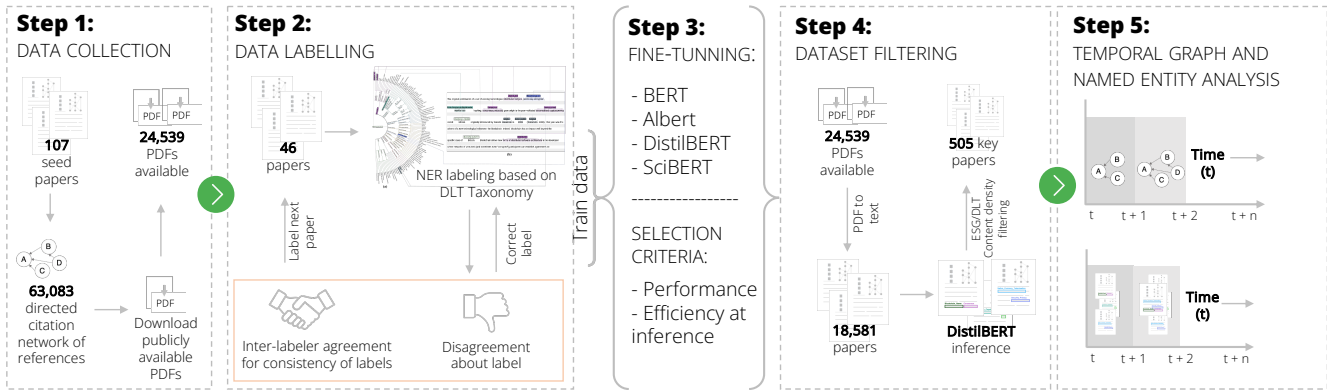


Figure 1: Methodology for the systematic literature review of ESG/DLT publications evolution using NER for content filtering, for which temporal graph and named entities (representing specific DLT technologies, e.g., PoW, PoS, etc.) analysis is carried.

differ in scope and depth compared to our systematic review, particularly in terms of article quantity and the manual nature of their analyses.

Studies have also focused on blockchain’s role in decentralization and privacy, particularly in IoT [27], and analyzed trends of centralization in decentralized systems like Bitcoin and Ethereum [81]. [93] deconstructed 107 blockchain technologies using a specific taxonomy, emphasizing consensus mechanisms and cryptographic primitives. Our work, in contrast, provides a broader perspective on the evolution of DLT, including its ESG implications and uses a bigger corpus.

In the context of ESG, [13, 50, 65, 74, 87, 112] have explored blockchain’s potential in energy management, environmental sustainability, and transparent reporting. Our study extends these approaches by examining the intersection of ESG and DLT through a literature analysis.

Regarding NLP applications, studies have shown the use of advanced techniques for automated ESG scoring [3] and opinion summarization [34]. Outside the DLT field, systematic literature reviews using NLP-driven methodologies, such as in medical genomics, have been conducted [5]. These studies used database term searches and NLP models for abstract-based filtering, differing from our approach of building a corpus through directed citation graphs and full-text filtering using NLP.

3 METHODOLOGY

Ontologies, specifically hierarchical taxonomies, are pivotal in developing NER datasets for text mining [5, 18, 48, 64, 69, 92]. For example, the GENIA corpus [51], a NER dataset from 2,000 biological abstracts, employs the GENIA ontology’s hierarchical tree structure of 47 biological entities, including top-level categories like biological source, substance, and others, to facilitate text mining in biomedical literature. Similarly, the Human Phenotype Ontology is used for creating and expanding NER datasets in biomedicine [48, 59]. [5, 18, 64] further demonstrate the use of ontology-based NER datasets for domain-specific literature text mining.

Learning from these biomedical field precedents, our methodology for NLP-based text mining and filtering in the DLT field

employs a hierarchical taxonomy [101] to annotate a NER dataset from 46 systematically reviewed publications of DLT’s sustainability [37]. Therefore, we demonstrate the generalizability and transferability of these biomedical field precedents by successfully applying some of their elements in our methodology, demonstrating their versatility across different domains.

On the other hand, alternative approaches for methodologies to carry literature mining are keyword extraction[79] and topic modelling[7]. These options provide a broad or holistic view of the main themes for a literature review. Therefore, we initially gain a broad perspective of the DLT field’s evolution by constructing a topics graph with the keyword topics for the full corpus metadata (more than 60,000 records). Then, we narrow our analysis by taking a more targeted approach by fine-tuning a transformer-based language model for a NER task for ESG/DLT content density corpus filtering. This method allows us to categorize technologies in DLT in detail that would not normally emerge as single topics or keywords for a literature review. Therefore, we can focus on specific technologies in DLT, like different Consensus mechanisms (e.g., Proof of Work, Proof of Stake) and their ESG effects, such as “energy consumption”, “hash rate”, “computational power”, etc.

Finally, we perform a temporal graph and named entities analysis to track and understand the development and changes in these topics/keywords and DLT technologies (represented as named entities) and their ESG implications over time.

