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Design Analysis for a Distributed Business Innovation System Employing Generated Expert Profiles, Matchmaking, and Blockchain Technology

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Abstract: Innovation ecosystems often face challenges such as inadequate coordination, insufficient protection of intellectual property, limited access to quality expertise, and inefficient matchmaking between innovators and experts. This paper provides an in-depth design analysis of SPARK-IT, a novel business innovation platform specifically addressing these challenges. The platform leverages advanced AI to precisely match innovators with suitable mentors, supported by a distributed web scraper that constructs expert profiles from reliable sources (e.g., LinkedIn and BrainMap). Data privacy and security are prioritized through robust encryption that restricts sensitive content exclusively to innovators and mentors, preventing unauthorized access even by platform administrators. Additionally, documents are stored encrypted on decentralized storage, with their cryptographic hashes anchored on blockchain to ensure transparency, traceability, non-repudiation, and immutability. To incentivize active participation, SPARK-IT utilizes a dual-token approach comprising reward and reputation tokens. The reward tokens, Spark-Coins, are wrapped stablecoins with tangible monetary value, enabling seamless internal transactions and external exchanges. Finally, the paper discusses key design challenges and critical architectural trade-offs and evaluates the socio-economic impacts of implementing this innovative solution.

Keywords: business innovation; blockchain; decentralized storage; artificial intelligence; matchmaking; expert profile; security; trust; intellectual property; design analysis

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1. Introduction

Innovation ecosystems are fundamental to fostering economic growth, entrepreneurship, and societal progress. Initiatives such as business incubators, hackathons, and in-person meetups have been widely deployed. However, the current environment remains fragmented and insufficiently integrated. Many innovators, particularly those in remote or under-represented regions, lack consistent pathways to engage with expert networks, secure financial resources, or access high-quality mentorship. As a result, valuable ideas often fail to mature into robust, market-ready solutions.

A common challenge faced by university students with innovative ideas and creative young people in general is the lack of access to experienced mentors. These mentors can help transform technical concepts into viable startups. For example, a group of students from a university's AI research lab developed an advanced machine-learning model for fraud detection. They struggled to commercialize it due to their limited knowledge of market strategies, customer acquisition, and funding opportunities. They attended hackathons and online entrepreneurship courses but still lacked structured guidance. They needed more support in refining their business model, pitching to investors, and securing industry partnerships. Similarly, another team developing a blockchain-based credential verification system found it difficult to connect with legal and compliance experts. They faced challenges navigating regulatory requirements, which slowed their progress. These cases highlight the gap between technical innovation and the business ecosystem. They clearly demonstrate the need for our proposed solution to bridge this divide.

There are existing approaches, most notably incubators, that offer structured environments that combine operational infrastructure, investor connections, and curated mentorship. While these models are effective for certain use cases, they are frequently constrained by geographic accessibility, limited participant capacity, and rigid program schedules. Similarly, hackathons and physical meetups encourage rapid prototyping and peer interaction but typically occur as isolated, time-bounded events, leaving little room for sustained iterative development or long-term support mechanisms. These shortcomings are exacerbated by the logistical and financial barriers that prevent broader participation.

Existing platforms for fostering innovation and dedicated startup accelerators, like RubikHub (https://rubikhub.ro/ accessed on 23 January 2025) , ROTSA (https://rotsa.ro/en/homepage-en/ accessed on 23 January 2025), Techcelerator (https://techcelerator.co/ accessed on 23 January 2025), 100%Open (https://www.100open.com/ accessed on 23 January 2025), EdisonOpen (https://www.edison.it/en/open-innovation accessed on 23 January 2025), NineSigma (https://www.ninesigma.com/ accessed on 23 January 2025), or Y Combinator (https://www.ycombinator.com/ accessed on 23 January 2025), offer valuable opportunities for connecting innovators with potential mentors, investors, and collaborators. These platforms often provide tools for networking, funding, and showcasing business ideas.

These platforms can provide initial networking opportunities and exposure to potential investors. However, the depth and sustainability of these relationships can be inconsistent. Follow-up mechanisms for long-term mentorship or support are frequently insufficient. Additionally, current approaches often lack robust systems to protect intellectual property, maintain trustworthy data exchange, and ensure secure collaboration. As a result, participants may hesitate to share sensitive ideas or fully engage with potential partners. Many platforms also depend on manual or ad hoc methods of pairing innovators with mentors and investors, leading to suboptimal matches that fail to leverage the full potential of their expert networks.

While global initiatives and platforms aim to support entrepreneurs and researchers, they often fall short of addressing the critical challenges faced by innovators, particularly those in smaller startups, under-represented regions, or academic institutions.

Therefore, the main challenges of systems that support innovation are as follows:

Access to expertise: Innovators often struggle to connect with domain-specific experts who can provide the mentorship and guidance necessary for refining their ideas into viable business models. Current innovation hubs or consultancy platforms typically cater to larger organizations or well-connected individuals, creating an uneven playing field. This results in a gap where smaller startups or individual innovators lack the support required to thrive.

Lack of secure collaboration frameworks: The exchange of ideas between innovators and mentors poses risks related to intellectual property (IP) protection. Without robust mechanisms to ensure the confidentiality of sensitive information, innovators may hesitate to share their ideas, fearing unauthorized usage or theft. Existing platforms rarely provide tamper-proof, transparent, and traceable systems to safeguard such collaborations.

Inefficiency in matchmaking: Traditional matchmaking between innovators and mentors is often manual, relying on limited databases or personal networks. This approach fails to consider the specific needs of the innovator, the expertise of the mentor, or the potential synergies between the two. As a result, many promising collaborations are either delayed or fail to materialize altogether.

Little or no incentivization: The lack of structured and transparent reward mechanisms for mentors discourages high-quality participation from domain experts. Existing platforms typically do not have adequate systems to recognize or incentivize meaningful contributions, resulting in low engagement levels and diminished trust in the ecosystem.

Under-representation of marginalized groups: Innovators from under-represented regions or demographics frequently lack access to innovation resources, mentors, and funding. These systemic barriers perpetuate inequality and exclude valuable contributions from diverse perspectives that could enrich the innovation landscape.

Absence of scalable and transparent systems: The innovation process involves multiple stakeholders, such as mentors, innovators, investors, and regulators. Each stakeholder requires secure access to data and a transparent workflow. Current centralized platforms struggle to scale while maintaining transparency, trust, and accountability across these diverse groups.

Without accessible and secure platforms, many brilliant ideas fail to see the light of day, ultimately resulting in lost opportunities for economic growth and societal benefit. Furthermore, the absence of transparent systems contributes to mistrust among stakeholders, hindering collaboration and investment.

The proposed solution is **SPARK-IT: Igniting Innovation with Trust, Collaboration, and Expert Mentorship**, which is a decentralized innovation ecosystem designed to address critical challenges in connecting innovators with experts, fostering collaboration, and enabling secure idea development. By leveraging cutting-edge technologies such as blockchain, artificial intelligence, and tokenomics, SPARK-IT creates a transparent, scalable, and inclusive environment that empowers innovators from diverse backgrounds to access mentorship, refine their ideas, and build viable business models.

The platform integrates the business model canvas (BMC) as a structured tool for innovators to articulate their proposals for collaboration and specific guidance needs. This strategic management template allows innovators to map out and analyze critical aspects of their business ideas, such as key activities, value propositions, customer segments, and revenue streams. Through the platform, innovators can submit their BMC in an interactive or document-based format, highlighting areas where mentorship is required. By encouraging innovators to approach their ideas systematically and enabling experts to focus their guidance, the integration of the BMC fosters clarity, precision, and productive collaborations within the SPARK-IT ecosystem.

At the core of SPARK-IT is its decentralized architecture, which ensures the security, traceability, and transparency of all interactions. Blockchain technology and decentralized storage underline the platform's key functionalities, including secure storage of proposals, immutable records of non-disclosure agreements (NDAs), and tamper-proof tracking of interactions between innovators and mentors. This creates a trusted environment where intellectual property is protected, fostering confidence among participants.

The platform's AI-driven matchmaking engine enhances efficiency and personalization by analyzing innovator proposals and expert profiles to recommend the most suitable mentors. This dynamic and feedback-driven system ensures that each collaboration is tailored to the specific needs and expertise of its participants, thereby maximizing the potential for success.

SPARK-IT also incorporates a dual-token system to incentivize meaningful participation and high-quality contributions. Reputation tokens reflect user performance and influence future matchmaking, while reward tokens have monetary value, compensating mentors for their guidance and expertise. This mechanism ensures sustained engagement and accountability while fostering a vibrant and trustworthy community.

The modular design of the proposed solution allows for flexibility and scalability, making it adaptable to various use cases, such as startup acceleration, academic collaboration, and investment opportunities. By bridging gaps between innovators, experts, academia, and the private sector, SPARK-IT represents a transformative step in democratizing access to innovation resources and driving economic and social progress.

The SPARK-IT platform builds upon and integrates existing methodologies and tools to create a robust ecosystem for innovation. The following section describes the state-of-the-art research and methodologies that serve at the base of SPARK-IT's design, focusing on the use of the business model canvas, AI-powered matchmaking, and secure information storage to establish a foundation for its novel contributions.

The remainder of this paper is structured as follows. Section 2 presents a comprehensive review of the state-of-the-art approaches in business innovation platforms, expert profiling, AI-driven matchmaking, decentralized storage, and reward and reputation systems. Section 3 introduces the SPARK-IT system architecture, detailing its modular components, decentralized data management, intellectual property protection, and token-based incentives. Section 4 describes the design challenges and trade-offs, including balancing decentralization with usability, managing tokenomics in a permissioned blockchain, scalability, and the financial model design. Moreover, the socio-economic impacts are discussed when it comes to democratizing access to mentorship, enhancing trust in global innovation and potential use cases in academia and industry. Finally, Section 5 provides conclusions, summarizing key contributions, identifying potential limitations, and outlining future research directions.

2. State-of-the-Art

This section provides a structured overview of the key technologies and methodologies that inform and inspire the design and development of the SPARK-IT platform. We examine state-of-the-art solutions in four core dimensions: business model innovation, expert profile validation, AI-driven matchmaking, and decentralized data management with incentive mechanisms. This clearly illustrates how SPARK-IT addresses existing gaps and introduces novel enhancements.

Firstly, we discuss the business model canvas (BMC) and its contemporary variations. We highlight their strengths in organizing and visualizing business ideas. We also address limitations, such as their complexity and lack of standardization. By analyzing these models, SPARK-IT can strategically adopt or adapt specific canvas structures. The goal is to make them user-friendly and tailored specifically to innovators and mentors on our platform.

Secondly, we examine techniques for creating accurate and verified expert profiles from external sources, emphasizing methods such as data scraping and AI-driven information extraction from platforms like LinkedIn. These methods allow SPARK-IT to ensure expert credibility and reliability, directly addressing common concerns innovators have about finding trusted mentors.

Next, the analysis focuses on AI-driven matchmaking solutions, comparing various methods including ontology-based approaches, NLP algorithms, and advanced deep learning models. Understanding the advantages and challenges associated with these techniques guides SPARK-IT towards a balanced, hybrid matchmaking strategy, combining semantic understanding with keyword analysis to achieve precise and meaningful connections between innovators and experts.

Lastly, we review current blockchain-enabled decentralized storage, reward, and reputation management systems, illustrating their importance in fostering trust, transparency, and effective collaboration. We highlight how incentive mechanisms, such as reputation scores and reward tokens, motivate high-quality interactions. This underscores SPARK-IT's commitment to transparency, accountability, and user-centric incentives within its ecosystem.

By clearly outlining these technological foundations, this section sets the stage for SPARK-IT's unique contributions, showcasing how our platform builds upon and advances current state-of-the-art approaches to better support secure, transparent, and effective innovation-driven collaborations.

2.1. Business Model Canvas for Innovation

The business model canvas (BMC) was first introduced in [1]. Its purpose was to facilitate business model innovation. It helps businesses and entrepreneurs visualize, design, and improve their business models clearly and systematically.

To apply the business model canvas, an entrepreneur must complete nine building blocks that represent the key elements of any business model. The process should begin by defining the customer segments, which are the different groups of people or organizations the business aims to reach and serve. Following this, the value propositions must be described, outlining the bundle of products and services that create value for these customer segments. Next, the channels should be outlined, detailing how the company communicates with and reaches its customer segments to deliver the value proposition. It is essential to specify the types of customer relationships the company establishes with its customer segments. Additionally, revenue streams must be identified, which represent the cash generated from each customer segment. The key resources, or the most important assets required to make the business model work, should be listed. Furthermore, the key activities, which are the essential actions a company must take to operate successfully, need to be detailed. Identifying the key partnerships is crucial, as these are the networks of suppliers and partners that help the business model function. Finally, the cost structure must be described, encompassing all costs incurred to operate the business model.

