Constructing Knowledge Graph in Blockchain Teaching Program Using Formal Concept Analysis

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***Abstract*—The rapid evolution of blockchain technology calls for innovative educational frameworks to effectively convey its complex principles and applications. This paper investigates the use of Formal Concept Analysis (FCA) for constructing knowledge graphs as part of a blockchain teaching program. FCA, grounded in lattice theory, provides a mathematical foundation for analyzing relationships between concepts, making it an ideal tool for organizing and visualizing knowledge structure within blockchain education. This study aims to develop an interactive, context-based graph that captures the intricate interrelations among blockchain topics. The methodology includes mapping key blockchain concepts and their applications into a structured graph, which enhances both the understanding and the systematic delivery of educational content. The research demonstrates that FCA not only facilitates the creation of scalable and adaptable educational materials but also enhances students' conceptual understanding by presenting the interconnected nature of blockchain concepts in an accessible format. Knowledge graph aids in identifying interconnected learning outcomes that cover overlapping subjects. It serves as a valueable resource for educators focusing on cryptocurrencies, making it easier to create a thorough list of key topics related to particular cryptocurrency characteristics.**

***Keywords*—Knowledge graph; formal concept analysis; blockchain education; curriculum optimization; interactive learning tools**

I. Introduction

In the rapidly evolving landscape of cryptocurrencies, understanding the intricate relationships between various concepts is pivotal for effective analysis, decision-making, and innovation. Cryptocurrencies have not only revolutionized financial transactions but have also sparked interest in interdisciplinary research spanning economics, computer science, and cryptography. In various industries, blockchain enables the transfer of digital assets within a peer-to-peer network (such as currencies, securities, votes, shares, and commodities), facilitates data tracing (for financial assets, products, and other goods), and automates the management of contracts of all types (including insurance and programmable payments) [1-4].

The impact of blockchain will extend across various sectors, including finance, industry, renewable energy, government, and educational applications [5-10]. In this way, it has appeared the demand in creating educational programs of blockchain domain. Kazakhstan pioneered an educational initiative, becoming the first country globally to integrate blockchain into the standard university curriculum on a national level. During the pilot phase, the Blockchain Center chose 22 out of 116 universities to participate, developing six unique courses in blockchain engineering for them [11]. Presently, 16 universities have incorporated blockchain courses into their educational offerings. Building on the success of the pilot project, The Global University Outreach Program, the Binance Academy education center and the Blockchain Center research laboratory have announced the expansion of their blockchain educational initiative to incorporate Web3 education into the curricula of over 200 universities across 50 countries [12]. The utilization of data mining tools is essential for the rapid development and optimization of educational programs on blockchain, enabling a data-driven approach to tailor content that meets the evolving needs of the academic and professional landscape.

Due to this complexity, constructing a robust knowledge graph becomes indispensable for organizing knowledge and facilitating efficient information retrieval and inference. Hsu [13] summarized a study that systematically reviews 60 data science course syllabi from general education classes in Taiwan, highlighting the need to address diverse student backgrounds by evaluating course content, instructional materials, assessment methods, and learning objectives, with an emphasis on Python programming and big data competency.

Sumangali and Kumar [14] introduced a novel approach for generating a smaller, meaningful concept lattice in FCA by organizing attributes into clusters based on structural similarities and dissimilarities, thereby simplifying the extraction of valueable information while preserving the structural relationships of the original lattice. Cui et. al [15] addresses the challenge of handling extensive linguistic information in uncertain environments by introducing a property-oriented linguistic concept lattice combined with a neural network to improve rule extraction and inference accuracy, ultimately demonstrating the efficiency of the method through experiments.

FCA is a mathematical method for data analysis grounded in lattice theory [16,17]. In FCA, a concept lattice graphically portrays the underlying relationships between the objects and attributes of an information system. One of the key complexity problems of concept lattices lies in extracting the valueable information. The unorganized nature of attributes in huge contexts often does not yield an informative lattice in FCA. Moreover, understanding the collective relationships between attributes and objects in a larger many valued context is more complicated.

Hao et. al [18] proposed a knowledge point navigation approach for autonomous learning using three-way concept lattices to describe correlations and hierarchical relationships among knowledge points, generating AE-concept and OE-concept lattices to provide effective learning paths and guidance. Lara-Bercial et al. [19] concluded that students who engaged with Project-Based Learning (PBL) in the Computer Engineering degree at Universidad Europea perceive a better acquisition of technical and soft skills, as well as improved motivation and adaptability to the work environment compared to those who did not use PBL.

While previous studies have leveraged various methodologies for ontology construction, the adoption of FCA holds promise for capturing contextual information and conceptual hierarchies within the cryptocurrency ecosystem. By employing FCA as a methodological framework, researchers can construct context-aware knowledge graph that serve as valuable resources for semantic analysis, data integration, and knowledge representation in this dynamic and rapidly evolving domain.

In this paper, It was introduced a novel approach for deducing a smaller and meaningful concept lattice from which excerpts of concepts can be inferred. In existing attribute-based concept lattice reduction methods for FCA, mostly either the attribute size or the context size is reduced. This approach organized the attributes and objects within the blockchain teaching program into clusters based on their structural relationships, using FCA to create a derived formal context. Through this process, It was observed that the generated concept lattice preserves the hierarchical relationships present in the original dataset. Moreover, It was demonstrated mathematically that there exists a unique surjective inclusion mapping from the original concept lattice to the derived one, ensuring the structural integrity and completeness of knowledge graph constructed.

The primary objective of this paper is twofold: firstly, to demonstrate the feasibility and efficacy of FCA in knowledge graph building within the blockchain context, and secondly, to showcase the practical applications of the resulting the graph in enhancing data interpretation, knowledge discovery, and decision support in creating educational program.

This paper focused on the realm of knowledge graph construction within the blockchain domain in educational purposes, employing FCA as a methodological framework. FCA, rooted in lattice theory and order theory, offers a systematic approach to conceptual analysis, allowing for the extraction of meaningful relationships between entities and attributes. By leveraging contextual information inherent in cryptocurrency data, this approach aims to capture the nuanced semantics and interdependencies prevalent in this dynamic domain.

Furthermore, it was illustrated the applicability of this methodology through an experiment wherein It was constructed knowledge graph adapted to the blockchain domain, capturing essential concepts, relationships, and properties pertinent to this burgeoning field.

While previous research, such as that by Sumangali and Kumar [14] and Hao et al. [18], has explored the application of Formal Concept Analysis (FCA) in various domains, including simplifying concept lattices and generating effective learning paths, this work is distinct in its integration of FCA with clustering methods for structuring educational programs in the blockchain domain. Unlike traditional applications of FCA [19-21], which primarily focus on organizing attributes within a specific context, its approach introduces a novel combination of FCA and clustering to generate an interactive knowledge graph tailored specifically for blockchain education [22]. This innovation enables a more scalable and adaptable educational framework compared to existing methods, such as ontology-based approaches [23-25]. Furthermore, the integration of association rules into the knowledge graph enhances decision-making for educators, providing them with data-driven insights on curriculum organization. Table I presents a comparison of previous methods with our proposed approach, highlighting key differences in terms of methodology, scalability, and application domain.

TABLE I. COMPARISON OF PREVIOUS WORKS WITH OUR APPROACH

Method	Domain	Methodology	Strengths	Weaknesses
Sumangali & Kumar [14]	Various domains	FCA with attribute clustering	Simplifies extraction of valuable information	Does not incorporate association rules
Hao et al. [18]	Autonomous learning	FCA and three-way lattices	Improves learning path accuracy	Limited scalability
Chang et al. [25]	Intelligent Tutoring Systems	Ontology-driven tutoring	Automates rule derivation from tutoring sessions	No formal concept lattice structure
Our Work	Blockchain education	FCA + Clustering + Assoc. Rules	Scalable, adaptable, enhances decision-making	Focuses specifically on blockchain domain

The organization of the following sections is as follows: the Related Works section provides a detailed overview of the current approaches in blockchain education, focusing on the use of knowledge graphs and FCA; the Materials and Methods section explains the experimental setup and the design of the educational program using FCA and clustering methods; in the Results section, we present the results of the experiment, emphasizing the construction of the knowledge graph and its application in blockchain education; the Discussion and Conclusion section summarizes the findings of our work, compares our approach with previous methodologies, and outlines future research directions.