3.1 Data Collection

The seed papers for our directed citation network were selected from two sources:

- (1) 89 papers from [37], reviewing sustainability in popular DLT consensus algorithms.
- (2) 18 recent publications (2018-2022) with at least three citations each, chosen to update the corpus with more current research relevant to DLT/ESG [4, 6, 9, 26, 30, 38, 39, 43, 54, 61, 62, 70, 73, 75, 84, 86, 89, 90].

The key benefit of using seed papers to build a citation network for a systematic literature review is the ease of expanding and

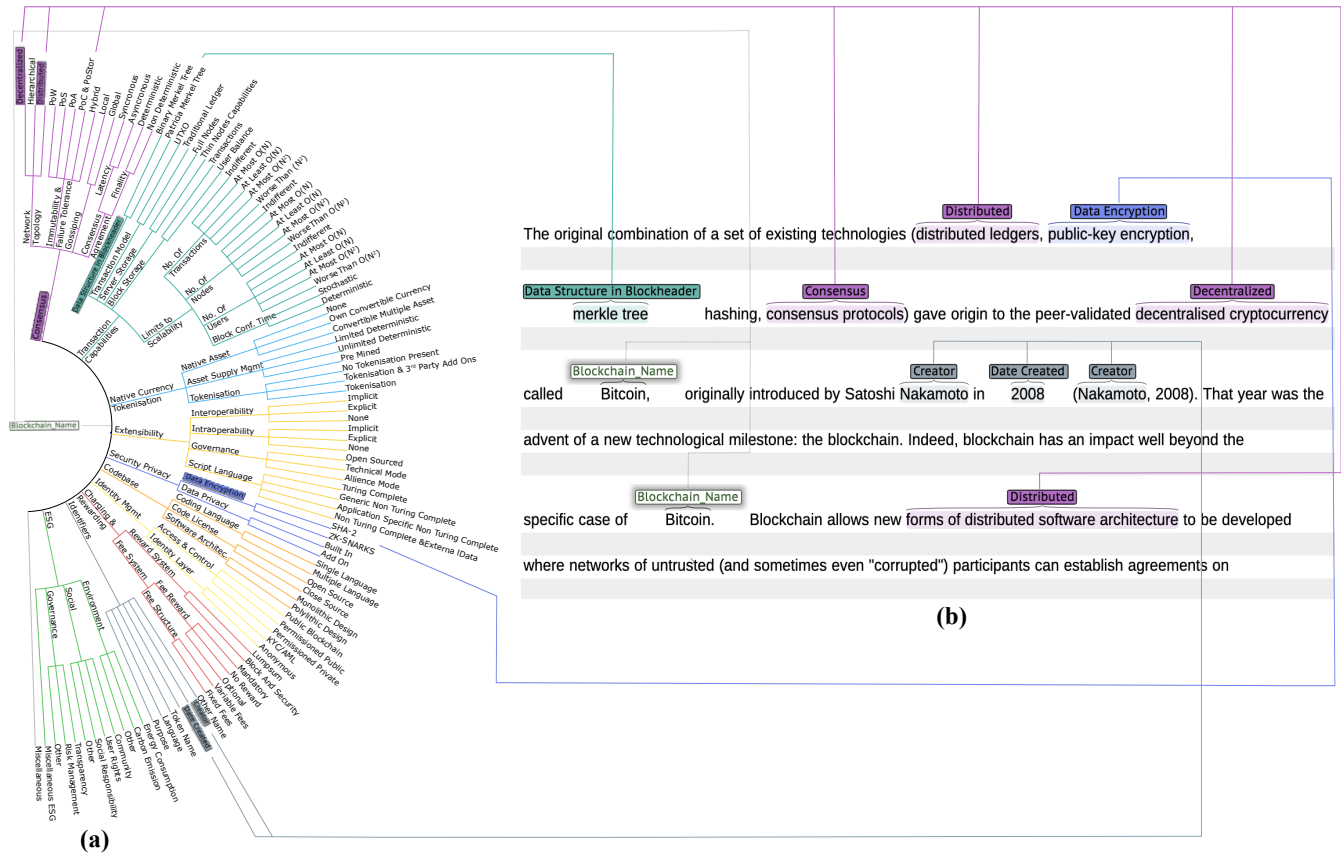


Figure 2: (a) The taxonomy of [101] extended with Blockchain_Name, ESG, and Miscellaneous (see 3.2) for the purpose of this research. (b) Example of parsed text with the taxonomy label associated with a span of text labeled. The labels used in the paragraph are highlighted in the taxonomy tree.

