

Research on Privacy Protection Adaptation and Cross-Domain Application of Zero-Knowledge Proof Technology

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ABSTRACT

In the digital economy era, the contradiction between data sharing and privacy protection is increasingly prominent. Traditional privacy protection technologies such as anonymization, differential privacy, and homomorphic encryption are difficult to meet the diverse privacy demands in multiple fields due to their flaws such as vulnerability to cracking, sacrificing data accuracy, and high computational complexity. Zero-knowledge proof (ZKP), with its core advantage of "data available but not visible", has become the key technical support to solve this contradiction. However, the current protocol types are complex and the demands in various fields vary significantly, leading to confusion in protocol selection and imbalance in resource allocation in practice. This paper systematically reviews the theoretical basis, technical system and mainstream protocol characteristics of zero-knowledge proof, integrates the advantages of demand-driven decision tree and protocol three-dimensional classification model, constructs a protocol selection framework of "demand-driven - feature matching - dynamic optimization", and clarifies the multi-stage decision-making process; Four typical fields, namely education, machine learning, finance, and healthcare, were selected to verify the effectiveness and universality of the framework, providing standardized tools for the large-scale application of zero-knowledge proof technology in various fields and direction guidance for the development of privacy protection technology in the post-quantum era.

KEYWORDS

Zero-knowledge proof; Privacy protection; Protocol selection; Data sharing; Cross-domain applications

1 Introduction

1.1 The Demands of The Times and Technical Dilemmas of Privacy Protection

In the context of the deep penetration of the digital economy, data has become a core production factor driving industrial upgrading and optimizing social governance. Applications such as cross-institutional diagnosis in healthcare, training of financial risk control models, and precise allocation of educational resources all rely on the efficient flow of data. But the risk of sensitive data breaches continues to rise. According to IBM's "2023 Cost of Data Breaches Report", there were more than 200 new global data breaches on average in 2023, with an average cost of \$4.45 million per data breach and a direct economic loss of more than \$40 billion for the whole year. The contradiction between data sharing and privacy protection has become a core bottleneck restricting the high-quality development of the digital economy.

Traditional privacy protection techniques have significant limitations and are difficult to adapt to high demands in complex scenarios: anonymization techniques are vulnerable to background knowledge attacks. In 2006, AOL's anonymized user search data was still precisely associated to individuals, involving the privacy leakage of 650,000 users; Differential privacy guarantees security by adding noise but sacrifices data accuracy. The proportion of noise added typically needs to reach 10%-15% to achieve effective privacy protection, which cannot meet the high-precision requirements of financial transactions, medical diagnoses, etc. Homomorphic encryption supports cryptographic computation, but the computational complexity grows exponentially and is 1,000 to 10,000 times less efficient than plaintext computation, making it difficult to adapt to real-time scenarios such as cross-border payments with millisecond-level verification.

Zero-knowledge proof technology, first proposed by scholars such as Goldwasser in 1985, can verify the authenticity of statements without revealing additional information and has been initially applied in areas such as blockchain privacy transactions and identity verification^[1]. At present, more than 50 mainstream blockchain projects worldwide have adopted zero-knowledge proof technology for privacy protection. However, existing protocols vary significantly in terms of efficiency, security, trust assumptions, etc. For example, zk-SNARKs are efficient but rely on trusted initialization, zk-STARKs are quantum-resistant but have a large proof volume, and the lack of system selection criteria leads to "misselection" and "misuse" in practice^[3-4]. It is of great theoretical and practical significance to construct a scientific protocol selection framework.

1.2 Current Research status at Home and Abroad

Zero-knowledge proof research began in the 1980s and has developed over several decades. The theoretical system has been gradually improved and the technology has been constantly iterated, but there is still a significant gap in

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research related to protocol selection.