II. RELATED WORKS

The advent of cryptocurrencies has not only revolutionized financial transactions but has also stimulated interdisciplinary research across various domains. Among the challenges posed by this burgeoning field is the need for effective knowledge organization and representation to navigate the complex network of concepts, entities, and relationships inherent in cryptocurrency systems. Blockchain offers significant advantages to businesses, including transparency, privacy, fault tolerance, security, risk control, democratization, tokenization, immutability, durability, and reliability [20-23]. In response to this challenge, scholars have increasingly turned to ontology engineering as a means to formalize and structure domain knowledge, facilitating data interpretation, semantic search, and decision-making processes.

Cowart and Jin [24] highlighted that while all ten design elements in an online professional development series were beneficial for Instructional Technology Coaches' TPACK development, some participants experienced hindrances such as collaboration challenges, technical issues, and time constraints, underscoring the need for improvements in these areas. Chang et al. [25] introduced an innovative method to preserve the advantages of using a semantic web-based approach for representing pedagogical rules in an Intelligent Tutoring System (ITS). They addressed its primary limitation by utilizing a data mining technique to automatically derive rules from real-world tutoring sessions and represent them using the Web Ontology Language. Cristea et al. [26] indicated algorithms that integrate FCA with Pylint, a static code analysis tool, to identify and evaluate behavioral patterns in students' programming styles, aiming to enhance teaching content and methods. Hao et al. [27] define the stability of a three-way concept and examine its relevant properties. This concept can be applied to measure the cohesion of sub-graphs, enhance personalized recommendation systems, and facilitate team formation in crowdsourcing systems. Muangprathub et al. [28] developed a learning recommendation component for an intelligent tutoring system (ITS) that dynamically predicts and adapts to a learner's style. To create an effective ITS, they presented an enhanced knowledge base that supports adaptive learning, achievable through appropriate knowledge construction.

The construction of knowledge graph tailored to the cryptocurrency domain has emerged as a pressing research endeavor, driven by the need to capture the evolving semantics and interdependencies inherent in blockchain-based systems. Prior studies have highlighted the significance of ontology engineering in facilitating data interoperability, semantic integration, and knowledge discovery across disparate cryptocurrency platforms [29]. By representing domain knowledge in a formalized and machine-interpretable manner, ontologies enable stakeholders to discern meaningful patterns, infer implicit relationships, and extract actionable insights from cryptocurrency data.

Song et al. [30] utilized IP protection as a case study to demonstrate the development of their PoC consensus mechanism. It was compared PoC to various existing consensus mechanisms. The experimental results indicated that the PoC consensus mechanism retains most of the essential security features of blockchain and outperforms current consensus mechanisms, thereby enhancing the security and efficiency of blockchain technology for managing digital information.

Gustavo Betarte et. al [31] presented and briefly discussed these properties, and outlined the foundation of a model-driven verification approach aimed at certifying the correctness of a specific protocol implementation. Son D-H. [32] analyzed the effects of reward schemes on on-demand ride-sourcing markets through a mathematical model in which a ride-sourcing platform determines the trip fare, vehicle fleet size, and cryptocurrency reward size.

Kobayakawa et. al [33] analyzed cryptocurrency projects on GitHub to understand the relationship between market capitalization and contributor activity, finding that an increase in market capitalization leads to a rise in the number of contributors two months later, highlighting the influence of a project's future prospects on participation. Vidal-Tomás's [34] analysis of 174 tokens revealed that this new crypto niche exhibits long-term positive performance, low correlation with the broader cryptocurrency market, the presence of bubbles, and minimal correlation with NFT features like transaction numbers, sales, and Google searches.

Aquilina et. al [35] discussed the advantages and disadvantages of various regulatory approaches, proposes a framework for determining the appropriateness of bans, containment, and regulation, and describes Japan's pioneering methods, suggesting that central banks and public authorities can enhance traditional financial systems to support responsible innovation. Subramanian & Rouxelin [36] examined the impact of cryptocurrency rewards and token prices on user-generated content (UGC) on Steemit, finding that while higher rewards boost UGC contributions, token price increases alone do not, and that UGC growth does not necessarily enhance market capitalization, highlighting the need for well-designed reward mechanisms to sustain user engagement and platform growth. Hajiaghapour-Moghimi et. al [37] introduced cryptocurrency mining loads (CMLs) as virtual energy storage systems (CESSs) to store excess renewable energy in cryptocurrency units like Bitcoin, proposing an energy management system for microgrids (MGs) that reduces operational costs and renewable energy curtailment, demonstrated with a Finnish island dataset to decrease MG operating costs by about 46.5% and nearly eliminate energy curtailment.

The literature on ontology engineering within the cryptocurrency domain underscores the importance of formalizing domain knowledge to facilitate data interpretation, knowledge discovery, and decision support. While previous studies have leveraged various methodologies for ontology construction, the adoption of FCA holds promise for capturing contextual information and conceptual hierarchies within the cryptocurrency ecosystem. By employing FCA as a methodological framework, researchers can construct context-aware knowledge graphs that serve as valuable resources for semantic analysis, data integration, and knowledge representation in this dynamic and rapidly evolving domain.

While the application of FCA in ontology engineering has been widely explored across various domains, its utilization within the cryptocurrency domain remains relatively underexplored. Nonetheless, recent studies have demonstrated the efficacy of FCA in capturing the contextual nuances and semantic relationships prevalent in cryptocurrency data [38]. By employing FCA as a methodological framework, researchers have successfully constructed context-aware ontologies that encapsulate essential concepts, attributes, and relationships within the cryptocurrency ecosystem [39].

In this literature review, It was explored the existing research landscape pertaining to knowledge graph construction within the cryptocurrency properties, with a specific focus on the application of FCA as a methodological framework.

III. Materials and Methods

This empirical investigation focused on all the topics relevant to the study of Blockchain as a discipline, getting from diverse sources including Massive Open Online Courses (MOOCs) and various syllabuses. These syllabuses were specifically provided as part of a comprehensive Blockchain technology training program, organized by the Blockchain Center in the framework of University Outreach program during the spring of 2024. This program is designed to learn university educators with the necessary knowledge and tools to proficiently teach blockchain technology.

The duration of this primary course includes three months, equivalent to 14 weeks, with a weekly commitment of six hours, totaling 84 instructional hours, exclusive of practical sessions. In addition to this, a specialized course titled “Blockchain Compliance” was introduced, targeting students in economics and legal studies. This course emphasizes the legal and policy implications of blockchain technology and cryptocurrencies, crucial for educators in these fields. The “Blockchain Compliance” course is structured over six weeks, with six hours of instruction per week, culminating in 36 hours of learning, not including practical sessions. The division by specialization was carried out by conducting a survey among the teachers who took part in Global University Outreach Program, initiated by the Binance Academy education center and the Blockchain Center research laboratory.

These courses are designed to ensure that participants are well-versed in both the technical and regulatory aspects of blockchain, preparing them to navigate and impart the complexities of this emerging field effectively.

Totally, the program for the Blockchain technology courses encompassed a comprehensive range of over 100 distinct topics, distributed across two separate courses. These courses collectively aimed to achieve 20 specific learning outcomes. Each week, students were required to engage in four hours of practical sessions, resulting in a cumulative total of 80 hours dedicated to hands-on practice over the duration of the courses. Despite the extensive educational content and the structured practical experience, the demanding nature of the coursework proved to be challenging. Consequently, only 60% of the enrolled participants successfully completed the courses in their entirety.