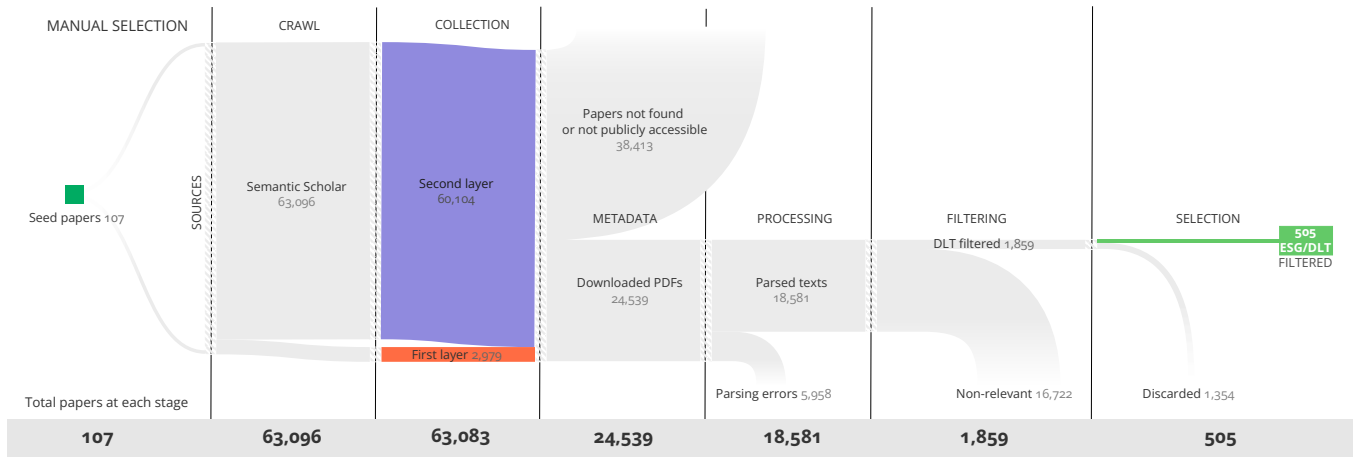


Figure 3: Processing pipeline for collecting and filtering papers in the review. The total number of papers present at each stage of processing is shown. See Table 1 for the description of the labels in the corpus.

updating the literature review by adjusting the number of seed papers.

We limited our citation network to references made by the seed papers, ensuring thematic relevance to DLT/ESG. We restricted the

Group entities	Description
Blockchain_Name	The name of a blockchain system (E.g., Bitcoin, Ethereum, XRP Ledger), but also including other types of DLTs, such as Hedera, IOTA
Consensus	Rules and mechanisms to ensure the immutability of transaction records (E.g., PoW, PoS, Blockchain, Hashgraph).
Identifiers	Information related to the token names, creators, and purpose (E.g., Satoshi Nakamoto, Ripple, USDC, USDT).
Security_Privacy	Cryptographic methods to ensure data privacy and encryption in a blockchain ecosystem.
ESG	Entities relevant to ESG issues.
Transaction_Capabilities	Information related to the details of transactions, such as Data Structure in the Blockheader, Transaction Model, Server Storage, Block Storage, and Limits to Scalability.
ChargingAndRewardingSystem	Cost models for the operation and maintenance of blockchain systems.
Extensibility	Capabilities of Interoperability, Intraoperability, Governance, and Script Language of a blockchain ecosystem.
Identity_Management	Attributes to identify participants and their system access level.
Native_Currency_Tokenisation	Asset classes for transactions within a blockchain system (E.g., BTC, ETH, XRP, HBAR).
Codebase	Coding Language, Code License, and Software Architecture of a blockchain ecosystem (E.g. Solidity, Rust, MIT License, Apache License).
Miscellaneous	Miscellaneous entities that are ambiguous in a given context and are relevant for the DLT topic but are not captured by any of the above categories.

Table 1: List of 12 ESG/DLT groups of entity types based on the taxonomy from [100]

expansion to two levels of references to avoid divergence from the theme. This led to a directed network with over 63,083 publications, from which 24,539 publicly available PDFs were retrieved using Semantic Scholar’s PDF links provided in the metadata for each publication (see Figure 1 and Figure 3).

3.2 Labeling

We manually annotated 46 papers using the brat tool [96], following the taxonomy framework of [101]. This taxonomy provides a hierarchical structure of DLT technology components, with each principal component (e.g., Consensus) divided into sub-components (e.g., Gossiping) and further into sub-sub-components if needed (e.g., Local). We introduced categories like Blockchain_Name to identify specific blockchains and the initial definition of Security_Privacy was expanded to label security threats (Sybil attack, 51% attack, etc.) while a Miscellaneous category was added for ambiguous contexts (see Figure 2 and Table 1), following the example of the CoNLL-2003 dataset for a similar category [103]. We further extended [101]’s taxonomy to identify sustainability-related concepts referred to in the ESG criterion (see Figure 2).

3.3 Text analysis/language processing

The label hierarchy within the taxonomy was pruned for class balance, where specific labels like PoW were replaced by broader categories like Consensus to maintain focus on primary taxonomy components (Figure 2). To improve NER model performance, which is sensitive to label consistency [49, 115], we employed a systematic process for enhancing inter-labeler consistency. This involved correcting inconsistent labeling of entities, such as "Sybil attack" sometimes categorized as Consensus and other times as

Text: In this paper, the PoW consensus algorithm used in blockchains are analyzed in terms of difficulty, hash count, and probability of successful mining.

Output: In this paper, the \langle Consensus \rangle consensus algorithm used in \langle Identifiers \rangle is analyzed in terms of \langle Consensus \rangle , \langle TransactionCapabilities \rangle , and \langle TransactionCapabilities \rangle .

