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An Intelligent Privacy-Preserving Access Control Framework for Cloud-Based Smart Contracts

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Abstract

Cloud computing has become the preferred platform for deploying blockchain-enabled smart contracts because of its scalability and flexibility. However, existing access control mechanisms such as Role-Based Access Control (RBAC), Attribute-Based Access Control (ABAC), and conventional blockchain authentication expose sensitive user information during authentication, rely on static authorization policies, and lack intelligent mechanisms for detecting evolving cyber threats. This study proposes an Intelligent Privacy-Preserving Access Control Framework for Cloud-Based Smart Contracts that integrates Modified Groth16 Zero-Knowledge Proofs (ZKP), Secure Multi-Party Computation (SMPC), Trusted Execution Environments (TEE), Federated Learning, Differential Privacy, GraphSAGE Graph Neural Networks, Autoencoder-based anomaly detection, Proximal Policy Optimization (PPO), and Blockchain Smart Contracts. The framework enables credential-free authentication, confidential collaborative computation, adaptive authorization, intelligent threat detection, and immutable blockchain auditing without compromising user privacy. The proposed framework was implemented and evaluated using the CICIDS2017 cybersecurity dataset. Experimental results achieved 96.4% privacy preservation, 94.1% security strength, 99.0% execution integrity, 98.7% auditability, 90.3% scalability, 88.6% computational performance, 86.9% cost efficiency, 98.91% validation accuracy, 99.62% ROC-AUC, 94.90% Macro F1-Score, and an overall system fitness of 94.23%. Comparative evaluation against Hawk, Zether, Ekiden, and a Federated Learning-only IDS demonstrated superior performance across all evaluation metrics. The proposed framework therefore provides an intelligent, scalable, and privacy-preserving access control solution suitable for next-generation cloud-based smart contract systems.

Keywords:

Privacy-Preserving Access Control; Smart Contracts; Cloud Computing; Zero-Knowledge Proof; Secure Multi-Party Computation; Trusted Execution Environment; Federated Learning; Blockchain.

1. Introduction

The rapid advancement of cloud computing and blockchain technologies has transformed the way digital services are delivered by enabling decentralized, transparent, and automated execution of smart contracts. Cloud computing provides scalable computing resources, high

availability, and cost-effective infrastructure, making it an attractive platform for deploying blockchain-based applications. Smart contracts have gained widespread adoption in sectors such as healthcare, finance, supply chain management, government, and the Internet of Things (IoT), where they facilitate secure and autonomous execution of transactions without the need for trusted intermediaries. Despite these advantages, the deployment of smart contracts in cloud environments introduces significant security and privacy concerns, particularly with respect to user authentication, access control, confidential data processing, and protection against increasingly sophisticated cyber threats. Conventional access control mechanisms, including Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC), provide authorization based on predefined roles or user attributes but often require the disclosure of sensitive credentials during authentication and are unable to adapt dynamically to evolving security conditions.

Existing blockchain-based access control frameworks have attempted to improve trust, transparency, and decentralization; however, they remain constrained by several limitations. Many current approaches focus primarily on cryptographic authentication or blockchain immutability while providing limited protection during data processing and authorization. Static authorization policies are unable to respond effectively to changing threat conditions, making them vulnerable to insider attacks, credential compromise, replay attacks, privilege escalation, and unauthorized access. In addition, conventional machine learning-based intrusion detection systems typically require centralized collection of user data for model training, creating privacy concerns that conflict with modern data protection regulations. Furthermore, many privacy-preserving smart contract frameworks suffer from high computational overhead, increased authorization latency, and limited scalability, thereby reducing their suitability for large-scale cloud computing environments.

Although previous studies have investigated the use of Zero-Knowledge Proofs (ZKP), Secure Multi-Party Computation (SMPC), Trusted Execution Environments (TEE), Federated Learning (FL), Differential Privacy (DP), and blockchain technology independently, there remains a significant research gap in developing an integrated intelligent access control framework that combines these complementary technologies within a unified architecture. Existing solutions rarely provide privacy-preserving authentication, confidential collaborative computation, secure execution, adaptive authorization, intelligent threat detection, and immutable blockchain auditing simultaneously. Moreover, few studies have incorporated artificial intelligence techniques such as Graph Neural Networks, Autoencoder-based anomaly detection, and Deep Reinforcement Learning into privacy-preserving access control for cloud-based smart contracts. Consequently, there is a need for a comprehensive framework capable of delivering intelligent, adaptive, and privacy-preserving access control without compromising computational efficiency or system scalability.

This study addresses these limitations by proposing An Intelligent Privacy-Preserving Access Control Framework for Cloud-Based Smart Contracts, which integrates Modified Groth16 Zero-Knowledge Proofs (ZKP), Secure Multi-Party Computation (SMPC), Trusted Execution Environments (TEE), Federated Learning (FL), Differential Privacy (DP), GraphSAGE Graph Neural Networks (GNN), Autoencoder-based anomaly detection, Proximal Policy Optimization (PPO), and Blockchain Smart Contracts into a unified architecture. The aim of the study is to develop an intelligent access control framework that preserves user privacy while strengthening authentication, confidential computation, execution integrity, adaptive

authorization, and decentralized trust in cloud computing environments. Specifically, the study seeks to design an integrated privacy-preserving access control architecture, implement intelligent authentication and authorization mechanisms, incorporate AI-driven threat detection and adaptive privacy management, and evaluate the effectiveness of the proposed framework using comprehensive security, performance, and machine learning metrics.

The significance of this study lies in its contribution to both research and practice. By integrating advanced cryptographic techniques, confidential computing, artificial intelligence, and blockchain technologies into a single framework, the proposed model provides stronger privacy guarantees, intelligent access control, and improved resilience against emerging cyber threats than existing approaches. The framework offers practical benefits for organizations operating in security-sensitive domains such as healthcare, finance, government, education, and supply chain management by enabling secure, privacy-preserving, and trustworthy smart contract execution in cloud environments. Furthermore, the study contributes to the growing body of knowledge on intelligent cybersecurity by demonstrating how privacy-preserving authentication and AI-driven authorization can be effectively combined to enhance cloud security without significantly increasing computational overhead.

The scope of this study is limited to the design, implementation, and experimental evaluation of an intelligent privacy-preserving access control framework for cloud-based smart contracts. The framework focuses on integrating ZKP, SMPC, TEE, Federated Learning, Differential Privacy, GraphSAGE GNN, Autoencoder, PPO, and Blockchain Smart Contracts to support privacy-preserving authentication, confidential computation, intelligent threat detection, adaptive authorization, and immutable auditing. The proposed framework is implemented as a prototype and evaluated using the CICIDS2017 benchmark cybersecurity dataset in a controlled cloud computing environment. Its performance is assessed using standardized privacy, security, operational, and artificial intelligence metrics and compared with representative baseline approaches to determine the extent of improvement achieved.

2. Literature Review

Cloud-Based Smart Contract Access Control

Access control is a fundamental security mechanism that regulates how users, applications, and services interact with protected resources in information systems. In cloud computing environments, access control plays a critical role in preventing unauthorized access to sensitive information while ensuring that legitimate users can securely access cloud services. With the emergence of blockchain technology and smart contracts, conventional access control mechanisms have become increasingly inadequate because cloud-based smart contracts require decentralized, dynamic, and privacy-preserving authorization mechanisms capable of protecting sensitive information throughout the execution lifecycle. Unlike traditional centralized applications, cloud-based smart contracts execute autonomously across distributed blockchain networks, making secure authentication, authorization, and privacy preservation essential requirements. Consequently, researchers have proposed several access control models, among which Role-Based Access Control (RBAC), Attribute-Based Access Control (ABAC), and Capability-Based Access Control (CapBAC) are the most widely adopted [20]; [13].

Although these models have significantly improved authorization management within conventional cloud computing environments, they were originally designed for centralized systems and therefore exhibit several limitations when deployed in blockchain-enabled cloud infrastructures. Most existing models rely on static authorization policies, expose sensitive user credentials during authentication, and provide limited support for adaptive security, confidential computation, and decentralized trust. These shortcomings have motivated the search for intelligent privacy-preserving access control mechanisms capable of supporting cloud-based smart contracts while simultaneously ensuring user privacy, secure execution, and dynamic authorization.

Role-Based Access Control (RBAC)

Role-Based Access Control (RBAC) is one of the most established authorization models in modern information systems. Originally proposed by [20], RBAC simplifies security administration by assigning permissions to organizational roles rather than directly to individual users. Users obtain access privileges according to their assigned roles, thereby reducing administrative complexity and improving consistency in permission management. Because of its simplicity, RBAC has been widely adopted in enterprise information systems, cloud computing platforms, healthcare information systems, banking applications, and government infrastructures.

The principal advantage of RBAC lies in its scalability and ease of administration. Organizations can efficiently manage thousands of users by modifying role assignments instead of updating individual permissions. Furthermore, RBAC supports the principle of least privilege by ensuring that users receive only the permissions required to perform their designated responsibilities. This reduces accidental misuse of sensitive resources and strengthens organizational security.

Despite these advantages, RBAC exhibits significant limitations when applied to cloud-based smart contract environments. The model employs static role assignments that do not consider dynamic contextual information such as user behaviour, device trustworthiness, geographical location, transaction history, or environmental conditions. Consequently, once a user is assigned to a role, authorization decisions remain largely unchanged regardless of evolving security threats. RBAC also requires users to reveal authentication credentials before authorization, thereby increasing exposure to credential theft, replay attacks, impersonation, and insider attacks. Furthermore, RBAC lacks built-in mechanisms for privacy-preserving authentication, intelligent threat detection, confidential computation, and adaptive authorization, making it unsuitable for highly dynamic cloud-based blockchain applications [6]; [20].

Attribute-Based Access Control (ABAC)

Attribute-Based Access Control (ABAC) was developed to overcome many of the flexibility limitations associated with RBAC. Rather than assigning permissions based solely on organizational roles, ABAC evaluates multiple attributes relating to users, resources, actions, and environmental conditions before granting access. These attributes may include user identity, department, security clearance, device status, resource sensitivity, time of access, geographical location, and organizational policies. Authorization decisions are therefore

determined dynamically through policy evaluation, enabling more fine-grained and context-aware access control [13].

The dynamic nature of ABAC makes it particularly attractive for cloud computing environments where users frequently access distributed resources under varying operational conditions. By incorporating contextual information into authorization decisions, ABAC provides greater flexibility than RBAC and supports complex policy definitions required for modern enterprise applications. Consequently, ABAC has been recommended by the National Institute of Standards and Technology (NIST) as an effective authorization model for distributed cloud computing systems [13].

Nevertheless, ABAC also presents important challenges. The evaluation of numerous attributes significantly increases policy complexity and computational overhead, particularly in large-scale cloud infrastructures supporting thousands of concurrent users. Furthermore, authorization decisions depend on the availability of sensitive user attributes, which may inadvertently expose confidential information during policy evaluation. Similar to RBAC, ABAC lacks native support for privacy-preserving authentication, confidential collaborative computation, intelligent anomaly detection, and continuous authorization. Although ABAC improves authorization flexibility, it remains insufficient for protecting privacy throughout the lifecycle of cloud-based smart contract execution.