It was conducted an experiment of an educational program for blockchain technology. The aim of this study was to create knowledge graph with visualization of visualize the interconnections among various components of blockchain area. Knowledge graph includes specialty nodes, learning outcome nodes and topic nodes related to blockchain and cryptocurrency. This research was valueable for development of syllabus and educational program using knowledge graph. Additionally, it presents the outcomes of the experiment, demonstrating the effectiveness of this approach in curriculum development. The knowledge graph incorporates the following components:

- Specialties: Courses that encompass the study of blockchain technology.
- Learning Outcomes: Key results that students are expected to achieve through their blockchain education.
- Topics: Specific subjects related to the learning outcomes.
- Properties of Cryptocurrencies: Essential characteristics of cryptocurrencies, including decentralization, scalability, and security.
- Types of Cryptocurrencies: Various categories of cryptocurrencies, each associated with specific properties.

Each node in the graph was assigned a specific size and color to clearly differentiate between categories of elements. The connections between nodes illustrate the interactions among various program components, thereby providing a comprehensive visualization of how these elements collectively contribute to the overall learning framework.

The formal context (X,Y,I) is constructed from the dataset provided according to Ganter and Wille [40], where:

1) Formal context: $X = \{x_1, x_2,\ldots,x_n\}$ represents the set of objects, which in this case includes Specialties, Learning Outcomes, Topics, and Cryptocurrencies.

$Y=\{y_1,y_2,\ldots,y_m\}$ represents the set of attributes associated with these objects, capturing the relationships between them.

I is the binary relation $I \subseteq X \times Y$, indicating the presence of an association between a particular object and its corresponding attribute (e.g., a specific learning outcome being related to a particular topic or specialty).

2) Concept-Forming operators: In the context of this code, the concept-forming operators α and β can be defined as:

$$\alpha (A) = \{y \in Y \mid \forall x \in A, (x, y) \in I\} \text{ for } A \subseteq X \quad (1)$$

$$\beta (B) = \{x \in X \mid \forall y \in B, (x,y) \in I\} \text{ for } B \subseteq Y \quad (2)$$

Here, α (A) retrieves all the attributes (e.g., related topics or cryptocurrencies) that are common to the selected set of objects (e.g., specialties or learning outcomes), and β (B) finds the set of objects that share a given set of attributes.

3) Formal concept: A formal concept in this framework is a pair (A, B) where:

$$A = \beta (B) \text{ and } B = \alpha (A) \quad (3)$$

A (extent) is the set of all objects (e.g., all learning outcomes) associated with a particular set of attributes (e.g., all related topics or cryptocurrencies).

B (intent) is the set of all attributes associated with a particular set of objects.

4) Concept lattice: The concept lattice B(X, Y, I) formed from this context is a partially ordered set, where each node represents a formal concept, and the ordering is determined by the subset relations between the extents and intents of these concepts:

$(A_1, B_1) \leq (A_2, B_2)$ if and only $A_1 \subseteq A_2$ and $B_2 \subseteq B_1$

This lattice structure visually and hierarchically organizes the relationships between specialties, learning outcomes, topics, and cryptocurrencies.

Galois Connection: The Galois connection between the concept-forming operators α and β ensures that:

$$A \subseteq \beta(B)\ if\ and\ only\ if\ B \subseteq \alpha(A) \qquad (4)$$

This duality allows the formal concepts to be derived efficiently, ensuring that every set of related attributes can be linked to a specific group of objects.

5) Algorithm: The algorithm is constructed using the formulas from Chapter 3.1, in particular formulas (1), (2) and (3). At each stage, the data is analyzed using the operators α and β, which allows identifying the relationships between objects and attributes. These formulas are used to determine the relationships between the elements of the system, which ensures the efficient construction of the knowledge graph. Then, using the partially ordered set of formal concepts, as specified in formula (4), a knowledge graph is constructed that visualizes the relationships between learning outcomes, topics and cryptocurrencies. The Galois relationship (5) ensures the correctness of the construction of formal concepts and is used to efficiently extract the relationships between objects and attributes during the execution of the algorithm.

Here is the algorithm for constructing a knowledge graph based on syllabi:

Algorithm 1: Heading

Input: *D, N* $\leftarrow \varnothing$*, E* $\leftarrow \varnothing$*, S, LO, T, CP, CT* $\leftarrow \varnothing$

Output: *G=(V,E)*, where *V={ S, LO, T, CP, CT }, E* $\subseteq V \times V$

For each row d ∈ D do:

Extract *s* ← *d['Specialty'], lo* ← *d['Learning_Outcome'], t* ← *d['Theme'], cp* ← *d['Crypto_Properties'], ct* ← *d['Crypto_Types]*.

Define the formal context *(X, Y, I)*, where:

$X = \{x_1, x_2, \ldots, x_n\}$, where *X = {Specialties, Learning Outcomes, Topics, Cryptocurrencies}*,

$Y = \{y_1, y_2, \ldots, y_m\}$, where *Y = {attributes such as learning outcomes related to topics and specialties}*,

$I \subseteq X \times Y$

Apply concept-forming operators α and β as follows:

$\alpha(A) = \{y \in Y \mid \forall x \in A, (x,y) \in I\}$ (6) (6)

$\beta(B) = \{x \in X \mid \forall y \in B, (x,y) \in I\}$ (7)

Define a formal concept as a pair (A,B), where A=β(B) and B=α(A).

Node and Edge Addition:

If *s∉N then:* Add s (specialty) as a node and connect it to lo.

If *lo∉N then:* Add lo as a node and connect it to t.

If *t∉N then:* Add t as a node and connect it to cp.

If *cp∉N then:* Add cp as a node and connect it to ct.

If *ct∉N then:* Add ct as a node.

Construct the concept lattice *B(X,Y,I)*, a partially ordered set of formal concepts:

$(A1,B1) \leq (A2,B2)$ *if* $A1 \subseteq A2$ *and* $B2 \subseteq B1$ (8)

Maintain the Galois connection between α and β:

$A \subseteq \beta(B)$ *if* $B \subseteq \alpha(A)$ (9)

Update *V={ S, LO, T, CP, CT}* for later use in tooltip visualization.

If all rows are processed ***then***: Represents the graph *G*.

End

End

where, D - an Excel file containing data on specialties, learning outcomes, topics, and cryptocurrencies, N - set of graph nodes, E - set of edges between nodes, S - specialties, LO - learning outcomes, T - theme, CP - crypto properties, CT - crypto types, G - represents the graph, V - set of nodes, I - binary relation linking objects and attributes, A - set of all objects (e.g., learning outcomes), B - set of all attributes (e.g., related topics).

Below in Fig. 1 is a sequence diagram of these steps for visual demonstration.

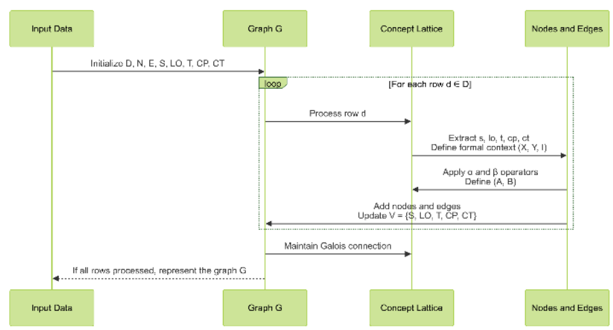

Fig. 1. Sequence diagram of the algorithm for creating knowledge graphs based on blockchain topics.

IV. RESULTS

During the review process of the syllabuses on Blockchain technologies, particularly those offered through Massive Open Online Courses (MOOCs), experts in the field of blockchain concluded that it would be beneficial to divide the original two syllabuses into four distinct specializations: (1) Information Technology, (2) Information Security, (3) Economics, and (4) Jurisprudence. Each specialization is associated with specific, required learning outcomes, as detailed in Table II. Besides, it includes the final five learning outcomes without any particular specialization due to relation to general topics.