Text: As a result, the amount of electrical energy needed to process the work is immense.

Output: As a result, the \langle ESG \rangle to process the work is immense..

Text: It provides a distributed, immutable, transparent, secure, and auditable ledger.

Output: It provides a \langle Consensus \rangle , \langle Consensus \rangle , transparent, \langle ESG \rangle .

Text: Blockchain was first introduced with the creation of Bitcoin back in 2008.

Output: Blockchain was first introduced with the creation of \langle BlockchainName \rangle back in \langle Identifiers \rangle .

Table 2: Training examples for ESG/DLT labeling task.

Security_Privacy, following each labeler’s approval and using programmatic cleaning to ensure consistency for non-context-dependent labels.

We applied text resampling for overlapping named entities that could fit into multiple categories, such as belonging to Blockchain_Name and Native_Currency_Tokenisation. This process involves duplicating text and assigning distinct entities to each copy, thereby enhancing the capture of rare entities. This resampling strategy is beneficial, especially for datasets of modest size [110], improving model performance by accommodating diverse entity categories. Additionally, the duplication of training data has been found beneficial in enhancing a language model’s ability to learn from limited examples [68].

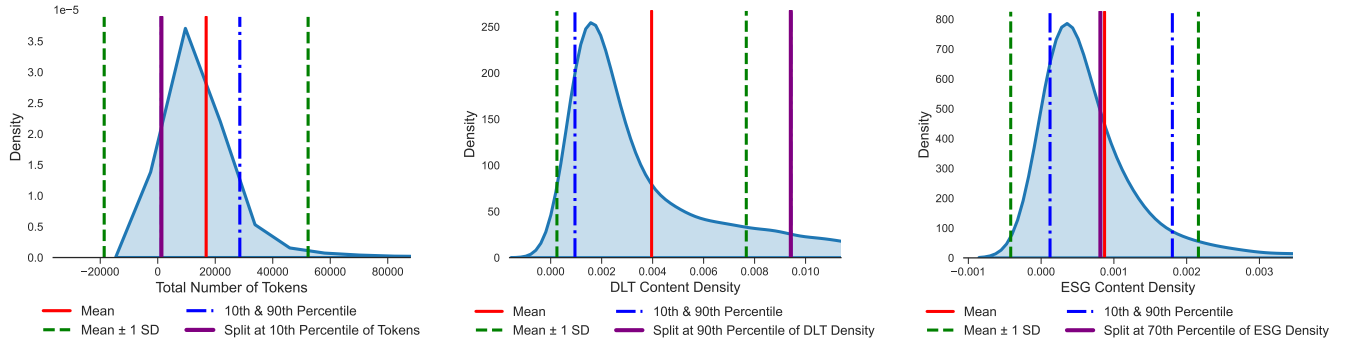
3.4 Mapping taxonomies using NLP

Recent advancements in NLP, including data acquisition [15, 77], model architecture development [97, 105], and large-scale pre-training [31, 46, 58, 72, 76, 104], have significantly propelled the field forward. For example, we considered Large Language Models (LLMs) for NER tasks, inspired by the effectiveness of models like ChatGPT and GPT4 in zero-shot and few-shot learning scenarios [47, 57]. However, despite their capabilities, [47, 57] noted that domain-specific NER tasks often perform better with supervised learning models than with current LLMs. Therefore, we adopted a supervised learning approach, fine-tuning transformer-based pre-trained language models such as BERT [31], Albert[56], DistilBERT [83], and SciBERT [12]. Our selection criterion for the final model was based on its performance in our NER task and efficiency at inference.

Then, we applied a percentile-based filtering process to the corpus of publications based on the ESG and DLT classified named entities within the corpus. This method selects publications with substantial DLT and ESG content, using a threshold percentile to exclude marginally relevant papers. Seed papers were included to maintain foundational references. The filtering is represented as:

$$F = \{P_i : D(P_i) > T\} \cup S \quad (1)$$

Where F is the final set of papers, P_i is an individual paper, $D(P_i)$ is the ESG and DLT content density of a paper, T is the threshold percentile, and S is the set of seed papers. Content density $D(P_i)$ for each paper is calculated by the ratio of the number of DLT and



(a) Filter for papers below the 10th percentile of total numbers of tokens. **(b) Filter for papers with a DLT content density above the 90th percentile.** **(c) Filter for papers with an ESG content density above the 70th percentile.**

Figure 4: Steps for the percentile-based filtering

ESG relevant named entities (N_{DLT} and N_{ESG}) to the total number of tokens $N(P_i)$ (Equation 2):

$$D(P_i) = \frac{N_{DLT}(P_i) + N_{ESG}(P_i)}{N(P_i)} \quad (2)$$

Our filtering methodology involved:

- (1) Excluding papers below the 10th percentile (see Figure 4a) in the total token count to avoid distortions due to PDF-to-text conversion issues or unusually short papers (e.g., below 100 tokens).
- (2) Computing DLT content density and retaining papers above the 90th percentile (see Figure 4b), ensuring a strong focus on DLT topics.
- (3) Filtering for at least the 70th percentile (see Figure 4c) in ESG content density to confirm relevance to ESG.

