Research on Modeling and Application Mechanisms for Decentralized Future Learning Centers

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Abstract

Objective This study explores how to apply key decentralized technologies to construct a decentralized application model for future learning centers. Methods First, we provide an overview of decentralized technology and its current research status in future learning centers. Then, we propose a four-layer application model based on decentralized technology along with its working mechanism, and simulate the model's workflow in privacy protection and efficient learning support through an application scenario. Results We propose a four-layer application model comprising a data layer, computation layer, contract layer, and application layer, including the structure and working mechanism of each layer, and clearly describe the interactions between layers through the data flow of a simulation case. Limitations The model design requires further optimization, and research is needed on how to integrate it with existing learning systems. Conclusion Decentralized technology has broad application prospects in future learning centers. The proposed application model provides a reference for future learning center research, but requires further in-depth study and improvement.

Full Text

Preamble

Decentralized Future Learning Center Model Construction and Application Mechanism Research

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[**Objective**] This study explores how to apply decentralized key technologies to construct a decentralized application model for future learning centers. [**Methods**] First, we provide an overview of decentralized technologies and their research status in future learning centers. Then, we propose a four-layer application model based on decentralized technologies along with its working mechanisms, and simulate an application scenario to demonstrate the model's workflow in privacy protection and efficient learning support. [**Results**] We propose a four-layer application model comprising data, computing, contract, and application layers, including the structure and working mechanisms of each layer. The interaction between layers is clearly described through simulated data flows in application scenarios. [**Limitations**] The model design requires further optimization, and research is needed on how to integrate it with existing learning systems. [**Conclusion**] Decentralized technologies have broad application prospects in future learning centers. The proposed application model provides a reference for future learning center research, though it requires further in-depth study and improvement.

Keywords: Decentralized; Future Learning Center; Model and Mechanism
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1 Introduction

The future learning center represents a novel learning organizational form based on Internet technologies and educational philosophies. Centered on learners and characterized by personalization and socialization, it aims for collaboration and innovation while adhering to principles of openness and sharing, thereby providing a flexible, diverse, and efficient learning approach and environment [1]. Research on future learning centers spans multiple domains, including artificial intelligence, virtual reality, gamification, big data, and social media. This represents not only a transformation of educational paradigms but also a shift in social culture, exerting profound impacts on individuals, organizations, and society.

However, future learning centers also face significant challenges and issues, such as data security, privacy, and trustworthiness [2], as well as learner collaboration, fairness, and openness [3]. These problems may affect the effectiveness and impact of future learning center research and could trigger distrust and resistance among learners, educators, and organizations, necessitating solutions through new technologies and concepts. Decentralization, as a distributed network technology based on cryptography and consensus algorithms [4], offers high security, transparency, and credibility. It can provide future learning centers with a data storage and transaction platform that eliminates or reduces third-party intervention or control, enabling autonomous data management and sharing, as well as peer-to-peer communication and collaboration among learners [5], thereby achieving the research objectives of future learning centers.

2.1 Overview of Decentralization

The decentralized model enables distributed, autonomous, and secure data, computation, and collaboration, reducing reliance on centralized institutions or platforms while improving efficiency and transparency and protecting privacy and security. This model encompasses key decentralized technologies including blockchain, federated learning, IPFS, secure multi-party computation, zero-knowledge proof, linked data, and Resource Description Framework (RDF).

(1) Blockchain: Blockchain is a distributed ledger technology that achieves data immutability, traceability, and verifiability through cryptography and consensus mechanisms. It supports peer-to-peer transactions, smart contracts, digital identity, and other applications, featuring decentralization, trustlessness, and tamper resistance. Its primary advantage lies in providing a public, transparent, and trustworthy data sharing platform for multiple participants, thereby promoting collaboration and innovation [6].

(2) IPFS: IPFS is a distributed file system [7] that uses content addressing and hash tables to store files in blocks across multiple nodes, enabling file lookup, transmission, and replication through self-organizing network protocols. IPFS addresses issues in traditional file systems such as single points of failure, low efficiency, and high costs, providing more secure, faster, and more convenient file services. Its goal is to build a more open, free, and decentralized Internet.

