

## RESEARCH ARTICLE

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# BLOCKCHAIN-ENABLED EXPLAINABLE ARTIFICIAL INTELLIGENCE FRAMEWORK FOR TRUSTED AND AUDITABLE DIABETES RISK PREDICTION

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## ABSTRACT

Diabetes mellitus remains a major global health challenge, with its long-term complications imposing substantial economic and social burdens on healthcare systems worldwide. Although machine learning models have demonstrated strong predictive performance in identifying diabetes risk, their black-box nature severely limits clinical interpretability, trust, and accountability, thereby hindering widespread adoption in medical practice. This study introduces the Explainable Blockchain (XBC) framework, which integrates Random Forest-based diabetes risk prediction with local SHAP explanations, followed by permanent, immutable storage of concise explanation summaries on an Ethereum smart contract. Patient identifiers are pseudonymized via cryptographic hashing to preserve privacy while enabling independent auditability by clinicians, patients, and regulators. Experiments conducted on the Pima Indians Diabetes dataset yielded an accuracy of 74.68%, an AUC of 0.8118, and perfect ML-to-chain consistency (100%) across 154 test instances, with average transaction latency of 54.6 ms and gas consumption of approximately 50,595 units on a private Ganache testnet. By bridging explainable artificial intelligence and blockchain at the individual decision level, XBC establishes a verifiable, tamper-proof audit trail for AI-driven clinical decisions, significantly advancing transparency, accountability, and regulatory compliance in healthcare artificial intelligence applications.



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## I. INTRODUCTION

Diabetes mellitus has emerged as one of the most serious global public health challenges of the 21st century [1]. The disease affects hundreds of millions of individuals worldwide and imposes a substantial economic and social burden due to long-term complications, including cardiovascular disease, renal failure, blindness, and amputations [2],[3]. Despite ongoing advances in prevention and clinical management, early detection of diabetes risk in individuals remains frequently delayed, particularly in regions with limited access to healthcare services [4],[5]. In this context, artificial intelligence (AI) and machine learning (ML) approaches have demonstrated significant potential to enhance the accuracy of diabetes risk prediction well before the onset of clinical symptoms [6-8]. Nevertheless, many machine learning models used for diabetes risk prediction operate as black-box systems, limiting their interpretability for healthcare professionals, patients, and regulators [9-11].

This lack of transparency poses a significant barrier to clinical adoption, as clinicians require clear and trustworthy rationales when classifying individuals as high- or low-risk [12-14]. In addition, AI-generated decisions often lack verifiable audit trails, further raising concerns regarding accountability and trust in clinical decision-making [15],[16]. Although various Explainable Artificial Intelligence (XAI) methods have been proposed to improve the interpretability of model predictions, current approaches generally do not guarantee that explanations are stored in a permanent, tamper-proof, and independently auditable manner [17-19]. At the same time, blockchain technology has attracted attention in healthcare for its ability to enhance data integrity and traceability, yet existing applications remain largely focused on record management rather than decision-level accountability [20-22].

Consequently, the integration of local XAI-based explanations with blockchain infrastructure to support explainable, immutable, and auditable AI-driven clinical decisions at the individual level remains an open research gap, particularly under increasing regulatory demands for transparency and accountability. To address these limitations, this study proposes the Explainable Blockchain (XBC) framework, which integrates machine learning-based diabetes risk prediction with local explanations generated using SHAP, followed by permanent on-chain storage of explanation summaries via smart contracts [23-25]. This approach is designed to yield decisions that are not only accurate but also transparent, explainable, immutable, and independently verifiable by healthcare professionals, patients, and regulators without disclosing individual identities.

The primary contributions of this research include: (1) the development of an XBC architecture that combines machine learning prediction with on-chain storage of local explanations, (2) the implementation of an efficient explanation summarization mechanism to accommodate blockchain storage constraints, and (3) empirical demonstration of decision consistency and auditability within a private blockchain environment. The remainder of this paper is organized as follows: literature review, methodology, results and discussion, and conclusion with recommendations for future research.

## II. RELATED WORK

### II.1 MACHINE LEARNING-BASED DIABETES RISK PREDICTION

Various machine learning approaches have long been applied to predict the risk of type 2 diabetes, particularly by leveraging relatively simple clinical datasets such as the Pima Indians Diabetes Dataset. Classic methods, including logistic regression, decision trees, and naive Bayes, are frequently employed as baselines owing to their relative ease of interpretability, although their capacity to handle complex nonlinear relationships among variables remains limited [26],[27]. Subsequently, ensemble methods such as Random Forest and Gradient Boosting Machines have emerged as dominant choices due to their superior ability to capture feature interactions and address class imbalance, a common issue in medical datasets [28],[29].