Finally, we manually reviewed the filtered publications to validate the accuracy of their ESG/DLT content density and relevance.

3.5 Network graphs and entities evolution

We analyzed the ESG/DLT content density filtered citation network as $G(V, E)$, with papers as vertices V and citations as edges E . Using $G(V, E)$, we did temporal graph analysis with one-year time windows W_1, W_2, \dots, W_n , as per the rolling window approach in [45, 94, 95]. For each window W_i , we created a subgraph $G_i(V_i, E_i)$ for which we can analyze the nodes, edges, average degree, and the authority scores (using the HITS algorithm[53]) to determine temporal shifts within the network. These metrics facilitated determining how publications and future research rely on pivotal or existing work.

In addition to the temporal graph analysis of the ESG/DLT citation network, we constructed a separate graph based on the full corpus of more than 60,000 metadata records. This graph, denoted as $G_{topics}(V_{topics}, E_{topics})$, was structured around various topics identified by Semantic Scholar for each publication. We defined the vertices V_{topics} as individual topics, and the edges E_{topics} represented the co-occurrence of two topics within the same paper. This network helps us visually and quantitatively understand topic interconnections. We can observe the evolution and significance of

specific topics over time by analyzing the degree centrality (normalized degrees based on this graph’s maximum degree) with one-year time rolling windows W_1, W_2, \dots, W_n . This analysis provides insights into how some of the research from these topics was foundational for the DLT field and facilitated the emergence of innovations based on them, adding more depth to our understanding of the DLT field’s development.

Furthermore, we tracked the evolution of named entities in the ESG/DLT content density filtered citation network. Using lemmatization and programmatic grouping, we consolidated variations of similar entities (e.g., all forms of “Proof of Work” were unified under “PoW”) to capture changes in entity prevalence accurately.

4 EVALUATION

Figure 3 details our systematic literature review’s collection and filtering stages. The next sections provide more details of the results after applying our methodology (Figure 1).

4.1 Taxonomy labelling result

Our NER dataset organizes 54,808 named entities into a tree structure with 136 labels under 12 top-level categories (Figure 2a and Table 3). This structure facilitated targeted analysis in our study. Table 2 provides examples from the dataset.

4.2 NLP result

We fine-tuned four models – bert-base-cased⁶, albert-base-v2⁷, distilbert-base-cased⁸, and allenai/scibert_scivocab_cased⁹ – using 5-fold cross-validation according to the titles of the publications to avoid a publication’s data appearing in both the training and test set for each fold (see Table 2 for some samples of training data). Each model underwent 100 training epochs, 20 epochs per fold, with a learning rate of 5×10^{-5} , a training batch size of 16, and a validation batch size of 32. The maximum sequence length was 256 tokens.

⁶<https://huggingface.co/bert-base-cased>

⁷<https://huggingface.co/albert-base-v2>

⁸<https://huggingface.co/distilbert-base-cased>

⁹https://huggingface.co/allenai/scibert_scivocab_cased

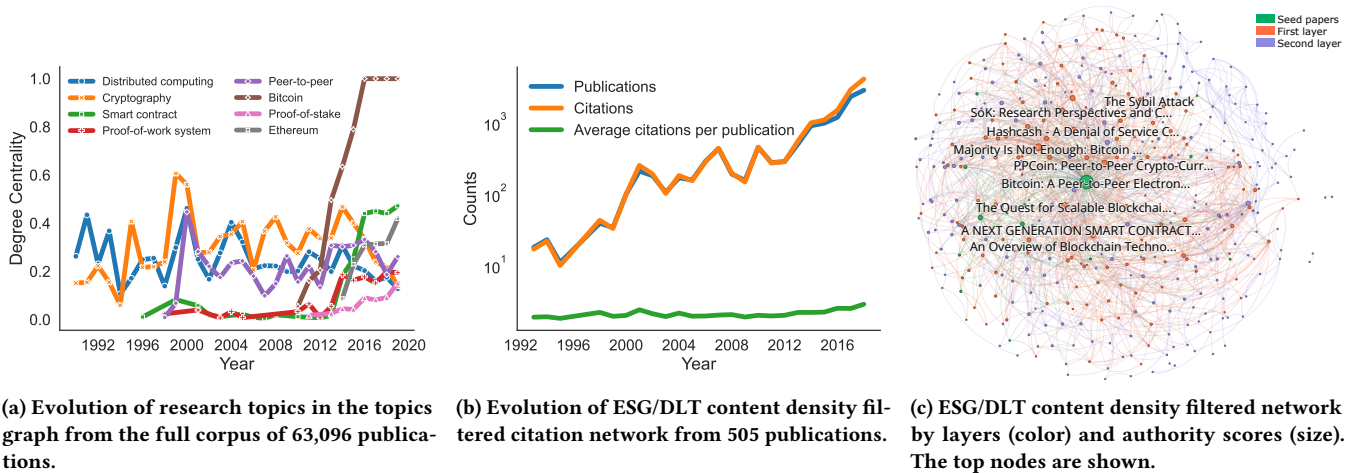


Figure 5: Citation Networks

Entity Category	Number of Entities
Blockchain_Name	5,358
Consensus	25,378
Transaction_Capabilities	4,729
Native_Currency_Tokenisation	2,671
Extensibility	1,752
Security_Privacy	4,838
Codebase	1,339
Identity_Management	1,305
ChargingAndRewardingSystem	1,531
Identifiers	1,511
ESG	3,468
Miscellaneous	928

Table 3: Number of labelled named entities for each category in the dataset.