(3) Federated Learning: Federated learning is a distributed machine learning technology that allows multiple participants to train models locally and share model parameters or updates with a central server, thereby achieving model integration and optimization. It protects participant data privacy, reduces data transmission and storage overhead, and improves model generalization capabilities. Challenges include handling data heterogeneity, communication efficiency, and incentive mechanisms [8].

(4) Secure Multi-Party Computation: This cryptographic technology enables multiple participants to jointly compute a function's output without revealing their respective inputs [9]. It achieves both data privacy protection and functional guarantees, supporting various complex computational tasks such as data mining, machine learning, and electronic voting. The main difficulty lies in designing efficient, secure, and scalable protocols.

(5) Zero-Knowledge Proof: This cryptographic technology allows a prover to demonstrate to a verifier that a statement is true without revealing any additional information [10]. It enables minimal data disclosure and integrity verification, supporting various privacy protection and identity authentication applications such as digital currencies and anonymous credentials. The key challenge is constructing effective, general, and trustworthy proof systems.

(6) Semantic Data Technologies: These primarily include Resource Description Framework (RDF) and linked data technologies. RDF is a metadata model for representing information resources using subject-predicate-object

(SPO) triples to express semantic relationships between resources [11]. Linked data is a method for data representation and publication that uses Uniform Resource Identifiers (URIs) to identify entities and attributes in data and RDF to describe relationships between data [12]. Linked data enables data interoperability and connectivity, supporting various knowledge graph and semantic web applications by integrating dispersed data from different sources and formats into a meaningful, queryable network.

2.2 Research Status of Decentralized Technologies in Future Learning

Since its inception at the beginning of this century, the concept of future learning centers has evolved through an embryonic stage (early 2000s) and a development period (post-2010s), with continuously expanding and improving functions. However, with increasing data volume and diversity, future learning centers face challenges in data security, privacy, and trustworthiness, as well as demands for promoting learner collaboration, fairness, and openness. To address these issues, researchers began exploring decentralized concepts, such as Wiley D's 2002 proposal of an Online Self-Organizing Social System (OSOSS) model discussing OSOSS applications in online learning [13].

2.2.1 Blockchain Applications in Future Learning Centers

With continuous development and innovation in decentralized technologies, particularly blockchain, researchers have focused on its impact on core functions of future learning centers. For example, Woolf University, created in 2018 [14], is the world's first "borderless distance education" platform based on blockchain technology. It uses blockchain smart contracts to achieve complete digital automatic recording and generation of key processes including teaching, resource management, quality assurance, and teacher evaluation. In 2022, Scott Meyer proposed a new approach to creating decentralized learning centers based on blockchain technology—Learning Decentralized Autonomous Organizations (Learning DAOs)—allowing learners to join communities to study any topics of interest and receive rewards and incentives through token economics [15].

Additional researchers have focused on how blockchain changes learning models and methods. Bernard Marr [16] argues that emerging technologies like blockchain can significantly transform learning approaches and outcomes. Shuai Wang et al. [17] propose using blockchain to transform digital learning credential assessment and management. Li Min and Ge Bin [18] contend that blockchain-based online courses can improve teaching quality and trust in online education among all stakeholders.

2.2.2 Applications of Other Decentralized Technologies in Future Learning Centers

As research on blockchain applications deepens, an increasing number of decentralized technologies have been integrated, such as IPFS and federated learning. Ujjal Marjit [19] proposed a decentralized and distributed framework for Open Educational Resources (OER) based on Ethereum blockchain and IPFS, providing smart contracts, transactions, and consensus mechanisms for distributed applications. Nan Meng [20] proposed a university education resource sharing method based on blockchain and IPFS, storing educational resources in IPFS distributed storage while recording hash addresses and basic information on the blockchain to achieve resource protection and sharing.

Song Guo [21] proposed FEEDAN, an educational data analysis framework based on federated learning that allows multiple institutions to form educational data analysis alliances without directly sharing student data, thereby protecting student privacy. YangJie Qin [22] proposed a privacy-preserving federated learning framework for multimedia course recommendation that can utilize users' historical course selection records for personalized recommendations without sharing user data. Carla Barcelos [23] introduced AgCAT, an agent-based federated learning object search service that can retrieve and obtain learning objects from multiple distributed warehouses without sharing learning object data.