Several studies have also begun adopting deep learning models, including feed-forward artificial neural networks, convolutional neural networks adapted for tabular data, and transformer architectures designed to capture long-range dependencies among physiological parameters [30],[31]. Although these models can achieve high area under the curve (AUC) values on specific datasets, nearly all such approaches prioritize the optimization of predictive performance metrics and rarely address the transparency and accountability of the decisions they produce.

### II.2 EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI) IN THE HEALTHCARE DOMAIN

despite the advances in predictive accuracy, the black-box nature of many ML models poses significant challenges in healthcare, particularly regarding clinical interpretability and trust. This has driven rapid advancements in Explainable Artificial Intelligence (XAI), especially in applications with high clinical and legal implications [32-34]. Post-hoc approaches such as LIME and SHAP have become highly popular because they enable the generation of local explanations for black-box model predictions without requiring modifications to the internal structure of the models themselves [35-37]. SHAP, which is based on the concept of Shapley values from cooperative game theory, is regarded as one of the most mathematically consistent methods, satisfying important properties such as additivity and consistency.

Zhang *et al.* have demonstrated that SHAP is capable of producing explanations that align with clinical knowledge across various disease prediction tasks, including diabetes and cardiovascular diseases [38]. In addition, several studies have begun to develop global explanations by aggregating absolute SHAP values to identify features with the greatest overall influence. Nevertheless, nearly all existing XAI implementations currently operate off-chain and lack mechanisms to ensure that explanations are permanent, immutable, independently auditable, or possess a trail that can be verified by third parties after clinical decisions are made [39-41].

### II.3 APPLICATION OF BLOCKCHAIN IN HEALTHCARE SYSTEMS

On the other hand, blockchain technology has attracted substantial attention in the healthcare domain primarily due to its decentralized nature, immutability, and strong support for auditability. Most early studies have utilized blockchain for electronic medical record storage, patient consent management, pharmaceutical supply chain tracking, and data exchange among healthcare institutions while preserving privacy through encryption techniques and zero-knowledge proofs [42-44].

Several studies have also begun exploring blockchain as a trust layer for clinical decision support systems, for example by recording prediction outcomes or treatment recommendations on-chain. However, the primary focus remains on the integrity and availability of raw data or final prediction results, rather than on explanations of how specific decisions are derived [45-47]. As a result, blockchain is more commonly used as a secure ledger, while its potential for storing explanatory artifacts directly associated with individual decisions remains largely underexplored.

### II.4 INTEGRATION OF EXPLAINABLE ARTIFICIAL INTELLIGENCE AND BLOCKCHAIN AND RESEARCH GAP

Although Explainable Artificial Intelligence and blockchain have each been extensively studied in healthcare contexts, research that meaningfully integrates both remains relatively limited and often fragmented. Existing studies typically treat blockchain as a mechanism for recording prediction outcomes or decision artifacts, while explanations generated by AI models are rarely considered first-class decision components that require persistent, verifiable, and auditable storage. As a result, the integration of individual-level local explanations with efficient and deterministic on-chain storage mechanisms has not been widely explored, leaving an open research gap in addressing transparency and accountability requirements for AI-driven decision-making in healthcare systems.

### III. MATERIALS AND METHODS

#### III.1 RESEARCH DESIGN AND OVERALL SYSTEM FRAMEWORK

This study focuses on the development of an Explainable Blockchain (XBC) framework by integrating Explainable Artificial Intelligence (XAI) into blockchain infrastructure to enable transparent, explainable, immutable, and auditable diabetes risk prediction [48],[49]. XAI serves as a supporting component, with particular emphasis on the representation, summarization, and on-chain storage of AI decision explanations. The proposed framework combines machine learning based prediction with local SHAP explanations, which are subsequently summarized and recorded via smart contracts implemented in Solidity on an Ethereum network (local Ganache testnet) [50-52].

As a result, each medical decision is not only accurate but also accompanied by a permanent and verifiable explanatory trace. The objective of this research is to establish an XBC-based clinical decision support system that addresses key limitations of conventional AI, particularly black-box behavior and the absence of trustworthy, tamper-proof, and privacy-preserving audit trails. Figure 1 illustrates the overall system workflow, from data processing to on-chain storage, enabling independent auditing by regulators, healthcare professionals, and patients without revealing individual identities, thereby enhancing trust, accountability, and clinical acceptance of AI in healthcare.