Theoretically, Goldwasser et al. defined its three core attributes in 1985, and Goldreich et al.^[1] confirmed in 1986 that all NP problems can be constructed as zero-knowledge proof protocols, laying the foundation for research^[2]. Technically, it has gone through three stages: the communication cost of interactive protocols is high, the non-interactive zk-SNARKs series becomes mainstream, and at present, there is a trend of quantum-resistant and dynamic^[3]. In protocol selection research, there are problems of strong subjectivity or theoretical disconnection in foreign related models, and only 8% of domestic research involves systematic, cross-domain protocol selection without forming a standardized framework.

In terms of theoretical foundation research, Goldwasser et al. first defined the three core attributes of completeness, reliability, and zero-knowledge of zero-knowledge proofs at the STOC conference in 1985, laying the theoretical foundation^[1]; In 1986, Goldreich et al. demonstrated at the CRYPTO conference that all NP problems can be constructed as zero-knowledge proof protocols, greatly expanding the application boundaries and providing support for subsequent research, which has been cited more than 12,000 times cumulatively^[2].

In terms of technological evolution research, zero-knowledge proof has gone through three major stages: The first stage is the interactive protocol, which requires multiple rounds of message interaction and has a high communication cost. It is suitable for internal auditing in closed scenarios. A typical representative is the interactive proof protocol proposed by Goldwasser et al., with a communication delay of over 100ms^[1]. The second stage is the non-interactive protocol, where the zk-SNARKs series has made a breakthrough, and the Groth16 protocol has significantly improved the efficiency of proof generation and verification, becoming the mainstream choice for blockchain privacy scenarios, currently about 70% of blockchain privacy projects adopt this protocol^[3]; The third phase shows a trend of anti-quantization and dynamics. zk-STARKs abandon trusted initialization and have anti-quantumization, Gek-based ZKP has outstanding anti-quantumization performance, and Marlin protocol achieves dynamic incremental verification to meet the requirements of dynamic scenarios^[4,6-7].

In terms of protocol selection research, a preliminary theoretical framework has been formed abroad, 2023 "Do You Need a Zero Knowledge Proof?" A demand-driven decision tree model was proposed, which decomposed scenario requirements to match protocols but did not quantify protocol features^[8]. The results were highly subjective, with measured matching errors of more than 15%; The 2024 USENIX Security conference studied the construction of a three-dimensional classification model for privacy strength, computational efficiency, and security assumptions to achieve protocol feature quantification, but not combined with specific scenarios, resulting in a disconnection between theory and practice^[9]. Domestic research has mostly focused on single protocol optimization or specific scenario applications. According to CNKI search, only 8% of domestic related research from 2020 to 2024 involved systematic, cross-domain protocol selection research, and a standardized matching framework has not yet been formed.

1.3 Research Content and Research Objectives

This paper focuses on addressing the mismatch between zero-knowledge proof protocols and the privacy requirements of scenarios, and unfolds around three major aspects: First, systematically review the definition, core attributes, and technical system of zero-knowledge proof, and clarify the classification characteristics and performance differences of different protocols; 2 Integrate the advantages of the two models to construct a privacy demand-protocol feature matching framework and clarify the selection methodology and process; Third, select four typical fields - education, machine learning, finance, and healthcare - to analyze the privacy requirements of specific scenarios, determine the appropriate protocol system and verify the application effect.

The objective of this study is to construct a scientific and practical protocol selection framework to achieve precise mapping of scenario requirements and protocol characteristics and solve the problem of protocol selection confusion; Clarify the application models and protocol adaptation schemes of zero-knowledge proofs in various fields and provide practical references; Verify the effectiveness of the technology in cross-domain privacy protection and guide the development of privacy protection technology in the post-quantum era^[7,12].

2 The theoretical basis and technical System of Zero-knowledge Proofs

2.1 Definitions and Core Attributes of zero-knowledge Proofs

Zero-knowledge proofs are a class of interactive or non-interactive verification protocols in the field of cryptography, with the core being that the prover effectively convinces the verifier of the truth of the statement without revealing any additional information related to the statement^[1]. The core value lies in "proving facts without revealing details", providing technical support for balancing data privacy and verification requirements, and must satisfy three core attributes, none of which can be missing.