The evaluation results (Table 4) showed that SciBERT and BERT had the best performance. However, DistilBERT’s efficiency made it more suitable for our large corpus of 24,539 publications. DistilBERT, being 60% faster than BERT, and likewise SciBERT, at inference and achieving 97% [83] of BERT’s performance, was selected for its balance between effectiveness and efficiency.

5 DISCUSSION

5.1 Transferability

Recent developments in LLMs, like Google DeepMind’s Gemini¹⁰, highlight the significance of our work in systematic literature review. Gemini’s demonstration of a systematic literature review, where terms like "Chip" and "CRISPR-Cas9" are searched in publications’ titles and abstracts to filter them¹¹ is akin to our methodology (section 3) of applying NER for field-specific filtering of literature, demonstrating the generalizability and applicability of our approach. However, Gemini faces limitations like potential hallucinations that could undermine its filtering of publications. On the other hand, despite that supervised learning approaches

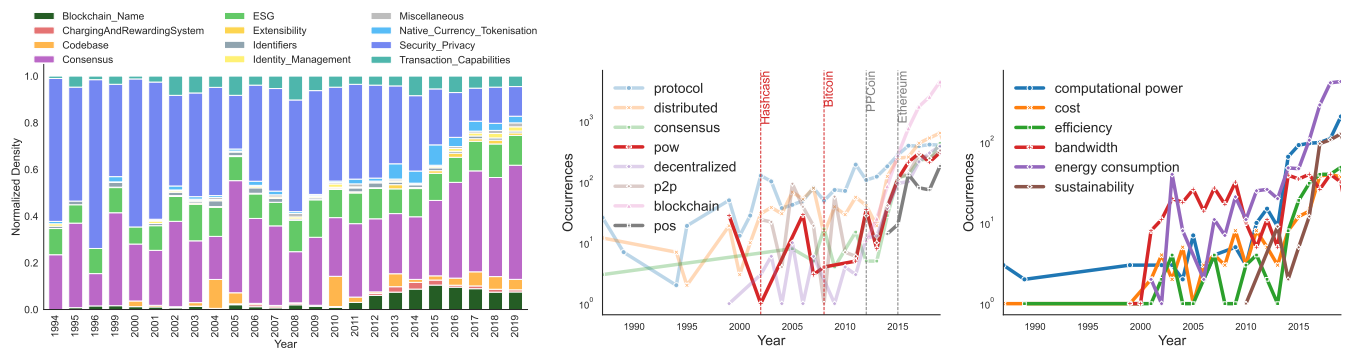
¹⁰https://www.youtube.com/watch?v=sPiOP_CB54A

¹¹See https://youtu.be/sPiOP_CB54A?feature=shared&t=64 for the prompt used in the demonstration

Model	Metrics				
	Fold	Precision	Recall	F1	Accuracy
BERT	1	0.43342	0.42502	0.42918	0.96443
	2	0.55149	0.58924	0.56974	0.96754
	3	0.57820	0.55315	0.56510	0.94566
	4	0.55809	0.58072	0.56918	0.94728
	5	0.58671	0.60786	0.59710	0.96414
	Mean	0.54158	0.55120	0.54606	0.95781
Albert	1	0.50650	0.34185	0.40820	0.96984
	2	0.57694	0.53416	0.55473	0.97207
	3	0.53164	0.43772	0.48013	0.95174
	4	0.52687	0.55281	0.53953	0.95577
	5	0.57680	0.60863	0.59229	0.97286
	Mean	0.54375	0.49503	0.51498	0.96446
DistilBERT	1	0.45704	0.38093	0.41553	0.96607
	2	0.55631	0.55364	0.55497	0.96713
	3	0.57937	0.54156	0.55983	0.94562
	4	0.55962	0.58406	0.57158	0.94747
	5	0.58537	0.61668	0.60062	0.96414
	Mean	0.54754	0.53537	0.54051	0.95809
SciBERT	1	0.46651	0.46432	0.46542	0.96983
	2	0.52566	0.61680	0.56760	0.96649
	3	0.55980	0.62262	0.58954	0.94162
	4	0.54930	0.64023	0.59129	0.94435
	5	0.57721	0.63896	0.60652	0.96544
	Mean	0.53570	0.59659	0.56407	0.95755

Table 4: Performance results after fine-tuning for BERT, Albert, DistilBERT, and SciBERT with the ESG/DLT NER dataset.

outperform current LLMs for NER tasks [47, 57], Gemini shows the potential of LLMs in few-shot learning for NER tasks. Additionally, as a commercial product, Gemini has limited accessibility, and its higher-performing models (Pro and Ultra versions) are not widely available. In contrast, our methodology (section 3) leverages a domain-specific labeled NER dataset and a fine-tuned language model to analyze full-text publications, not just their title and abstracts. This approach enhances the accuracy and depth of literature reviews. More importantly, our openly available methodology and NER dataset allow the research community and others to build upon and improve systematic literature review processes at scale, ensuring more reliable filtered results.