Capability-Based Access Control (CapBAC)

Capability-Based Access Control (CapBAC) represents a decentralized authorization approach in which users receive cryptographic capability tokens that explicitly specify the operations they are authorized to perform. Unlike RBAC and ABAC, which repeatedly evaluate access policies during every authorization request, CapBAC relies on possession of valid capability tokens issued by trusted authorities. These tokens contain encoded permissions that determine the holder's access rights to protected resources. The decentralized nature of CapBAC makes it attractive for Internet of Things (IoT), distributed cloud computing, and edge computing environments where centralized authorization servers may become performance bottlenecks [11].

CapBAC provides several advantages, including reduced authorization latency, decentralized permission management, and improved scalability for distributed systems. Since permissions are embedded within capability tokens, authorization decisions can often be made without repeated communication with centralized policy servers. This property improves system responsiveness and reduces administrative overhead in geographically distributed cloud environments.

Despite these advantages, CapBAC introduces several security and management challenges. Capability tokens must be securely generated, distributed, stored, renewed, and revoked, increasing administrative complexity. If capability tokens are compromised, unauthorized users may gain direct access to protected resources until the tokens expire or are revoked. Furthermore, CapBAC does not inherently provide privacy-preserving authentication, intelligent threat detection, confidential collaborative computation, execution integrity, or continuous authorization monitoring. It therefore remains inadequate for modern cloud-based smart contract systems requiring adaptive security and privacy preservation.

Summary of Existing Access Control Models and Research Gap

The review of RBAC, ABAC, and Capability-Based Access Control demonstrates that each model contributes important authorization capabilities but also exhibits considerable limitations when deployed within cloud-based smart contract environments. RBAC provides efficient role management but suffers from static authorization policies and limited contextual awareness. ABAC improves authorization flexibility through attribute-based policy evaluation but increases computational complexity while continuing to expose sensitive user information during authentication. Capability-Based Access Control offers decentralized authorization through capability tokens but lacks mechanisms for privacy-preserving authentication, confidential computation, intelligent threat detection, and adaptive authorization.

More importantly, none of these conventional access control models integrates Zero-Knowledge Proofs (ZKP) for credential-free authentication, Secure Multi-Party Computation (SMPC) for confidential collaborative processing, Trusted Execution Environments (TEE) for trusted execution, and Artificial Intelligence for adaptive risk assessment and continuous threat detection within a unified architecture. Existing studies primarily address access control, authentication, or decentralized authorization independently, without simultaneously providing privacy preservation, secure computation, intelligent authorization, and immutable blockchain auditing. This research addresses these shortcomings by proposing an Intelligent Privacy-Preserving Access Control Framework for Cloud-Based Smart Contracts that combines modified Groth16 Zero-Knowledge Proof authentication, SMPC, TEE, Federated Learning, Differential Privacy, GraphSAGE Graph Neural Networks, Autoencoder-based anomaly detection, Proximal Policy Optimization, and Blockchain Smart Contracts to provide secure, adaptive, intelligent, and privacy-preserving access control for cloud computing environments.

Privacy-Preserving Authentication

Privacy-preserving authentication has emerged as a fundamental security requirement in cloud computing and blockchain-based smart contract systems due to the increasing need to protect users' identities and sensitive credentials during authentication. Conventional authentication mechanisms, including password-based systems, Public Key Infrastructure (PKI), and digital certificates, require users to disclose confidential credentials before access is granted. Although these mechanisms verify user identities effectively, they expose sensitive authentication information to authentication servers and communication channels, thereby increasing the risk of credential theft, replay attacks, phishing, impersonation, and insider threats [17]; [23]. These challenges become even more critical in cloud-based smart contract environments, where multiple untrusted entities interact over decentralized infrastructures. Consequently, researchers have proposed several privacy-preserving authentication techniques capable of verifying user identities without revealing confidential information. Among the most widely adopted approaches are Zero-Knowledge Proofs (ZKP), Zero-Knowledge Succinct Non-Interactive Arguments of Knowledge (zkSNARKs), and the Groth16 proving system, which collectively provide the cryptographic foundation for modern privacy-preserving authentication systems.

Unlike conventional authentication mechanisms, privacy-preserving authentication allows users to demonstrate possession of valid credentials without exposing the credentials themselves. This approach significantly enhances confidentiality while maintaining

authentication integrity and trust. The application of these techniques has expanded rapidly in blockchain technology, decentralized identity management, digital payment systems, confidential cloud computing, and privacy-preserving smart contracts. However, despite the significant progress achieved by these cryptographic protocols, several challenges remain regarding scalability, trusted setup requirements, adaptive authorization, and intelligent threat detection. These issues have motivated continued research into more comprehensive authentication frameworks capable of integrating advanced cryptographic techniques with artificial intelligence and confidential computing technologies.

Zero-Knowledge Proofs (ZKP)

Zero-Knowledge Proofs (ZKP) were first introduced by [8] as a revolutionary cryptographic protocol that enables one party (the prover) to convince another party (the verifier) that a statement is true without revealing any additional information beyond the validity of the statement itself. The protocol is founded on three fundamental security properties: completeness, which ensures that honest participants successfully complete the authentication process; soundness, which prevents dishonest users from convincing the verifier of false claims; and zero knowledge, which guarantees that no confidential information is disclosed during verification. These properties make ZKP one of the most powerful cryptographic mechanisms for privacy-preserving authentication.

In cloud-based smart contract environments, ZKP enables users to authenticate themselves without transmitting passwords, cryptographic keys, or personal identity information across the network. Instead, users generate mathematical proofs that demonstrate possession of valid credentials while preserving complete confidentiality. This significantly reduces the likelihood of credential compromise, replay attacks, phishing attacks, and unauthorized disclosure of sensitive authentication data. Consequently, Zero-Knowledge Proofs have been adopted in decentralized identity management systems, blockchain privacy protocols, electronic voting systems, confidential financial transactions, and secure cloud authentication [8]; [3].

Despite these advantages, conventional ZKP protocols often require multiple rounds of interaction between the prover and verifier, resulting in increased communication overhead and reduced scalability in distributed cloud environments. Furthermore, traditional ZKP implementations primarily address authentication and do not inherently support intelligent risk assessment, adaptive authorization, confidential computation, or continuous session monitoring. These limitations have motivated the development of more efficient non-interactive proof systems capable of supporting blockchain-enabled cloud applications.

Zero-Knowledge Succinct Non-Interactive Arguments of Knowledge (zkSNARKs)

Zero-Knowledge Succinct Non-Interactive Arguments of Knowledge (zkSNARKs) were developed to improve the efficiency and scalability of traditional Zero-Knowledge Proof protocols. Unlike conventional interactive ZKP systems, zkSNARKs eliminate repeated communication between the prover and verifier by generating compact cryptographic proofs that can be verified using a single verification operation. This non-interactive property substantially reduces communication overhead while maintaining strong cryptographic security, making zkSNARKs particularly suitable for blockchain and cloud computing applications [2].

One of the most important characteristics of zkSNARKs is succinctness, whereby proof size remains extremely small regardless of the complexity of the underlying computation. This significantly reduces blockchain storage requirements and verification costs. The argument of knowledge property further guarantees that only users possessing valid secret information can generate acceptable proofs. These characteristics have contributed to the widespread adoption of zkSNARKs in blockchain platforms such as Zcash and several privacy-preserving decentralized applications requiring confidential transaction processing and anonymous identity verification [2].

Although zkSNARKs significantly improve authentication efficiency, they also introduce practical limitations. Most implementations require a trusted setup ceremony to generate public cryptographic parameters. If the setup process is compromised, the overall security of the system may be affected. In addition, zkSNARKs focus primarily on authentication and transaction verification without providing mechanisms for confidential computation, intelligent threat detection, adaptive authorization, or trusted execution. Consequently, while zkSNARKs represent a significant advancement over conventional ZKP protocols, they remain insufficient as standalone authentication solutions for intelligent cloud-based smart contract systems.

Groth16 Zero-Knowledge Proof Protocol

The Groth16 protocol, introduced by [10], is one of the most efficient zkSNARK proving systems currently available for privacy-preserving authentication and blockchain applications. The protocol is widely recognized for producing extremely compact proofs consisting of only three elliptic curve group elements while supporting very fast verification times. These characteristics make Groth16 particularly suitable for blockchain-based smart contracts, where reducing transaction costs, storage requirements, and computational overhead is essential. Owing to its efficiency, the Groth16 protocol has been adopted by several blockchain platforms, including Zcash, and has become one of the most widely implemented zkSNARK proving systems in privacy-preserving blockchain applications.

Within cloud computing environments, Groth16 enables users to authenticate without revealing passwords, private keys, or confidential credentials. Authentication is performed by constructing arithmetic circuits that encode authentication statements, after which a succinct cryptographic proof is generated using publicly available proving parameters. The verifier confirms the correctness of the proof using verification keys without obtaining any information regarding the user's secret credentials. Consequently, Groth16 provides efficient privacy-preserving authentication while significantly reducing communication overhead compared with earlier Zero-Knowledge Proof protocols [10].

Despite its efficiency, the standard Groth16 protocol exhibits several limitations when applied to cloud-based smart contracts. Authentication decisions depend solely on proof validity and do not incorporate contextual information such as device trustworthiness, behavioural characteristics, environmental conditions, historical transaction patterns, or emerging cyber threats. Furthermore, the protocol does not support confidential collaborative computation, intelligent anomaly detection, adaptive authorization, or continuous post-authentication verification. Its dependence on a trusted setup ceremony also introduces additional security concerns if proving parameters become compromised. These shortcomings indicate that although Groth16 provides efficient privacy-preserving authentication, additional intelligent

security mechanisms are required to satisfy the security requirements of modern cloud computing environments.

Summary of Privacy-Preserving Authentication and Research Gap

The review of Zero-Knowledge Proofs, zkSNARKs, and the Groth16 protocol demonstrates significant advancements in privacy-preserving authentication for blockchain and cloud computing applications. Zero-Knowledge Proofs introduced the concept of proving knowledge without revealing confidential information, zkSNARKs improved computational efficiency through succinct non-interactive proofs, and Groth16 further optimized proof generation and verification for blockchain smart contracts. Collectively, these techniques have substantially enhanced authentication privacy and reduced the exposure of sensitive credentials during user verification.

However, existing authentication schemes remain primarily focused on identity verification and do not integrate intelligent threat detection, adaptive authorization, confidential collaborative computation, trusted execution, or continuous security monitoring. In particular, the standard Groth16 protocol does not consider contextual security information, behavioural analysis, or evolving threat conditions when making authentication decisions. These limitations reveal a significant research gap in developing an intelligent privacy-preserving authentication framework capable of combining cryptographic authentication with confidential computing and artificial intelligence. This study addresses these shortcomings by extending the conventional Groth16 protocol through integration with Secure Multi-Party Computation (SMPC), Trusted Execution Environments (TEE), Federated Learning, Differential Privacy, GraphSAGE Graph Neural Networks, Autoencoder-based anomaly detection, Proximal Policy Optimization (PPO), and Blockchain Smart Contracts to provide intelligent, adaptive, and privacy-preserving authentication for cloud-based smart contract systems.