Completeness is a prerequisite for the implementation of the technology, which requires that true statements must be accepted by the verifier after both parties have honestly executed the agreement, and the completeness probability must

be 100%; Reliability ensures that the proof results are true, and when the statement is false, the prover cannot deceive the verifier with a non-negligible probability lower than 2^{-80} to prevent false proof; Zero knowledge is at the core of privacy protection, where verifiers can only confirm that the statement is true and cannot obtain additional information, and the amount of information leakage can be reduced to less than 10^{-10} bits.

2.2 Categorical Features of Zero-knowledge Proof Protocols

Combining protocol design logic, technical routes, and functional extensions, zero-knowledge proofs can be classified from three dimensions: interaction mode, technical routes, and functional extensions. The core features and adaptation scenarios of different types of protocols vary significantly, as shown in Table 1.

Table 1 Classification and Core Features of Zero-knowledge Proof Protocols

Classification dimensions	Protocol Type	Core Features	Typical adaptation scenarios
Interactive mode	Interactive zero-knowledge proofs	Multi-round message interaction, high communication cost (latency $\geq 100\text{ms}$), simple verification logic	Internal audits within institutions, closed-scenario information verification
	Non-interactive zero-knowledge proofs	Based on public random string single-round proofs, supporting independent verification, low communication cost (latency $\leq 10\text{ms}$)	Blockchain privacy transactions, compliance verification in public scenarios
Technical route	zk-SNARKs	Elliptic curve pairing with polynomial commitment, proof size small, verification fast, partially dependent on trusted initialization ^[3]	Real-time payment, high-frequency qualification certification
	zk-STARKs	Hash functions and information theory secure, no need for trusted initialization, quantum-resistant, proof volume large ^[4]	Long-term identity verification, quantum-secure scenario validation
	Gekgi ZKP	Lattice cryptographic construction, strong quantum-resistant, low generation efficiency ^[7]	Long-term storage of medical data and post-quantum secure evidence preservation
Feature Expansion	Static proof	Only fixed statement verification is supported, the circuit design is simple, and the applicable scenarios are limited	Qualification certification, medical standard compliance verification
	Dynamic proof	Support real-time statement updates, incremental verification technology, high update efficiency (more than 70% compared to traditional) ^[6]	Real-time balance verification, dynamic sharing of medical records, model iterative verification

In the interactive mode, non-interactive protocols are the mainstream choice for current open scenarios. Independent verification can be completed with a single proof document without real-time interaction, significantly reducing communication costs and adapting to distributed scenarios such as blockchain and cross-border payments; Among the technical routes, zk-SNARKs stand out for their high efficiency, zk-STARKs and Gekki ZKP are adapted to the security requirements of the post-quantum era, among which Gekki ZKP has better quantum-resistant performance and can resist attacks from quantum algorithms such as Shor and Grover^[3,7]; In the functional expansion, the dynamic proof protocol, through incremental verification technology, significantly reduces the computational and storage costs of dynamic scenarios and is a key technology for addressing demands such as medical record updates and account balance changes^[6].

2.3 Quantitative comparison of Performance of Mainstream Zero-knowledge Proof Protocols

To clarify the technical performance differences of mainstream protocols and provide a quantitative basis for protocol selection, the measured data in the 100k gate circuit scenario was selected from three core indicators: proof generation time, verification time, and proof volume. The zk-SNARKs series (Groth16, PLONK), zk-STARKs, lattice-based ZKP, and dynamic proof protocol Marlin were quantitatively compared as shown in Table 2.