(a) Publications showing the normalized ratio of labels for each part of a branch of the taxonomy. (b) Top Consensus' named entities evolution. (c) Top ESG's named entities evolution.

Figure 6: Named entities evolution in the citation network

5.2 Topics network

The topics graph comprises 25,048 topics as nodes with 3,042,397 edges and 4,847,870 temporal edges connecting the topics across time. Figure 5a visually and quantitatively shows the evolution of the key areas like Cryptography, Peer-to-Peer, Proof of Work, Proof of Stake, and smart contracts that laid the foundation for advancements in DLT at different points in time. The research in the Cryptography topic provided the foundations for using public and private key pairs for identity management [21], elliptic curves [67], hashing and merkle trees [66]. Similarly, Peer-to-Peer research focused on network communication [25, 32], timestamping [11, 44, 63], and the need for solving the Byzantine Generals Problem [55], vital for decentralized network functionality. The research related to Proof of Work delineated the first consensus system used in Blockchain building in the works from the early 1990s of [36] and early 2000s of [8, 41].

The emergence of Bitcoin [71] marked a significant convergence of these technologies. Its degree centrality as a research topic rapidly soared from 0.056 in the late 2010s to 1 in the 2020s, a growth of ~1,692.42%. This surge in interest, possibly fueled by the socio-economic and political climate following the 2008 financial crisis [29, 42, 85, 114, 116] and Bitcoin's technological innovation, contrasted with digital money projects [20, 28, 99] in the 1990s and early 2000s that did not become as popular as Bitcoin in the same amount of time.

Parallel to Bitcoin's rise, or inspired by it [24], Ethereum emerged, introducing around 2014-2015 the Solidity programming language and the Ethereum Virtual Machine (EVM) [16], for coding smart contracts and to execute them, respectively. Ethereum's degree centrality increased from 0.088 in 2014 to 0.419 in the 2020s, a ~376.64% growth. Additionally, Ethereum increased the interest in smart contracts, which appeared in the mid-1990s [98] remaining seemingly static in degree centrality until 2014-2015 when Ethereum adopted smart contracts in its platform [16] and facilitated their development with Solidity and deployment and execution in a Blockchain with its EVM. Interest in smart contracts grew significantly, from 0.011 in the mid-1990s to 0.472 in the 2020s, an increase of ~4,299.04%. This interest is reflected in efforts to extend

smart contracts' applicability, including legal aspects [78] through Smart Legal Contracts and their generation using NLP [22].

Amid these developments, Proof of Stake was introduced as an energy-efficient alternative to Proof of Work by [52] in 2012, which grew from 0.017 degree centrality since its introduction to 0.152 in the 2020s, a ~768.68% growth. This innovation demonstrates the DLT community's response to Bitcoin's popularity and its search to improve upon existing consensus mechanisms, such as PoW.

5.3 ESG/DLT citation networks

The ESG/DLT content density citation graph, derived from 505 papers, comprises 10,172 nodes (each node representing a citation) with 15,898 edges and 20,111 temporal edges connecting the publications across time. This graph facilitates narrowing down the publications specific to the ESG/DLT intersection.

In terms of our analysis of the citation network, Figure 5b and Figure 5c indicate that foundational publications, particularly those introducing Bitcoin, Ethereum, and other early blockchain technologies, have significantly influenced subsequent research. This is evident from their high citation counts and anchoring positions in the network (see Figure 5c). Similar to the topics graph (Figure 5a), in our ESG/DLT citation network, Nakamoto's Bitcoin whitepaper [71] emerges as a central node (Figure 5c), emphasizing its foundational impact on DLT research [93, 113]. This network also prominently features other key DLT innovations, including Hashcash [8] as a precursor to Bitcoin's PoW implementation, Ethereum's popularization of smart contracts in 2014 [16], and PPCoin's 2012 development of PoS [52], indicating significant milestones in DLT evolution.

The network (Figure 5b) shows a publication surge between 2008 and 2011 of ~191.03%, aligning with Bitcoin's release and its subsequent influence on diverse DLT research areas, notably in consensus mechanisms (Figure 6a). Post-2012, the network saw a marked increase in publications, especially after 2014, reflecting the impact of seminal works like PPCoin and Ethereum's whitepapers [16, 52]. The growth in citations and publications from 2012 until the 2020s was ~901.75%.