2.2.3 Status Review

The aforementioned research demonstrates that decentralized technologies such as blockchain, IPFS, and federated learning have attracted widespread attention from researchers for enhancing core functions of future learning centers, achieving distributed, autonomous, and secure data management, as well as learner collaboration, innovation, and sharing. Applying decentralized technologies in future learning centers represents a new research trend and an effective approach to solving various problems in their construction.

However, current research primarily focuses on applications of blockchain, IPFS, federated learning, and other decentralized technologies in future learning and education, while rarely exploring the impact of secure multi-party computation, zero-knowledge proof, linked data, and RDF on future learning and education. This paper attempts to integrate these key decentralized technologies in future learning center research, providing new perspectives and ideas for constructing future learning centers and thereby helping to implement the 3A (Active, Anytime, Anywhere) learning philosophy in their construction.

3.1 Application Model for Future Learning Centers Based on Decentralized Technologies

Decentralized technologies can be applied to future learning centers at the data, computation, and application levels, effectively addressing issues of data security, trust, efficiency, effectiveness, fairness, and openness. The application model for future learning centers based on decentralized technologies consists of four layers: data, computing, contract, and application layers, as shown in Figure 1 [Figure 1: see original paper].

Figure 1. Application Model for Future Learning Centers Based on Decentralized Technologies

In the model illustrated in Figure 1: - The **data layer** forms the foundation of the entire application model. It stores learning resource and data metadata on the blockchain, uses IPFS technology to distribute resources across multiple nodes, and employs linked data and RDF technologies for semantic annotation and relationship description, thereby enhancing data security, consistency, reusability, and exchangeability. - The **computing layer** utilizes federated learning and secure multi-party computation to provide distributed and privacy-preserving computing services, and uses zero-knowledge proof to generate and verify learning credentials, protecting privacy while ensuring trustworthiness. - The **contract layer** automatically executes learning-related contracts such as funding contracts and evaluation contracts through blockchain smart contracts, and uses incentive mechanisms and zero-knowledge proof to ensure contract fairness and credibility. - The **application layer** provides an open learning application platform and services based on Web3 technology, using linked data to enable knowledge representation and reasoning, thereby enriching the learning experience.

These four layers interact and collaborate through Web3 protocols for data, computation, and contract interfaces, forming a complete decentralized learning ecosystem: the contract layer executes contracts and provides incentives, the computing layer offers computational support, the data layer manages learning data, and the application layer displays learning content. This model leverages multiple decentralized technologies to address problems at different levels, with each layer collaborating through standardized interfaces to build an open and efficient decentralized learning system.

3.2 Data Layer

The data layer serves as the foundation of the future learning center application model, responsible for storing, managing, and organizing data including learning resources, learner information, and learning activities and outcomes. Its working principles are based on applications of blockchain, IPFS, linked data, and RDF technologies to achieve data security, trustworthiness, interoperability, and connectivity.

3.2.1 Data Layer Structure

In the data layer, blockchain technology ensures data immutability, IPFS technology improves resource access efficiency, and RDF and linked data technologies identify entities through URIs to support semantic-based personalized recommendations and knowledge services. Together, they construct an efficient, secure, and semantically rich learning data infrastructure that provides reliable support for upper-layer applications. The data layer comprises the following main components:

(1) Blockchain as the core support for data management. Blockchain's application in the data layer primarily manifests in data security and trustworthiness. In future learning centers, blockchain stores metadata and hash values of learning resources, data, and credentials, achieving data immutability through cryptography and consensus mechanisms. Blockchain can also protect learner privacy and data ownership, giving learners complete control over their data and the ability to choose with whom to share or exchange it.

(2) IPFS as the foundation for distributed data storage. IPFS's application in the data layer primarily manifests in storage efficiency and access speed. Using content addressing and hash tables, IPFS stores learning resources in blocks across multiple nodes, enabling rapid file lookup, transmission, and replication through self-organizing network protocols. In future learning centers, IPFS can store large or complex learning resources such as multimedia courses, educational games, and virtual reality content, enabling fast and accurate retrieval through content addressing. Additionally, IPFS can support learning activities in offline or low-bandwidth environments, allowing learners to study anytime and anywhere.