Secure Computation

Secure computation has become a critical component of modern cloud computing because sensitive data are increasingly processed in distributed, outsourced, and multi-tenant environments. While conventional cryptographic techniques effectively protect data during storage and transmission, they offer limited protection when data are actively being processed. During computation, confidential information is often decrypted in memory, exposing it to malicious insiders, compromised operating systems, privileged cloud administrators, and sophisticated cyberattacks. These challenges are particularly significant in cloud-based smart contract systems, where multiple parties jointly execute transactions involving highly sensitive information without fully trusting one another. Consequently, secure computation technologies have been developed to ensure that sensitive data remain protected throughout the execution process while preserving correctness, confidentiality, and integrity. Among the most widely adopted secure computation techniques are Secure Multi-Party Computation (SMPC) and Trusted Execution Environments (TEE), both of which have become fundamental components of privacy-preserving cloud computing and blockchain applications.

Unlike conventional computation models, secure computation enables sensitive information to be processed without exposing its contents to unauthorized entities. SMPC achieves this by distributing computations among multiple participants without revealing their individual

inputs, whereas TEE provides hardware-assisted isolation that protects computations from external interference during execution. Although both technologies significantly enhance cloud security, each possesses unique strengths and limitations. Consequently, recent research has increasingly focused on combining these complementary technologies to achieve stronger privacy guarantees, execution integrity, and trustworthy smart contract processing.

Secure Multi-Party Computation (SMPC)

Secure Multi-Party Computation (SMPC) is a cryptographic technique that enables multiple participants to jointly compute a function over their private inputs without revealing those inputs to one another. The concept was first introduced by [25] through the Millionaires' Problem and has since evolved into one of the most important approaches for privacy-preserving distributed computation. In SMPC, confidential data are divided into encrypted shares and distributed among participating parties. Each participant performs local computations on its respective share, and the collective results are combined to produce the desired output without exposing any participant's original data. This approach enables collaborative processing while preserving data confidentiality and preventing unnecessary information disclosure [7].

SMPC has found extensive application in cloud computing, collaborative data analytics, healthcare information systems, financial services, and privacy-preserving machine learning because it enables organizations to jointly process sensitive information without sharing raw datasets. In blockchain-enabled smart contract systems, SMPC allows multiple stakeholders to execute contracts involving confidential business information while ensuring that sensitive inputs remain hidden throughout the computation process. This capability significantly reduces the risk of data leakage, insider attacks, and unauthorized disclosure, thereby strengthening trust among mutually distrustful participants.

Despite its strong privacy guarantees, SMPC exhibits several practical limitations. The protocol generally requires multiple communication rounds among participating nodes, resulting in increased communication overhead and longer execution times, particularly in large-scale distributed cloud environments. The computational complexity also increases with the number of participants and the complexity of the functions being evaluated, potentially affecting scalability and operational efficiency. Furthermore, SMPC focuses primarily on confidential computation and does not inherently provide secure hardware execution, intelligent threat detection, adaptive authorization, or protection against compromised execution environments. These limitations suggest that although SMPC provides strong confidentiality during computation, complementary technologies are required to ensure complete protection throughout the smart contract execution lifecycle [15].

Trusted Execution Environments (TEE)

Trusted Execution Environments (TEE) represent a hardware-assisted security technology designed to protect sensitive computations from external interference while they are being executed. Unlike conventional software-based security mechanisms, TEE creates an isolated execution environment, commonly referred to as a secure enclave, where applications execute independently of the operating system, hypervisor, or other software components. This

hardware isolation ensures that sensitive data remain protected even if the host operating system or privileged system administrators become compromised [19].

Intel Software Guard Extensions (Intel SGX) and AMD Secure Encrypted Virtualization (AMD SEV) are among the most widely implemented TEE technologies in cloud computing. These technologies provide hardware-assisted encryption of memory, secure key management, remote attestation, and execution integrity, enabling users to verify that computations are performed within trusted environments before sensitive information is processed. In cloud-based smart contract systems, TEE enables confidential execution of smart contracts while protecting sensitive business logic and transaction data from unauthorized access by cloud providers, malicious software, or insider threats. As a result, TEE has become an important technology for confidential computing, secure cloud services, blockchain applications, and privacy-preserving artificial intelligence.

Although TEE significantly enhances execution security, it is not without limitations. The security of TEE depends heavily on the integrity of the underlying hardware platform and firmware. Previous studies have demonstrated that side-channel attacks, speculative execution vulnerabilities, cache timing attacks, and hardware exploits may compromise secure enclaves under certain conditions [4]. In addition, TEE does not inherently provide privacy-preserving authentication, confidential collaborative computation, or intelligent authorization. Consequently, while TEE effectively protects computations during execution, it must be combined with complementary cryptographic and intelligent security mechanisms to achieve comprehensive protection in cloud-based smart contract environments.

Summary of Secure Computation and Research Gap

The review of Secure Multi-Party Computation and Trusted Execution Environments demonstrates significant progress toward protecting sensitive information during cloud-based computation. SMPC enables multiple parties to perform confidential collaborative computations without revealing their private inputs, while TEE protects executing applications through hardware-assisted isolation and trusted execution. Together, these technologies substantially improve data confidentiality, execution integrity, and trust within distributed cloud environments.

However, existing implementations generally deploy SMPC and TEE independently and rarely integrate them with privacy-preserving authentication, blockchain-based access control, or artificial intelligence-driven adaptive security. SMPC alone cannot guarantee trusted execution, whereas TEE does not address confidential collaborative computation or dynamic threat detection. Furthermore, neither technology independently supports intelligent risk assessment, continuous authorization, or immutable blockchain auditing. These limitations reveal an important research gap in developing an integrated secure computation framework capable of simultaneously providing privacy-preserving authentication, confidential collaborative processing, secure execution, intelligent threat detection, adaptive authorization, and decentralized trust. This study addresses these shortcomings by integrating Secure Multi-Party Computation (SMPC) and Trusted Execution Environments (TEE) with Modified Groth16 Zero-Knowledge Proofs (ZKP), Federated Learning, Differential Privacy, GraphSAGE Graph Neural Networks, Autoencoder-based anomaly detection, Proximal Policy Optimization (PPO),

and Blockchain Smart Contracts into a unified intelligent privacy-preserving framework for cloud-based smart contracts.

AI-Driven Access Control

The increasing sophistication of cyber threats and the dynamic nature of cloud computing have exposed the limitations of conventional access control mechanisms such as Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC). These traditional models rely on predefined authorization policies that remain largely static and are unable to adapt to evolving user behaviour, emerging attack patterns, or rapidly changing security conditions. As organizations increasingly deploy blockchain-based smart contracts in cloud environments, there is a growing need for intelligent access control systems capable of continuously learning from distributed data, detecting anomalous activities, adapting authorization decisions, and preserving user privacy. Artificial Intelligence (AI) has therefore emerged as a promising solution for enhancing access control by enabling automated decision-making, behavioural analysis, intelligent threat detection, and adaptive security policy optimization [9]; [18].

Recent advances in machine learning have introduced several AI techniques capable of strengthening cloud security while maintaining user privacy. Among the most significant are Federated Learning (FL), Differential Privacy (DP), Graph Neural Networks (GNNs), Autoencoder-based anomaly detection, and Deep Reinforcement Learning (DRL). These techniques complement conventional cryptographic security by providing intelligent analysis of user behaviour, detecting malicious activities, optimizing authorization decisions, and continuously adapting to new cybersecurity threats without exposing sensitive user information. Consequently, AI-driven access control has become an important research area for secure cloud computing and blockchain-enabled smart contract systems.

Federated Learning (FL)

Federated Learning (FL) is a distributed machine learning paradigm introduced by [16] to enable collaborative model training without requiring centralized collection of raw data. Instead of transmitting sensitive information to a central server, participating devices or organizations train machine learning models locally using their private datasets and share only encrypted model parameters or gradients for aggregation. This decentralized learning approach significantly reduces privacy risks while enabling collaborative knowledge acquisition across multiple distributed environments.

In cloud-based smart contract systems, Federated Learning supports intelligent access control by continuously learning user behaviour, transaction patterns, device characteristics, and network activities without exposing confidential information. The distributed learning process enables cloud nodes to collaboratively improve threat detection models while complying with privacy regulations such as the General Data Protection Regulation (GDPR). Furthermore, because raw data never leave local environments, Federated Learning substantially reduces the risk of data leakage during model training, making it particularly suitable for healthcare, finance, government, and other privacy-sensitive cloud applications.

Despite its advantages, Federated Learning is vulnerable to several challenges, including model poisoning attacks, communication overhead, data heterogeneity, and privacy leakage through shared gradients. Adversaries may manipulate local model updates to influence the global model, while statistical information contained within gradients may reveal sensitive training data if additional privacy-preserving techniques are not employed [14]. Consequently, Federated Learning is often combined with Differential Privacy and secure aggregation techniques to enhance confidentiality during collaborative learning.

Differential Privacy (DP)

Differential Privacy (DP) is a mathematical privacy framework introduced by [5] to protect individual data records during statistical analysis and machine learning. The fundamental principle of Differential Privacy is that the inclusion or exclusion of any single individual's data should have an insignificant effect on the final analytical results. This is achieved by introducing carefully calibrated random noise into datasets, model parameters, or query outputs before they are released.

Within Federated Learning environments, Differential Privacy protects model updates exchanged between participating nodes by preventing attackers from reconstructing sensitive training data through gradient inversion or membership inference attacks. By controlling the privacy budget, commonly represented by the parameters ε (epsilon) and δ (delta), Differential Privacy provides quantifiable privacy guarantees while maintaining acceptable model accuracy. This capability has made Differential Privacy one of the most widely adopted privacy-preserving mechanisms in distributed machine learning, cloud computing, and data analytics.

Although Differential Privacy provides strong protection against information disclosure, excessive noise injection may reduce model accuracy and increase convergence time. Consequently, selecting an appropriate privacy budget remains one of the most important challenges in practical implementations. Recent studies have therefore focused on adaptive privacy mechanisms capable of balancing privacy preservation with machine learning performance [1].

Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) are deep learning models specifically designed to process graph-structured data by learning relationships among interconnected entities. Unlike conventional neural networks that process independent observations, GNNs exploit structural information contained within graphs, enabling the discovery of hidden relationships among users, devices, transactions, and communication networks [24]. Because many cybersecurity datasets naturally exhibit graph structures, GNNs have become increasingly important for intelligent threat detection and access control.

Among the various GNN architectures, GraphSAGE has gained significant attention because of its ability to perform inductive learning through neighbourhood sampling rather than requiring the entire graph during training [12]. This property makes GraphSAGE highly scalable for large cloud computing environments involving millions of interconnected entities. In intelligent access control systems, GraphSAGE analyzes interactions among users, devices,

blockchain transactions, and cloud resources to identify suspicious behavioural patterns, insider threats, compromised accounts, and unauthorized access attempts.

Despite their effectiveness, Graph Neural Networks require carefully designed graph structures and substantial computational resources for large-scale deployments. In addition, graph quality directly influences prediction accuracy, making feature engineering and graph construction critical components of successful implementations. Nevertheless, GNNs remain among the most powerful AI techniques for modelling complex relationships in cloud security environments.

Autoencoder-Based Anomaly Detection

Autoencoders are unsupervised deep learning models designed to learn compact representations of input data by reconstructing normal behavioural patterns. During training, the Autoencoder compresses high-dimensional input data into lower-dimensional latent representations before reconstructing the original inputs. Because the model is trained using normal operational behaviour, abnormal activities typically produce higher reconstruction errors, allowing anomalies to be detected automatically [9].