TABLE II. LEARNING OUTCOMES BY SPECIALTY

№	Learning_Outcome	Specialty
1.	Blockchain architecture and algorithms	Information technology
2.	Security and cryptographic methods in blockchain	Information technology
3.	Using oracles and simplified programming languages in blockchain	Information technology
4.	Development of decentralized applications (DApps)	Information technology
5.	Development of smart contracts	Information technology
6.	Security of hardware wallets and other storage media	Information security
7.	Security of smart contracts and decentralized applications (DApps)	Information security
8.	Data protection and privacy in blockchain networks	Information security
9.	Cryptographic methods and protocols in blockchain	Information security
10.	Ensuring the security of blockchain systems	Information security
11.	Cryptocurrency market analysis and forecasting	Economy
12.	Application of blockchain in banking and international transfers	Economy
13.	Development and implementation of decentralized financial applications (DeFi)	Economy
14.	Regulation of cryptocurrency exchanges and financial security	Economy
15.	Asset tokenization and blockchain-based crowdfunding	Economy
16.	Intellectual property and data protection in blockchain	Jurisprudence
17.	Application of blockchain in notarial activities and public administration	Jurisprudence
18.	Regulation and legal aspects of blockchain technologies	Jurisprudence
19.	Legal aspects of decentralized autonomous organizations (DAO)	Jurisprudence
20.	Legal aspects of tokenization and use DeFi	Jurisprudence
21.	The impact of blockchain on the economy and various industries	General topics
22.	Application of blockchain in government agencies and healthcare	General topics
23.	Application of blockchain in smart cities and digital identity	General topics
24.	Comparison and use of different blockchain platforms	General topics
25.	Technological innovation and development of blockchain ecosystems	General topics

Each learning outcome encompasses specific topics, with the potential for a single topic to correspond to multiple learning outcomes, and conversely, for a learning outcome to span several topics. Table III highlights the example of the relation mentioned. Consequently, certain topics may be essential across various specializations in order to fulfill the requirements of different learning outcomes.

TABLE III. EXAMPLE OF SOME CONNECTIONS BETWEEN TOPICS AND LEARNING OUTCOMES

№	Topics	Learning outcomes
1.	Consensus Algorithms: Proof of Stake	Blockchain architecture and algorithms
2.	Consensus Algorithms: Proof of Work	Blockchain architecture and algorithms
3.	Security of decentralized applications (DApps)	Security and cryptographic methods in blockchain
3.	Security of decentralized applications (DApps)	Security of smart contracts and decentralized applications (DApps)
4.	Consensus algorithms: Proof of Stake	Blockchain architecture and algorithms
5.	Consensus algorithms: Proof of Work	Blockchain architecture and algorithms
6.	Blockchain architecture	Blockchain architecture and algorithms
7.	Methods for protecting consensus algorithms	Blockchain architecture and algorithms
8.	Scalability issues and security	Blockchain architecture and algorithms
9.	Comparison of different consensus algorithms	Blockchain architecture and algorithms
10	Distributed ledger technology (DLT)	Blockchain architecture and algorithms
11	Verification and audits of smart contracts	Security and cryptographic methods in blockchain
11	Verification and audits of smart contracts	Security of smart contracts and decentralized applications (DApps)
11	Verification and audits of smart contracts	Cryptographic methods and protocols in blockchain
11	Verification and audits of smart contracts	Application of blockchain in banking and international transfers

Cryptocurrencies have become an integral component of the global economy and financial system, due to blockchain serving as the foundational technology that underpins their functionality and growth. This highlights that, the existence and operation of cryptocurrencies are inextricably linked to blockchain technology, making it indispensable to the cryptocurrency ecosystem, it was essential to incorporate the types and properties of cryptocurrencies into the educational curriculum on blockchain technologies. As can be seen from Table IV, an analysis of popular cryptocurrencies and the properties they support is provided.

TABLE IV. TYPES AND PROPERTIES OF CRYPTOCURRENCIES

Cryptocurrency properties	Bitcoin (BTC)	Ethereum (ETH)	Ripple (XRP)	Litecoin (LTC)	Monero (XMR)	Cardano (ADA)	Polkadot (DOT)	Chainlink (LINK)
Decentralization	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Smart Contract	No	Yes	Yes	No	Limited	Yes	Yes	Yes
Privacy	No	No	No	No	Yes	No	No	No
Scalability	No	Yes	Yes	No	No	Yes	Yes	Yes
Proof of Work	Yes	No	No	Yes	Yes	No	No	No
Proof of Stake	No	Yes	No	No	No	Yes	Yes	No
Limited Supply	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Mainstream Adoption	Yes	Yes	Yes	Moderate	Limited	Moderate	Moderate	Moderate
Cross-Chain	No	No	No	No	No	No	Yes	Yes
Exchange Availability	Yes	Yes	Yes	Yes	Moderate	Yes	Yes	Yes
Mining Requirement	Yes	No	No	Yes	Yes	No	No	No
Governance Model	No	Yes	Yes	No	No	Yes	Yes	No
Deflationary Mechanism	No	No	No	No	No	No	No	No
Staking Rewards	No	Yes	No	No	No	Yes	Yes	No
Energy Efficiency	No	No	Yes	No	No	Yes	Yes	Yes
Regulatory Compliance	Yes	Yes	Yes	Moderate	Limited	Yes	Moderate	Moderate
Developer Community	Yes	Yes	Moderate	Yes	Moderate	Yes	Yes	Yes
NFT Support	No	Yes	Limited	No	No	Yes	Yes	Yes

The study of cryptocurrency properties and types aligns closely with the existing topics and learning outcomes within the blockchain curriculum. In collaboration with experts from the Blockchain Center, It was established a framework that connects the properties and types of cryptocurrencies to the relevant general topics and learning outcomes. This integrative approach ensures a cohesive learning experience, reinforcing key concepts across both areas of study. Table V presents a partial mapping of these connections, demonstrating how the properties and types of cryptocurrencies are integrated with specific learning outcomes.

TABLE V. RELATIONSHIP BETWEEN THE PROPERTIES AND TYPES OF CRYPTOCURRENCIES AND LEARNING OUTCOMES

№	Learning outcomes	Properties of cryptocurrencies	Types of cryptocurrencies
1.	Using oracles and simplified programming languages in blockchain	Cross-Chain	Polkadot (DOT), Chainlink (LINK)
2.	Development of decentralized applications (DApps)		
3.	Blockchain architecture and algorithms	Decentralization	Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Monero (XMR), Cardano (ADA), Polkadot (DOT), Chainlink (LINK)
4.	Legal aspects of decentralized autonomous organizations (DAO)		
5.	Blockchain architecture and algorithms		
6.	Security of smart contracts and decentralized applications (DApps)		
7.	Application of blockchain in notarial activities and public administration		
8.	Development of smart contracts	Developer Community	Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Monero (XMR), Cardano (ADA), Polkadot (DOT), Chainlink (LINK)
9.	Technological innovation and development of blockchain ecosystems		
10.	Ensuring the security of blockchain systems	Energy Efficiency	Ripple (XRP), Cardano (ADA), Polkadot (DOT), Chainlink (LINK)
11.	Security of hardware wallets and other storage media		
12.	Cryptocurrency market analysis and forecasting	Exchange Availability	Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Monero (XMR), Cardano (ADA), Polkadot (DOT), Chainlink (LINK)

From an analysis of Table VI, it emerges summarized information of the connections between all topics, required learning outcomes, specializations, and data on cryptocurrencies, comprises 2,054 rows and 5 columns. This table serves as an extensive resource, capturing the intricate relationships among these elements.

TABLE VI. FINAL TABLE INDICATING CONNECTIONS BETWEEN TOPICS, LEARNING OUTCOMES, SPECIALTIES, PROPERTIES AND TYPES OF CRYPTOCURRENCIES

Theme	Learning_Outcome	Specialty	Crypto Properties	Supporting Cryptocurrencies
Anomaly monitoring and detection methods	Cryptographic methods and protocols in blockchain	Information security	Privacy	Monero (XMR)
Anomaly monitoring and detection methods	Cryptographic methods and protocols in blockchain	Information security	Security	
Anomaly monitoring and detection methods	Security of hardware wallets and other storage media	Information security	Security	
Anomaly monitoring and detection methods	Security of hardware wallets and other storage media	Information security	Energy Efficiency	Ripple (XRP)
Anomaly monitoring and detection methods	Security of hardware wallets and other storage media	Information security	Energy Efficiency	Cardano (ADA)
Anomaly monitoring and detection methods	Security of hardware wallets and other storage media	Information security	Energy Efficiency	Polkadot (DOT)
Anomaly monitoring and detection methods	Security of hardware wallets and other storage media	Information security	Energy Efficiency	Chainlink (LINK)
Anonymous cryptocurrencies and their security	Data protection and privacy in blockchain networks	Information security	Privacy	Monero (XMR)
Anonymous cryptocurrencies and their security	Data protection and privacy in blockchain networks	Information security	Security	
Application of blockchain in banking	Application of blockchain in banking and international transfers	Economy	Regulatory Compliance	Bitcoin (BTC)
Application of blockchain in banking	Application of blockchain in banking and international transfers	Economy	Regulatory Compliance	Ethereum (ETH)
Application of blockchain in banking	Application of blockchain in banking and international transfers	Economy	Mainstream Adoption	Chainlink (LINK)

As a result, an aggregated data set with all topics, learning outcomes, specialties and properties, and types of cryptocurrencies was used to build knowledge graph.