(3) Semantic data technologies for data association and semantic annotation. Semantic data technologies enable semantic annotation of data, supporting the description of various entities and their attributes and relationships—including learning resources, learners, and learning objectives—and cross-system data linking through URIs. Their primary role in the data layer is to enhance semantic expressiveness, interoperability, and connectivity, thereby enabling data integration and reasoning and supporting personalized learning applications.

3.2.2 Data Layer Working Mechanism

The data layer provides data interfaces to other layers through Web3 protocols, enabling convenient data access and usage, thereby providing a trustworthy, accessible, usable, and interoperable data infrastructure that supports upper-layer computation, contracts, and applications. The integrated working mechanisms include:

(1) Data Representation and Storage Mechanism. This mechanism achieves efficient storage and semantic expression of learning resources through deep integration of IPFS, blockchain, and semantic data technologies. In the specific data flow, IPFS stores learning resources in blocks across multiple P2P network nodes through content addressing, achieving distributed storage. The blockchain records the hash values and attribute information of each resource block, forming an immutable ledger that tracks version change history. Simultaneously, semantic data uses RDF technology to describe each learning resource, its attributes, and relationships in detail, constructing a complete semantic network knowledge graph. The blockchain also records standard URI identifiers and key attributes from the RDF relationship graph.

Semantic data helps IPFS manage distributed resources more intelligently and efficiently. The data layer's scheduling mechanism periodically extracts new and updated RDF triples from IPFS and the blockchain to improve the semantic network knowledge graph. When new resources are discovered through the RDF relationship graph, the IPFS node network can quickly locate and transmit resource blocks based on resource CIDs, thereby achieving standardized data management. Through this technology integration, the data layer enables dynamic management, semantic querying, and version control of learning resources. Resource information supports cross-system expression through standardized descriptions, enabling efficient resource sharing and utilization.

(2) Data Management and Access Mechanism. The data layer provides standardized APIs that support other layers in retrieving resources and knowledge through conditional queries. It records version update histories of resources in IPFS and the blockchain, enabling tracking and comparison between different versions. Additionally, it interacts with the computing layer in real-time, dynamically updating knowledge graph content based on resource version updates to ensure real-time knowledge graph freshness, providing support for upper-layer services.

(3) Synchronization and Security Mechanism. The data layer synchronizes in real-time with the application layer, pushing the latest resources and activity data to ensure data timeliness. Simultaneously, it uses cryptographic technologies for encrypted data storage, protecting data privacy and ownership. The blockchain records immutable access controls and ledgers, ensuring data security. Through effective technology integration, it provides open and reliable data service support while protecting learner privacy and intellectual property rights.

3.3 Computation Layer

The computation layer supports core functions of future learning centers. Based on decentralized computing technologies, it provides computing interfaces to other layers through Web3 protocols. Under the premise of privacy protection and trustworthiness, the computation layer provides reliable and efficient computing services and support for upper-layer applications, thereby offering secure, efficient, and intelligent computing services that support upper-layer contracts and applications.

3.3.1 Computation Layer Structure

To fully leverage the advantages of various decentralized technologies in computational support while meeting learning center requirements for personalization, privacy protection, and functional completeness, the computation layer primarily includes three technical support modules:

(1) Zero-Knowledge Proof Module. This module uses zero-knowledge proof technology to generate and verify learning credentials. The process is as follows: After completing learning tasks, learners interact with the module to submit task content summaries; the module generates digital certificates based on these summaries without revealing specific content; certificates are stored on the blockchain, and learners can provide them to any verification authority, which can verify certificate authenticity through interaction with the module without obtaining content details, enabling secure credential circulation. This module effectively generates digital certificates for learning outcomes while ensuring credential privacy and trustworthiness.

(2) Secure Multi-Party Computation Module. This module protects data privacy while supporting various complex computational tasks and enabling distributed secure computation among multiple parties. It supports joint model training, allowing parties to collaboratively train models without sharing data or updating parameters; supports data mining computation, enabling parties to perform data mining analysis while keeping inputs and results confidential; and supports electronic voting, allowing parties to conduct anonymous voting with public results.

(3) Federated Learning Module. This module supports joint model training across multiple institutions, enabling model training and personalized services without privacy leakage in big data scenarios. Each institution trains initial models using local data without sharing data, while a central server collects models from all institutions and generates unified models through parameter aggregation. Based on these unified models, personalized services such as content recommendation are provided for different institutions, protecting each user's privacy.