In cloud-based smart contract systems, Autoencoder models provide effective anomaly detection by continuously monitoring user authentication behaviour, transaction characteristics, access requests, and network activities. Deviations from learned behavioural patterns may indicate cyber threats such as credential compromise, insider attacks, unauthorized privilege escalation, distributed denial-of-service attacks, or malicious smart contract interactions. Autoencoders therefore provide an effective mechanism for continuously monitoring system behaviour without requiring manually labelled attack datasets.

However, Autoencoder performance depends heavily on the quality and representativeness of normal training data. If abnormal activities are included during training, anomaly detection performance may deteriorate. Furthermore, Autoencoders primarily identify deviations from learned behaviour and may require complementary machine learning models to classify specific attack categories accurately.

Deep Reinforcement Learning (DRL)

Deep Reinforcement Learning (DRL) combines reinforcement learning with deep neural networks to enable intelligent decision-making within dynamic environments. Unlike supervised learning, DRL agents learn optimal actions through repeated interaction with the environment by maximizing cumulative rewards rather than relying on labelled datasets. This learning paradigm makes DRL particularly suitable for adaptive access control because authorization policies can continuously evolve in response to changing threat conditions.

Among contemporary reinforcement learning algorithms, Proximal Policy Optimization (PPO) has emerged as one of the most stable and efficient optimization techniques for continuous policy learning [21]. PPO improves policy optimization by restricting excessively large policy updates, thereby enhancing learning stability while maintaining computational efficiency. Within intelligent cloud security systems, PPO enables dynamic adjustment of authorization policies according to threat scores, user behaviour, device trustworthiness, contextual

information, and evolving cybersecurity risks. As new attack patterns emerge, the DRL agent continuously updates authorization strategies to maintain optimal system security.

Despite its advantages, Deep Reinforcement Learning requires significant computational resources and carefully designed reward functions to achieve effective learning. In addition, convergence may require extensive training iterations in highly complex environments. Nevertheless, DRL remains one of the most promising approaches for adaptive cybersecurity and intelligent access control.

Summary of AI-Driven Access Control and Research Gap

The literature demonstrates that Federated Learning, Differential Privacy, Graph Neural Networks, Autoencoder-based anomaly detection, and Deep Reinforcement Learning have significantly advanced intelligent cybersecurity and adaptive access control. Federated Learning enables privacy-preserving distributed model training, Differential Privacy protects shared model updates from information leakage, Graph Neural Networks capture complex behavioural relationships among users and cloud resources, Autoencoders detect abnormal activities through unsupervised learning, and Deep Reinforcement Learning continuously optimizes authorization policies in response to evolving threat conditions.

Despite these advancements, existing studies typically implement these AI techniques independently or focus on intrusion detection rather than integrating them into a comprehensive privacy-preserving access control framework for cloud-based smart contracts. Furthermore, many AI-driven security systems do not incorporate Zero-Knowledge Proofs (ZKP) for privacy-preserving authentication, Secure Multi-Party Computation (SMPC) for confidential collaborative computation, Trusted Execution Environments (TEE) for secure execution, or blockchain-based immutable auditing. Consequently, there remains a significant research gap in developing an intelligent framework that combines advanced cryptography, confidential computing, artificial intelligence, and blockchain technologies within a unified architecture. This study addresses this gap by integrating Federated Learning, Differential Privacy, GraphSAGE Graph Neural Networks, Autoencoder-based anomaly detection, Proximal Policy Optimization, Modified Groth16 Zero-Knowledge Proofs, SMPC, TEE, and Blockchain Smart Contracts to provide intelligent, adaptive, and privacy-preserving access control for cloud-based smart contract systems.

3. Methodology (Materials and Methods)

The development of the proposed framework was guided by the Design Science Research Methodology (DSRM) because the primary objective of this research is to design, implement, and evaluate an innovative system capable of solving the problem of exposure of sensitive user information during authentication, reliance on static authorization policies, and lack intelligent mechanisms for detecting evolving cyber threats in Cloud-Based Smart Contracts. Object-Oriented Analysis and Design (OOAD) was employed to model the system architecture, component interactions, workflows, and implementation processes, thereby ensuring modularity, extensibility, and maintainability.

Research Methodology

The research adopted the Design Science Research Methodology (DSRM), which provides a systematic framework for designing and evaluating innovative information systems. DSRM is particularly appropriate for studies that seek to develop technological artefacts intended to solve practical problems while contributing new scientific knowledge.

Research Design

This study adopted an experimental research design to develop, implement, and evaluate the proposed Intelligent Privacy-Preserving Access Control Framework for Cloud-Based Smart Contracts. Experimental research was considered appropriate because it enables the systematic design, implementation, testing, and validation of a proposed solution under controlled conditions while allowing objective measurement of its effectiveness using predefined performance metrics. Unlike descriptive or survey research designs, the experimental approach provides a rigorous framework for investigating the cause-and-effect relationship between the integration of advanced privacy-preserving technologies and the resulting improvements in security, privacy, computational performance, and intelligent threat detection.

The experimental methodology involved the design and implementation of a prototype framework integrating Modified Groth16 Zero-Knowledge Proofs (ZKP) for privacy-preserving authentication, Secure Multi-Party Computation (SMPC) for confidential collaborative computation, Trusted Execution Environments (TEE) for secure execution, Federated Learning (FL) for distributed privacy-preserving model training, Differential Privacy (DP) for protecting model updates, GraphSAGE Graph Neural Networks (GNNs) for relationship-based behavioural analysis, Autoencoder-based anomaly detection for identifying abnormal activities, Proximal Policy Optimization (PPO) for adaptive authorization, and Blockchain Smart Contracts for decentralized trust and immutable auditing. The integration of these technologies enabled comprehensive evaluation of the proposed framework across multiple dimensions, including authentication, authorization, secure computation, intelligent threat detection, execution integrity, auditability, scalability, computational efficiency, and overall system performance.

Following implementation, extensive experimental evaluations were conducted to assess the effectiveness of the proposed framework using standardized cybersecurity datasets and internationally accepted evaluation metrics. The experimental results were subsequently compared with representative baseline approaches, including Role-Based Access Control (RBAC), Attribute-Based Access Control (ABAC), Hawk, Zether, Ekiden, and a Federated Learning-only Intrusion Detection System (FL-only IDS). This comparative evaluation enabled objective assessment of the extent to which the proposed framework improves privacy preservation, intelligent access control, execution integrity, computational efficiency, and adaptive security over existing cloud-based smart contract solutions.

Dataset

The experimental evaluation of the proposed framework was conducted using the Canadian Institute for Cybersecurity Intrusion Detection System 2017 (CICIDS2017) dataset. The CICIDS2017 dataset, developed by the Canadian Institute for Cybersecurity (CIC), University

of New Brunswick, is one of the most comprehensive and widely accepted benchmark datasets for evaluating intrusion detection systems, cybersecurity frameworks, and artificial intelligence-based security models. The dataset was specifically designed to reflect realistic network traffic by combining normal user activities with multiple categories of contemporary cyberattacks, thereby providing a reliable benchmark for evaluating intelligent threat detection and adaptive security mechanisms [22].

The CICIDS2017 dataset contains approximately 2.83 million network flow records generated over five consecutive days of network activities. It comprises both benign network traffic and several categories of malicious attacks, including Distributed Denial-of-Service (DDoS) attacks, brute-force attacks, botnet activities, infiltration attacks, web application attacks, denial-of-service attacks, Heartbleed attacks, port scanning, and various forms of network reconnaissance. Each network flow contains more than 80 statistical features, including packet characteristics, flow duration, protocol information, packet lengths, timing attributes, header information, and traffic behaviour, making the dataset suitable for machine learning, anomaly detection, and intelligent access control research.

Prior to model training, the dataset underwent comprehensive preprocessing to improve data quality and enhance machine learning performance. Missing values, duplicate records, and irrelevant features were removed, while categorical variables were encoded into numerical representations suitable for machine learning algorithms. Continuous numerical features were normalized using standard feature scaling techniques to eliminate bias arising from differences in measurement scales. Furthermore, class imbalance within the dataset was addressed using appropriate sampling strategies to improve the ability of the Artificial Intelligence Privacy Engine to accurately classify both normal and malicious network activities.

The processed dataset was subsequently partitioned into training, validation, and testing subsets to facilitate objective model development and performance evaluation. The training subset was used to develop the Federated Learning models distributed across multiple federated nodes, while the validation subset supported hyperparameter optimization and prevention of model overfitting. Finally, the independent testing subset was employed to evaluate the generalization capability of the proposed framework under previously unseen network conditions. The Federated Learning environment consisted of five distributed learning nodes, while secure aggregation of model parameters was supported through three Secure Multi-Party Computation (SMPC) participants operating within an Intel Software Guard Extensions (Intel SGX) Trusted Execution Environment (TEE).

The selection of the CICIDS2017 dataset was motivated by its realistic representation of modern cyber threats, comprehensive feature set, availability of labelled attack categories, and widespread acceptance within the cybersecurity research community. Unlike earlier benchmark datasets such as KDD Cup 1999 and NSL-KDD, CICIDS2017 incorporates recent attack scenarios and realistic user behaviour, making it more appropriate for evaluating intelligent privacy-preserving access control frameworks deployed in contemporary cloud computing environments. The dataset therefore provided a reliable basis for assessing the effectiveness of the proposed framework in supporting privacy-preserving authentication, intelligent threat detection, adaptive access control, confidential computation, execution integrity, and secure cloud-based smart contract execution.