The BMC offers numerous benefits that contribute to its widespread adoption and effectiveness. It provides clarity and focus by breaking down the business model into key components, offering a clear and structured view of the business, and its visual nature enhances communication between team members and stakeholders. The BMC is also highly flexible, allowing for quick modifications and iterations and enabling businesses to adapt rapidly to changes. By covering all critical aspects of a business, it provides a holistic view, ensuring that no important area is overlooked. Additionally, the canvas encourages collaboration through brainstorming sessions, fostering teamwork and collective problem-solving.

The triple layered business model canvas [2] extends the traditional business model canvas by adding two additional layers: an environmental layer, based on lifecycle assessment, and a social layer, based on stakeholder management. These additional layers offer a more comprehensive understanding of the company's value creation and of the impact that the product can have on the market. However, a drawback of this model is its increased complexity and the time required to fill out all layers. This complexity may overwhelm some users, especially if it is their first experience with the model. The tool may also necessitate a higher level of expertise to effectively apply life cycle assessments and stakeholder management principles, potentially limiting its accessibility to smaller businesses or those with limited resources.

Recent proposals have suggested various improvements and adaptations to the BMC, particularly for startups and innovation-focused businesses. One such framework is the blitz canvas [3], which incorporates ten different stages specifically designed for software startups. Initially, the focus is on building the foundation by establishing the mission, vision, goals, core culture, and competencies of the business. This is followed by studying the user, which involves utilizing personas and user stories to understand the users' goals, frustrations, and motivations. The next stage, defining the solution, outlines product goals and features while creating prototypes for user feedback. Identifying key differentiators and customer touchpoints forms the unique selling proposition. The framework then emphasizes collecting qualitative feedback in the user's feedback stage to validate the solution concept. It also involves studying the competition to analyze competing market offerings and inform product development. Business model elements are incorporated from the BMC, including IP and "As a Service" offerings. The synergies stage identifies interdependencies and synergies within the business model. Managing growth involves planning for growth management and complementary product offerings. Finally, metrics are established to identify key performance indicators (KPIs) and track progress, ensuring the business remains on course. In [4], the authors proposed enhancements to the BMC for startups focused on innovation. These enhancements include a section entitled disruptive strategy, which comprises elements such as product democratization, new business models for new technologies, fulfilling unmet customer needs, defending against low-end disruptors, and adapting to shifts in competition.

The advantage of tailoring the business model canvas to specific domains consists in its ability to better address the challenges and opportunities of that domain, which increases the relevance of the analysis. This, however, happens at the cost of the level of standardization. Benchmarking solutions that use different frameworks is a more difficult task, as different metrics and models are used. In addition to that, tailored models can have a steeper learning curve, which may prevent new users from properly applying them.

Another suggested improvement is the integration of the BMC with customer experience aspects. For example, [5] suggests defining the cognitive, emotional, physical, sensorial, and social elements marking a customer's interactions with the company. This framework better aligns business model innovation with customer values and needs, ensuring that strategic decisions are directly informed by customer experiences. This focus can lead to more relevant and appealing offerings, improving customer satisfaction and loyalty. Nevertheless, there is a risk of misalignment if the insights derived do not accurately reflect customer priorities or if the strategic orientation of the company changes rapidly due to market conditions.

To mitigate the previously described problem of requiring very specialized knowledge from users for them to be able to implement the BMC, in [6], the authors propose implementing the BMC, taking into consideration the three maturity levels defined by a user: novice, expert, and master. The BMC helps novices by providing a structured framework to elicit and build coherent business models. Experts use the BMC to evaluate interactions between business model elements and outline key threads in the business model's story. Masters create multiple versions of business models to evaluate alternatives and retain the history of the model's evolution.

Alternatives to the BMC, although not as widely adopted, have also been discussed. In [7], the authors suggest using the value proposition canvas (VPC) instead of the BMC to focus on why customers should buy the products/services of the company. The VPC promotes a more customer-oriented strategy, but there is a risk that businesses might oversimplify their approach to value creation, ignoring the interconnectedness of various business model components that the BMC emphasizes.

2.2. Creating an Expert Profile Using External Sources

Creating a comprehensive and accurate expert profile involves various technologies and methodologies. These methods gather, verify, and synthesize data from multiple external platforms. The following papers mainly focused on the LinkedIn platform, as it is one of the most popular platforms for professional endeavors and career related networking.

In [8], the authors present how LinkedIn data can be mined in order to create expert profiles using LinkedIn API. The data available on LinkedIn contain redundancies because users enter their information in various ways. For example, in the "Education" section, the name of a university might appear in different formats across profiles, even though all refer to the same institution. Because of this, the paper presents how the collected data are normalized before being used so that redundancies are removed.

A novel approach to extracting expert information from personal homepages using deep learning techniques is described in [9]. A key contribution is the segmentation of web pages into smaller text units, enabling the model to focus on relevant information more effectively. Integrating prior knowledge, such as named entity recognition and regular expressions, significantly enhances the model's ability to accurately identify and extract crucial data.

The authors propose using a long short-term memory (LSTM) network to capture the contextual dependencies within text units. This allows a more precise classification of words and segments, leading to improved overall extraction performance. The experimental results presented in the paper demonstrate the model's superior accuracy in generating comprehensive expert profiles compared to traditional methods. While the model presented in the paper handles diverse web page formats, there are still challenges related to varying page structures. The paper highlights the potential for future work to address these issues and further enhance the model's capabilities.

In [10], the authors present a data-driven approach for profile extraction based on Resumes. In the article, the authors leverage natural language processing (NLP) techniques like keyword extraction and document representation to create profiles. While the paper focuses on resumes, the underlying techniques used can be similarly applied for creating expert profiles from LinkedIn profiles.

Another paper related to profile extraction is [11], in which the authors aim to create a comprehensive database of college alumni by scraping data from LinkedIn profiles. To do this, web scraping techniques are leveraged to collect and organize details from the user's profiles, such as employment history, educational background, skills, and professional connections. The methodology presented involves using Python programming and web scraping libraries to extract information from public LinkedIn profiles. This is carried out while ensuring compliance with LinkedIn's terms of service and privacy policies. After collecting the data, data cleaning and structuring techniques are necessary to ensure the accuracy and consistency in the collected data.

The paper demonstrates that web scraping techniques can collect data from LinkedIn profiles. However, a limitation is that it does not address interpreting unstructured data such as descriptions or comments. In order to overcome this issue NLP, techniques can be used to extract the essential information from these unstructured data sources.

In [12], the authors aim to extract content-based user profiles from the data available on LinkedIn to have an image of the users' interests that can be used to recommend interesting academic research papers. In order to do so, an extractor system is developed, which processes the information extracted from LinkedIn for building the researcher profile.

A novel idea presented in the paper was to utilize both the professional data of the researcher and that of their social graph connections. This provides a more accurate picture of the researcher's interests. The paper shows that the data extracted from the connections have been revealed to be a valuable source of information, increasing the performance of the system since social networks grow around common interests.

2.3. Matchmaking Solutions Using AI

The application of artificial intelligence techniques to matchmaking systems has gathered significant attention in recent years. This section reviews key contributions in this domain, highlighting their methodologies, innovations, and limitations.

Wu et al. [13] introduce a method for matching experts to projects by employing domain ontologies to model expertise and project requirements. Using Protégé [14], the authors formalize concepts into structured trees, facilitating the computation of semantic similarities. While this approach effectively organizes knowledge, it is susceptible to semantic heterogeneity, where different terms refer to the same concept, resulting in potential mismatches. Although partially mitigated, this limitation remains unresolved, affecting the method's overall reliability.

In ref. [15], the authors propose a system for automating the pairing of researcher biosketches with funders' requests for proposals (RFPs) using advanced natural language processing techniques. The authors develop four deep neural network architectures based on a fine-tuned BERT model, comparing their performance with support vector machines and logistic regression as baselines. The DNNs utilize cross-encoding and Siamese encoding strategies, with CNNs or Bi-LSTMs as post-BERT layers. Among these, the cross-encoder BERT model with a Bi-LSTM layer and BC2BT-based data augmentation achieves the highest accuracy. This work demonstrates the potential of sophisticated NLP methods for automating complex matchmaking tasks, emphasizing the benefits of effective data augmentation techniques.

A matchmaking system for linking resumes with job descriptions to identify suitable candidates is presented in [16]. The approach integrates two models: a content-based recommender system and an NLP-based method using gensim for text summarization. The gensim model employs the TextRank algorithm and transformers to summarize resumes and job descriptions into comparable lengths, followed by k-nearest neighbors for similarity measurement. The TextRank algorithm focuses on keyword extraction, while transformer-based models paraphrase and abstract text. These complementary approaches enhance flexibility but underscore the challenge of balancing keyword-based and semantic representations in matchmaking.

In [17], the authors introduce an AI-powered platform to connect industry experts with companies seeking specialized skills. The system relies on the Word2Vec model with a Skip-Gram architecture to calculate semantic similarity between keywords provided by mentors and companies. By analyzing these keywords, the platform identifies and recommends experts whose skills align closely with organizational needs. However, the dependency on keyword-based inputs poses a limitation, requiring precise articulation of expertise and requirements to achieve effective matches.

The reviewed studies collectively underscore the diverse methodologies applied to matchmaking, ranging from ontology-based approaches to deep learning and NLP techniques. While ontology-based methods excel in knowledge organization, they are prone to semantic mismatches. In contrast, deep learning and transformer-based models offer advanced semantic understanding but may require extensive computational resources and well-curated training data. These works pave the way for further research to address limitations such as semantic heterogeneity and reliance on structured input formats.

2.4. Storing Information/Documents with Managed Access and Methods Employing Decentralized Storage and Blockchain Technology

Controlling access to data in decentralized computing systems represents a manifold challenge in itself. Today, managing different user roles and access rights is complicated. This complexity arises from the variety of available sources for user authentication and validation. The second difficult task is handling the increasing mixture of data formats, representations and storage options that are available. Kayes et al. [18] present a possible solution for representation heterogeneity and access control. The authors focus on data that is available from multiple sources and introduce a unified data ontology to normalize different forms of data description. They then extend context-aware role-based access control (CAAC) models with a unified set of context-sensitive access control policies to manage data access. While the paper does not focus on decentralized storage per se or on blockchain, it does have the merit of standardizing access control policies for different data sources.

In [19] the authors use argumentation-based agents to model data access interfaces. The focus of the paper is on solving data sharing, access control, and privacy protection in Internet-of-Things (IoT) environments and smart applications. IoT data are categorized into private and public, and agents are divided into internal and external. The authors then expand category-based access control meta-models and emergency policies and introduce two argumentation schemes:

- An argumentation scheme for data access control, which allows access control management for internal data requests;
- An argumentation scheme for access-category assignment, which allows access control for external data requests.

Agents process these schemes in argumentation-based reasoning patterns and decide whether or not to allow access to the requested data. Aside from handling multiple data sources, the authors also address the issue of multiple authentication solutions.

An ontology-based access control (OBAC) model is presented in [20]. The authors address secure access to FAIR (findability, accessibility, interoperability, and reusability) data and consider three categories of information: the data itself, associated metadata expressing FAIR information, and additional metadata about the users. Target metadata are represented as a knowledge graph used to describe semantic relationships between the concepts (categories) expressed by the actual data. OBAC allows implementation of role and context dependent access policies based on these knowledge graphs. If authorized, users received access to data described by the current category stratum (i.e., graph neighbors of the same "parent" node) and to all the "parents" included on the path generated by the same "parent" category (i.e., the origin major concept for the current graph path). The proof-of-concept presented by the authors is agnostic to the actual location of the data (e.g., a Web API or a classic database) through these metadata categories describing the data.

Kiran et al. [21] focus on cloud computing and data access control. The authors introduce SA-ODAC (security-aware mechanism and ontology-based data access control) as a potential solution to control access rights over data stored in such open, decentralized, and distributed systems. The proposed model is composed of two distinct operational components: secure awareness techniques (SAT) and an ontology-based data access control (ODAC) module. ODAC is employed to handle data access control based on role and permission policies. SAT operates on the cloud level and encompasses the components required to encrypt and decrypt data and handle encryption key management. Through SAT, the authors ensure that sensitive data are encrypted before being transmitted to the cloud for storage and decrypted by authorized clients. The scenario is similar to the one required by SPARK-IT to store project proposals in IPFS.