Through modular design and functional synergy, these three modules provide various computational supports for learning centers—such as learning credential management, model training and data analysis, and personalized recommendation services—while protecting data privacy, effectively meeting the functional requirements of the computation layer. This design fully leverages the advantages of decentralized technologies in computational support, achieving functional completeness for the learning center's computation layer.

3.3.2 Computation Layer Working Mechanism

In practical applications, zero-knowledge proof, secure multi-party computation, and federated learning are highly complementary in characteristics, and their integration can fully leverage respective advantages while compensating for individual limitations. Zero-knowledge proof enables minimal data disclosure, secure multi-party computation enables functional computation without revealing inputs, and federated learning enables distributed model training with privacy protection. Their combination enhances security, privacy, and functionality in identity verification, secure computation, model training, and personalized model services.

(1) Data Preprocessing Mechanism. Learners encrypt and encode local data/models using zero-knowledge proof technology to generate encrypted data/parameters, proofs, and metadata. Homomorphic encryption algorithms can be used for data encryption, and zero-knowledge interactive proof protocols can generate proofs. These proofs can verify data authenticity without revealing details, achieving a balance between privacy and functionality, while metadata records data characteristics for subsequent personalized services.

(2) Upload and Computation Mechanism. Through secure multi-party computation protocols, learners upload encrypted data/parameters and proofs to the computation layer. After verifying the proofs, the computation layer uses secure aggregation algorithms to aggregate encrypted data, with the aggregated results serving as initial parameters for federated learning, thereby ensuring security in data upload and computation.

(3) Model Training Mechanism. The computation layer uses secure multi-party computation aggregation results as input and employs federated learning algorithms for distributed iterative training. In each iteration, the computation layer distributes the global model to learners, who perform encrypted training locally to obtain updated parameters. Learners upload encrypted updated parameters through secure multi-party computation; the computation layer aggregates these parameters as input for the next round of training, continuing until convergence to obtain the final model.

(4) Personalized Service and Result Return Mechanism. Based on metadata uploaded by learners, the computation layer provides personalized query/recommendation services through secure multi-party computation without obtaining plaintext feature data, then distributes personalized results to corresponding learners without revealing them to other learners. Through this mechanism, learners' model parameters are protected while the computation layer can provide personalized model services.

(5) Auditability Optimization. To ensure fairness and trustworthiness in computation processes, the computation layer records each computation stage using immutable technology in a decentralized ledger, enabling learners to audit and trace computation processes without obtaining other learners' data details.

The computation layer based on the integration of these three technologies offers several advantages: achieving full-process privacy protection for data, models, and results; supporting various complex secure computation and model training tasks; improving computational efficiency and system throughput; enhancing the security and accuracy of personalized services; and ensuring system functional completeness and auditability.

3.4 Contract Layer

The contract layer constitutes an important component responsible for developing and executing various learning-related smart contracts. Leveraging blockchain and zero-knowledge proof technologies, it provides fair, efficient, and trustworthy automated support for learning activities, thereby enhancing the operational efficiency of the entire decentralized learning system.

3.4.1 Contract Layer Structure

The ultimate goal of the contract layer is to support learning contracts. Traditional learning contract support relies on centralized institutions, creating single points of failure and trust issues. A decentralized contract layer based on blockchain and zero-knowledge proof technologies can effectively address these problems. The contract layer primarily includes three modules:

(1) Contract Script Module. This module designs rules for various learning activities. Using smart contract technology, it leverages blockchain consensus mechanisms to design rules for learning activities such as funding contracts and evaluation contracts. It also uses IPFS and other technologies for distributed storage of contract scripts to improve system fault tolerance. Additionally, it includes transaction processing functionality, capable of receiving contracts, invoking transactions, triggering contract execution, and recording execution results. Through decentralized design, it avoids single-point control, ensuring fairness and reliability in rule design processes, while distributed storage prevents rule execution failures caused by single-point data loss. This module establishes the foundation for learning activity rules, providing the basis for subsequent contract execution.