A significant outcome of the experiment was the development of a visual representation of the blockchain educational program structure, as illustrated in Fig. 2. This knowledge graph facilitates course developers in comprehensively understanding the interrelationships among majors, learning outcomes, topics, and the properties and types of cryptocurrencies. For instance, the connection between the learning outcome "Smart Contract Development" and topics such as "Smart Contract Security" and "Using Blockchain Programming Languages" highlights the specific aspects that must be incorporated into the curriculum. This visualization enables a detailed and systematic approach to curriculum design.

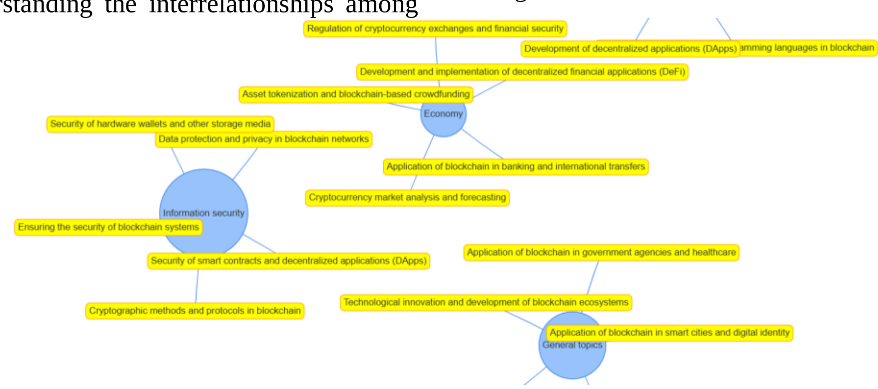

Fig. 2. Interactive graph on blockchain topics.

Fig. 3 shows knowledge graph illustrating the relationships between various elements within a blockchain education program. Knowledge graph presents structure of nodes defined by categories and different colors: Specialties (pink), learning outcomes (green), topics (yellow), cryptocurrency properties (orange), and cryptocurrency types (blue). The interconnections between nodes depict how these different components interact and relate to each other, thereby providing a clear and comprehensive overview of the program's structure.

Thus, the connections between nodes in knowledge graph provides the relationships among various components of the educational program:

Links between Specialties and Learning Outcomes indicate relation between learning outcomes and specific specialties. For instance, the learning outcome "Security and Cryptographic Methods in Blockchain" is associated with the specialty of "Information Security."

Links between Learning Outcomes and Topics reveal the topics that must be covered for achieving particular learning outcomes.

Links between Learning Outcomes and Cryptocurrency Properties demonstrate how specific properties of cryptocurrencies are incorporated into the educational framework.

Links between Cryptocurrency Properties and Cryptocurrency Types illustrate the association between different types of cryptocurrencies and their properties. For example, the property of "Limited Supply" is exemplified by Bitcoin, showcasing how certain cryptocurrencies embody specific characteristics.

Overall, these links provide a comprehensive view of how the components of the educational program interrelate, facilitating a structured approach to curriculum development.

Fig. 2 presents a visualization of the structure of the educational program dedicated to the study of blockchain technologies. At the core of this visualization is the specialty "Information Security," represented by a prominent pink node. This central node is connected to various green nodes, which denote the learning outcomes associated with blockchain security.

They were depicted among the key learning outcomes the aspects such as the security of hardware wallets, data protection and privacy within blockchain networks, and the security of smart contracts and decentralized applications (DApps). These connections illustrate the program's focus on ensuring a comprehensive understanding of security issues pertinent to blockchain technology.

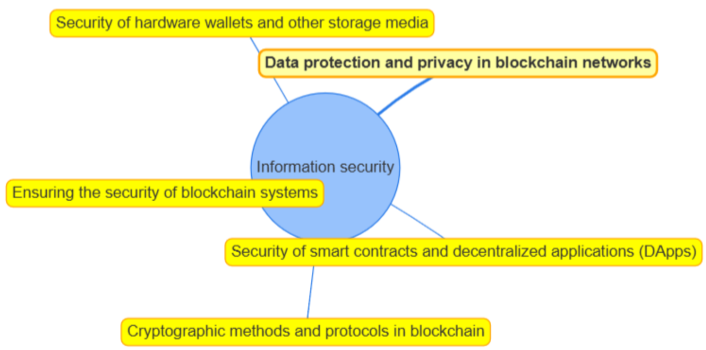

Fig. 3. List of learning outcomes related to the specialty "Information Security".

Fig. 4 reveals a segment of knowledge graph representing the blockchain educational program, with the learning outcome "Security and Cryptographic Methods in Blockchain" serving as the central node, highlighted in green. This node is interconnected with various topics that students are required to explore in relation to this outcome.

The pop-up window appears detailing a list of topics associated with this learning outcome, including the key topics such as "Introduction to Blockchain and Its Basic Principles," "Cryptographic Methods in Blockchain," and "Smart Contract Security".

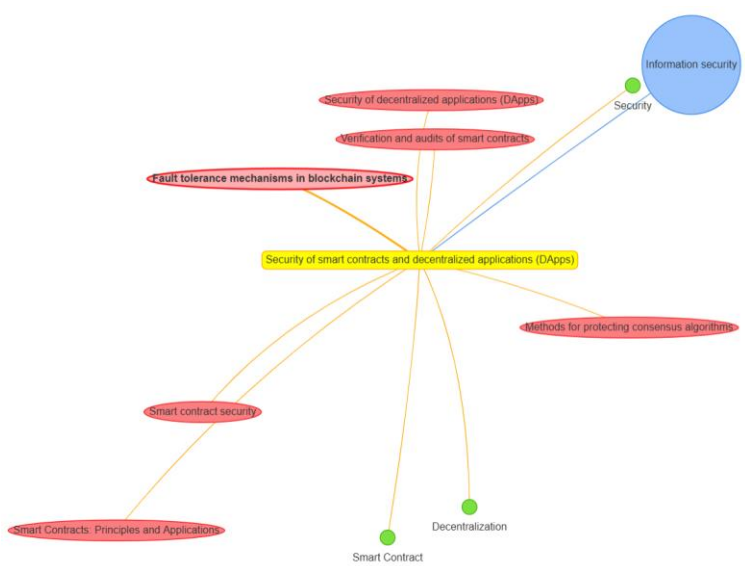

Fig. 4. Displaying a list of topics related to the learning outcome.

As can be seen from Fig. 5, knowledge graph illustrates various types of cryptocurrencies, exemplified here by Chainlink (LINK), along with their associated characteristics and properties. To do this, it is activated a pop-up window over the "Chainlink (LINK)" node with the list of key properties and aspects pertinent to this cryptocurrency. This feature enhances the visualization by offering comprehensive information about Chainlink's specific attributes and its role within the broader context of cryptocurrency types.