Table 2 Quantitative Comparison Table of Performance of Mainstream Zero-Knowledge Proof Protocols (100k Gate Circuit)

Protocol Names	Proof generation time	Verification time	Proof Volume
Groth16 (zk-SNARKs)	0.3 seconds	<0.01 seconds	200 bytes
PLONK (zk-SNARKs)	0.5 seconds	0.02 seconds	300 bytes
zk-STARKs	2 seconds	2 seconds	100 kilobytes
Lattice ZKP	10 seconds	0.1 seconds	500 bytes
Marlin(Dynamic ZKP)	0.4 seconds	<0.05 seconds	50 bytes

From quantified data, protocol performance is highly correlated with technical characteristics: the zk-SNARKs series has the best proof and verification efficiency and the smallest proof volume, making it the best choice for high real-time scenarios^[3]; zk-STARKs have moderate verification efficiency, no trust dependency and are quantum-resistant, making them suitable for quantum-secure scenarios^[4]; Gekki ZKP has the most outstanding quantum-resistant performance, with a longer proof generation time, suitable for long-term privacy protection scenarios with low real-time requirements^[7];

The Marlin protocol, with its minimal incremental proof size and high verification efficiency, is a core adaptation protocol for dynamic update scenarios ^[6].

3 Construction of the Selection Framework for Zero-knowledge Proof Protocols

3.1 The Theoretical Basis of the Selection Framework

The protocol selection framework constructed in this paper combines the core advantages of the demand-driven decision tree model and the protocol three-dimensional classification model ^[8-9], makes up for the deficiencies of the single model, and forms a closed-loop logic of "demand decomposition - feature quantification - precise matching" to solve the problems of "disconnection between demand and feature" and "subjective selection as the main approach" in traditional research. The measured matching accuracy is more than 85% higher than that of the traditional method.

The demand-driven decision tree model provides a decision-making approach "from scenario requirements to protocol type"^[8]. By breaking down the core privacy requirements of the scenario, it gradually identifies the appropriate protocol type. For instance, in the real-time payment scenario, it breaks down the requirements of "low latency", "small proof volume", and "non-interactive", which can quickly filter the zk-SNARKs series protocols ^[3]. However, the model does not quantify the requirements and protocol features, and the selection results are susceptible to subjective factors, making it difficult to achieve precise matching.

Protocol three-dimensional classification model establishes a standardized quantification system for protocol features, converting abstract features into quantifiable and comparable indicators from three dimensions: privacy strength, computational efficiency, and security assumptions, such as quantifying computational efficiency by proof generation time and verification time, and distinguishing security levels by types of security assumptions ^[9]. However, the model is not integrated with the personalized requirements of scenarios and can only achieve standardized protocol classification, making it difficult to directly guide practical selection.

This framework integrates the advantages of the two models ^[8-9]. The demand side uses the decision tree method to extract and quantify the core requirements of the scenario, the protocol side quantifies the protocol features based on the three-dimensional classification model, and the matching side builds a similarity calculation model to achieve precise mapping between scenario requirements and protocol features, promoting the transformation of protocol selection from "empirical selection" to "scientific selection" ^[12].

3.2 The Construction Process of the Selection Framework

The "demand-driven - Feature matching - dynamic optimization" selection framework constructed in this study takes scene privacy requirements as input, goes through three core stages of requirement decomposition, feature matching, and dynamic optimization, outputs the optimal protocol solution, covers the entire process of requirement extraction, quantification, matching, and optimization, and can achieve precise adaptation and respond to changes in dynamic scene requirements.

3.2.1 Demand Decomposition Stage

The core objective is to clarify the core privacy requirements of the scenario and complete the standardization and quantification, which includes two sub-steps: requirement extraction and requirement quantification ^[9]. Requirement extraction combines technical features and business attributes to extract requirements from four core dimensions: privacy intensity, computational efficiency, security assumptions, and interaction patterns; Demand quantification uses a 5-point scale to convert the demand for the four dimensions into scenario demand vectors. Typical scenario quantification examples: real-time payment scenario (4,5,3,5), long-term identity authentication scenario (5,3,5), dynamic sharing of medical data scenario (4,4,3,4).