(2) Proof and Verification Module. This module generates and verifies learning proofs. Using zero-knowledge proof technology, it generates corresponding learning proofs based on learning activity results, providing the basis for subsequent contract execution while protecting learner privacy and data security. It also includes proof verification functionality, capable of verifying the authenticity of learning proofs without revealing learning content. Finally, to enhance the credibility of proofs and execution results, it permanently records verified learning proofs in blockchain's immutable storage. This module ensures proof authenticity and learner privacy data security.

(3) Execution and Recording Module. This module automatically executes contracts to achieve automated management of various learning activities. Based on proof results, it automatically executes corresponding contracts, such as automatically disbursing funds for funding contracts or automatically generating scores for evaluation contracts. Additionally, to ensure contract execution integrity and fairness, it includes monitoring and repair functionality. Once contract execution anomalies are detected, it can promptly repair vulnerabilities and correct execution results. This module achieves efficient management of learning activities through automatic execution while ensuring fairness in execution processes and results.

3.4.2 Contract Layer Working Mechanism

The contract layer utilizes blockchain and zero-knowledge proof technologies to achieve automatic execution, incentives, and verification of learning-related contracts, protecting learner privacy while building a publicly transparent and trustworthy learning ecosystem. The working mechanism primarily includes:

(1) Contract Design Mechanism. Before learning begins, learning-related smart contracts and incentive mechanisms are automatically generated and executed based on blockchain, achieving contract immutability, traceability, and verifiability, as well as fair, effective, and trustworthy incentives. These smart contracts include: Learning task contracts that record learning task content and requirements; Funding contracts that automatically disburse funds from sponsors based on learners' or institutions' progress or achievements; Collaboration contracts that automatically distribute rewards among multiple learners or institutions based on their contributions to collaborative projects; and Evaluation contracts that automatically generate scores from multiple evaluators based on their assessments of learners or institutions.

(2) Task Execution Mechanism. After completing learning tasks, learners generate proof values for completed tasks through zero-knowledge proof interfaces. These proof values can verify task completion without revealing any learning content details, thereby protecting learner privacy. The proof verification module then validates these proof values using zero-knowledge proof algorithms to determine authenticity and validity. Upon successful verification, the execution module automatically triggers corresponding business logic, such as issuing learning rewards or generating evaluations. Finally, execution results and corresponding proof value hashes are recorded in IPFS distributed storage, while a recording contract stores proof value hashes in blockchain's immutable storage, creating a globally traceable execution record system. Anyone can verify from the blockchain whether an execution matches the proof value provided by the learner, thereby ensuring the credibility of execution results.

(3) Application Presentation. The application layer can display not only learners' completed tasks and results through contract layer query interfaces but also their performance and growth trajectories across different learning tasks without exposing specific learning content and processes, thereby protecting personal privacy. Additionally, nodes participating in verification and service provision receive compensation for ecosystem construction, which can be publicly recorded using distributed ledger technology to ensure fairness and transparency in incentive mechanisms.

The contract layer's working mechanism effectively solves data privacy and incentive mechanism issues in traditional learning models, laying the foundation for truly fair and efficient learning ecosystems.

3.5 Application Layer

The application layer provides and displays learning-related applications. By leveraging Web3 technology, it establishes an open, collaborative, innovative, and fair learning ecosystem where learners can participate in various learning activities and share learning resources and experiences with others.

3.5.1 Application Layer Structure

The application layer uses linked data and RDF technologies to achieve knowledge representation and reasoning, enhancing learning intelligence and innovation. Learners can conduct in-depth research and exploration by connecting relevant knowledge and resources, discovering and creating new knowledge. The application layer provides diverse learning applications including online learning platforms, learning communities, and learning assistance tools, thereby promoting interaction and collaboration among learners and improving learning effectiveness and experience.

(1) Learning Platform Module. This module includes various learning application interfaces such as funding platforms, collaboration platforms, evaluation platforms, online learning platforms, and learning community platforms. It supports learners or institutions in initiating and participating in various learning tasks within platforms, automatically distributing and managing funds, rewards, or scores through smart contracts, and recording learning footprints. It also supports learner communication and collaboration through forums or chat rooms.