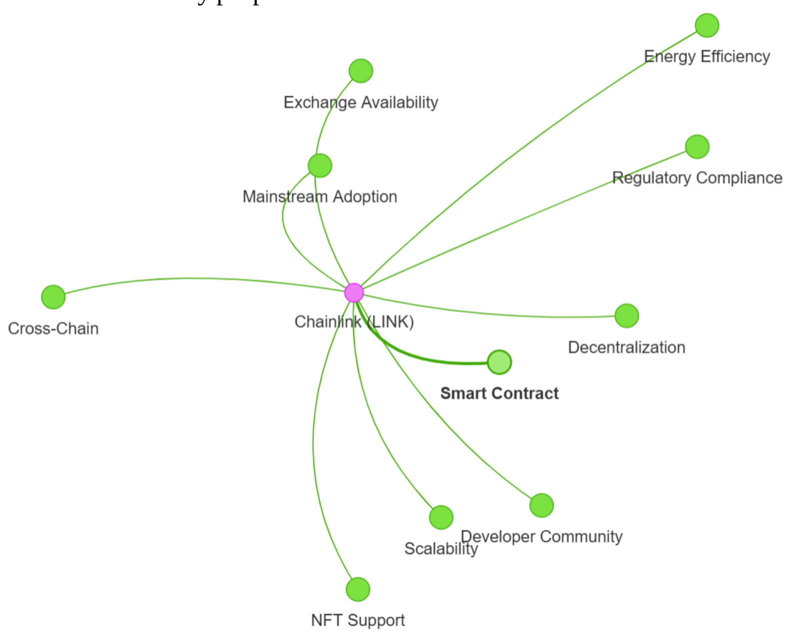

Fig. 5. A type of cryptocurrency with associated cryptocurrency properties.

Knowledge graph facilitates the identification of related learning outcomes that encompass overlapping topics. It provides a valuable tool for educators specializing in cryptocurrencies by simplifying the process of compiling a comprehensive list of essential topics associated with specific cryptocurrency properties. This functionality aids instructors in effectively organizing and delivering curriculum content adapted to various aspects of cryptocurrency education.

Following this, the association rules method is employed to determine the relationships between topics by utilizing the parameters of support, confidence, and lift. The effectiveness of this method for evaluating the significance of parameters within a dataset has been demonstrated by the authors in [42]. Analyzing these indicators enables the identification of the most critical and interrelated topics that should be incorporated into the course curriculum. The identified relationships can assist in structuring the course content more effectively. For instance, the course modules can be organized to initially cover foundational concepts such as blockchain and decentralization, before progressing to more advanced topics like smart contracts and their applications. To calculate Support, we use formula (10):

$$\text{Support}(A \rightarrow B)=(\text{Number of transactions containing } (A \cup B))/(\text{Total number of transactions}) \quad (10)$$

Support quantifies the frequency with which elements A and B co-occur within the dataset. It is defined as the ratio of the number of transactions containing both elements to the total number of transactions. Confidence, on the other hand, assesses the likelihood that element B appears in transactions that already include element A. This is calculated as the ratio of the support for A∪B (the joint occurrence of A and B) to the support for A. The formula for this metric is provided in Formula (11):

$$\text{Confidence } (A \rightarrow B) = (\text{Support } (A \cup B))/(\text{Support}(A)) \quad (11)$$

In association rule analysis, lift measures the strength of the relationship between two events or data sets. Specifically, for an association rule of the form A→B, lift quantifies how frequently elements A and B occur together compared to their expected co-occurrence if they were statistically independent. The formula for calculating lift is presented in Formula (12).

$$\text{Lift}(A \rightarrow B) = (\text{Support}(A \cup B))/(\text{Support}(A)*\text{Support}(B)) \quad (12)$$

The interpretation of lift values is as follows:

- If Lift=1, then events A and B are independent, meaning the occurrence of one event does not influence the probability of the occurrence of the other.
- If Lift>1, then events A and B co-occur more frequently than would be expected under conditions of independence, indicating a positive association between them.
- If Lift<1, then events A and B co-occur less frequently than would be expected if they were independent, suggesting a negative association between them.

Table VI presents a selection of the results obtained from applying the association rules, while the complete table can be found in Appendix.

Based on the obtained results, we have come to the following conclusions:

- The rule linking 'Privacy' and 'Security' shows high confidence (Confidence = 0.8) and significant support (Support = 0.16). This indicates a frequent relationship between these concepts in the data, which is logical given that improved privacy is often associated with stronger security measures.
- The rules linking 'Decentralization' and 'Smart Contract' have moderate confidence (Confidence = 0.400) and support (Support = 0.16). This emphasizes their role in the context of each other, but does not indicate as close a relationship as in the case of 'Privacy' and 'Security'.
- The rule between 'Smart Contracts: Principles and Applications' and 'Smart Con-tract' has the highest confidence value (Confidence = 1.000), indicating a direct dependence of these concepts. The high level of confidence and support (Support = 0.16) shows that there is a clear and frequent relationship between these concepts in the data, which is logical since the principles and applications of smart contracts are closely related to the concept of a smart contract itself.

These findings underscore the significance of the relationships between key concepts in blockchain technologies and provide insight into which aspects require particular emphasis when learning about or developing blockchain solutions.

Analyzing the distribution of support scores for association rules provides insight into the frequency of various concept combinations within the dataset. This analysis is particularly valuable for selecting study topics, as infrequent combinations may high-light specialized or unique areas of knowledge that warrant further exploration. Consequently, the distribution of support scores assists in prioritizing the content of educational programs, enabling a focus on the most significant and frequently occurring concepts.

In the context of designing a blockchain course, analyzing the confidence values in the association rule table is instrumental in identifying critical topics and their interrelationships for inclusion in the syllabus. High confidence values, such as 1.0, denote concepts that are strongly related and should ideally be taught together. For instance, a high confidence value between 'smart contracts' and 'their principles and applications' suggested that these topics should be integrated into a single module to facilitate a comprehensive understanding of their interdependencies.

Conversely, topics with lower confidence values, such as 'decentralization' and 'smart contracts,' indicate a less direct relationship. Although these concepts are still relevant, their connection is not as evident and may warrant separate modules. Nonetheless, it remains important to highlight potential intersections in various use cases.

Thus, the analysis of confidence values can guide the structuring of a blockchain curriculum by organizing modules to reflect real-world connections and dependencies among key concepts. This approach enhances students' understanding by aligning the course content with practical and conceptual relationships.

An analysis of the distribution of lift values for association rules reveals a marked predominance of rules with elevated lift values, signifying a strong relationship between the antecedents and consequences within the dataset. Lift values exceeding 1.0 indicate that the co-occurrence of antecedent and consequence is more frequent than would be expected under conditions of independence, thereby underscoring the significance of examining these relationships within the realm of blockchain technologies. The distribution diagram demonstrates that a substantial number of rules exhibit a considerable degree of association. This finding enables the identification of key topics and concepts for inclusion in educational curricula and highlights areas that may benefit from further research and detailed investigation.

For illustrative purposes, we present the most significant connections, such as 'Blockchain Data Protection' and 'Fair Use and Data Protection in Blockchain,' in current graphical representations (see Fig. 6 and Fig. 7). These connections are characterized by a maximum lift score of 8.33, indicating a strong relationship between the topics. This high lift score suggests that these subjects are closely related and should be incorporated into the syllabus together to effectively address the same learning outcomes.

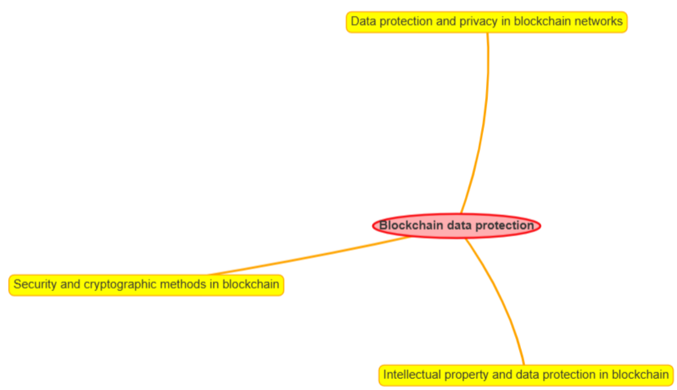

Fig. 6. Theme 'Blockchain data protection' with learning outcomes.