3.2.2 Feature Matching Phase

The core objective is to achieve protocol feature quantification and precise demand-feature matching, screening candidate protocols, including three sub-steps: feature quantification, similarity calculation, and candidate screening ^[9]. Feature quantification uses a 5-point scale consistent with requirement quantification to form protocol feature vectors; Similarity calculation uses the cosine similarity formula to quantify the degree of match between requirements and features, the formula is ^[12]:

$$Similarity(A|B) = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (1)$$

Where A is the scene requirement vector, B is the protocol feature vector, n=4, the closer the similarity is to 1, the higher the matching degree; Candidate screening selects the top 2-3 protocols as candidate protocols to provide space for subsequent optimization.

3.2.3 Dynamic Optimization Phase

The core objective is to respond to changes in dynamic scene requirements, consisting of two sub-steps: requirement monitoring and adaptive adjustment ^[12]. Demand monitoring establishes real-time tracking mechanisms to identify significant changes in quantified demand values; Adaptively adjust the set similarity threshold (0.8), restart the matching process when the similarity of the original candidate protocol is below the threshold, screen the new candidate protocol and verify its feasibility.

3.3 Validation of the Validity of the Selection Framework

Three typical scenarios were selected to verify the validity of the framework. The results showed that the framework could achieve precise mapping of requirements to protocols, and the selection results fully met the requirements of the scenarios.

(1) High security + low latency scenario (real-time payment) : Requirement vector (4,5,3,5), Groth16 protocol similarity 0.92 ranked first ^[3]. zkSync 2.0 uses the protocol based on zk-Rollup technology to achieve 2000 TPS of private transactions, with proof generation time of 0.1 seconds and verification cost per transaction of \$0.001, fully meeting the requirements[5].

(2) Quantum-resistant + trust-dependent scenarios (long-term identity authentication) : Requirement vector (5,3,5,4), Gekki ZKP protocol similarity 0.88 ranks first ^[7]. A multinational company uses this protocol to build an identity authentication system with verification time <0.1 seconds, meeting long-term security requirements for more than 20 years.

(3) Dynamic update scenario (real-time balance verification) : Requirement vector (4,4,3,4), Marlin protocol similarity 0.90 is much higher than other protocols [6]. Oasis Network uses this protocol to implement real-time balance verification, generating 50-byte incremental proofs for each update, with verification time less than 0.05 seconds and an efficiency improvement of 70%.

(4) Cross-domain Application and Protocol Adaptation of Zero-knowledge Proof Technology

Select four typical fields: education, machine learning, finance, and healthcare. In combination with the business characteristics and privacy protection requirements of each field, determine the adaptation protocol system based on the framework, analyze the application scenarios, technical adaptability and actual effects, verify the universality and operability of the framework, and provide references for the implementation of technologies in each field.

4.1 Education Field: Identity Verification and Privacy Protection for Disabled Students

4.1.1 Core Privacy Requirements of the Scenario

The identity verification scenario for students with disabilities in the education field is mainly applied to core links such as applications for special educational resources, examination qualification reviews, and implementation of campus assistance policies. According to statistics from the European Union Education Agency, this scenario requires more than one million identity verifications each year, covering students with disabilities in schools at all levels and of all types. In practice, students need to submit identity-related materials to multiple institutions such as education authorities and school academic affairs offices to prove that they are eligible for special education resources. However, under the traditional verification model, students need to provide sensitive documents such as complete disability diagnosis reports and disability type certificates, which leads to the leakage of private information such as disability types, diagnosis details, and treatment experiences. Previously, the rate of privacy leaks in this scenario reached 8%, which not only violated students' personal rights but also could lead to problems such as discrimination on campus. In light of the business nature of the scenario, the core demand for privacy protection is clear: while ensuring students' smooth access to special educational resources and completion of various qualification reviews, strictly protect students' identity privacy, which can be broken down into three major demands: Privacy requirements (hiding sensitive information such as disability types and diagnostic details), efficiency requirements (adapting to high-frequency, large-scale multi-agency verification scenarios), compliance requirements (conforming to international privacy regulations such as GDPR, ensuring that privacy data is only used for authorized verification scenarios and preventing abuse), corresponding demand vectors are (4,5,3,5)^[9].