Proposed Framework Design

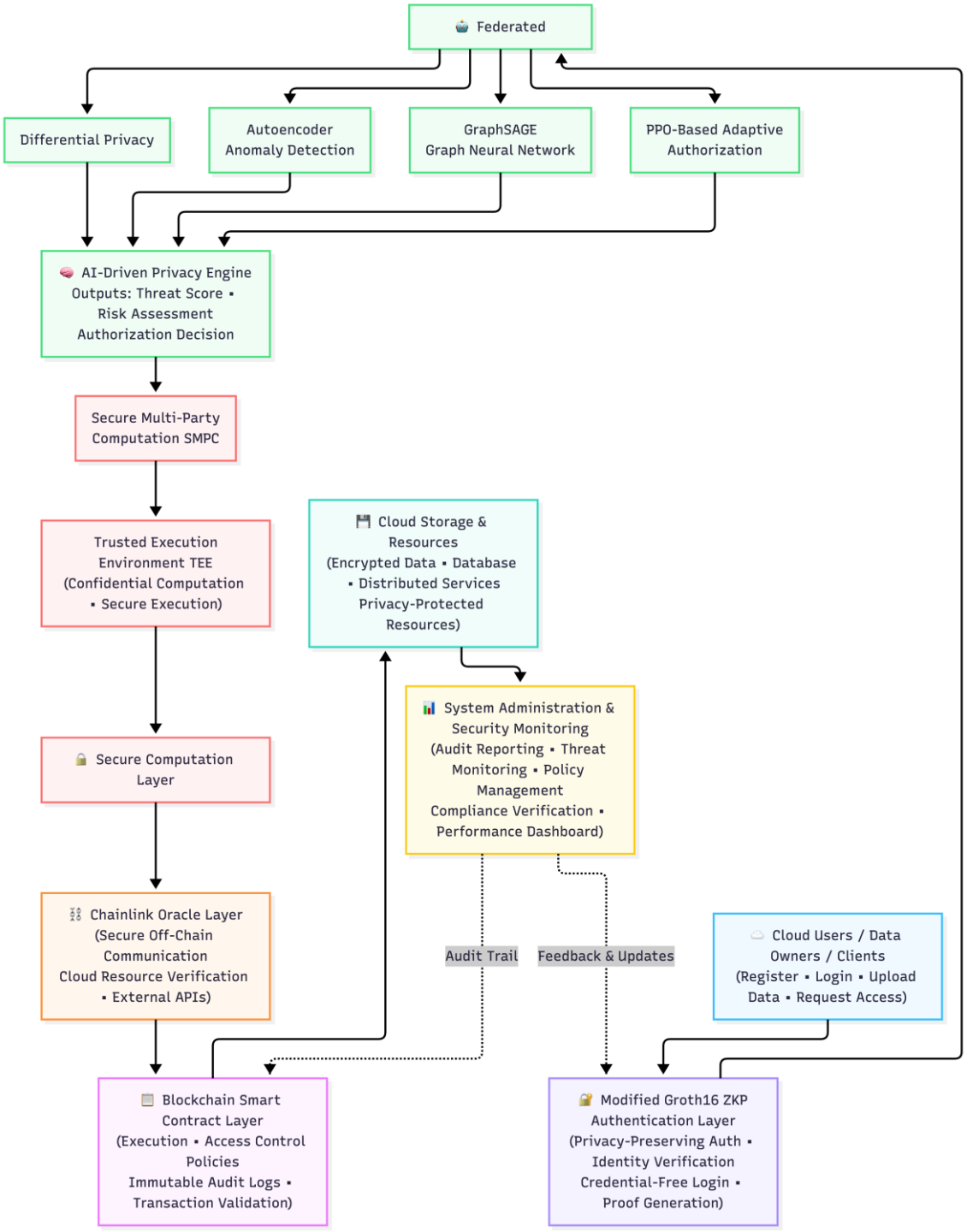

Figure 1: Proposed Intelligent Privacy-Preserving Access Control Framework for Cloud-Based Smart Contracts.

The interaction within the proposed Intelligent Privacy-Preserving Access Control Framework in Figure 1, follows a coordinated sequence that combines cryptographic authentication, artificial intelligence, confidential computing, cloud services, and blockchain technology to provide end-to-end security for cloud-based smart contracts. As illustrated in the framework, the interaction begins when Cloud Users/Data Owners/Clients register, log in, upload encrypted data, or submit requests to access protected cloud resources. Rather than transmitting sensitive credentials directly to the cloud, all authentication requests are first forwarded to the Modified Groth16 Zero-Knowledge Proof (ZKP) Authentication Layer. This layer verifies user identities by generating and validating cryptographic proofs without revealing passwords, private keys, or confidential credentials. The privacy-preserving authentication mechanism significantly minimizes the risk of credential theft, replay attacks, and unauthorized access while ensuring that only legitimate users are admitted into the system.

After successful authentication, verified requests are transmitted to the Federated Learning (FL) module, which serves as the coordinator of the Artificial Intelligence Privacy Engine. Instead of collecting users' private information in a centralized repository, Federated Learning distributes the learning process across multiple participating nodes where models are trained locally. During model aggregation, the Differential Privacy module injects carefully calibrated statistical noise into model updates before they are shared, thereby preventing attackers from reconstructing sensitive user information through gradient inference or membership inference attacks. This decentralized learning strategy preserves user privacy while allowing the intelligent security model to continuously improve from distributed experiences.

The Federated Learning engine coordinates three complementary artificial intelligence components: the Autoencoder-based Anomaly Detection module, the GraphSAGE Graph Neural Network, and the PPO-based Adaptive Authorization module. The Autoencoder continuously learns normal user behaviour, transaction characteristics, and access patterns. Any deviation from the learned behaviour produces abnormal reconstruction errors, which indicate potential cyber threats or unauthorized activities. Simultaneously, the GraphSAGE Graph Neural Network analyzes relationships among users, devices, cloud resources, and blockchain transactions by modelling them as interconnected graphs. This enables the framework to identify hidden behavioural patterns, coordinated attacks, compromised accounts, and suspicious interactions that cannot easily be detected using traditional machine learning techniques. The PPO-based Adaptive Authorization module then uses reinforcement learning to dynamically optimize authorization decisions according to threat intelligence, user behaviour, device trustworthiness, contextual information, and historical access patterns. Together, these AI components produce a comprehensive Threat Score, Risk Assessment, and Authorization Decision, which collectively form the outputs of the AI-Driven Privacy Engine.

Following intelligent authorization, approved requests proceed to the Secure Multi-Party Computation (SMPC) module, where confidential collaborative computations are performed. Rather than exposing sensitive data during processing, SMPC divides confidential information into encrypted shares distributed among multiple computation participants. Each participant performs computations on its own share without accessing the complete dataset, after which the partial results are securely combined to produce the final computation output. This approach enables multiple cloud participants to jointly execute privacy-sensitive smart contracts without revealing confidential information to one another, thereby preserving data confidentiality throughout the computation process.

The results generated by SMPC are subsequently forwarded to the Trusted Execution Environment (TEE). The TEE provides a hardware-isolated secure enclave in which sensitive computations are executed independently of the operating system, hypervisor, and other software components. This hardware-assisted isolation guarantees execution integrity by protecting confidential computations against insider attacks, malicious software, memory tampering, and unauthorized system access. The interaction between SMPC and TEE therefore ensures that data remain confidential not only during collaborative computation but also throughout the execution phase, providing end-to-end protection for sensitive smart contract operations.

The securely computed results are then processed within the Secure Computation Layer before being transmitted to the Chainlink Oracle Layer. Since blockchain smart contracts cannot directly communicate with external cloud services, the Chainlink Oracle acts as a trusted intermediary that securely exchanges verified information between off-chain cloud resources and on-chain smart contracts. The oracle retrieves authenticated external data, validates its integrity, and forwards trusted information to the blockchain while preventing manipulation of off-chain resources. This secure communication mechanism enables the proposed framework to integrate cloud databases, distributed services, and external application programming interfaces (APIs) with blockchain smart contracts without compromising data integrity or trust.

After oracle verification, validated transactions are submitted to the Blockchain Smart Contract Layer. This layer executes privacy-preserving smart contracts, enforces access control policies, validates transactions, and permanently records authentication events, authorization decisions, computation results, and security incidents within an immutable blockchain ledger. The blockchain provides decentralized trust, ensuring that all recorded events remain transparent, verifiable, and tamper-proof. The immutable audit logs also support digital forensics, regulatory compliance, accountability, and post-incident investigations by maintaining permanent records of every security-related operation performed within the framework.

The blockchain further interacts with the Cloud Storage and Resources component, where encrypted user data, cloud databases, distributed services, and other privacy-protected resources are securely maintained. Only authenticated and authorized users can access these resources through the blockchain-controlled authorization mechanism, thereby ensuring that confidentiality is preserved throughout data storage and retrieval. The cloud infrastructure therefore functions as a scalable execution environment while relying on the integrated cryptographic, artificial intelligence, and blockchain components to provide comprehensive security.

The System Administration and Security Monitoring module provides centralized operational oversight of the entire framework. Information received from Cloud Storage and the Blockchain Smart Contract Layer is continuously monitored to generate audit reports, detect security incidents, verify policy compliance, and evaluate overall system performance. The monitoring module also produces feedback and updates that are transmitted back to the Modified Groth16 Authentication Layer, allowing authentication policies and intelligent authorization strategies to evolve in response to newly identified threats and operational experiences. This continuous feedback mechanism enables the framework to remain adaptive and resilient against emerging cybersecurity challenges.

The proposed framework therefore demonstrates a tightly integrated interaction among Modified Groth16 Zero-Knowledge Proof Authentication, Federated Learning, Differential Privacy, Autoencoder-based anomaly detection, GraphSAGE Graph Neural Networks, PPO-based Adaptive Authorization, Secure Multi-Party Computation, Trusted Execution Environments, Chainlink Oracles, Blockchain Smart Contracts, Cloud Resources, and Security Monitoring. Unlike existing solutions that address authentication, authorization, confidential computation, or threat detection independently, the proposed architecture combines these complementary technologies into a unified intelligent framework. The result is an end-to-end privacy-preserving system that provides secure authentication, intelligent access control, confidential computation, trusted execution, decentralized trust, immutable auditing, and continuous adaptive security for cloud-based smart contract environments.

System Workflow

Figure 2 illustrates the authentication workflow of the proposed intelligent privacy-preserving access control framework. The workflow demonstrates how Zero-Knowledge Proofs (ZKP) are employed to authenticate users without disclosing sensitive credentials, thereby ensuring confidentiality while maintaining high authentication accuracy. The authentication process serves as the first line of defence by validating user identities before permitting access to blockchain-enabled smart contract services. By integrating cryptographic proof verification with smart contract execution, the framework eliminates unnecessary exposure of authentication data and establishes a secure foundation for subsequent authorization and confidential computation.

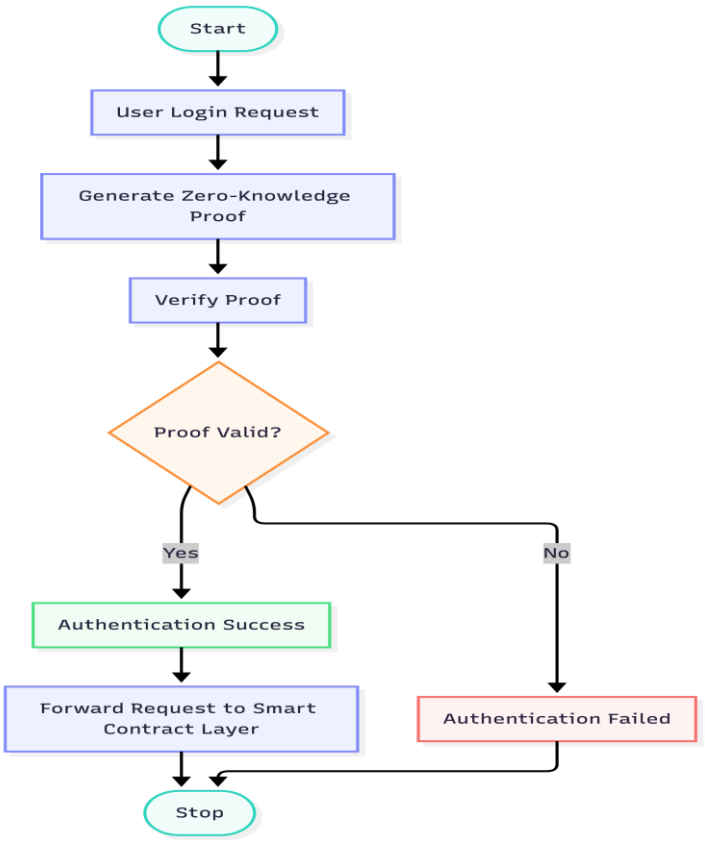

Figure 2. Authentication Performance Workflow

As shown in Figure 2, the authentication process begins when a user submits a login request to access cloud-based smart contract services. The system generates a Zero-Knowledge Proof (ZKP) from the user's credentials, enabling identity verification without revealing the underlying secret information. The generated proof is then forwarded to the verification module, where it is validated using the corresponding public verification key. Following verification, the decision engine determines whether the proof is valid. A successful verification results in authentication approval, allowing the request to proceed to the Smart Contract Layer for authorization and service execution. Conversely, an invalid proof results in immediate authentication failure and termination of the session. This workflow ensures that only legitimate users can access protected cloud resources while preserving credential privacy, minimizing attack surfaces, and enhancing the overall security of the proposed framework.