The challenges of decentralized data access control (DDAC) over consortium blockchains are addressed in [22]. Blockchains do not employ centralized data administration, unlike traditional, centralized database systems. Participants in such public networks have limited or no control over access control policies since the ledger data are replicated to all the nodes in the network. Consequently, participants must keep confidential data outside the ledger or encrypt data before storing it. The authors formally define DDAC with atomicity, consensus, and confidentiality (ACC) constraints:

- *Atomicity* implies that a transaction is either discarded or applied to the nodes of all allowed participants and that write operations included in such a transaction must be atomic.
- *Consensus* implies that data owners may veto a transaction involving their data with a single vote.
- *Confidentiality* implies that participants have read access to data if and only if they are included in the corresponding read-allowed group.

Following this definition, the authors implement a DDAC framework using Hyperledger Fabric. ACC modules are embedded within this framework as access control managers. The framework also employs encryption modules and ledger partitioning techniques to further control data access based on attribute-based access control (ABAC) rules.

In [23], the authors present a blockchain-based role-based access control (B-RBAC) mechanism for data sharing within federated systems. The authors focus on medical data and IoT environments. The access control mechanism is based on smart contracts, and the required access control policies are stored as key/value pairs through these smart contracts. The key represents data's security attribute level, and the value describes the corresponding set of conditions that must be matched to grant access. The authors further rely on the concept of "colored coins" to define security attribute tokens, which are then used to assess different user permissions and data access layers. Distributed access control decisions are performed through automatic executions of smart contracts. The solution also has the much-required advantage of supplying traceability information alongside solving RBAC in distributed federated environments. The prototype system is developed using HyperLedger Fabric.

Data privacy and security are the focus of [24]. The authors address the issues raised by multidimensional data aggregation and access control in cloud-based IoT scenarios. Data collected from different smart things are encrypted using EBGN homomorphic encryption before being aggregated and pushed into the blockchain. Furthermore, different data access attributes are handled through ciphertext-policy attribute-based encryption (CP-ABE): the EBGN private keys for each data dimension are encrypted using the CP-ABE algorithm. This ensures that authorized parties are able to access only the corresponding required data. The authors propose the use of a trusted authority to handle key management and renewal. Access renewal is ensured through the regeneration of EBGN's public and private keys for each affected data dimension.

In [25], the authors are primarily focusing on the development of a new blockchain-based protocol for secure data sharing and access. The article emphasizes the growing interest in decentralized storage solutions, particularly those based on blockchain technology. Blockchain's inherent features, such as immutability, transparency, and decentralization, offer potential advantages in addressing the limitations of centralized systems. The paper utilizes the InterPlanetary file system (IPFS) to store large files. IPFS is a peer-to-peer distributed file system that provides content addressing and versioning. The authors acknowledge that blockchain is not suitable for storing large amounts of data and leverages IPFS to complement the blockchain's capabilities. The reference text emphasizes the importance of encrypting files before they are added to the IPFS to ensure data confidentiality. The authors state that "the files should be encrypted before added to IPFS to ensure data confidentiality." However, the paper does not delve into the specifics of the encryption approach, such as the encryption algorithms or key management schemes employed. The primary focus of the paper is on the blockchain-based protocol for secure data access and collaboration rather than the intricacies of the encryption process itself.

The framework in [26] proposes the use of a permissioned blockchain and distributed hash tables (DHTs) to decentralize the storage of PingER data, thereby eliminating the reliance on a central repository. The metadata of files are stored on the blockchain, while the actual files are stored off-chain using DHTs at multiple locations within a peer-to-peer network of PingER monitoring agents. The use of DHTs enables efficient data lookup and retrieval in a decentralized manner. The framework addresses the issue of blockchain bloat by storing the actual PingER data files off-chain. It employs erasure coding (K-of-M) to ensure data redundancy and availability, even if some nodes in the network go offline. The Merkle root, stored on the blockchain, provides a mechanism for auditing the integrity and immutability of the stored data. The permissioned blockchain serves as the foundation for managing identity and access control within the network. The use of digital signatures and cryptographic hash functions ensures the security and integrity of transactions and data stored on the blockchain. The simplified Byzantine fault tolerance (SBFT) consensus algorithm is proposed to achieve agreement on the state of the data across the distributed network, enhancing the system's fault tolerance and security.

The framework presented in [27] leverages the strengths of both IPFS (InterPlanetary file system) for decentralized storage and proxy re-encryption (PRE) for secure access control to healthcare data. The combination of these technologies allows the system to securely store large volumes of healthcare data while ensuring that only authorized users can access and decrypt specific files. In the proposed framework, sensitive data (such as medical records) are first encrypted using symmetric encryption, and then the encrypted data are stored on the IPFS network. The resulting IPFS hash (which serves as a unique identifier for the data) is stored on the blockchain. Using the PRE cryptographic technique, the system allows a third party (proxy) to convert ciphertext from one public key to another. The proxy does not learn anything about the underlying plaintext during this conversion. In this framework, PRE is used to manage access control for the encrypted data stored on IPFS.

In [28,29], the authors propose a complex architecture for decentralized news article extraction. Articles are stored off-chain, and proofs in the form of content hashes are saved on the blockchain. This way, anyone can verify the integrity of the stored article and be certain that it was not tampered with in any way. A variation of the decentralized retrieval system is presented in [30], where the emphasis is on modularity, which is also the case for our system. Another work that employs storing important information on decentralized storage and the proof on the blockchain network is the one from [31], which is related to real estate transactions. Blockchain is also used to ensure data integrity in the context of monitoring the driver's sobriety level [32].

2.5. Reward Systems with Monetary Value

Incentive mechanisms, as the driving force for maintaining long-term system operation, are indispensable elements of blockchain systems. The advanced properties of blockchain can also contribute to designing effective and efficient incentive mechanisms.

Han et al. [33] broadly review academic papers related to the incentive mechanisms in blockchain and blockchain-based incentive mechanisms. To systematically evaluate these papers, the authors proposed a set of requirements based on incentive properties and costs.

In [34], the authors propose a general decentralized rating framework based on blockchain, supporting recommender systems and rewarding its users for their reviews. The ratings of items, the reputations, the tokens of users, and the algorithms exploited to compute the score of the items are stored on the blockchain. The system directly supports cryptocurrency payments. It also allows item owners to accept off-chain payments by manually invoking a smart contract to confirm payment execution.

Merrill et al. [35] present a token-locking reward model that can be used to incentivize miners to accept transactions without forcing clients to sacrifice their tokens. The model can also be used to incentivize service providers. The authors' analysis showed that the model reduces volatility commonly associated with cryptocurrencies. Paying interest to token holders lowers the opportunity cost than holding fiat currencies. The authors claim that their model of rewarding service providers with interest generated from locked tokens is more profitable for clients compared to paying for services directly. An interesting aspect of the model is that the locked tokens are temporarily out of circulation.

In [36], the authors developed a dynamic model of the platform economy, where tokens are used as a means of payment among users and issued by the platform to finance investment. Tokens facilitate user transactions and compensate distributed ledger-keepers, open-source developers, and crowdfunders for their contributions to platform development. Platform owners maximize their seigniorage by carefully managing the token supply. This management considers that users optimally determine token demand and form rational expectations about token price changes.

By focusing on token price volatility, in [37], the authors investigate how reward uncertainty affects user contribution to a tokenized digital platform. The results reveal that, for systems that involve and reward user creativity, token price volatility facilitates the platform's short-term effect but impairs long-term user creativity.

In [38], the authors examined whether blockchain can serve as the technology underpinning decentralized marketplaces to promote trust. By utilizing tokens as an incentive mechanism, the authors demonstrated that rewarding peers for reporting malicious behaviors can mitigate misconduct. Despite its simplicity, the token rewarding mechanism can be used to incentivize users to behave consistently and tackle trust issues.

In [39], the authors suggest three adjustments to make a currency more stable. Firstly, they propose minimizing the difficulty of mining new blocks to prevent rapid changes in the supply of coins. Secondly, they recommend adjusting mining rewards if block intervals significantly change, thereby stabilizing the coin supply. Lastly, they introduce negative interest concepts to remove old coins from circulation. Mechanisms such as fees gradually reduce the coin's value over time. This approach encourages spending instead of hoarding.

The first suggestion only applies to proof-of-work (PoW) blockchains, but the other two have a broader applicability zone and can be used in other solutions as well. For example, in [40], the authors explain that cryptocurrencies are not widely adopted online due to their high volatility and propose the use of stable coins to solve the volatility issue by securing cryptocurrency with a stable asset.

Four types of collaterals are discussed for stablecoins, each with its own strong points and weak points. Fiat-collateralized stablecoins are pegged to fiat currency and are centralized, which contradicts decentralization principles. Crypto-collateralized stablecoins are pegged to other cryptocurrencies and are often over-collateralized due to volatility. Commodity-collateralized stablecoins are pegged to commodities like gold or oil and are centralized in a similar way to fiat-collateralized stablecoins. Non-collateralized stablecoins have no backing assets and use algorithms to adjust supply based on demand to stabilize the price.

The solution proposed in [41] is a dual-deposit escrow smart contract that ensures cheat-proof delivery and payment for digital goods without third-party intervention. Necessary assumptions include the following: (1) the product can be secured with a digital key, (2) the buyer can verify the product using a pre-known hash value, (3) both parties have asymmetric key pairs known to each other, and (4) transaction fees for deploying and interacting with the smart contract are negligible. The purpose of this solution is to secure transactions by guaranteeing that both the buyer and the seller fulfill their obligations.

Building on the previous idea, the system presented in [42] uses a smart contract to act as an escrow, holding the buyer's payment until the trade is completed. Disputes are handled by having parties wager on their honesty, with an arbiter deciding the outcome. The contract requires both parties to place a deposit (wager) that is refunded if they behave honestly. An interesting concept is that there is both a penalty and a reward system. They are computed based on the wager size and a repayment constant.

The contract's security is analyzed using game theory, proving that it ensures honest behavior if the arbiter is biased towards honesty. The contract achieves strong game-theoretic security if the penalties for dishonesty are sufficiently high, making deviation from honesty unprofitable.

In [43], the author explains how a cryptocurrency should be designed to be valuable. Some guidelines are provided, which must be followed before and after the creation of the currency. Pre-creation guidelines include the following: defining the purpose of issuance, determining desirable behaviors and appropriate rewards, establishing measures to prevent undesirable behaviors such as hacking and spam attacks, and deciding on the block generation cycle along with the amount of cryptocurrency to be issued.

Post-creation guidelines include maintaining scarcity by controlling total issuance. They also involve creating continuous market demand and balancing these methods to stabilize or increase cryptocurrency value.

An example of how value can be created for a cryptocurrency is found in [44]. Cyclists earn cycle tokens by cycling, with the tokens calculated based on the plausibility and distance of the ride. The real-world value of these tokens is derived from the economic, health, and ecological benefits associated with cycling. A marketplace is established where cycle tokens can be exchanged for various incentives, such as discounts or spare parts. The number of tokens generated corresponds to the square root of the kilometers cycled, with a cap on the maximum number of tokens that can be earned per track and per day.

This example highlights the importance of aligning cryptocurrency incentives with real-world benefits. It also emphasizes controlling token supply and providing practical uses. These measures ensure cryptocurrency sustainability and value.

2.6. Reputation Systems

Reputation systems are of the utmost importance in decentralized networks, as they enforce trust and accountability among participants. These systems evaluate and quantify entities' trustworthiness based on their behaviors and interactions. This evaluation ensures reliability and promotes honest participation. Unlike traditional centralized reputation systems, decentralized approaches leverage blockchain technology to offer enhanced transparency, immutability, and security.

The authors in [45] have created a separate blockchain for storing reputation, where reputation is quantified objectively by storing binary ratings, 1 for a positive transaction and 0 for a negative one. A positive transaction is one where the user receives the requested file. Identity creation is linked to IP addresses, which increases the cost of creating multiple identities. A Proof-of-Stake mechanism is used for low-reputation users; they must stake a small amount of currency into a triple-signed wallet (involving the sender, receiver, and a third party) to discourage dishonest behavior.