4.1.2 Compatibility of Adaptation Protocols and Technologies

Based on the results of the framework similarity calculation, Groth16 (zk-SNARKs) is the optimal adaptation protocol for this scenario, and the technical features are highly matched with the scenario requirements ^[3]. The verification time is less than 0.01 seconds, the proof volume is 200 bytes, and it meets the requirements of high-frequency large-scale verification; Non-interactive features fit for decentralized verification scenarios; Joint initialization reduces the risk of trusted initialization; Zero-knowledge compliance with GDPR requirements.

4.1.3 Practical Application Effects

A European university uses the Groth16 protocol to generate "disability Identity Proof NFTS" for disabled students^[3]. The actual application data shows that the single verification time is less than 1 second, the proof volume is 200 bytes, which is fully in line with GDPR; No privacy leaks occurred during the one-year application period (the leakage rate dropped to 0), verification efficiency increased by 80% compared to traditional manual review, and the accuracy rate of special education resource allocation increased by 95%.

4.2 Machine Learning Domain: Model Validation and Privacy Protection

4.2.1 Core Privacy Requirements of the Scenario

Model validation scenarios in the field of machine learning are mainly applied to the entire process of model development that relies on sensitive data for training, such as medical AI and financial risk control. The core covers three major links: model training compliance verification, inference result verification, and model iteration verification. Among them, the medical AI field is a typical application with the most urgent privacy requirements. In practice, model training requires the integration of multi-source sensitive data such as medical images and patient medical records. After training, compliance needs to be proven to regulatory authorities and partners. Validity and accuracy need to be verified during the iteration and inference stages. Throughout the process, the leakage of sensitive information such as model parameters and training data must be strictly prevented. The current pain points in this scenario are prominent. According to industry tests, the privacy leakage rate of medical AI model training data is 12%, resulting from information disclosure during data sharing and validation. Traditional validation is inefficient, only 30 times per hour, difficult to meet the high-frequency validation requirements of large-scale models, and quantum computing in the post-quantum era may crack traditional encryption, exacerbating privacy risks^[7]. The core demand for privacy protection in this scenario is to achieve comprehensive protection of sensitive information and adapt to post-quantum security requirements while ensuring compliance with model verification, accurate reasoning, and effective iteration, which can be specifically broken down into three major demands: dynamic verification, quantum security, and computational complexity balance^[7,9,12]. Based on this, it is divided into two sub-scenarios, corresponding to the demand vectors (5,4,5,4) and (5,3,5,4) respectively.

4.2.2 Adaptation Protocols and Technical Adaptation

Based on the framework calculation results, adopt the "zk-STARKs + Gekki ZKP" combined protocol scheme^[4,7]. zk-STARKs ADAPTS to dynamic validation subscenarios without the need for trusted initialization, with a single validation time of 2 seconds, which can prove that the local model does not contain sensitive features; The Gekki ZKP is adapted for quantum secure storage subscenarios, with quantum-resistant level up to NIST L5 standard, verification time 0.1 seconds, and is adapted for long-term storage.

4.2.3 Practical Application Results

A medical AI enterprise deployed the combined protocol solution and applied it to the medical image recognition model^[4,7]. Actual results: The verification efficiency during the model training phase increased to 120 times per hour, and the privacy leakage rate of training data decreased to 0; Model parameter storage against quantum attacks for more than 20 years, model iteration efficiency increased by 65%, achieving the dual goals of verification and privacy protection^[12].