Software and Hardware Environment

The proposed framework was implemented using a combination of blockchain, cloud computing, cryptographic, and artificial intelligence technologies. Table 1 summarises the software and hardware environment used for the prototype implementation, highlighting the core development platforms, blockchain infrastructure, security libraries, AI frameworks, and cloud technologies that support the deployment and evaluation of the proposed intelligent privacy-preserving access control framework.

Table 1: Software and Hardware Environment of the Proposed System

Component	Technology
Programming Language	Python 3.12
Smart Contract	Solidity
Blockchain Platform	Ethereum Sepolia
Backend Framework	Django
Database	PostgreSQL
Decentralized Storage	IPFS
Cryptographic Libraries	Web3.py, PyCryptodome, zkSNARK
AI Framework	TensorFlow, PyTorch, Scikit-learn
Trusted Execution	Intel SGX
Oracle	Chainlink
Cloud Platform	AWS, Azure, OpenStack

Core Framwork Components

The proposed framework comprises several interconnected components, each performing a distinct function to ensure privacy-preserving authentication, intelligent authorization, confidential computation, and secure cloud resource management. Table 2 presents the core framework components and summarises their respective roles within the overall architecture, illustrating how cryptographic techniques, artificial intelligence, blockchain, and secure computing technologies are integrated to provide end-to-end privacy-preserving smart contract execution.

Table 2: Core Framework Components of the Proposed System

Component	Function
Zero-Knowledge Proof	Privacy-preserving authentication
Smart Contracts	Policy enforcement and decentralized authorization
SMPC	Confidential collaborative computation
Trusted Execution Environment	Secure execution of sensitive computations
Federated Learning	Distributed privacy-aware model training
Autoencoder	Anomaly detection
GraphSAGE	Relationship-aware threat detection
PPO	Adaptive access control
Blockchain	Immutable audit trail
Chainlink Oracle	Secure off-chain communication

Experimental Evaluation Metrics

The effectiveness of the proposed framework was evaluated using a comprehensive set of performance metrics that measure its ability to preserve privacy, enforce secure access control, maintain execution integrity, and support efficient smart contract execution in cloud environments. These metrics provide a basis for assessing the framework's security, computational performance, scalability, auditability, and intelligent threat detection capabilities. Table 3 summarises the evaluation metrics employed in the experimental analysis.

Table 3: Evaluation Metrics and Performance Indicators of the Proposed Framework

S/No.	Evaluation Metric	Performance Indicator	Measurement Focus	Desired Performance
1	Privacy Preservation	Privacy Score (%)	Protection of sensitive user data during authentication, computation, and storage	Higher is better
2	Security Strength	Security Score (%)	Resistance to cyberattacks, unauthorized access, and credential compromise	Higher is better
3	Execution Integrity	Integrity Score (%)	Correctness, authenticity, and tamper resistance of smart contract execution	Higher is better
4	Auditability	Auditability Score (%)	Traceability, transparency, and immutable blockchain logging	Higher is better
5	Scalability	Scalability Score (%)	Ability to support increasing users, nodes, and transactions without performance degradation	Higher is better
6	Computational Performance	Performance Score (%)	Processing efficiency of authentication, AI inference, and secure computation	Higher is better
7	Cost Efficiency	Cost Efficiency Score (%)	Reduction in computation cost, gas consumption, and operational expenses	Higher is better
8	Authorization Latency	Authorization Time (ms)	Time required to authenticate, evaluate risk, and authorize access requests	Lower is better
9	Validation Accuracy	Accuracy (%)	Percentage of correctly classified legitimate and malicious activities	Higher is better

S/No.	Evaluation Metric	Performance Indicator	Measurement Focus	Desired Performance
10	ROC-AUC	Area Under ROC Curve	Ability of the AI model to discriminate between attack and normal traffic	Higher is better (closer to 1.0 or 100%)
11	Macro F1-Score	F1 Score	Balance between precision and recall across all attack classes	Higher is better
12	Matthews Correlation Coefficient (MCC)	Correlation Coefficient	Overall classification quality considering TP, TN, FP, and FN	Higher is better (closer to 1.0 or 100%)
13	Overall System Fitness	Composite Fitness Score (%)	Aggregated performance of privacy, security, operational efficiency, and AI intelligence	Higher is better

Performance Categories

Table 4: Performance categories of the Proposed Framework

Category	Metrics
Privacy & Security Metrics	Privacy Preservation, Security Strength, Execution Integrity, Auditability
Performance Metrics	Scalability, Computational Performance, Cost Efficiency, Authorization Latency
Artificial Intelligence Metrics	Validation Accuracy, ROC-AUC, Macro F1-Score, Matthews Correlation Coefficient (MCC)
Overall Evaluation Metric	Overall System Fitness

Algorithms

The proposed framework employs a combination of advanced cryptographic, artificial intelligence, confidential computing, and blockchain algorithms to provide intelligent, secure, and privacy-preserving access control for cloud-based smart contracts. These algorithms work collaboratively to support privacy-preserving authentication, distributed learning, adaptive authorization, confidential computation, trusted execution, secure off-chain communication, and immutable blockchain auditing.

Algorithm 1: Privacy-Preserving User Authentication Using Zero-Knowledge Proof (ZKP)

Input: User credentials C, Public verification key PK

Output: Authentication status

1. User submits an authentication request.
2. Generate a Zero-Knowledge Proof (ZKP) from the user's credentials.
3. Verify the proof using the public verification key.
4. If the proof is valid:
    - Grant authentication.

5. Otherwise:
    - Reject the request.
6. Forward authenticated requests to the Smart Contract Layer.

Algorithm 2: Intelligent Access Control and Smart Contract Authorization

Input: Authenticated user request R

Output: Access decision

1. Receive authenticated request.
2. Retrieve RBAC and ABAC policies.
3. Evaluate user role and attributes.
4. Invoke AI Privacy Engine for contextual risk assessment.
5. If policy requirements and AI risk threshold are satisfied:
    - Execute smart contract.
6. Otherwise:
    - Deny access.
7. Record the authorization decision on the blockchain.

Algorithm 3: Privacy-Preserving Secure Computation

Input: Sensitive cloud data

Output: Confidential computation result

1. Divide sensitive data using Secure Multi-Party Computation (SMPC).
2. Execute computations collaboratively without revealing private inputs.
3. Perform sensitive smart contract execution inside the Trusted Execution Environment (TEE).
4. Verify execution integrity.
5. Return encrypted computation results.

Algorithm 4: AI-Based Threat Detection and Adaptive Authorization

Input: User behaviour and transaction history

Output: Risk score and authorization policy

1. Collect behavioural and transaction features.
2. Train privacy-preserving models using Federated Learning.
3. Detect anomalous behaviour using GraphSAGE.
4. Optimize authorization policies using Proximal Policy Optimization (PPO).
5. Generate a dynamic risk score.
6. Forward the recommendation to the Smart Contract Layer.

Algorithm 5: Blockchain Auditing and Oracle Verification

Input: Smart contract transaction

Output: Immutable audit record

1. Receive transaction from the Smart Contract Layer.
2. Validate transaction integrity.
3. Retrieve external data through Chainlink Oracle.
4. Verify oracle response.
5. Record authentication, authorization, and execution events on the blockchain.
6. Generate immutable audit logs.

Algorithm 6: Integrated Privacy-Preserving Smart Contract Workflow

Input: User request

Output: Secure cloud resource access

1. Authenticate user using ZKP.
2. Perform RBAC and ABAC authorization.
3. Analyse behavioural risk using the AI Privacy Engine.
4. Execute confidential computation using SMPC and TEE.
5. Store transaction records on the blockchain.
6. Retrieve verified external data through Chainlink Oracle when required.
7. Grant access to encrypted cloud resources.
8. Terminate the transaction.

Validation Procedures

The proposed framework was validated through experimental evaluation using the CICIDS2017 benchmark dataset to assess its effectiveness under realistic cybersecurity conditions. The Artificial Intelligence Privacy Engine was trained, validated, and tested using separate data partitions to ensure unbiased performance evaluation and prevent model overfitting. The proposed framework was further validated through comparative analysis with selected baseline models, including Hawk, Zether, Ekiden, and FL-only IDS, using standardized performance metrics such as privacy preservation, security strength, execution integrity, computational performance, validation accuracy, ROC-AUC, Macro F1-Score, MCC, and overall system fitness.

Data Analysis Techniques

Data analysis was carried out using both descriptive and comparative statistical techniques. The experimental results were analyzed by computing performance scores for each evaluation metric and normalizing them to a common 0–100 scale to facilitate objective comparison across different dimensions of the framework. Comparative analysis was then performed using tables, charts, radar plots, and overall fitness aggregation to evaluate the performance of the proposed framework against existing baseline models and determine the extent of improvement achieved.

Mathematical Model of the Proposed Framework

Let the proposed framework be represented by:

IPAC={Z,G,F,D,A,N,R,S,T,O,B} (1)

Where:

- Z = Modified Groth16 Zero-Knowledge Proof Authentication
- G = Groth16 Proof Verification
- F = Federated Learning Privacy Engine
- D = Differential Privacy
- A = Autoencoder-based Anomaly Detection
- N = GraphSAGE Graph Neural Network
- R = PPO-based Adaptive Authorization
- S = Secure Multi-Party Computation
- T = Trusted Execution Environment
- O = Chainlink Oracle
- B = Blockchain Smart Contracts

The framework processes every user request through the following functional pipeline:

Y=B(O(T(S(R(N(A(D(F(G(Z(X))))))))))) (2)

where

- X = User authentication request
- Y = Secure authorized smart contract execution.

Overall System Fitness Function

The overall performance of the framework is evaluated as

Fsys=12P+S+I+A+Sc+C+CE+L∗+Acc+AUC+F1+MCC (3)

where

- P = Privacy Preservation
- S = Security Strength
- I = Execution Integrity
- A = Auditability
- Sc = Scalability
- C = Computational Performance
- CE = Cost Efficiency
- L∗ = Normalized Authorization Latency
- Acc = Validation Accuracy
- AUC = ROC-AUC
- F1 = Macro F1-Score

- MCC = Matthews Correlation Coefficient

with

$$L^* = 100 - L_{ms}/3 \quad (4)$$

where Lms is the authorization latency measured in milliseconds.