This binary approach to reputation has the advantage of simplicity. However, it lacks scalability because it cannot be applied to systems requiring more nuanced representations of reputation. In many scenarios, reputation is more nuanced and might need to be represented on a continuum, such as a rating scale from 1 to 10 or through qualitative feedback regarding user performance and behavior. Some notable proposals are made in [46], such as the weighting of feedback based on the evaluator's reputation, ensuring that feedback from low-reputation users matters less. To motivate users to provide ratings and comments, the system incorporates a monetary reward mechanism. The proposed system leverages the Ethereum blockchain, using Solidity for smart contracts, Truffle for development, Web3.js for blockchain interaction, and IPFS.js for decentralized storage.

The reputation system proposed in [47] uses a beta reputation model to calculate a vehicle's reputation score, which ranges between 0 and 1, based on its observed behavior. This computational model uses the beta distribution function, where the ratio of positive to negative behaviors determines the score. Positive behaviors, such as correctly reporting traffic conditions, increase the reputation score, while negative behaviors, such as false reports, decrease it.

The system incentivizes honest behavior by adjusting the number of coins a vehicle can use based on its reputation score, promoting active and honest participation in the network. To protect privacy, vehicles generate one-time public keys for local blockchain interactions, concealing their actual identities while maintaining the trustworthiness of their activities. This approach ensures that while a vehicle's temporary identity and reputation level are known to others in the network, its overall activity history remains hidden.

Bellini et al. [48] examine various decentralized reputation systems and divide them into three categories: deterministic, probabilistic, and flow models.

Deterministic methods use straightforward algorithms to compute reputation scores. These methods typically involve summing up ratings or feedback received from other participants. Probabilistic methods use statistical models to estimate the reliability of a participant based on past behavior. These models take into account the uncertainty and variability in user actions and make use of methods such as Bayesian networks, maximum likelihood estimation, and hidden Markov models. Flow models assess reputation by examining the flow of trust across the network. They consider both direct interactions (where one participant directly rates another) and indirect interactions (where reputation is influenced by ratings from trusted intermediaries). Examples of these models include the PageRank algorithm, EigenTrust algorithm, and trust propagation models (if user A trusts user B, and user B trusts user C, then user A might have a derived trust score for user C).

In the WorkerRep system [49], task completion involves evaluators scoring submissions based on two criteria: completeness and quality. These scores are then weighted according to the credibility of the evaluators, which is determined by their own reputation on the platform. Outlier scores are excluded, and a consensus score is calculated from the remaining evaluations. Workers who participate in evaluating peers also have their reputations updated based on the accuracy of their evaluations relative to the consensus. There is also a rewards system that takes reputation into account.

RepChain [50] uses a consortium blockchain (CBC) to enable e-commerce platforms to collaboratively maintain a decentralized ledger. It incorporates one-show anonymous credentials, created with two-move blind signatures, to protect customer identities and prevent multiple rating abuses. Zero-knowledge range proofs are used to verify the accuracy of ratings, protecting against abnormal rating attacks. Reputations are updated using secure multiparty computation. Additionally, consensus hashing is used to verify ratings through batch processing and consensus hashes.

The authors in [51] propose a reputation system that incorporates a trust value, a distrust value, and an uncertainty value that adds up to 1. The trust value represents the level of trust that node i has towards node j. It is a measure of positive interactions and indicates the probability that node j will perform as expected. The higher the trust value, the more confidence node i has in node j's reliability. The distrust value shows the level of distrust node i has toward node j. A higher distrust value indicates greater suspicion that node j won't meet expectations. The uncertainty value captures the level of uncertainty in the opinion of node i regarding node j. It accounts for the lack of sufficient interaction history or contradictory information, representing the extent to which node i is unsure about node j's trustworthiness. A higher uncertainty value means that node i has less information or is less certain about the performance of node j.

The reputation calculation includes the timeliness of interactions and the property of interactions. For example, the timeliness function applies a decay factor to older interactions to give more weight to recent activities. Positive and negative interactions are treated differently, with negative interactions leading to a more rapid decline in reputation.

3. System Design Overview

3.1. Platform Architecture

The SPARK-IT platform is designed to foster collaboration between innovators and experts through a secure, decentralized, and modular system. The design heavily leverages blockchain technology, AI-driven expert matching, and a decentralized storage architecture to ensure data security, transparency, and efficient communication between users.

Figure 1 presents the SPARK-IT platform architecture. The main components illustrated in this figure are as follows:

- Blockchain: permissioned blockchain and smart contracts for token management, proof of data records, contract execution records, and innovator and expert interaction records.
- Off-chain storage: templates for NDA contracts and the business model canvas, web application, and user data; high performance in-memory caches.
- IPFS (InterPlanetary File System): distributed storage for public and encrypted data.
- API Gateway: API front-end entry point that provides a unified API interface to the system; integrates/orchestrates back-end calls to all system components and provides authentication/authorization mechanisms, as well as support for audit services.
- Web App @innovator: front-end web application for innovators, used to interact with the system for profile and offer management, activity history, tokens, and various statistics; provides the means to interact with the matchmaking module to assist in expert selection.
- Web App @expert: front-end web application for experts, used to interact with the system for profile management, to accept/reject offers, activity history, score, accrued tokens, and various statistics.
- Web scraper: provides data to verify and prefill expert profiles; gathers data from professional social media platforms; can be extended to include other data sources.
- Data extractor: analyzes and extracts expert profile information from web scraper data; can be extended to extract data from different sources; written in a data-source agnostic way by means of pluggable extraction templates.
- Matchmaking module: employs AI and other algorithms used to perform the matchmaking between the innovators and experts; matchmaking data are recorded into blockchain along with reasoning data traces to ensure transparency into the selection process.

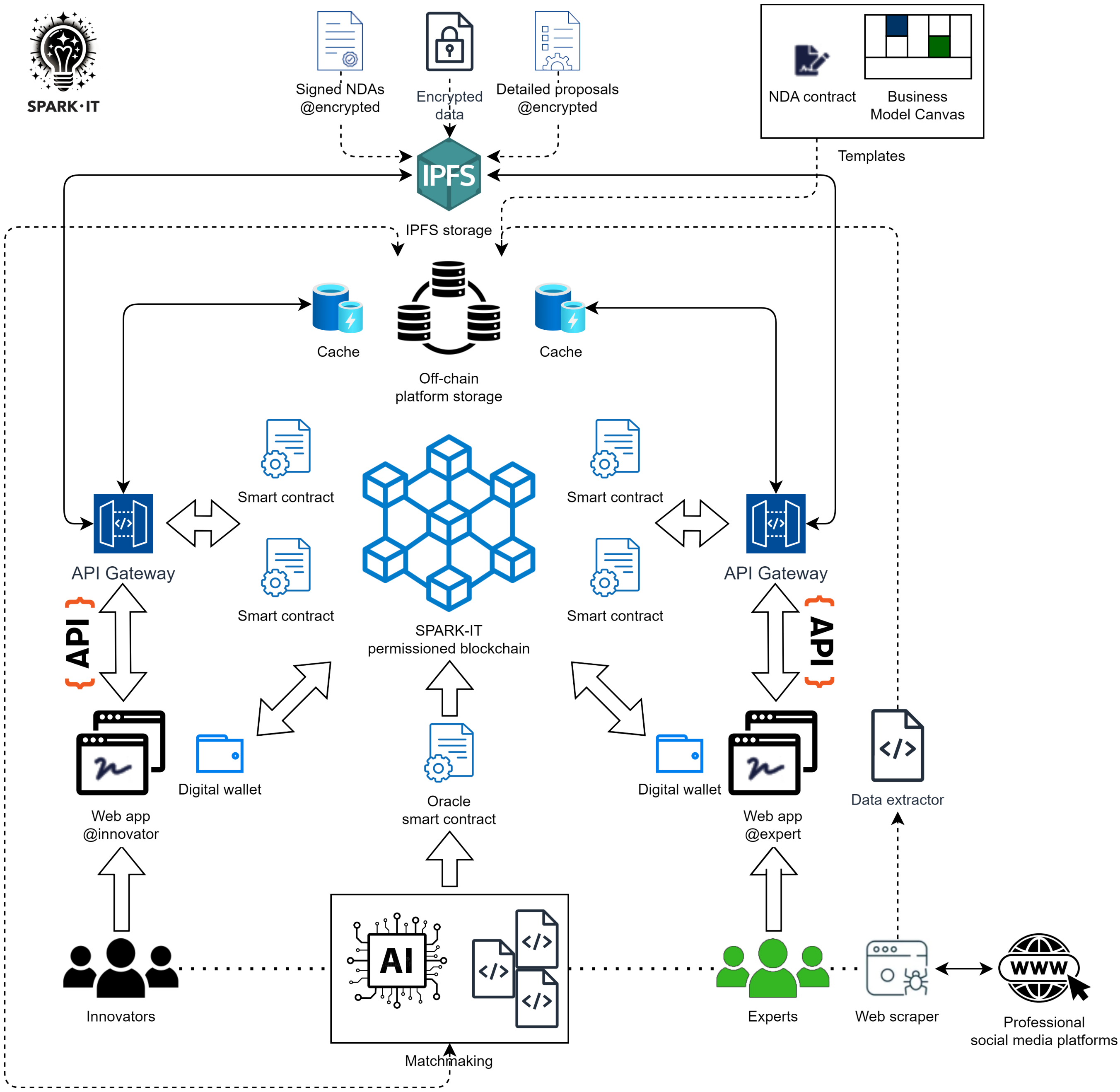

Figure 1. SPARK-IT platform architecture.

3.2. Functional Components

3.2.1. Expert Profile Generation

The expert profile component supports the creation and maintenance of expert profiles by merging user-provided information with automatically gathered data. Experts begin by entering their details through a user interface, supplying elements such as expertise, experience and education. This core data forms the initial profile and serves as a baseline for further enrichment.

The component employs two submodules for data acquisition and processing. The web scraper retrieves supplemental data from specified external platforms, such as LinkedIn, ResearchGate, ORCID, etc. By focusing on well-defined interfaces, it can be updated to incorporate additional sources as they become relevant. Once the web scraper acquires the raw data, the data extractor processes it, using configurable extraction templates designed to handle different source formats. Because these templates are pluggable, the data extractor can be adapted without altering the overall system whenever new formats or platforms arise.

The expert profile component integrates these steps into a single workflow. First, it verifies user input and identifies missing or outdated information. Next, it triggers the web scraper to gather relevant details that could fill the gaps or refresh the profile. Then, the data extractor refines and structures the retrieved data to align with the expert's existing information. After processing, the system presents the updated profile for expert verification or approval. If needed, the expert can correct or refine data within the interface, ensuring that the final profile remains accurate and aligned with the professional record.

This approach reduces the time experts spend manually updating their profiles and helps maintain current, consistent records. By supporting multiple data sources and flexible extraction methods, the component remains resilient to changes in the data landscape. Through its integrated workflow, profile creation, and maintenance process, the component helps experts present up-to-date information in a single, organized location.

3.2.2. Innovator–Expert Matchmaking

The matchmaking engine is a foundational element of the platform, designed to establish connections between innovators and mentors using natural language processing and machine learning algorithms. The engine evaluates several parameters, such as project requirements, expertise areas, reputation scores, and semantic details from proposals. This ensures the matches it generates are relevant.

A key strength of the matchmaking engine lies in its modular design. Each module represents a specialized approach to matchmaking, enabling a diverse range of techniques to be applied depending on the specific requirements of the task. These modules can be employed interchangeably or combined into hybrid solutions, providing flexibility and adaptability. The following paragraphs delve into the core modules of the matchmaking component, each contributing a unique capability to enhance the precision and effectiveness of the platform.

One foundational technique utilized in the matchmaking system is term frequency-inverse document frequency (TF-IDF), a classic approach to text analysis. This method transforms textual data into numerical vectors based on the frequency of keywords, enabling the system to compute the similarity between proposals and expert profiles using cosine similarity. By quantifying the angular relationship between the vectors, cosine similarity ensures that matches are not influenced by the magnitude of the documents.

Despite its simplicity, TF-IDF remains an indispensable component, particularly in contexts where computational efficiency is critical, or when keyword alignment is important. However, it is inherently limited in its ability to discern semantic relationships or account for variations in language. As such, while TF-IDF is well-suited for straightforward matching tasks, it lacks the depth required for more nuanced scenarios.

Advancing beyond keyword-based approaches, bidirectional encoder representations from transformers (BERT) bring significant innovation to the matchmaking process. Unlike traditional models, BERT captures the contextual relationships of words within a sentence by analyzing them in their bidirectional context. This results in dense embeddings that encapsulate the deeper semantic meaning of the text. By applying cosine similarity to these embeddings, the system is able to identify matches that align not only in terminology but also in context and intent.