The increasing ESG content density (Figure 6c) within DLT research (Figure 6a) highlights a shift in thematic interests (Figure 5a and Figure 6a), from an early focus on security and privacy driving adoption (subsection 5.2) and implementations, like Bitcoin, to a growing emphasis on efficient [52] and secure consensus algorithms [33], and blockchain architectures [14, 109]. Key historical developments include the emergence of PoW in the late 1990s, as exemplified by [8], and the rise of PoS-related entities around 2012, following [52]’s work (Figure 6b). The increased interest in PoS as an energy-efficient alternative to PoW is exemplified by the exploration of Vitalik Buterin, co-founder of Ethereum, of it before even Ethereum was launched in 2015 using PoW, evident in his 2014 Slasher algorithm post [108] and later posts that discuss PoS benefits [106], and the "nothing at stake" challenge [107]. Vitalik’s early public discussions of PoS may have been one of the catalysts that encouraged further research into PoS (Figure 5a and Figure 6b) before Ethereum’s transition from PoW to PoS in 2022 [1]. This is consistent with how Ethereum popularized smart contracts by adopting them in their platform despite the research around smart contracts existing since the mid-1990s [98], but remaining seemingly static as a topic of interest for the research community (Figure 5a) until after Ethereum’s adoption (subsection 5.2 and Figure 5a).

Recent years have seen an academic shift towards ESG [39] and consensus-related terms [6], reflecting an evolving focus on energy-efficient distributed systems [73, 89], decentralization, and sustainable blockchain research (Figure 6c). This shift, coupled with the increasing prominence of terms like "decentralization", "blockchain", and "sustainability", underscores a multidisciplinary approach in the field. The sustained interest in PoW, along with explorations into PoS and other consensus mechanisms, highlights the field’s adaptability to environmental and scalability challenges (Figure 6b). This evolution reflects a balance between technological advancements and societal ESG imperatives, demonstrating the academic community’s holistic and forward-thinking approach to addressing blockchain technology’s challenges and opportunities.

5.4 Limitations

Our literature review faces limitations, including potential biases in seed paper selection and a time lag in capturing recent publications, which may affect the comprehensiveness of our analysis. For instance, the choice of XRP’s 2018 whitepaper [19] over the more cited 2014 edition [88] could underestimate its influence in the citation network. Similarly, recent works like the 2018 Hedera whitepaper [10] are omitted due to unavailable citation data.

The retrospective approach of building the citation network predominantly from pre-2020 seed papers introduces a bias toward older publications, potentially overlooking newer research yet to achieve recognition (Figure 5b). While our methodology could theoretically filter *citations* to seed papers based on content density, our review focused solely on references within the seed papers, possibly limiting the thematic breadth.

Regarding our NER dataset performance, there is an expected level of noise for NER datasets [2, 40, 80] that we tried to reduce by enforcing interlabeler consistency (see subsection 3.3). Our dataset,

with 46 full-text labeled papers, is smaller than many general-purpose NER datasets (thousands or millions of labelled documents [60, 102, 103, 111]) but is comparable in size to those in specialized fields like materials science, such as [23]’s dataset composed of 146 papers and [35] composed of 100 labeled abstracts. However, expanding our dataset would likely improve its F1 score.

A significant constraint of this study is the reliance on publicly available research. Despite starting with an extensive citation network of 63,083 references (Figure 3), the analysis was limited to 24,539 publications with accessible full texts, highlighting the challenges of limited public access to some academic publications. This limitation points to the need for broader accessibility in research, especially in rapidly evolving fields like DLT. On the other hand, we acknowledge the growing importance of non-traditional literature, such as whitepapers and industry publications, in offering more inclusive access to technological developments in DLT.

5.5 Future work

Future work, as outlined in subsection 5.4, should focus on integrating metadata from different whitepaper versions, like XRP’s 2014 and 2018 editions [19, 88], and sourcing metadata from alternative databases for publications with missing information, such as Hedera’s whitepaper [10].

Further research should also include regular updates to the taxonomy’s named entity categories (refer to Table 1), expanding training data by annotating more seed papers, and exploring various language model architectures.

6 CONCLUSION

The expanding scientific corpus and rising significance of non-traditional literature, including whitepapers and academic preprints, emphasize the growing need for assisted analytical methods. Our research demonstrates the efficacy of using NLP for conducting systematic literature reviews on a large scale, particularly within the rapidly evolving DLT field.

Our key contributions include the creation of the first NER dataset focused on DLT and ESG and a scalable, adaptable NLP-based systematic literature review methodology. Additionally, we have conducted an inaugural systematic literature review using this dataset and methodology, demonstrating their practical applicability and effectiveness in analyzing DLT’s technological evolution, serving as valuable resources for researchers, policymakers, and industry experts or practitioners.

Our analysis reveals the critical intersections of topics like Cryptography, Peer-to-Peer, Proof of Work, Proof of Stake, and smart contracts in the evolution of DLT. We observed Bitcoin’s rise in research prominence and Ethereum’s significant impact on smart contract technology. These insights, coupled with the growing focus on ESG concerns and energy-efficient consensus mechanisms, highlight the field’s rapid adaptation to technological and environmental challenges.

Moreover, this research represents a step toward improving automated systematic literature review processes at scale. Our open methodology and NER dataset offer a foundation for further research, overcoming the limitations of commercial tools while meeting evolving research needs.

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