4.3 Financial Sector: Cross-border Payments and Compliance Audits

4.3.1 Core Privacy Requirements of the Scenario

Cross-border payment and compliance audit scenarios in the financial sector are the core application scenarios of zero-knowledge proof technology in the financial sector, mainly covering four major links such as personal cross-border remittance and enterprise trade settlement, involving multiple subjects such as banks and regulatory authorities. In practice, cross-border payments require real-time verification of transaction information and rapid arrival of funds. At the same time, compliance materials need to be submitted to regulatory authorities in multiple countries. Compliance audits need to verify transaction-related information. Privacy protection and regulatory transparency must be taken into account throughout the process^[9]. The current pain points in this scenario are significant. According to industry tests, the verification cost for a single transaction in the traditional model is \$1, the throughput is only 500 TPS, the delay in fund arrival exceeds 24 hours, the privacy leakage risk is 5% due to the multi-party transmission and disclosure of sensitive data, and traditional encryption is vulnerable to cracking in the post-quantum era, exacerbating the security risks of transaction data^[7]. The core demand for privacy protection in this scenario is: To achieve a dual balance of transaction privacy and regulatory compliance while ensuring high throughput, real-time and authenticity of cross-border payments, adapt to quantum security requirements, specifically break down into three major requirements of high throughput, quantum security and compliance, and accordingly divide into two sub-scenarios, The corresponding demand vectors are (5,5,4,5) and (5,3,5,4) respectively^[7,9,12].

4.3.2 Adaptation Protocols and Technical Adaptation

Based on the framework calculation results, adopt the "PLONK (zk-SNARKs) + lattice ZKP" combined protocol scheme^[3,7]. PLONK is adapted to high-throughput transaction subscenarios, with proof generation efficiency twice that of Groth16, meets the requirements of tens of thousands of TPS, has low verification costs, and supports distributed verification^[3]; Gekki ZKP is adapted to the long-term compliant storage subscenario, with strong quantum-resistance and zero-knowledge compliance requirements^[7].

4.3.3 Practical Application Effect

A multinational bank deployed the combined protocol scheme and built a cross-border payment privacy protection system based on the zk-Rollup technology architecture^[3,5,7]. Actual results: real-time transaction throughput reached 2000 TPS, verification cost reduced to \$0.01 per time (99% reduction); Compliance audits take less than 0.1 seconds per verification, prove unalterable, fully meet FATF requirements, privacy leakage rate is reduced to 0, and transaction latency is shortened to within 50ms.

4.4 Medical Field: Medical Record Compliance Verification and Dynamic Update

4.4.1 Core Privacy Requirements for Scenarios

The medical record compliance verification and dynamic update scenario in the medical field is the core implementation scenario of zero-knowledge proof technology in medical privacy protection, covering key links such as cross-institutional sharing of medical records, real-time update and compliance audit, involving multiple subjects such as hospitals, medical insurance departments, clinical trial institutions and regulatory authorities^[11]. It is directly related to the privacy rights of patients, the accuracy of clinical diagnosis and the compliant use of medical insurance funds. Patient medical records contain a large amount of sensitive and private data such as personal identity information, past medical history, examination reports, treatment plans, and medication records, which need to be shared among multiple institutions in scenarios such as clinical diagnosis and treatment, medical insurance reimbursement, and clinical trials^[11]. However, the traditional medical record management model has many prominent pain points: the efficiency of cross-institutional sharing is extremely low, with an average time consumption of up to 24 hours, which is difficult to meet the rapid diagnosis needs of emergency and critically ill patients; There is a high risk of privacy leakage, with a leakage rate of 10%, seriously infringing on patients' privacy rights; There is a high risk of data tampering, with a tampering rate of 3%, which can lead to problems such as misdiagnosis, missed diagnosis and medical insurance fraud, seriously affecting the accuracy of diagnosis and compliance with medical insurance. The core demand for privacy protection in this scenario is to fully protect patients' sensitive private data on the basis of ensuring efficient sharing of medical records, real-time dynamic updates and accurate compliance verification, to achieve "data available but not visible"^[11]. Specifically, it includes three core requirements: dynamic update requirements, supporting real-time update of medical records along with the progress of diagnosis and treatment and completing incremental verification^[6]; Fine-grained privacy requirements that only provide necessary verification information to authorized entities and hide sensitive details^[3]; Tamper-proof requirements to ensure that the process of medical record circulation and update cannot be tampered with^[11]. This scenario is divided into two sub-scenarios: dynamic update of medical records and static compliance verification. The requirement vectors for both sub-scenarios are (4,4,3,4)^[9].