The use of BERT is necessary for the matchmaking engine, as it ensures that the platform can recognize and connect related concepts even when they are expressed in different terms. This context-aware matching capability positions BERT as a critical tool in scenarios demanding precision and semantic depth.

Building on the foundation of BERT, Sentence-BERT (S-BERT) introduces optimizations tailored for sentence-level comparisons. S-BERT generates embeddings that are specifically designed for the rapid calculation of similarity between short text segments, such as proposal descriptions and expert profiles. As with BERT, cosine similarity is employed to measure alignment, but S-BERT achieves this with significantly improved efficiency.

The enhanced speed and computational efficiency of S-BERT make it particularly well-suited for real-time applications where responsiveness is key. Its fine-tuning for semantic textual similarity tasks further ensures that even subtle differences in language are captured with precision, enhancing the overall performance of the matchmaking engine.

An alternative approach within the matchmaking system is provided by latent Dirichlet allocation (LDA), which focuses on topic modeling rather than direct text comparison. LDA decomposes text into a mixture of topics, identifying overarching themes that can serve as the basis for matching. By aligning proposals and expert profiles based on thematic relevance, LDA offers a broader perspective that complements the more granular techniques used elsewhere in the system. This method adds an additional dimension to the matchmaking engine, enabling it to uncover connections that might not be apparent through keyword or semantic analysis alone.

Another critical component of the system is the clustering of proposals and profiles using embeddings generated by BERT. The system applies clustering algorithms, such as K-means or DBSCAN, to group similar entities. This helps manage large datasets and identify possible matches efficiently. This clustering approach leverages the rich contextual information encoded in BERT embeddings, ensuring that the groupings are meaningful and relevant.

The scalability of the clustering process is essential for accommodating the platform's growth. By pre-organizing proposals and profiles into clusters, the system is able to streamline matchmaking operations and maintain high levels of efficiency, even as the dataset expands.

The integration of Sentence-BERT embeddings into the clustering process further enhances the system's efficiency. By utilizing the computationally optimized embeddings produced by S-BERT, the system achieves faster clustering without compromising accuracy. This capability is particularly important in dynamic environments where real-time clustering is required, making S-BERT clustering a very important component of the matchmaking module.

Finally, the hybrid approach within the matchmaking system demonstrates the power of modularity and adaptability. The hybrid module combines techniques such as TF-IDF for keyword alignment, LDA for thematic matching, and BERT for semantic precision. This creates a comprehensive, balanced matchmaking solution. Cosine similarity is applied across the various embeddings to compute similarity scores, which are then combined using a weighted scoring system.

By leveraging the unique strengths of its individual components, the hybrid module achieves a level of precision and adaptability that would not be attainable with any singular method. This approach exemplifies the modular nature of the matchmaking system, positioning it as a robust and scalable solution for connecting innovators with mentors.

To evaluate the effectiveness of the different matchmaking algorithms, the mean reciprocal rank (MRR) metric will be utilized as the primary measure of performance. This metric is particularly well-suited to the platform's design, where an innovator selects a single expert from a ranked list of recommendations. MRR measures ranking quality by placing more importance on recommendations where the selected expert is higher on the list. It reflects the algorithm's effectiveness in prioritizing relevance. By averaging the reciprocal ranks of the selected experts across all sessions, MRR provides a robust and interpretable measure of ranking efficacy. This approach ensures a precise evaluation of the algorithms in their ability to deliver meaningful and contextually aligned matches, which is a fundamental objective of the platform.

3.2.3. Proposal Submission and Collaboration Workflow

SPARK-IT introduces a novel functionality that enables innovators to leverage expert guidance and obtain mentor feedback for submitted proposals, representing a key innovation in proposal evaluation systems. The overview of the basic innovator-expert flow is shown in Figure 2.

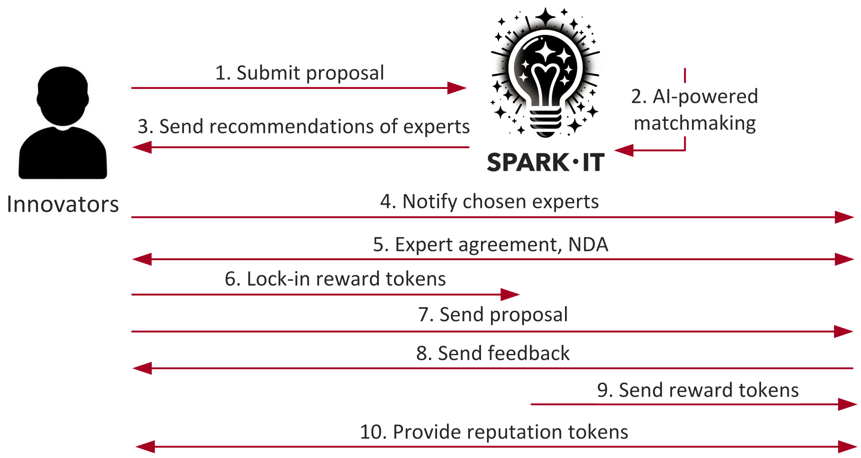

Figure 2. SPARK-IT collaboration workflow. Each arrow originates from the entity initiating the interaction—be it an innovator, expert, or the SPARK-IT platform—and points toward the intended recipient.

The SPARK-IT system features an AI-powered recommendation mechanism that identifies and suggests the best expert matches based on the innovator's specific proposal requirements. Once the chosen experts agree to collaborate, they must sign a non-disclosure agreement (NDA), which is stored on IPFS. By using blockchain to store proof of signing, SPARK-IT ensures that the NDA records are secure, immutable, and verifiable, providing both traceability of the signing process and non-repudiation, meaning the participants cannot deny their actions after the fact.

The detailed steps are as follows:

1. Proposal Submission by an Innovator
    (a) The *innovator* submits a short-version proposal in a preferred format, e.g., a plain document or business model canvas in which are underlined the aspects in which he/she needs guidance.
    (b) The proposal is encrypted and stored in the decentralized storage system (DSS, i.e., IPFS module in Figure 1) and a proof of submission is recorded on the blockchain for traceability.
2. AI-Powered Matching
    (a) The AI algorithm analyzes the proposal based on keywords, business needs, and innovator's requirements.
    (b) The system matches the proposal with suitable experts based on their areas of expertise, reputation, and profile data.
    (c) The *innovator* reviews matched experts and selects preferred mentors.

3. Expert Notification
   (a) *Experts* are notified through the platform if the innovator selected them regarding his/her proposal.
   (b) If they agree, they become *mentors* for that proposal.
4. Expert Agreement and NDA Signing
   (a) Both parties sign an NDA through the platform.
   (b) The NDA is encrypted and stored in the DSS, with proof on the blockchain network.
5. Collaboration and Communication
   (a) Secure communication channels are established using RESTful APIs through the SPARK-IT platform.
   (b) The *innovator* shares detailed proposal information with the mentor.
   (c) The collaboration is tracked, and feedback is provided through the platform.
6. Reputation and Reward Tokens
   (a) *Mentors* earn reputation tokens based on the quality of feedback and contributions.
   (b) *Innovators* use reward tokens to compensate *mentors* for their services.
   (c) All transactions and token exchanges are recorded on the blockchain for transparency.
7. Project Development and Feedback
   (a) *Innovators* and mentors work together to refine the project.
   (b) *Mentor* provides continuous feedback, which is stored securely.
   (c) Reputation tokens are awarded by both *innovators* and *mentors* based on the effectiveness of the collaboration.
8. Completion and Public Disclosure
   (a) Upon project completion, select details of the collaboration may be made public with consent.
   (b) Additional reputation tokens can be awarded based on public feedback and project success.

The objective is to establish a structured and legally robust framework for collaborations, ensuring the protection of intellectual property (IP). Innovators often hesitate to share their ideas and business plans with potential mentors due to concerns about the unauthorized use or theft of their IP. In the absence of proper legal agreements, enforcing IP rights and safeguarding sensitive information becomes difficult. The mentor choosing protocol requires the signing of a non-disclosure agreement (NDA) before any detailed project information is shared. Unstructured collaborations may lead to misunderstandings, misaligned expectations, and ineffective mentoring relationships. To mitigate these risks, the protocol ensures that both innovators and mentors have clear expectations and objectives, fostering more productive and successful outcomes.

All agreements and collaborations are securely recorded and stored using blockchain technology, providing an immutable record that can be referenced in case of disputes. This protocol is designed to protect intellectual property, build trust, ensure accountability, and enhance the platform's overall credibility and appeal. By addressing these critical challenges, SPARK-IT offers a secure and efficient environment for innovators and mentors to collaborate and drive innovation.

3.3. System Components

From a technical point of view, the main system components that are deployed are the frontend server, the backend core with the storage module, the matchmaker, the expert profile, the off-chain storage, the IPFS nodes and the blockchain nodes with the smart contracts, as can be observed in Figure 3. All these component deployments contain the conceptual functionalities shown in Figure 1.

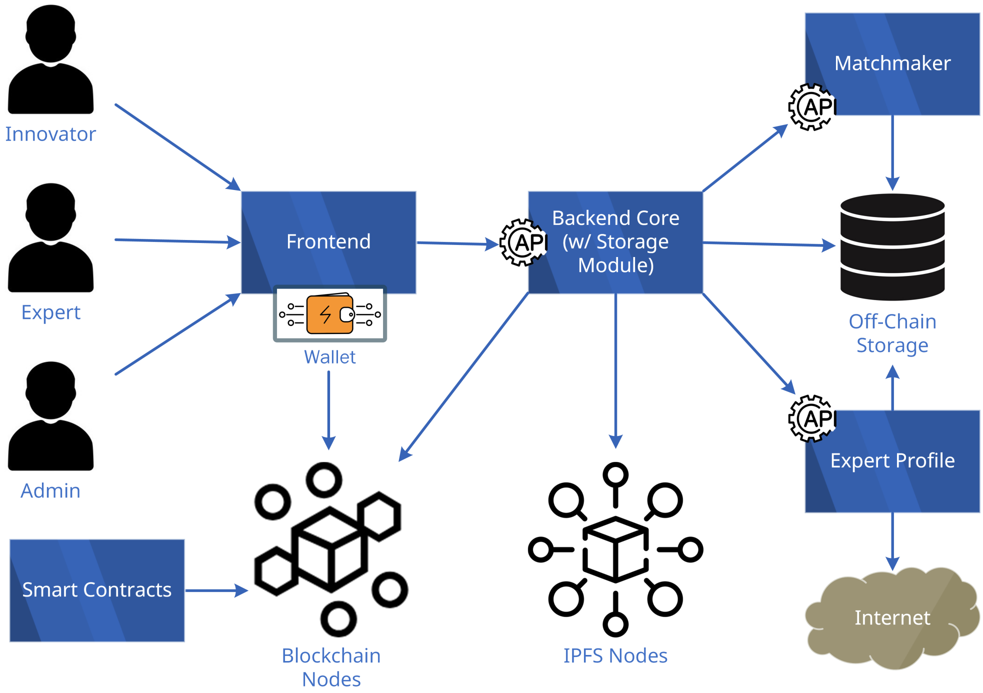

Figure 3. SPARK-IT system components.

One of the core flows from our proposed system is creating and sending a proposal for collaboration. This flow is showcased in the sequence diagram from Figure 4. There are several main components that interact with each other in this case. Those components are the user's browser, the frontend server, the backend server, the database, the decentralized storage (i.e., the IPFS) and the blockchain network. The other aforementioned communication scenarios follow a somewhat similar flow.