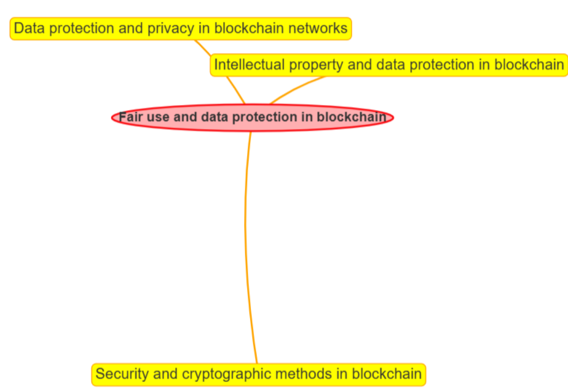

Fig. 7. Theme 'Fair use and data protection in blockchain' with learning outcomes.

The graph-based learning method demonstrates significant advantages over traditional and modern methods such as text mining and conceptual clustering (FCA). Firstly, the graph approach allows for flexible optimization of the duration and work-load depending on the specialty, while standard programs are rigidly fixed. It also offers an adaptive number of topics and learning outcomes, which ensures personalization of the educational process for the specific needs of students. An important aspect is the support of experts and the flexibility of choosing topics both by specialty and by learning outcomes. Teachers have more freedom in adapting courses, which increases the effectiveness of training. Due to its high flexibility and adaptability, the graph method creates a more dynamic and optimized educational environment that better meets modern challenges in education.

V. Discussion

The study demonstrated the effectiveness of formal concept analysis (FCA) and clustering methods for optimizing educational programs in the field of blockchain technologies. The results of the study showed that the use of an interactive knowledge graph simplifies the process of curriculum development and provides flexibility in the selection of topics, which is especially important for courses covering a wide range of disciplines, such as blockchain.

Currently, the Coursera platform offers more than 1,000 blockchain courses, covering a wide range of topics - from the basics of the technology to specialized courses such as smart contracts, decentralized applications (dApps), and blockchain security. The average duration of such courses is from 8 to 14 weeks for basic programs and from 3 to 6 months for advanced specializations, which makes training accessible to students with different levels of training and employment. The main blockchain courses relate to such specializations as Business, Computer Science, Information Technology, Data Science, etc. [43]. With such a wide range of courses, it can be difficult for students to choose the right program that best suits their educational needs. In this context, an interactive knowledge graph developed based on FCA will be a powerful tool to simplify the course selection process. It will help students analyze the connections between different topics and learning outcomes presented in blockchain courses. This is especially relevant in the context of constantly changing content in the blockchain technology field, where it is necessary to consider both basic knowledge and emerging trends such as decentralized finance (DeFi), cryptography, and smart contract security [4-8].

By visualizing the relationships between topics, a knowledge graph can help students and teachers navigate the materials more easily, compare them with their existing knowledge and skills, and identify gaps in their knowledge. For example, a student who is already familiar with the basics of cryptography can use the graph to quickly identify which courses cover advanced aspects of this topic, thereby avoiding the need to re-learn concepts already known. In addition, the graph allows you to systematize not only educational programs, but also types of blockchain technologies, which helps students better understand their application in real life. This is important for those who want to get more practical training and learn about specific technologies, such as the use of blockchain in financial systems or smart contracts.

Approach of this article differs from traditional text mining and curriculum analysis methods. Unlike standard syllabi, where the topics are fixed for all specialties, our method allows for flexible adaptation of course duration and teaching load depending on the specialty and learning outcomes. This is confirmed by comparison with works [17-21], where a simplified concept lattice improved information extraction while preserving the data structure.

One of the key results of the study is the development of an adaptive curriculum model based on formal conceptual analysis and clustering. This solution provides teachers and curriculum developers with the opportunity not only to automate the course planning process, but also to ensure its relevance in light of the rapidly changing requirements of the educational process in the field of blockchain and cryptocurrency.

In the future, it is planned to expand the capabilities of the knowledge graph and use it to assess students' knowledge, as provided by the authors of [17]. This will allow automatic matching of the studied topics with the learning outcomes and determine how fully students have mastered the key concepts of the course. Such an assessment system would be based on association rules identified during the construction of the graph, which would allow for a more accurate assessment of the level of understanding of the material and the identification of potential knowledge gaps. Despite the significant advantages of the proposed approach, there are certain limitations, such as the need for expert support at the stage of model setup and limited ability to automate the analysis of new topics. Future research will focus on developing more versatile algorithms that can automatically update the knowledge graph taking into account new data and trends in the blockchain field. In addition, the development of a student assessment system based on the graph will be an important step in improving the learning process.

VI. Conclusion

In conclusion, the conducted study shows that the application of FCA and clustering methods to create an interactive knowledge graph in educational programs on blockchain technologies is highly effective. The work developed an approach that allows teachers to flexibly adapt curricula depending on the level of students' training and their specialization, which is especially important in the context of blockchain technologies, covering a wide range of topics from cryptography to smart contract development. The interactive knowledge graph helps to systematize information on learning outcomes, topics, and key skills, which makes the course planning process more transparent and simplified. As a result of the study, it was possible to significantly reduce the teaching load by focusing on the main topics, which helps to reduce student overload and prevent them from dropping out due to difficulties. This is especially important for courses covering complex and multi-layered topics, as is the case with blockchain, where the amount of information can easily become excessive. The knowledge graph not only simplifies the selection of topics for teaching, but also helps teachers create more flexible and adaptive curricula that meet the rapidly changing requirements of the market and new technologies. It was also found that the use of association rules and clustering methods helps to identify key relationships between topics and learning outcomes. This allows teachers and students to see a clearer picture of how various aspects of blockchain technology are interconnected and helps to better structure the learning process. The experiments demonstrated the possibility of using the knowledge graph not only for developing curricula, but also for further assessment of the level of students' knowledge. In the future, it is planned to use this tool to automatically assess the extent to which students have mastered key topics and learning outcomes, which will allow teachers to more effectively adjust educational materials and improve the educational process.

Despite the obvious advantages of the proposed approach, the study also revealed certain limitations. In particular, significant efforts are required from experts at the stage of developing the knowledge graph and setting up its structure. Further research is planned to develop algorithms that will automate the process of updating the knowledge graph and adapting its structure to new educational requirements and trends in the field of blockchain.

Thus, the proposed approach to organizing educational programs using formal conceptual analysis and clustering methods is an innovative tool that can significantly improve the effectiveness of blockchain technology training courses. The interactive knowledge graph makes the process of developing educational programs easier, more flexible and adaptive, which is especially important for such rapidly developing areas as blockchain.

Acknowledgment

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References

[1] Cunha, P. R. D., Soja, P., & Themistocleous, M. (2021). Blockchain for development: a guiding framework. Information Technology for Development, 27(3), 417–438. https://doi.org/10.1080/02681102.2021.1935453

[2] Fosso Wamba, S., Kala Kamdjoug, J. R., Epie Bawack, R., & Keogh, J. G. (2020). Bitcoin, Blockchain and Fintech: a systematic review and case studies in the supply chain. Production Planning and Control, 31(2–3), 115–142. https://doi.org/10.1080/09537287.2019.1631460

[3] Grover, P., Kar, A. K., Janssen, M., & Ilavarasan, P. V. (2019). Perceived usefulness, ease of use and user acceptance of blockchain technology for digital transactions – insights from user-generated content on Twitter. Enterprise Information Systems, 13(6), 771–800. https://doi.org/10.1080/17517575.2019.1599446

[4] Hughes, A., Park, A., Kietzmann, J., & Archer-Brown, C. (2019). Beyond Bitcoin: What blockchain and distributed ledger technologies mean for firms. Business Horizons, 62(3), 273–281. https://doi.org/10.1016/j.bushor.2019.01.002

[5] Allessie, D., Sobolewski, M., Vaccari, L., & Pignatelli, F. (2019). Blockchain for digital government (JRC115049). (Luxembourg: Publications Office of the European Union. Issue https://www.mafr.fr/media/assets/publications/blockchain-for-digital-government-2019.pdf.

[6] Galici, M., Mureddu, M., Ghiani, E., Celli, G., Pilo, F., Porcu, P., & Canetto, B. (2021). Energy blockchain for public energy communities. Applied Sciences, 11(8).