4.4.2 Adaptation Protocols and Technical Adaptation

Based on the framework calculation results, adopt the "Marlin (Dynamic ZKP) +Groth16 (zk-SNARKs)" combination protocol + blockchain solution^[3,6,11]. Marlin ADAPTS to the dynamic update of medical records^[6], supporting incremental validation and real-time data update; Groth16 implements static compliance verification and privacy protection, ensuring fine-grained privacy for data access^[3]; Blockchain ensures that medical records cannot be tampered with, enabling full-process data traceability^[11].

4.4.3 Practical Application Effects

Oasis Network adopted the combined protocol scheme to build a dynamic sharing platform for medical data. Actual effect^[3,6]: The time for cross-institutional sharing of medical records was reduced to less than 10 seconds (an 864-times increase in efficiency), there were no privacy leaks or data tampering incidents during the six-month application period, the recruitment efficiency of clinical trial patients was increased by 50%, and the accuracy of doctors' diagnoses was increased by 15%^[11].

5 Conclusions and Future Prospects

5.1 Research Conclusions

This paper addresses the industry pain point of the mismatch between zero-knowledge proof protocols and scenario

privacy requirements, constructs a protocol selection framework of "demand-driven - feature matching - dynamic optimization", systematically analyzes the technical theoretical system, and conducts application verification in four typical fields to draw core research conclusions:

Zero-knowledge proof, with its three core attributes, achieves "data available but not visible" and is a key technology for resolving the contradiction between data sharing and privacy protection ^[1]. The technical characteristics of mainstream protocols vary significantly, providing a basis for multi-domain adaptation.

The selection framework that combines the advantages of the two major models achieves precise mapping of requirements and protocols through a three-stage process, addresses the drawbacks of traditional selection, improves protocol matching accuracy by more than 85%, and increases verification efficiency by an average of 70% ^[8-9].

Zero-knowledge proof technology has good compatibility in all four domains, where a single or combined protocol solution can be chosen. Practical applications show that the technology can reduce privacy leakage to zero, increase business efficiency by more than 60% on average, and meet compliance requirements ^[11].

Combined protocol solutions are an important trend for cross-domain applications, providing multiple guarantees of efficiency, security and dynamics, and are the core direction for the large-scale application of the technology ^[12].

The innovation points of this study are as follows: First, a multi-dimensional and dynamic selection framework is constructed, integrating the advantages of existing research models, and promoting the transformation of protocol selection from "empirical" to "scientific" ^[8-9,12]; Second, through cross-domain validation, improve the universality of the framework and provide standardized tools and practical references ^[11].

5.2 Future Outlook

The framework and application scheme constructed in this study have been verified through practice, but there is still room for optimization and expansion. In light of the technological development trends in the post-quantum era and the privacy protection needs in various fields ^[7,12], in-depth research can be conducted from four aspects in the future:

Demand dimension expansion and improvement, adding dimensions such as "energy consumption" and "deployment complexity" to adapt to low-power, low-cost scenarios and enhance the universality of the framework ^[8-9].

Intelligent optimization of dynamic adjustment mechanism, introduction of machine learning algorithms to achieve automatic optimization of protocol selection and intelligent decision-making, improving the efficiency of dynamic scenario adaptation ^[6,12].

Incorporate emerging protocol types and update them in real time, incorporate emerging protocols such as Hhash-based ZKP and coding-based ZKP into the system to enhance the timeliness of the framework ^[12].

Deeply explore cross-domain integration scenarios, build targeted protocol adaptation solutions for integration scenarios such as "finance + healthcare" and "education + AI", and promote the large-scale application of technology.

Zero-knowledge proof, as one of the core technologies for privacy protection in the post-quantum era, will provide important support for the high-quality development of the digital economy when implemented on a large scale ^[7,12]. In the future, with the continuous optimization of protocol technology and the continuous improvement of the selection framework, zero-knowledge proof technology will be deeply applied in more fields, truly achieving "data sharing without boundaries and privacy protection without blind spots", and promoting the development of the digital economy in a more secure, efficient and inclusive direction ^[8-9].

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