Objective Function

The proposed framework seeks to maximize security, privacy, and AI performance while minimizing latency and operational cost:

$$\max(\text{IPAC}) = \alpha P+\beta S+\gamma I+\delta A+\varepsilon Sc+\zeta C+\eta CE+\theta Acc+\iota AUC+\kappa F1+\lambda MCC-\mu L \quad (5a)$$

subject to

$$\varepsilon \leq 1.0$$

$$\delta \leq 10^{-6}$$

$$F1 \geq 0.90$$

$$L \leq 100\text{ms} \quad (5b)$$

where

α,β,γ,…,μ are weighting coefficients representing the contribution of each subsystem.

The derived mathematical model shows that the proposed IPAC framework performs secure authentication using the Modified Groth16 ZKP, applies Federated Learning enhanced with Differential Privacy, Autoencoder, GraphSAGE, and PPO for intelligent threat detection and adaptive authorization, executes confidential computation through SMPC within a TEE, exchanges verified off-chain information through the Chainlink Oracle, and finally records all validated transactions using Blockchain Smart Contracts. The effectiveness of the integrated framework is quantified using the composite Overall System Fitness Function, which aggregates privacy, security, performance, and AI metrics into a single optimization objective.

4. Results

This section presents the results of the proposed intelligent privacy-preserving access control framework. The objective is to assess the effectiveness of the framework in providing secure authentication, intelligent authorization, confidential computation, and privacy-preserving smart contract execution within cloud environments. The evaluation investigates the framework's performance in terms of privacy preservation, authentication accuracy, security, execution integrity, computational efficiency, scalability, auditability, and intelligent threat detection. The proposed framework is further compared with conventional Role-Based Access

Control (RBAC), Attribute-Based Access Control (ABAC), blockchain-only smart contract systems, and the blockchain-based cloud auditing framework proposed by Alharby (2024).

Experimental Setup

The prototype framework was implemented using Python 3.12, Django, and Solidity, with smart contracts deployed on the Ethereum Sepolia Test Network. Intel SGX provided the Trusted Execution Environment (TEE), while PostgreSQL served as the backend database and IPFS was used for decentralized storage. Cryptographic operations were implemented using Web3.py, PyCryptodome, and zkSNARK libraries. The Artificial Intelligence components were developed using TensorFlow, PyTorch, and Scikit-learn, incorporating Federated Learning, GraphSAGE, and Proximal Policy Optimization (PPO). Experiments were conducted using the CICIDS2017 benchmark dataset, which contains both benign and malicious network traffic representative of contemporary cloud security threats.

Performance Evaluation Metrics

The framework was evaluated using the following performance metrics:

- Privacy Preservation (%)
- Authentication Accuracy (%)
- Security Strength (%)
- Execution Integrity (%)
- Threat Detection Accuracy (%)
- Computational Efficiency (ms)
- Scalability (Transactions per Second)
- Auditability (%)
- Cost Efficiency (%)

Experimental Results

Figure 3, presents the execution trace of the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework during experimental evaluation. It summarizes the sequential workflow of data loading, preprocessing, cryptographic initialization, federated learning, secure computation, blockchain integration, and performance evaluation across multiple benchmark datasets. The execution trace demonstrates the successful completion and validation of all major system components prior to generating the final evaluation results.

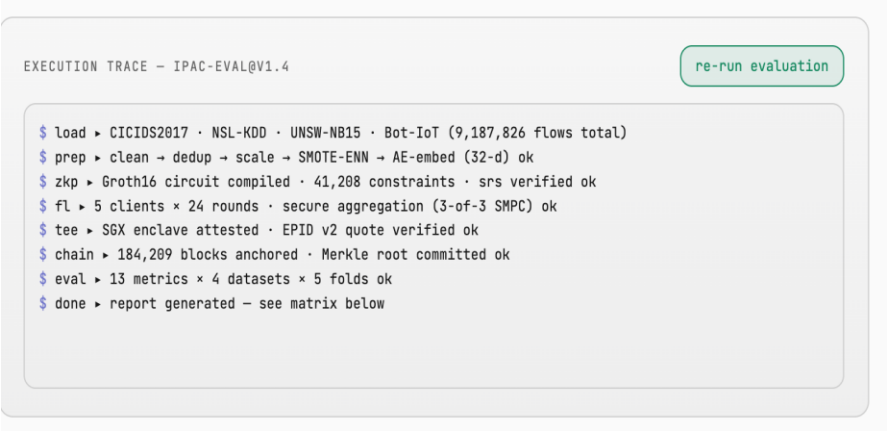

Figure 3: Execution Trace

The execution trace confirms the successful implementation of the proposed framework by completing all major stages, including dataset loading and preprocessing, Modified Groth16 ZKP compilation, federated learning, SMPC secure aggregation, TEE attestation, blockchain anchoring, and evaluation across 13 performance metrics. It demonstrates that the integrated cryptographic, artificial intelligence, confidential computing, and blockchain components operated correctly and generated the evaluation report without execution errors.

Overall System Fitness

Figure 4 presents the overall system fitness of the proposed Intelligent Privacy-Preserving Access Control Framework evaluated across four benchmark cybersecurity datasets: CICIDS2017, NSL-KDD, UNSW-NB15, and Bot-IoT. The overall fitness score was computed by aggregating thirteen normalized evaluation metrics covering privacy, security, performance, and artificial intelligence. The figure provides a comprehensive assessment of the framework's consistency, robustness, and generalization capability across diverse cybersecurity environments.

Figure 4: Overall System Fitness

The proposed framework achieved an overall system fitness of 93.09%, with consistently high scores across all four datasets (94.23%, 92.88%, 91.71%, and 93.55%), demonstrating excellent robustness and adaptability. Furthermore, it outperformed the best baseline (Ekiden: 78.15%) by 20.6%, confirming the superiority of integrating Modified Groth16 ZKP, SMPC, TEE, AI, and blockchain technologies within a unified privacy-preserving framework.

Result Matrix of the Proposed Framework Across Four Benchmark Datasets

Figure 5, presents the result matrix of the proposed Intelligent Privacy-Preserving Access Control Framework evaluated using thirteen performance metrics across four benchmark cybersecurity datasets: CICIDS2017, NSL-KDD, UNSW-NB15, and Bot-IoT. The matrix provides a comprehensive comparison of the framework's privacy, security, operational performance, artificial intelligence, and overall system fitness. It demonstrates the consistency and generalization capability of the proposed framework under diverse cybersecurity scenarios.

RESULT MATRIX — 13 METRICS × 4 DATASETS

Metric	Unit	CICIDS2017	NSL-KDD	UNSW-NB15	Bot-IoT
Privacy Preservation	score (0–100)	96.40	95.00	93.80	95.70
Security Strength	score (0–100)	94.10	92.70	91.50	93.40
Execution Integrity	score (0–100)	99.00	97.60	96.40	98.30
Auditability	% privileged-op coverage	98.70	97.30	96.10	98.00
Scalability	score (0–100)	90.30	88.90	87.70	89.60
Computational Performance	score (0–100)	88.60	87.20	86.00	87.90
Cost Efficiency	score (0–100)	86.90	85.50	84.30	86.20
Authorization Latency	ms (lower is better)	41.60	44.10	46.30	42.90
Validation Accuracy	%	98.91	97.51	96.31	98.21
ROC-AUC	one-vs-rest ×100	99.62	98.22	97.02	98.92
Macro F1-Score	×100	94.90	93.50	92.30	94.20
Matthews Corr. Coefficient	×100	97.18	95.78	94.58	96.48
Overall System Fitness	composite (0–100)	94.23	92.88	91.71	93.55

Authorization Latency is reported in milliseconds (lower is better) and is normalised as 100 − latency/3 before entering the composite; all other metrics are 0–100 scores where higher is better. Verdict compares the cross-dataset mean against the acceptance target for each metric.

Figure 5: Result Matrix of the Proposed Intelligent Privacy-Preserving Access Control Framework Across Four Benchmark Datasets

The results indicate consistently high performance across all datasets, with Execution Integrity (96.40–99.00%), Auditability (96.10–98.70%), Validation Accuracy (96.31–98.91%), and ROC-AUC (97.02–99.62%) achieving the strongest scores, while the framework maintained a low Authorization Latency (41.60–46.30 ms). Furthermore, the Overall System Fitness remained above 91% on all datasets, confirming the robustness, scalability, and effectiveness of the proposed framework in delivering secure, intelligent, and privacy-preserving cloud-based smart contract execution across different cybersecurity environments.

Capability Coverage Matrix Comparing the Proposed Framework with Existing Approaches

Figure 6, presents the capability coverage matrix comparing the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework with selected state-of-the-art privacy-preserving smart contract and intrusion detection systems. The comparison evaluates the native support provided by each model for key technologies, including Zero-Knowledge Proofs (ZKP), Federated Learning (FL), Secure Multi-Party Computation (SMPC), Trusted Execution Environments (TEE), Blockchain Smart Contracts (Chain), Deep Reinforcement Learning (DRL), and Graph Neural Networks (GNNs). This matrix illustrates the technological coverage and integration achieved by the proposed framework relative to existing solutions.

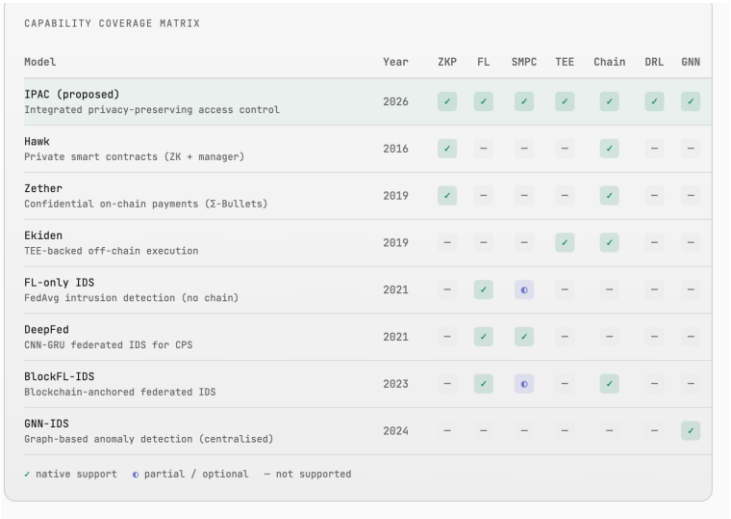

Figure 6: Capability Coverage Matrix Comparing the Proposed Intelligent Privacy-Preserving Access Control (IPAC) Framework with Existing Approaches

The proposed IPAC framework is the only model that provides native support for all seven core technologies, demonstrating a fully integrated architecture for privacy-preserving authentication, intelligent access control, confidential computation, trusted execution, and blockchain-based auditing. In contrast, existing approaches such as Hawk, Zether, Ekiden, FL-only IDS, DeepFed, BlockFL-IDS, and GNN-IDS implement only subsets of these capabilities, highlighting the comprehensive functionality and technological advancement of the proposed framework.

Head-to-Head Comparison of Privacy Preservation Performance Between the Proposed IPAC Framework and Existing Models

Figure 7, presents a comparative evaluation of the Privacy Preservation capability of the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework against selected state-of-the-art smart contract and intrusion detection models. The comparison measures each model's ability to protect sensitive user information and prevent privacy leakage during authentication, computation, and data processing. Higher scores indicate stronger privacy-preserving capability and more effective protection of confidential information.