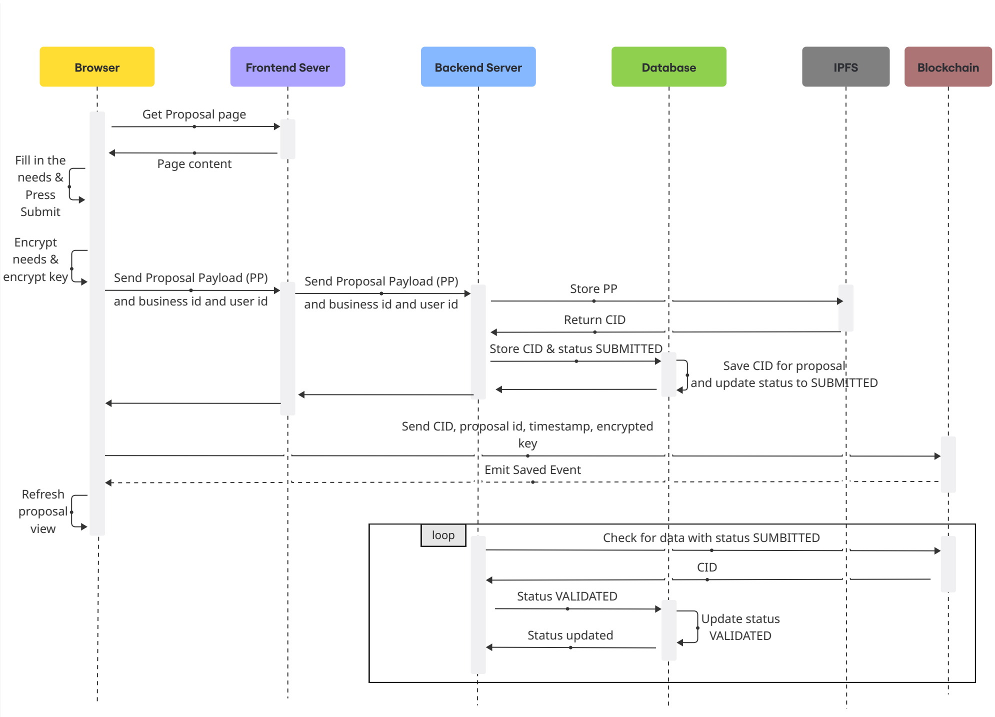

Figure 4. SPARK-IT sequence diagram for creating and sending a proposal.

The proposal information is stored encrypted on IPFS, and the proof is on the blockchain network. Periodically, the backend server checks that the proof was properly stored on the blockchain and updates the database status accordingly.

3.4. Intellectual Property Protection

SPARK-IT offers both protection of intellectual property and efficient matchmaking between innovators and experts, ensuring the protection of intellectual property and building trust among participants. Innovators often fear that sharing their ideas and business plans with potential mentors could lead to unauthorized use or theft of their intellectual property. In addition to struggling to find suitable mentors, innovators must also ensure their intellectual property is safeguarded and secure access to funding opportunities. The innovator–expert collaboration protocol described in Section 3.1 is a structured process. It enables innovators to get feedback from experts while protecting intellectual property through NDAs and secure communication channels. The protocol aims to build trust, ensure accountability, and enhance the platform's credibility and attractiveness.

User information, including the NDA and expert feedback, is stored in a custom encrypted format that leverages blockchain and decentralized storage, as outlined in Section 3.2. Proposals and associated data are encrypted and stored on IPFS, with proofs stored on the blockchain. This ensures that only authorized parties can access the data, providing trust, traceability, and verifiable transparency. The main motivation for this functionality is to ensure the security and privacy of intellectual property and sensitive data, fostering a trusted environment for collaboration. Innovators need assurance that their ideas and business plans are protected from unauthorized access and potential theft. By providing robust security measures, SPARK-IT fosters a trusted environment where innovators feel safe to share their intellectual property. Ensuring data privacy and transparency through blockchain technology builds trust among users, encouraging more participation from innovators and experts. Experts and mentors are more likely to participate in a platform that guarantees the protection of their contributions and maintains a high standard of data privacy.

The primary advantage of utilizing blockchain for intellectual property lies in eliminating reliance on credit from third-party intermediaries. This enables more individuals to store data on distributed blockchains, ensuring that the information remains immutable. Blockchain-based intellectual property solutions offer key benefits, including traceability, tamper resistance, and resource efficiency.

3.5. Token-Based Incentives

The platform includes a dual-token system consisting of reward tokens (SparkCoins) and reputation tokens to incentivize meaningful participation and encourage trustworthy behavior. The system is designed to balance financial rewards and reputational impact, encouraging both innovators and experts to contribute actively and responsibly.

3.5.1. Reward Tokens

SparkCoins serve as the main monetary incentive for experts. These tokens hold tangible value and can be used for transactions within the platform or exchanged externally (e.g., converted to stablecoins using an exchange). The reward token system employs blockchain-based escrow accounts, smart contracts, and tokenomics principles to ensure secure and dispute-resilient transactions.

Innovators submit their proposals through the platform, specifying the mentorship requirements. As part of this submission process, they lock a predetermined amount of SparkCoins into a blockchain-based escrow account. This locking mechanism provides a guarantee of payment for the expert's services, creating trust and accountability between participants.

Upon mutual agreement, the expert commences the mentoring process. During this period, the following is true:

- The locked SparkCoins remain in escrow, accessible only under the conditions explicitly defined within the associated smart contract.
- The release of tokens to the expert is contingent upon one of the following:
    1. **Approval by the innovator (manual release):** The innovator manually triggers the release of funds upon satisfactory completion of the mentorship process.
    2. **Automatic release:** Tokens are automatically disbursed to the expert upon the conclusion of the collaboration period, provided no disputes have been raised.

In the event of a dispute, the platform retains the locked SparkCoins in escrow until the conflict is resolved. Although dispute resolution mechanisms are beyond the scope of the current implementation, future versions could integrate transparent processes to address such issues effectively.

SparkCoins are implemented as wrapped USDT tokens on the platform's permissioned blockchain. The process of obtaining these coins involves the following steps:

1. A smart contract deployed on the Ethereum blockchain locks the specified amount of USDT when a user initiates a swap. The user sends the amount of USDT to this contract.
2. Upon successfully locking the tokens, the smart contract emits an event that records the amount of USDT locked and specifies the recipient address on the permissioned blockchain.
3. An off-chain service, referred to as the bridge component, monitors the Ethereum network for these lock events. The service validates the event to ensure the correct amount of USDT is locked and that the transaction is legitimate.
4. Once the lock event is validated, the bridge component transmits a message to the permissioned blockchain, relaying the details of the locked USDT.
5. A corresponding smart contract on the permissioned blockchain mints an equivalent amount of SparkCoins upon receiving the validated message from the bridge component. This contract implements the ERC20 standard and manages the SparkCoins, facilitating their minting or transfer based on user actions, such as compensating experts for completed services.

This mechanism ensures the secure and transparent exchange of value between the Ethereum network and the platform's permissioned blockchain, providing liquidity and maintaining a 1:1 backing ratio between USDT and SparkCoins.

3.5.2. Reputation Scores and Reputation Tokens

A clear distinction that has to be made within the system is between reputation scores and reputation tokens:

- **Reputation score:** This is an average of all ratings received by a user (on a scale from 1 to 10). For example, if an expert consistently receives high ratings, their reputation score reflects their overall performance and reliability.
- **Reputation tokens:** These are derived from the reputation score received after each interaction with an innovator and are directly tied to monetary incentives. For instance, for each collaboration with an innovator, up to five reputation tokens can be earned. A score of 10 yields five reputation tokens, while lower scores yield proportionally fewer tokens. Accumulated tokens contribute to a pool that can later be converted into reward tokens. These tokens are specifically designed for experts.

The reputation scheme within the SPARK-IT platform is designed to incentivize high-quality contributions from both experts and innovators while maintaining a transparent and reliable system for evaluating interactions and expertise. The purpose of enforcing this mechanism is to create a culture of accountability, reward useful contributions, and improve trust.

Reputation scores are used in the matchmaking phase to ensure that experts with higher reputation scores are prioritized in the process. Therefore, these tokens directly influence the visibility of users on the platform, with higher scores increasing their prominence in search results and recommendations.

The platform incentivizes users through a structured process:

- **Innovators' Perspective:**
  - Innovators receive ratings from mentors, which reflect the quality of their proposals and collaborative interactions. These ratings contribute to their innovation reputation score, which can attract future mentors and potential investors.
  - The platform can serve as a gateway for innovators to showcase projects to potential investors, using their reputation scores as an indicator of trustworthiness and project viability.
- **Experts' Perspective:**
  - Experts contribute to innovative projects, contributing to their professional growth and helping others.
  - Experts are rated by innovators on criteria such as relevance, depth of feedback, and overall helpfulness. These ratings translate into reputation tokens, which build a mentoring reputation score visible on their profile.
  - Experts can earn additional SparkCoins by maintaining high standards of quality when working with innovators, achieving strong reputation scores and then exchanging reputation tokens for reward tokens

At predefined intervals, reputation tokens can be exchanged for reward tokens at a fixed exchange rate. This ensures stability and predictability in the platform's ecosystem, increasing user trust and encouraging sustained engagement. To cover exchange expenses, a fixed fee policy is implemented, applying a small percentage to all transactions between innovators and experts.

The initial implementation allows both innovators and experts to award scores ranging from 1 to 10 based on the quality of their interactions. To ensure unbiased evaluations, these scores are not visible to the counterpart until both parties have completed their assessments.

3.6. Technology and Method Selection

SPARK-IT integrates blockchain technology, AI-driven matchmaking, and decentralized collaboration to create a secure and scalable innovation ecosystem. The selection of blockchain frameworks, AI models, and consensus mechanisms is guided by the need for high efficiency, data integrity, scalability, and low transaction costs while ensuring trust and transparency in mentor-innovator interactions.

3.6.1. Blockchain Framework Selection

The platform employs Hyperledger Besu, an Ethereum-compatible permissioned blockchain, to balance decentralization with governance control. Hyperledger Besu is chosen over fully public blockchains like Ethereum due to its lower transaction costs, enterprise-grade security, and flexibility in defining access control policies. The permissioned nature of the blockchain ensures that only verified participants (innovators, mentors, and stakeholders) can validate transactions, reducing the risk of spam and fraudulent activity.

Additionally, InterPlanetary file system (IPFS) is used for decentralized storage of intellectual property, business proposals, and NDAs, ensuring data availability while maintaining privacy. IPFS is selected over traditional cloud storage due to its tamper-proof nature and cryptographic content address, which prevent unauthorized data manipulation. Blockchain stores cryptographic hashes of IPFS files, ensuring data integrity while keeping large files off-chain to maintain efficiency.

3.6.2. Consensus Mechanism Selection

The system uses the QBFT (quorum Byzantine fault tolerance) consensus mechanism, which is optimized for permissioned blockchains. Unlike proof-of-work (PoW), which is computationally expensive and inefficient for enterprise applications, QBFT provides fast, deterministic finality, ensuring that transactions (such as mentorship agreements, token-based incentives, and proposal submissions) are processed quickly and reliably.

QBFT is selected over proof-of-stake (PoS) and delegated proof-of-stake (DPoS) because it provides enhanced security against Sybil attacks while maintaining low energy consumption. It ensures that only approved validators participate in transaction validation, reducing the risk of malicious actors influencing the network.

3.6.3. AI Model Selection for Expert Matchmaking

SPARK-IT leverages a hybrid AI-driven matchmaking system that combines natural language processing (NLP), machine learning (ML), and graph-based recommendation algorithms. The bidirectional encoder representations from transformers (BERT) model is selected for semantic analysis of business proposals and mentor profiles, ensuring that AI recommendations consider contextual nuances rather than relying solely on keyword matching. Sentence-BERT (S-BERT) is used to generate dense vector embeddings, which help measure the similarity between mentor expertise and innovator needs more accurately.

Additionally, graph-based recommendation models such as Node2Vec and graph convolutional networks (GCNs) analyze expert networks to identify the most well-connected, highly-rated mentors for a given business challenge. A reinforcement learning (RL) feedback loop continuously refines matchmaking accuracy by incorporating user satisfaction ratings and engagement metrics to improve recommendations over time.

4. Discussion

4.1. Design Challenges and Trade-Offs

Designing a decentralized platform that facilitates interactions between innovators and experts involves navigating several challenges and trade-offs across various technical and operational layers. Key design challenges and trade-offs we considered for the SPARK-IT platform are described below.

4.1.1. Balancing Decentralization with Usability

In decentralized platforms, the user experience can often be complex due to the need for users to manage their own private keys, interact with blockchain networks, and handle decentralized storage systems. Balancing the inherent complexity of decentralized technologies with the need for a seamless, intuitive user experience is a significant challenge.

- *Security vs. usability*: To achieve true decentralization, users need to control their private keys, which can be difficult for non-technical users. Managing keys and cryptographic signatures can be cumbersome but is essential for maintaining security. Offering simplified solutions, such as dedicated wallets or social recovery systems, can improve usability but may introduce centralization risks. In SPARK-IT, we opted for a decentralized blockchain-based solution, where the centralized components assist in interaction flows. The essential data are stored encrypted in IPFS, and proof-of-data is anchored in blockchain. Moreover, the user can choose any digital wallet solution as long as it is compatible with an Ethereum blockchain.