(2) Knowledge Representation and Reasoning Module. This module includes knowledge graph and reasoning query sub-modules. The knowledge graph sub-module uses linked data technology to describe various learning resources, learner information, and other entities and their attributes and relationships as a knowledge graph, expressing semantic relationships between resources in triple form to build a linkable and cross-queryable knowledge network. It uses RDF technology for more detailed descriptions of entities and relationships in the knowledge graph, enabling cross-system resource sharing and utilization, ultimately constructing a knowledge graph for the learning domain. The knowledge reasoning sub-module performs reasoning on implicit and potential knowledge within the learning domain based on the knowledge graph and RDF triple descriptions, supporting various conditional queries and personalized learning.

This module interacts with the data layer to update knowledge graph content in real-time. Through the knowledge graph, it enables rapid resource location and related resource recommendations, provides query interfaces for other modules to retrieve resource relationships, and implements content-based personalized recommendations based on learner characteristics and learning history. It also enables automatic retrieval of related knowledge based on specific topics or concepts to help learners conduct in-depth study.

(3) Content Display Module. This module supports online playback of learning resources such as documents, videos, and animations. It can also invoke the computing layer to achieve personalized content recommendation and display learners' learning certificates and achievements while protecting personal privacy.

(4) Ecosystem Support Module. This module includes open API and incentive mechanism sub-modules. The open API sub-module provides third-party access, while the incentive mechanism sub-module designs learning contribution incentives to attract more participants to jointly build the learning ecosystem.

These modules interact in real-time with the data and computing layers to ensure real-time synchronization of resources and knowledge, enabling personalized recommendations and in-depth learning, thereby supporting the overall architecture to adapt to open and collaborative decentralized learning models.

3.5.2 Application Layer Working Mechanism

(1) Content Acquisition and Recommendation Mechanism. This mechanism primarily obtains and recommends learning content. It interacts with the data layer to obtain various learning resources stored in IPFS and blockchain in real-time, such as courses, textbooks, and learning tools. It also invokes content filtering, recommendation, and clustering algorithms provided by the computing layer to recommend the most suitable learning content based on learner preferences and behavioral characteristics. Additionally, it periodically synchronizes with the data layer to obtain the latest learning resource updates. Through precise content recommendation, learning efficiency and satisfaction can be improved.

(2) Knowledge Representation and Reasoning Mechanism. This mechanism primarily builds and maintains knowledge graphs to achieve knowledge representation and reasoning. It interacts with the data layer to obtain structured knowledge from learning resources in real-time, such as dependencies between courses and relationships between knowledge points. It then uses RDF to describe this knowledge, constructing a dynamically updated knowledge graph. Simultaneously, it performs content recommendation and related knowledge retrieval based on the knowledge graph, supporting conditional knowledge graph queries to help learners better absorb and apply knowledge.

(3) Content Display Mechanism. This mechanism primarily displays learning content online. It provides interfaces for online playback of various learning resources, supporting learners in conveniently browsing learning videos, reading e-books, and other content. It also displays personalized recommendation results from the content acquisition and recommendation module, precisely showing content that learners may find interesting. Additionally, it displays learners' learning certificates and achievements, supporting learner growth and sharing.

(4) Ecosystem Support Mechanism. This mechanism primarily supports the healthy operation of the application layer. It provides open API interfaces for third-party developers to access platform resources. It also designs comprehensive incentive mechanisms to attract and retain more learning participants through learning contribution rewards. Furthermore, it interacts in real-time with other modules to ensure resource and service synchronization and monitors application operation quality to solve problems and perform optimization upgrades.

4.1 Data Flow in the Application Model

In the future learning center application model, data flow constitutes a crucial component for collaborative work among layers. Based on the four-layer architecture (data, computing, contract, and application layers), the data flow process in learning centers can be described as shown in Figure 3 [Figure 3: see original paper].

Figure 3. Data Flow in the Decentralized Learning Center Application Model

(1) Data Layer. Learners can upload learning resources to the data layer through the application layer for storage. The data layer blocks these resources through content addressing, with each resource block stored across multiple nodes in the IPFS network. Simultaneously, the data layer uses linked data technology to describe these resources as RDF triples, constructing a knowledge graph. The data layer also synchronizes and updates knowledge graph information with the knowledge representation module in real-time. Additionally, it handles resource synchronization and sharing with IPFS to ensure resource accessibility.