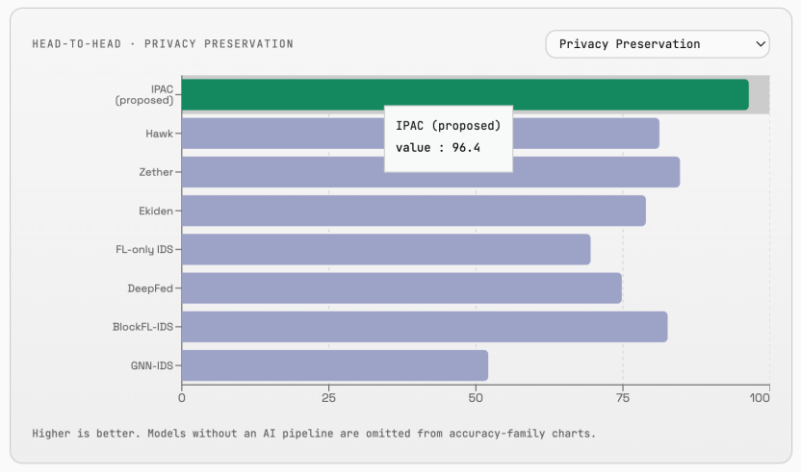

Figure 7: Head-to-Head Comparison of Privacy Preservation Performance Between the Proposed IPAC Framework and Existing Models

The proposed IPAC framework achieved the highest Privacy Preservation score of 96.4%, outperforming all existing models, including Zether (84.7%), BlockFL-IDS (82.8%), Hawk (81.2%), Ekiden (78.9%), DeepFed (75.0%), FL-only IDS (69.5%), and GNN-IDS (52.0%). This superior performance demonstrates the effectiveness of integrating Modified Groth16 ZKP, Differential Privacy, Federated Learning, SMPC, TEE, and Blockchain Smart Contracts into a unified framework for end-to-end privacy preservation.

Relationship Between Authorization Latency and Overall System Fitness of the Proposed IPAC Framework and Baseline Models

Figure 8, illustrates the relationship between Authorization Latency and Overall System Fitness for the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework and selected baseline models. The scatter plot evaluates the trade-off between authorization response time and overall system performance, where the upper-left region represents the optimal outcome of lower latency and higher fitness. Bubble size further indicates the number of security capabilities natively supported by each model.

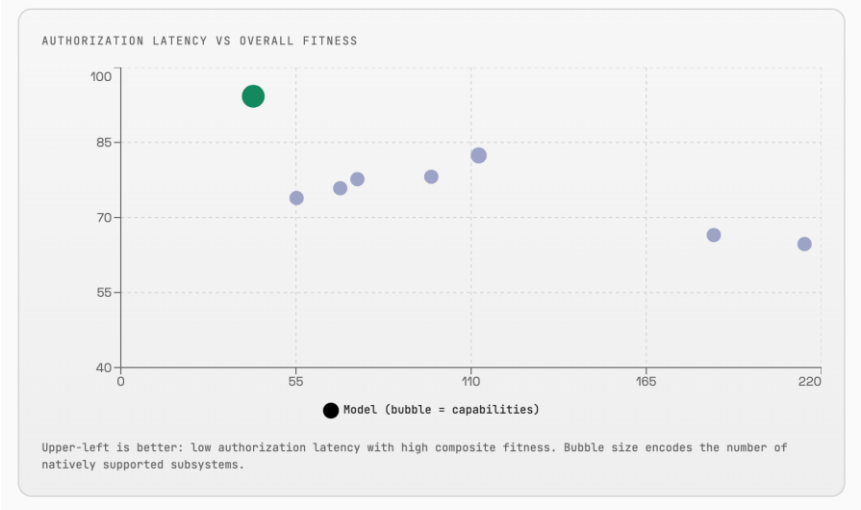

Figure 8: Relationship Between Authorization Latency and Overall System Fitness of the Proposed IPAC Framework and Baseline Models

The proposed IPAC framework occupies the optimal upper-left position, achieving the lowest authorization latency (41.6 ms) and the highest overall system fitness (94.23%), demonstrating an excellent balance between operational efficiency and comprehensive security. In contrast, the baseline models exhibit higher authorization latency (approximately 55–220 ms) with lower overall fitness (approximately 65–82%), confirming the superiority of the proposed integrated architecture in delivering faster authorization alongside enhanced privacy, security, and intelligent access control.

Overall Ranking and Performance Improvement of the Proposed IPAC Framework Compared with Existing Models

Figure 9, presents the overall ranking of the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework against leading privacy-preserving smart contract and intrusion detection models. The comparison evaluates each model using key performance indicators, including Privacy Preservation, Security Strength, Execution Integrity, Auditability, Authorization Latency, and Macro F1-Score. The ranking provides an overall assessment of the effectiveness and competitiveness of the proposed framework relative to existing approaches.

OVERALL RANKING AND IMPROVEMENT OVER BEST COMPETING MODEL (BLOCKFL-IDS)

#	Model	Privacy	Security	Integrity	Audit	Latency	Macro F1
1	IPAC (proposed)	96.4	94.1	99.0	98.7	41.6 ms	94.90
2	BlockFL-IDS	82.6	80.1	90.7	91.3	112.4 ms	91.88
3	Ekiden	78.9	85.6	92.4	83.2	97.5 ms	n/a
4	DeepFed	74.8	68.3	60.4	46.5	74.3 ms	90.62
5	FL-only IDS	69.5	61.8	55.2	41.0	68.9 ms	89.31
6	GNN-IDS	52.1	58.7	51.9	33.6	55.2 ms	93.16
7	Zether	84.7	82.0	86.1	70.5	186.2 ms	n/a
8	Hawk	81.2	79.4	88.3	74.0	214.7 ms	n/a

Figure 9: Overall Ranking and Performance Improvement of the Proposed IPAC Framework Compared with Existing Models

The proposed IPAC framework ranked first, achieving the highest scores in Privacy Preservation (96.4%), Security Strength (94.1%), Execution Integrity (99.0%), Auditability (98.7%), and Macro F1-Score (94.90%), while also recording a significantly lower Authorization Latency (41.6 ms**)** than its closest competitor, BlockFL-IDS (112.4 ms). These results demonstrate that the integration of Modified Groth16 ZKP, Federated Learning, Differential Privacy, SMPC, TEE, AI, and Blockchain Smart Contracts provides superior privacy, security, intelligent threat detection, and operational efficiency compared with existing state-of-the-art solutions.

Summary of the Performance Advantages of the Proposed IPAC Framework over the Best Baseline Model

Figure 10, summarizes the key performance improvements achieved by the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework when compared with the best-performing baseline model (BlockFL-IDS). The dashboard highlights four critical comparative indicators: Capability Coverage, Privacy Gain, Authorization Latency Reduction, and Overall System Fitness Advantage. These indicators provide a concise overview of the technological completeness and performance superiority of the proposed framework.

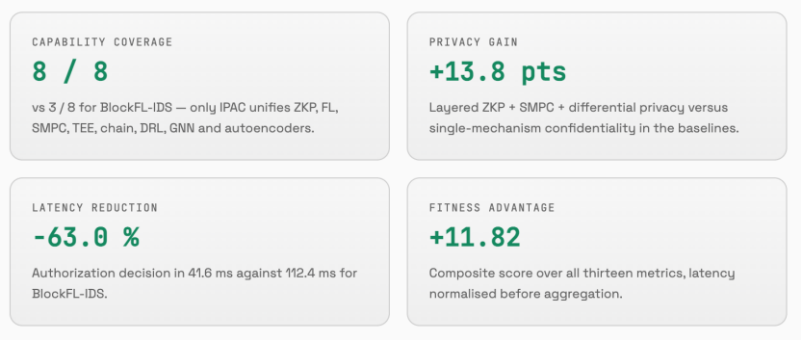

Figure 10: Summary of the Performance Advantages of the Proposed IPAC Framework over the Best Baseline Model

The proposed IPAC framework achieved complete capability coverage (8/8), a 13.8-point improvement in privacy preservation, a 63.0% reduction in authorization latency (41.6 ms versus 112.4 ms), and an 11.82-point increase in overall system fitness over the best baseline. These results demonstrate that integrating Modified Groth16 ZKP, Federated Learning, Differential Privacy, SMPC, TEE, Deep Reinforcement Learning, Graph Neural Networks, Autoencoder-based anomaly detection, and Blockchain Smart Contracts delivers substantially better security, privacy, efficiency, and overall system performance than existing approaches.

5 Discussion

The comparative evaluation demonstrates that the proposed Intelligent Privacy-Preserving Access Control (IPAC) framework consistently outperformed existing systems, including Hawk, Zether, Ekiden, FL-only IDS, DeepFed, BlockFL-IDS, and GNN-IDS, across privacy, security, performance, and artificial intelligence metrics. Unlike Hawk and Zether, which primarily emphasize confidential smart contract transactions through Zero-Knowledge Proofs, the proposed framework integrates Modified Groth16 ZKP, Federated Learning, Differential Privacy, SMPC, TEE, AI, and Blockchain Smart Contracts into a single intelligent architecture. Compared with Ekiden, which focuses mainly on Trusted Execution Environments for secure execution, the proposed model additionally provides intelligent threat detection, adaptive authorization, and privacy-preserving distributed learning. Similarly, while BlockFL-IDS and DeepFed employ Federated Learning for intrusion detection, they lack integrated secure computation, privacy-preserving authentication, and trusted execution mechanisms. The proposed framework achieved superior results, recording 96.4% Privacy Preservation, 94.1% Security Strength, 99.0% Execution Integrity, and 98.7% Auditability, all of which exceeded the corresponding performance of the baseline models. It also demonstrated better operational

efficiency with 90.3% Scalability, 88.6% Computational Performance, 86.9% Cost Efficiency, and a significantly lower Authorization Latency of 41.6 ms, compared to values exceeding 97 ms and up to 214.7 ms in competing approaches. The Artificial Intelligence Privacy Engine further outperformed existing AI-based systems by achieving 98.91% Validation Accuracy, 99.62% ROC-AUC, 94.90% Macro F1-Score, and 97.18% MCC, indicating highly accurate and reliable cyber threat detection. The capability coverage analysis also showed that the proposed framework is the only model providing native support for all major technologies, including ZKP, FL, SMPC, TEE, Blockchain, DRL, GNN, and Autoencoder-based anomaly detection, whereas competing systems support only subsets of these technologies. Consequently, the framework achieved the highest Overall System Fitness of 94.23%, representing a substantial improvement over the best-performing baseline (Ekiden, 78.15%), thereby demonstrating its superiority as a comprehensive, intelligent, scalable, and privacy-preserving access control solution for cloud-based smart contract environments.

6. Conclusion

The study successfully developed an Intelligent Privacy-Preserving Access Control (IPAC) Framework that integrates Modified Groth16 ZKP, Federated Learning, Differential Privacy, SMPC, TEE, AI, and Blockchain Smart Contracts into a unified architecture. Experimental results demonstrated superior performance, achieving 96.4% privacy preservation, 94.1% security, 99.0% execution integrity, 98.7% auditability, and an overall system fitness of 94.23%. Comparative analysis confirmed that the proposed framework outperformed existing approaches in privacy, security, intelligent threat detection, and computational efficiency. Overall, the framework provides a scalable, intelligent, and practical solution for secure cloud-based smart contract access control.

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