[7] Garg, P., Gupta, B., Chauhan, A. K., Sivarajah, U., Gupta, S., & Modgil, S. (2021). Measuring the perceived benefits of implementing blockchain technology in the banking sector. Technological Forecasting and Social Change, 163, Article 120407. https://doi.org/10.1016/j.techfore.2020.120407.

[8] Sharma, S. K., Dwivedi, Y. K., Misra, S. K., & Rana, N. P. (2023). Conjoint analysis of blockchain adoption challenges in government. Journal of Computer Information Systems, 1-14. https://doi.org/10.1080/08874417.2023.2185552.

[9] Kistaubayev, Y.; Mutanov, G.; Mansurova, M.; Saxenbayeva, Z.; Shakan, Y. Ethereum-Based Information System for Digital Higher Education Registry and Verification of Student Achievement Documents. Future Internet 2023, 15, 3. https://doi.org/10.3390/fi15010003.

[10] Zhaisanova, D., & Mansurova, M. (2024). Blockchain concept for the educational purposes: bibliometric analysis and conceptual structure. Procedia Computer Science, 231, 753-758. https://doi.org/https://doi.org/10.1016/j.procs.2023.12.142.

[11] Digital Business. (2023, October 18). Opyt Kazakhstana po izucheniyu blokcheyna v vuzakh masshtabiruyut na 200 universitetov v 50 stranakh mira [Kazakhstan's experience in studying blockchain in universities is being scaled to 200 universities in 50 countries]. https://digitalbusiness.kz/2023-10-18/opit-kazahstana-po-izucheniyu-blokcheyna-v-vuzah-masshtabiruyut-na-200-universitetov-v-50-stranah-mira.

[12] Digital Business. (2023, September 21). Blokchejn inzheneria i komplaens [Blockchain engineering and compliance]. https://digitalbusiness.kz/2023-09-21/blokchejn-inzheneria-i-komplaens/

[13] Hsu, Y.-C. (2024). "Mapping the Landscape of Data Science Education in Higher General Education in Taiwan: A Comprehensive Syllabi Analysis." Education Sciences 14(7).

[14] Sumangali K., Ch Aswani Kumar, Concept Lattice Simplification in Formal Concept Analysis Using Attribute Clustering. Journal of Ambient Intelligence and Humanized Computing. 2018;10(6):2327-43.

[15] Cui H, Yue G, Zou L, Liu X, Deng A. Multiple multidimensional linguistic reasoning algorithm based on property-oriented linguistic concept lattice. International Journal of Approximate Reasoning. 2021;131:80-92.

[16] W.L. Johnson, A. Valente, Tactical language and culture training systems: using artificial intelligence to teach foreign languages and cultures, in: Proceedings of the 20th National Conference on Innovative Applications of Artificial Intelligence, 2008, pp.1632–1639.

[17] J.R. van Seters, M.A. Ossevoort, J. Tramper, M. Goedhart, The influence of student characteristics on the use of adaptive e-learning material, Comput. Educ. 58 (2012) 942–952.

[18] Hao, F., J. Gao, C. Bisogni, G. Min, V. Loia and C. De Maio (2021). "Stability of three-way concepts and its application to natural language generation." Pattern Recognition Letters 149: 51-58.

[19] Lara-Bercial, P. J., M. C. Gaya-López, J.-M. Martínez-Orozco and S. Lavado-Anguera (2024). "PBL Impact on Learning Outcomes in Computer Engineering: A 12-Year Analysis." Education Sciences 14(6).

[20] Angelis, J., & Ribeiro da Silva, E. (2019). Blockchain adoption: A value driver perspective. Business Horizons, 62(3), 307–314. https://doi.org/10.1016/j.bushor.2018.12.001

[21] Garg, P., Gupta, B., Kapil, K. N., Sivarajah, U., & Gupta, S. (2023). Examining the relationship between blockchain capabilities and organizational performance in the Indian banking sector. Ann. Oper. Res. https://doi.org/10.1007/s10479-023-05254-0

[22] Hughes, A., Park, A., Kietzmann, J., & Archer-Brown, C. (2019). Beyond Bitcoin: What blockchain and distributed ledger technologies mean for firms. Business Horizons, 62 (3), 273–281. https://doi.org/10.1016/j.bushor.2019.01.002.

[23] Scholl, H. J., & Bolívar, M. P. R. (2019). Regulation as both enabler of technology use and global competitive tool: The Gibraltar case. Government Information Quarterly, 36(3), 601–613. https://doi.org/10.1016/j.giq.2019.05.003

[24] Cowart, J. and Y. Jin (2024). "Leading Online Professional Development for Instructional Technology Coaches with Effective Design Elements." Education Sciences 14(7).

[25] Chang, M., G. D'Aniello, M. Gaeta, F. Orciuoli, D. Sampson and C. Simonelli (2020). "Building Ontology-Driven Tutoring Models for Intelligent Tutoring Systems Using Data Mining." IEEE Access 8: 48151-48162.

[26] Cristea, D., D. Șotropa, A.-J. Molnar and S. Motogna (2021). On the Use of FCA Models in Static Analysis Tools to Detect Common Errors in Programming. Graph-Based Representation and Reasoning: 3-18.

[27] Hao F, Gao J, Bisogni C, Min G, Loia V, De Maio C. Stability of three-way concepts and its application to natural language generation. Pattern Recognition Letters. 2021;149:51-8.

[28] Muangprathub, J., V. Boonjing and K. Chamnongthai (2020). "Learning recommendation with formal concept analysis for intelligent tutoring system." Heliyon 6(10): e05227.

[29] Santana, F., Almeida, J. P. A., & Guizzardi, G. (2018). Ontology engineering for improving interoperability, semantic integration, and knowledge discovery in cryptocurrency platforms. Journal of Web Semantics, 52, 29-44. https://doi.org/10.1016/j.websem.2018.07.004

[30] Song H, Zhu N, Xue R, He J, Zhang K, Wang J. Proof-of-Contribution consensus mechanism for blockchain and its application in intellectual property protection. Information Processing & Management. 2021;58(3).

[31] Betarte, G., Cristiá, M., Luna, C., Silveira, A., Zanarini, D. (2020). Towards a Formally Verified Implementation of the MimbleWimble Cryptocurrency Protocol. In: Zhou, J., et al. Applied Cryptography and Network Security Workshops. ACNS 2020. Lecture Notes in Computer Science(), vol 12418. Springer, Cham. https://doi.org/10.1007/978-3-030-61638-0_1

[32] Son D-H. On-demand ride-sourcing markets with cryptocurrency-based fare-reward scheme. Transportation Research Part E: Logistics and Transportation Review. 2023;171.

[33] Kobayakawa N, Imamura M, Nakagawa K, Yoshida K. Impact of Cryptocurrency Market Capitalization on Open Source Software Participation. Journal of Information Processing. 2020;28(0):650-7.

[34] Vidal-Tomás D. The new crypto niche: NFTs, play-to-earn, and metaverse tokens. Finance Research Letters. 2022;47.

[35] Aquilina M, Frost J, Schrimpf A. Tackling the risks in crypto: Choosing among bans, containment and regulation. Journal of the Japanese and International Economies. 2024;71.

[36] Subramanian H, Rouxelin F. Do cryptocurrency rewards improve platform valuations? Information & Management. 2024;61(6).

[37] Hajiaghapour-Moghimi M, Hajipour E, Azimi Hosseini K, Vakilian M, Lehtonen M. Cryptocurrency mining as a novel virtual energy storage system in islanded and grid-connected microgrids. International Journal of Electrical Power & Energy Systems. 2024;158.

[38] Hajdu, D., Benczur, A., & Kertész, J. (2020). Formal Concept Analysis in the realm of cryptocurrency: Uncovering contextual nuances and semantic relationships. Journal of Cryptographic Research, 35(4), 212-228. https://doi.org/10.1016/j.jcr.2020.04.005

[39] Kölbl, T., Müller, R., & Schmid, F. (2019). Context-aware ontology construction using Formal Concept Analysis in the cryptocurrency ecosystem. International Journal of Semantic Computing, 13(2), 155-178. https://doi.org/10.1142/S1793351X19400042

[40] Ganter, B., & Wille, R. (1999). Formal Concept Analysis: Mathematical Foundations. Springer.