- *Speed vs. decentralization*: Decentralized systems can introduce latency, particularly when dealing with blockchain-based interactions or IPFS file retrieval. Optimizing for speed (e.g., using centralized servers or content delivery networks) might decrease decentralization, as centralized components may become single points of failure. In SPARK-IT, we use dedicated in-memory caches to make the overall system as responsive as possible. However, if these fail, the front-end client applications, for both innovator and experts, have a fallback alternative that goes directly to the decentralized components (blockchain and IPFS). Moreover, we opted for a POS (proof-of-stake) permissioned blockchain that can process a high number of transactions per second.
- *Complexity of interactions*: Decentralized platforms often require users to engage with more steps, such as verifying transactions on-chain, interacting with smart contracts, or managing encrypted data. While a decentralized system gives more control to the user, simplifying these processes without losing the core decentralized nature is not an easy task. Designing intuitive front-end systems that abstract away the complexities of blockchain and IPFS interactions while still ensuring underlying security and decentralization is crucial. In SPARK-IT, we streamline the workflows for the users so that the interactions with the employed decentralized technologies, blockchain and IPFS, as well as the entire process of encrypting/decrypting data, are seamless. Our system provides a straightforward wallet integration and guided workflows for on-chain actions. The front-end applications contain JavaScript libraries that perform the heavy-lifting tasks of connecting and interacting with the blockchain and IPFS.

4.1.2. Managing Token Economics in a Permissioned Blockchain

In a permissioned blockchain, tokens can be used to incentivize behaviors such as expert participation, mentoring session completion, or contribution to the platform's success. However, managing a token economy in a permissioned environment introduces complexities regarding distribution, valuation, and governance.

- *Centralized control vs. tokenomics flexibility*: In a permissioned blockchain, some degree of centralization is often necessary for governance, which can limit the flexibility of the token economy. For example, the entity managing the platform might need to control token issuance, governance, or rewards, potentially undermining the decentralization aspect of token management. In SPARK-IT, we designed governance smart contracts that are open to everyone. Even if we use a permissioned blockchain, any potential innovator or expert can join the platform. Therefore, the community formed around our governance protocol is not restricted and behaves in a similar way as the ones deployed in public blockchains.
- *Token valuation and liquidity*: In a permissioned blockchain, the token's value may be more difficult to establish without the market dynamics that come with a public blockchain. Users might be less willing to use or accept a token that lacks liquidity or a clear external value. In SPARK-IT, we decided to use wrapped tokens from public blockchains (such as USDT). Moreover, even if we can support any token from public blockchains, we decided to go for stablecoin tokens to assure predictability and to protect our users from excessive volatility inherent to crypto markets. We have developed dedicated blockchain bridges that assist in moving assets between public blockchains and our permissioned blockchain.
- *Governance mechanisms*: Without strong decentralization, governance around tokenomics could become a bottleneck. Decision-making about token issuance, rewards,

and penalties might rely on a small group of entities, leading to potential trust issues and reducing transparency. In SPARTK-IT, we employ a decentralized governance mechanism (through a dedicated DAO and governance tokens) that ensures that decisions regarding token distribution and rewards are made in a transparent and inclusive manner. Our protocol is open to everyone, as everyone can register in the SPARK-IT platform as either an innovator or an expert.

- *Fair reward distribution*: Allocating tokens equitably while ensuring they incentivize high-quality contributions is very important of the platform's tokenomics. This process requires balancing several critical aspects, including fairness, transparency, and alignment with the platform's overall objectives. SPARK-IT achieves this through a dual-token system, where reputation tokens serve as a measure of quality and reward tokens (SparkCoins) hold monetary value. This mechanism not only incentivizes meaningful participation but also ensures that the rewards are tied to measurable and impactful contributions.

4.1.3. System Scalability

Our solution is designed to scale efficiently as the number of users, data storage needs, and computational demands increase. The system achieves this through a modular service architecture, decentralized storage solutions, and optimized resource management. The platform relies on a service-based design where components such as storage, frontend, backend business logic, expert profile generation, and matchmaking operate independently. This allows for horizontal scaling by dynamically deploying additional backend instances as demand grows, ensuring that the system can handle increasing loads without performance degradation. A load-balancing mechanism can distribute requests across multiple backend servers, preventing bottlenecks and maintaining high availability.

For data storage, SPARK-IT employs a hybrid approach that combines blockchain, decentralized storage, and traditional databases. Business proposals, mentorship agreements, and intellectual property-related documents are stored using the InterPlanetary file system (IPFS), reducing the reliance on centralized storage while ensuring tamper-proof, efficient file access. Only critical data, such as cryptographic proofs of intellectual property and mentorship agreements, are stored on Hyperledger Besu's permissioned blockchain. User profiles, general metadata, and transactional records are maintained in a distributed MariaDB cluster, which is optimized for scalability through sharding and replication techniques. This ensures fast retrieval of essential data while minimizing the computational overhead of storing all records on-chain.

4.1.4. Scalability Considerations in AI-Driven Matchmaking

The matchmaking system must efficiently process and evaluate large data sets to match innovators with suitable experts. AI algorithms used for matchmaking could require significant computational resources, which may hinder the scalability of the platform as the number of users grows. The need for real-time performance and personalization also adds complexity to scaling the system.

- *AI accuracy vs. computational resources*: AI-driven matchmaking systems often rely on complex models that require considerable computational power. As the platform scales, maintaining the same level of personalization and accuracy in recommendations becomes challenging due to the increased resource demands. In SPARK-IT, we consider a federated learning approach where multiple systems make predictions and can be rewarded based on their input. Some of these systems can be hosted by third parties, thus ensuring the overall system scalability.

- *Real-time performance vs. scalability*: The need for real-time matchmaking (matching experts to innovators on-demand) adds another layer of complexity. Real-time AI processing can lead to bottlenecks in systems with growing data inputs, especially when scaling to thousands of innovators and experts. In SPARK-IT, we devised an asynchronous workflow, where the innovator initiates the matchmaking process from its front-end application and, at a later time, receives a notification that the results are ready.
- *Data privacy vs. matching precision*: For AI models to provide effective matchmaking, they need access to a large amount of data about both innovators and experts (e.g., skills, preferences, historical records, and reputation scores). However, the need for privacy and confidentiality may limit the amount of data accessible to AI systems, affecting the accuracy of the matches. In SPARK-IT, we defined a clear set of attributes that are available to the AI systems. These attributes are needed to achieve the objective of the matchmaking process without disclosing more information than needed. Moreover, an additional data anonymization layer can and will be deployed in the next versions of the platform.

4.1.5. Financial Model Design

To ensure financial sustainability and accessibility for diverse user groups, SPARK-IT has to use a multi-faceted financial model. Users can choose between the following:

- *Flat Transaction Fee*: A small, fixed percentage fee on transactions between innovators and experts ensures predictable costs, ideal for occasional users.
- *Subscription Model*:
  - *Basic Plans*: Provides low-cost access to essential features, allowing users to explore the platform without significant commitment.
  - *Premium Plans*: Offer advanced features such as enhanced matchmaking algorithms, analytics, and priority support.
- *Organization Sponsorship*: Larger entities (e.g., universities or corporations) can sponsor platform licenses for their members. They can purchase SparkCoins and then redistribute them to their members as they see fit.
- *Pay-Per-Use Extra Features*: Specific value-added features, like a badge that proves the profile information has been verified, are available for a fee.

Each of these design considerations requires a careful balance of trade-offs. Striking the right balance is essential for creating a platform that is both functional and scalable while maintaining the decentralized aspects and providing a user-friendly experience. The employed solutions and trade-offs must be iterated over time to optimize the system further as the platform grows.

4.2. Socio-Economic Impacts

4.2.1. Democratizing Access to Mentorship and Innovation

SPARK-IT has the potential to transform innovation ecosystems by democratizing access to mentorship and resources. The platform uses decentralized architecture and AI-driven matchmaking. This bridges the gap between innovators and experts, no matter their geographic location or socio-economic background. Innovators from under-represented regions, startups, and academic institutions can gain access to high-quality mentorship and collaboration opportunities traditionally reserved for well-connected individuals or larger organizations. This democratization fosters inclusivity, empowering a broader range of voices and ideas to contribute to global innovation.

4.2.2. Enhancing Trust in Global Innovation Ecosystems

Trust is a critical factor in successful collaborations within innovation ecosystems. SPARK-IT enhances trust by integrating blockchain technology to ensure data transparency, security, and immutability. The use of smart contracts and decentralized storage safeguards intellectual property and ensures that all transactions and interactions are traceable and verifiable. These measures reduce hesitation among participants to share sensitive information, promoting a culture of openness and collaboration. Furthermore, the dual-token incentive system ensures accountability, encouraging meaningful participation and reinforcing trust among all stakeholders.

4.2.3. Potential Use Cases in Academia and Industry

SPARK-IT's versatile design makes it highly applicable to both academic and industrial contexts. In academia, the platform can facilitate research collaborations by connecting researchers with industry experts, mentors, or funding opportunities. It provides a secure environment for sharing ideas, receiving feedback, and co-developing innovative solutions. In industry, SPARK-IT is effective in accelerating startup development. It connects entrepreneurs with experienced mentors and investors and helps foster partnerships across sectors. Its ability to adapt to various use cases ensures relevance across diverse domains, making it a valuable resource for driving economic growth and societal progress.

Through these impacts, SPARK-IT contributes to creating a more inclusive, trusted, and efficient global innovation ecosystem.

4.3. Performance Metrics for Evaluating the Platform's Effectiveness

To ensure the effectiveness of SPARK-IT in bridging the gap between technical innovators and business mentors, the performance can be evaluated using key metrics that assess recommendation accuracy, system efficiency, and user engagement. The accuracy of expert recommendations is measured through precision and recall based on user feedback that compares AI-generated mentor matches with successful mentorship engagements. By analyzing the percentage of mentor-innovator pairings that lead to productive collaborations, the platform continuously refines its AI-driven matchmaking engine. Additionally, SPARK-IT monitors user satisfaction by gathering structured feedback on mentorship quality, business advice relevance, and overall collaboration outcomes. Mentor retention rates serve as an indicator of expert engagement, showing how effectively the platform incentivizes and sustains long-term participation.

4.3.1. Qualitative and Quantitative Insights from User and Stakeholder Research

When designing the SPARK-IT platform, we first conducted a user research stage through questionnaires and stakeholder interviews. More specifically, we conducted an online survey through Typeform to gather insights. The survey was designed to adapt to the different personas of our target audience: startup founders or innovators, experts, and startup accelerators. Up until now, we have received 28 responses from individuals from Central and Eastern Europe and Brazil. The distribution among the three respondent categories (experts, innovators, and organizational representatives) is illustrated in Figure 5.

The questions addressed in the survey can be categorized into the following themes:

1. **Mentor Selection and Matchmaking**
    - Mentor information;
    - Importance of the mentor's professional network;
    - Validation criteria for mentors (experience, academic background, certifications, peer reviews, and mentee feedback);

- Method of mentor–startup matching (self-selection, automated algorithms, and manual review).

2. **Feedback and Validation**
    - Methods of incorporating mentee feedback;
    - Role of peer reviews;
    - Comfort level with publicly sharing mentorship outcomes;
    - Demonstrating mentor effectiveness (professional achievements, endorsements, and peer reviews).
3. **Mentorship Process and Success Metrics**
    - Elements of successful mentorship (continuous feedback, defined goals, communication, and respect);
    - Tracking and measuring progress (milestone achievements, mentee feedback, mentor evaluations, project outcomes, and KPIs).
4. **Mentorship Management**
    - Handling unsuccessful mentorships (switching mentors, feedback loops, and follow-ups);
    - Scheduling and appointment methods (calendar integration and availability slots).
5. **Budget and Financial Considerations**
    - Budget preferences and flexibility;
    - Factors affecting budget decisions (mentor expertise, project nature, and engagement duration).
6. **Intellectual Property Protection**
    - Methods for IP protection (NDAs, confidentiality agreements, secure document sharing, and legal support).
7. **Resources and Support**
    - Elements of a successful mentorship (networking opportunities, communication tools, administrative support, and training materials).