(2) Computing Layer. When learners submit learning tasks through the application layer, the computing layer performs zero-knowledge proof encryption on uploaded data to protect privacy and security. It then executes relevant computational tasks, such as federated learning model training, without obtaining detailed data information. The computing layer returns computational results to the contract layer and also invokes the data layer to provide personalized services based on learner characteristics without revealing user feature data secrets.

(3) Contract Layer. The application layer records learner task information in the blockchain through the contract layer, creating immutable records. The contract layer executes relevant contracts based on computational results returned from the computing layer, such as distributing rewards, and returns execution results to the application layer.

(4) Application Layer. Learners can submit various learning tasks through the application layer. The application layer requests computation from the computing layer for task information and interacts with the data layer to obtain updated knowledge graph information in real-time. The content display module provides personalized content recommendations based on the knowledge graph. Additionally, the application layer invokes the computing layer for personalized services, while the ecosystem support module coordinates resource sharing across layers.

4.2 Scenario-Based Data Flow Simulation

This case simulates a complete learning process for Learner A studying artificial intelligence in a future learning center, demonstrating deep collaboration among technical layers and how these technologies protect privacy while supporting efficient learning. The specific process is shown in Figure 4 [Figure 4: see original paper].

Figure 4. Scenario-Based Data Flow Simulation in the Decentralized Future Learning Center

The specific learning process is as follows: 1. Learner A searches for an artificial intelligence funding contract through the application layer. The contract layer uses smart contract technology to define funding rules and processes. 2. After Learner A submits an application, the computing layer uses zero-knowledge proof algorithms to generate a learning plan summary that proves authenticity without revealing details. 3. The proof is distributed to the contract layer through secure multi-party computation. After verification, the contract layer disburses tokens as learning funds according to the plan, ensuring fairness. 4. Learner A begins learning. The computing layer collects Learner A's learning data and uses federated learning technology for distributed training to generate personalized knowledge graph services. 5. Learner A uses the knowledge graph to study artificial intelligence fundamentals. The computing layer also uses IPFS technology for distributed storage of learning resources to support efficient access. 6. Learner A finds an artificial intelligence project collaboration platform through the application layer. The contract layer uses smart contracts to define fair distribution rules. 7. After project completion, the computing layer uses zero-knowledge proof to generate workload proofs for each member to prevent false claims. The contract layer verifies these and settles payments according to proof results. 8. The application layer integrates Learner A's previous learning processes and outcomes to generate a personal learning portfolio, using blockchain technology for immutable recording. 9. Learner A can share experiences with others based on the learning portfolio while protecting privacy, promoting openness.

In the above case, the roles of each layer in the proposed application model are: - The **application layer** provides various learning application interfaces such as funding platforms and project platforms where learners can find resources and opportunities. It also uses knowledge graph technology for personalized services, such as recommending relevant content based on learning history. - The **contract layer** uses blockchain technology to define rules for various learning contracts (funding, project, etc.) and executes these contracts through smart contracts, such as reviewing applications and disbursing funds. It also uses zero-knowledge proof technology to generate learner proofs while protecting privacy data. - The **computation layer** primarily provides computational support. It uses zero-knowledge proof to generate proofs without revealing secrets, employs federated learning for personalized learner modeling, and uses IPFS technology to manage learning resource storage and access. - The **data layer** stores various learning data such as resources and records. It uses blockchain for immutable data recording and IPFS for distributed resource storage. Additionally, it uses knowledge graph and other technologies for standardized data description and relationship modeling.

Through technical synergy, the layers effectively support privacy protection, efficient learning resource management, and personalized services during the learning process, forming deep collaborative relationships that jointly support open and collaborative learning models.

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5 Conclusion and Outlook

The application model proposed in this paper requires further improvement and optimization in many aspects, such as ensuring data quality and standards, improving computational efficiency and accuracy, enhancing contract security and flexibility, and expanding application diversity and compatibility. Additionally, this model must address practical challenges and issues, including defining data ownership and usage rights, allocating computational costs and benefits, assigning contract responsibilities and risks, and establishing application standards and regulations. Furthermore, the model needs effective integration and coordination with existing learning systems and mechanisms to achieve smooth transition and transformation. In conclusion, the application model of key decentralized technologies in future learning centers represents a field full of challenges and opportunities worthy of further exploration and development.

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Note: Figure translations are in progress. See original paper for figures.