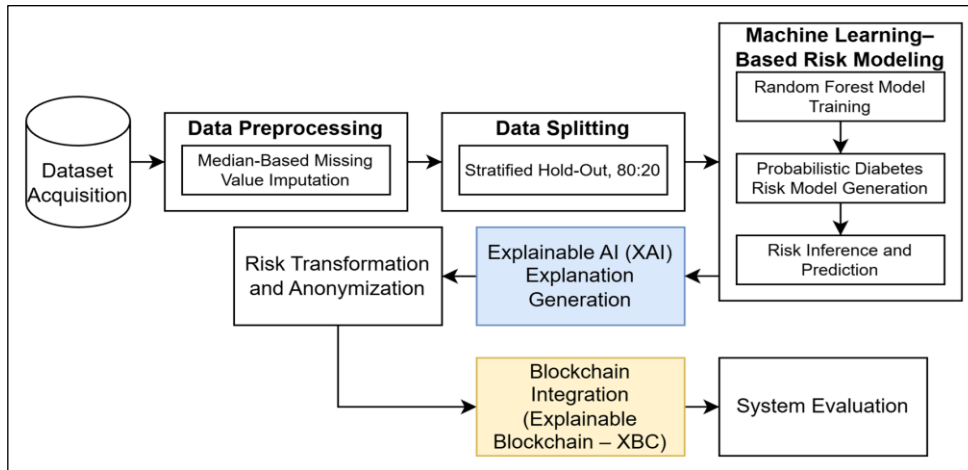


Figure 1: Research Flow.

Source: Authors, (2026).

#### III.2 DATASET AND DATA PREPROCESSING

This study utilizes the Pima Indians Diabetes Dataset provided by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) as the primary dataset for developing and evaluating the diabetes risk prediction model [53]. The dataset consists of 768 instances with eight numerical predictor features representing clinically relevant physiological parameters and one binary target variable (Outcome), where 0 indicates non-diabetic and 1 indicates diabetic status, as summarized in Table 1. The class distribution exhibits moderate imbalance, with 65.1% negative and 34.9% positive instances, as shown in Table 2. Prior to model training, missing values in each feature were handled using median-based imputation computed over the entire dataset, following common practice in predictive experiments using this dataset.

Table 1: Feature Descriptions in the Pima Indians Diabetes Dataset.

| Feature Name             | Description                                                               | Unit / Data Type  |
|--------------------------|---------------------------------------------------------------------------|-------------------|
| Pregnancies              | Number of times the patient has been pregnant                             | Integer           |
| Glucose                  | Plasma glucose concentration 2 hours after an oral glucose tolerance test | mg/dL             |
| BloodPressure            | Diastolic blood pressure                                                  | mm Hg             |
| SkinThickness            | Triceps skin fold thickness                                               | mm                |
| Insulin                  | Serum insulin level 2 hours after the test                                | μU/mL             |
| BMI                      | Body mass index                                                           | kg/m <sup>2</sup> |
| DiabetesPedigreeFunction | Score representing family history of diabetes                             | Numeric           |
| Age                      | Patient age                                                               | Years             |

Source: Authors, (2026).

Table 2: Distribution of Outcome Classes in the Overall Dataset.

| Class        | Number of Instances | Percentage (%) |
|--------------|---------------------|----------------|
| 0 (Negative) | 500                 | 65.10          |
| 1 (Positive) | 268                 | 34.90          |

Source: Authors, (2026).

### III.3 MACHINE LEARNING MODEL DEVELOPMENT

The primary predictive model employed in this study is the Random Forest Classifier, an ensemble learning method that constructs multiple decision trees in parallel and aggregates their outputs to produce a final prediction. The selection of Random Forest is motivated by its robust performance on tabular data and its suitability for post-hoc explainability analysis, which aligns with the research objectives emphasizing transparency, interpretability, and auditability of model decisions [54],[55]. As illustrated in Figure 2, Random Forest operates by training each decision tree using data generated through bootstrap sampling and a randomly selected subset of features at each node split [56]. This mechanism introduces diversity among the trees, contributing to improved model generalization and reducing the risk of overfitting. The final prediction is determined through a majority voting mechanism across all decision trees in the ensemble.