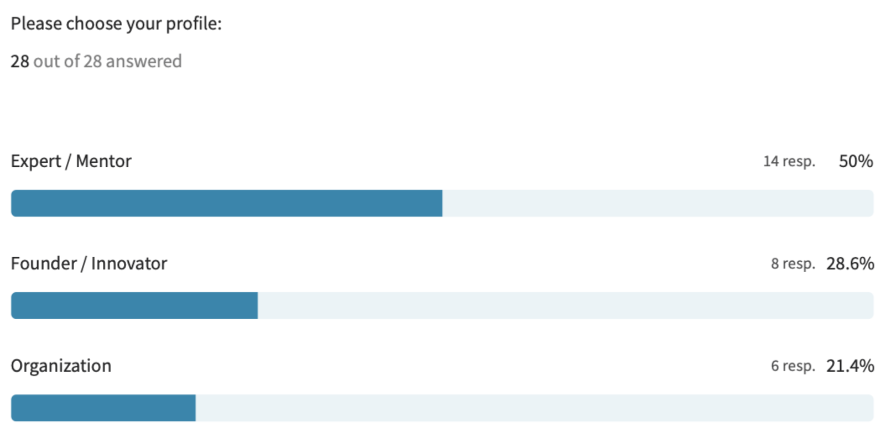

Figure 5. Distribution of respondents by profile type: experts/mentors, founders/innovators, and organization representatives (n = 28).

Regarding **mentor selection and matchmaking**, users emphasized industry experience (87.5%) and personality fit (75%) as the most important factors. A majority (71.4%) preferred a hybrid approach combining automated algorithms and human review for effective matchmaking. That is the reason behind our approach, where we designed an AI algorithm to perform the matchmaking and we present the results to the user so that the final decision is theirs.

In the area of **feedback and validation**, respondents significantly valued public mentee ratings (83.3%) and showed high comfort levels with publicly sharing mentorship experiences (71.4%). Participants considered professional achievements (85.7%) and endorsements (78.6%) to best showcase mentor effectiveness. Therefore, we designed the public reputation system from SPARK-IT, and we integrated logic to scrape for achievements and endorsements on platforms that allow it, such as LinkedIn.

Concerning the **mentorship process and success metrics**, most respondents identified continuous feedback and defined goals (78.6%) as critical elements for mentorship success. Progress measurement was highly recommended through milestone achievements (82.1%) and mentee feedback (67.9%). This led to the decision to impose financial penalties on the mentor in case the deadline for collaboration is not respected.

In terms of **intellectual property protection**, respondents had to choose between six different protection measures. Non-disclosure agreements (NDAs) were identified as the most important, endorsed by 64.3% of respondents, followed by confidentiality agreements (53.6%) and secure document sharing (35.7%). These findings strongly support our platform's integration of NDAs as a primary mechanism for safeguarding intellectual property, reflecting community preferences for structured legal protection.

During our research, we also conducted interviews with five ambassadors from organizations such as Rubik Hub, Launch Community, Innovation Labs, and Orange Fab, known for their exceptional work in supporting startups in Romania. Based on their input, we designed a SOTA analysis of our system, the baseline being the systems currently in use in their ecosystems. The results are presented in Table 1.

Table 1. SWOT analysis of the SPARK-IT project.

Strengths	Weaknesses
• **Matchmaking:** The AI based recommendation system, which takes into account both professional information and reputation scores, is considered a strong point. • **IP protection:** The platform provides the opportunity to sign an NDA and stores that NDA in a secure environment. The system cannot access sensitive information, which builds trust. • **User Centric Design:** Feedback loops and iterative enhancements increase the chances for the system to succeed. • **Data-Driven Approach:** SPARK-IT combines quantitative metrics (KPIs) with qualitative feedback.	• **Documentation Overhead:** Increased workload from detailed process documentation was a concern among the stakeholders. The final documents that the mentor has to upload can be perceived as unnecessary overhead. • **Resource Intensiveness:** Requires additional staffing and technological investments. • **Unfamiliarity with Blockchain:** Users can find it difficult to use web3 wallets and blockchain. • **Long-Term Monitoring:** The platform does not provide the opportunity for long-term monitoring of a project after a collaboration with a mentor.
Opportunities	**Threats**
• **Innovative Business Model:** The system innovates current approaches and relatively few competitors have been identified. • **Partnerships:** The project has a great potential to form alliances with academic institutions, industry leaders, and venture capital firms. • **Multiple Revenue Streams:** There are multiple monetization models that could be implemented, such as subscriptions, premium services, and data analytics offerings. • **Open-Source:** Open-source initiatives are generally regarded positively by the community.	• **Adoption Resistance:** Stakeholders might not be prepared to use the technological stack. • **Budgetary Constraints:** Limited resources could restrict technology implementation. • **Risk of Over-Documentation:** Excessive focus on documentation may hinder creative engagement.

4.3.2. Scalability and Cost Efficiency

SPARK-IT also prioritizes system efficiency and scalability. Transaction throughput is tracked by measuring the number of mentorship requests, proposal submissions, and confirmed collaborations processed per second, ensuring the platform remains responsive under high demand. System latency is continuously analyzed to maintain sub-second response times for matchmaking queries, proposal evaluations, and encrypted data retrieval from decentralized storage. Additionally, blockchain-related operations, such as executing smart contracts for mentor compensation and verifying non-disclosure agreements (NDAs), are optimized to minimize processing delays. Together, these metrics provide a comprehensive assessment of SPARK-IT's reliability, scalability, and impact. This ensures it effectively meets the needs of innovators and experts in a competitive innovation environment.

Using our own permissioned blockchain has the significant advantage of eliminating gas fees entirely. On a public blockchain network like Ethereum, however, a complete interaction between an innovator and an expert, comprising the creation of a business project, proposal submission, NDA signing, expert association, reward token locking and disbursement, reputation token transfer, and wrapped token bridge operations, would incur substantial transaction costs. Under the current network condition, the average gas price is 40 Gwei and ETH is at approximately USD 1600 at the time of writing. One ETH is equivalent to 1 billion Gwei (gigawei) and Wei represents the smallest unit of Ether (ETH). For one complete innovator–expert interaction there is a gas estimate of 455,000, which results, on Ethereum Mainnet, in an estimated cost of USD 29 per collaboration. Even when using a Layer 2 solution like Optimism, which reduces fees, the cost would still amount to approximately USD 0.23 per interaction. In contrast, the SPARK-IT platform's permissioned architecture enables cost-free transactions for users, removing a key barrier to adoption and making the platform particularly suitable for large-scale, inclusive innovation ecosystems.

Although operating our own blockchain nodes does incur infrastructure and maintenance costs, it offers greater control, eliminates unpredictable gas expenses, and ensures compliance with privacy and governance requirements.

4.3.3. API Performance Metrics

Table 2 presents the average response times for key backend operations within the SPARK-IT platform. These include user authentication, profile management, business project and proposal handling, and interactions with decentralized storage. The recorded times demonstrate that most API endpoints perform efficiently, with the majority of requests completed in under 200 ms, ensuring a responsive user experience even under typical operational loads.

Table 2. Response times for SPARK-IT platform operations (in ms).

Description	Method	Endpoint URL [a]	Duration (ms)
Access the account information	GET	/api/account	13
Authenticate	POST	/api/authenticate	164
Obtain the user profile	GET	/api/user-profiles/me	46
Update the user profile	PUT	/api/user-profiles/me	17
Create a business project	POST	/api/bp	148
Obtain the list of business projects	GET	/api/bp/me	19
Obtain the details of a business project	GET	/api/bp/{id}	23
Create a proposal for collaboration	POST	/api/bp/{id}/pfc	113
Obtain the list of proposals for collaboration	GET	/api/bp/{id}/pfc	17
Obtain the details referring to proposal	GET	/api/bp/{id}/pfc/{pid}	38
Various operations performed on a proposal	POST	/api/bp/{id}/pfc/{pid}/*	27
Obtain the list of found experts	GET	/api/bp/{id}/pfc/{pid}/experts-found	101
Obtain the list of collaborations	GET	/api/collaborations/me	33
Obtain a resource from IPFS	GET	/api/ipfs/cid/{cid}	11

[a] `bp` is shorthand for `business project`, and `pfc` is for `proposal-for-collaboration`, * the operations that are performed on a proposal are: `select-expert`, `mentorship-decision`, `sent-to-mentor`, `nda-skip`, `final-report`, `rating-submitted`, `mentor-paid`.

5. Conclusions

The SPARK-IT platform introduces a framework that addresses challenges within innovation ecosystems by combining blockchain infrastructure, AI-driven expertise matching, and decentralized governance models. The system builds a complete business innovation ecosystem on a single digital platform. It improves transparency and participation for innovators, entrepreneurs, mentors, experts, and investors. Furthermore, the system removes the barriers related to intellectual property handling, uneven access to mentorship, and difficult collaboration processes.

The research shows several key advantages. Firstly, AI-based algorithms guide innovators toward experts whose skills align with project needs, improving the quality of mentorship and the value of outcomes. Secondly, blockchain technology, together with the legally compliant NDA template provided in the platform, preserves a reliable record of intellectual property exchanges. By using a permissioned network, with nodes hosted at trusted universities and with zero gas fees, we eliminate the typical barriers of traditional public chains, encouraging broad participation. Thirdly, token-based incentives keep users engaged. Innovators and experts earn reputation tokens based on performance and contributions. SparkCoins, which are linked to fiat currency, further encourage knowledge sharing and long-term participation. Additionally, the integrated web scraper provides a simple method to create user profiles from trusted sources, and the encryption module ensures that only authorized parties can access sensitive data. To empower the community further, the platform allows mentors who wish to give back to waive their fees, facilitating access for innovators who may not have the financial means; this allows for building a truly inclusive ecosystem for collaboration and growth.

By using a modular, scalable architecture and focusing on usability, SPARK-IT can be adapted to multiple contexts. These may include startup accelerators who want to improve the success rate of mentorship, academic groups seeking to improve research collaborations, and investors looking for emerging opportunities. The design also makes room for integration with data analytics, decision-support systems, and predictive modeling, enabling the platform to evolve alongside changes in markets and technologies.

As SPARK-IT advances toward practical deployment, several areas warrant sustained effort. Enhancements in AI algorithms will improve the accuracy and applicability of matches, ensuring that participants gain practical guidance. Revisions to incentive structures and reward mechanisms will help maintain an active community and encourage value exchange among all users. Ongoing work on scaling the platform, both technically and organizationally, will accommodate a growing user base, a wider range of industries, and more extensive use cases.

Future research and development may broaden the platform's scope to include additional sectors such as manufacturing, healthcare, finance, and sustainability-focused fields. Enabling the possibility for a user to join a decentralized autonomous organization and to be able to influence its development through a transparent voting system will trigger an active and engaged community. Incorporating advanced analytics and structured decision-making processes will help participants identify trends, forecast opportunities, and make more informed choices. SPARK-IT expands access to expert networks and protects intellectual assets. It promotes balanced participation across regions and communities. This supports innovation-led growth and benefits society.

In closing, SPARK-IT's approach to resolving ecosystem challenges not only improves and sparks connections between innovators and a larger entrepreneurial arena but also creates a basis for new activities, spin-offs, and cross-sector partnerships. The work presented here provides a solid foundation for refining, scaling, and enriching the platform, paving the way for its ongoing role in encouraging global innovation and societal advancements.

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Abbreviations

The following abbreviations are used in this manuscript:

ABAC	Attribute-Based Access Control
ACC	Atomicity, Consensus, and Confidentiality
AI	Artificial Intelligence
B-RBAC	Blockchain-based Role-Based Access Control
BERT	Bidirectional Encoder Representations from Transformers
BMC	Business Model Canvas
CAAC	Context-Aware role-based Access Control
CBC	Consortium Blockchain
CNN	Convolutional Neural Network
CP-ABE	Ciphertext-Policy Attribute-Based Encryption
DAO	Decentralized Autonomous Organization
DDAC	Decentralized Data Access Control
DHT	Distributed Hash Table
DNN	Deep Neural Network
DSS	Decentralized Storage System
FAIR	Findability, Accessibility, Interoperability and Reusability
IP	Intellectual Property
IPFS	InterPlanetary File System
IoT	Internet of Things
KPI	Key Performance Indicator
LDA	Latent Dirichlet Allocation
LSTM	Long Short-Term Memory
MRR	Mean Reciprocal Rank
NDA	Non-Disclosure Agreement
NLP	Natural Language Processing
OBAC	Ontology-Based Access Control
PRE	Proxy re-Encryption
PoS	Proof-of-Stake
PoW	Proof-of-Work
RBAC	Role-Based Access Control

RFP	Requests for Proposal
S-BERT	Sentence-BERT
SA-ODAC	Security-Aware mechanism and Ontology-based Data Access Control
SAT	Secure Awareness Technique
SBFT	Simplified Byzantine Fault Tolerance
TF-IDF	Term Frequency-Inverse Document Frequency
VPC	Value Proposition Canvas

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