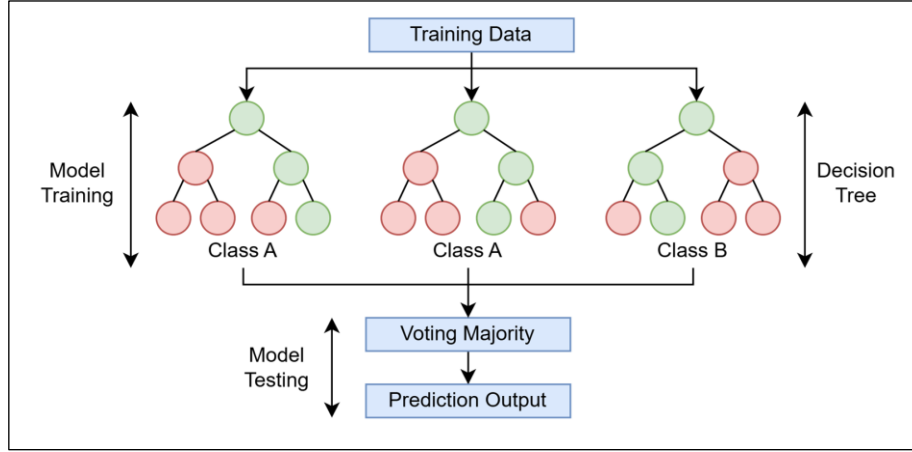


Figure 2: Random Forest Architecture.  
Source: Authors, (2026).

In the context of diabetes risk prediction, the model produces not only discrete class predictions (positive or negative) but also class probabilities that are used as risk scores [57],[58]. These probability values serve as the basis for the explainability process, as they enable the analysis of feature contributions to the predicted risk level. Within this study, Random Forest functions as the core component of the prediction layer, while the research novelty is centered on the integration of prediction results and their explanations (explainable outputs) into a blockchain-based system. Consequently, the machine learning model provides explainable decision outputs, whereas the blockchain ensures the integrity, traceability, and resistance to manipulation of both the predictions and their associated explanations.

### III.4 EXPLAINABLE ARTIFICIAL INTELLIGENCE COMPONENT (SHAP-BASED LOCAL AND GLOBAL EXPLANATION)

The Explainable Artificial Intelligence (XAI) component in this study serves as a critical link between black-box machine learning predictions and blockchain-based decision storage by providing interpretable explanations of model outputs. This component is based on SHapley Additive exPlanations (SHAP), which is employed to decompose each prediction into feature-level contributions that can be transparently recorded, verified, and audited. SHAP is selected due to its solid theoretical foundation, model-agnostic nature, and ability to generate consistent local explanations at the individual decision level, which is essential for medical auditability [59-61]. Conceptually, SHAP represents the prediction outcome as an additive combination of a baseline value and feature contributions. For a given input instance  $x$ , the model prediction can be expressed as Formula (1):

$$f(x) = f_0 + \sum_{j=1}^d \phi_j(x) \quad (1)$$

here  $f(x)$  denotes the model output,  $f_0$  represents the expected prediction over the background dataset,  $d$  is the number of input features, and  $\phi_j(x)$  corresponds to the contribution of the  $j$ -th feature to the prediction of instance  $x$ . This additive formulation ensures that individual feature effects are explicitly quantified and collectively reconstruct the original model output. In this study, the predictive model produces a probability score for the positive class (diabetes risk), which serves as the explained output. Accordingly, the prediction function analyzed by SHAP is defined as Formula (2):

$$f(x) = \hat{p}(y = 1 | x) \quad (2)$$

where  $\hat{p}(y = 1 | x)$  denotes the estimated probability of an individual being classified as diabetic. The resulting SHAP values indicate whether each feature increases or decreases the predicted risk relative to the baseline. Local explanations are generated by computing the SHAP value vector for each individual instance in the test dataset. This vector provides a patient-specific explanation that identifies the most influential features and the direction of their impact on the predicted risk.

It is important to emphasize that SHAP values reflect the predictive behavior of the trained model and do not imply causal medical relationships among variables. These local explanations are treated as first-class decision artifacts and constitute the primary explainability information associated with each prediction.

To support model-level interpretability, global explanations are derived by aggregating feature contributions across all evaluated instances. The global importance of feature  $j$  is computed as the mean absolute SHAP value, as shown in Formula (3):

$$\overline{\Phi_j} = \frac{1}{n} \sum_{i=1}^n |\Phi_j^{(i)}| \quad (3)$$

Where  $n$  denotes the number of instances in the test dataset and  $\Phi_j^{(i)}$  is the SHAP value of feature  $j$  for instance  $i$ . This metric is used to rank features according to their overall influence on model predictions and to assess alignment with known clinical risk factors. In the proposed Explainable Blockchain framework, only local SHAP-based explanations, which directly represent individual clinical decisions, are recorded on the blockchain, while global explanations are not stored on-chain because of their aggregate nature and lack of association with specific patient decision instances [62], [63]. This design ensures on-chain storage efficiency while preserving the relevance, traceability, and auditability of recorded decisions. Figure 3 illustrates the conceptual role of Explainable AI as an additional layer within the machine learning process that enables users to understand the rationale behind model decisions, why alternative outcomes were not selected, and under which conditions the predictions can be trusted, which serves as a prerequisite for persistently recording individual-level explanations in a blockchain-based system.

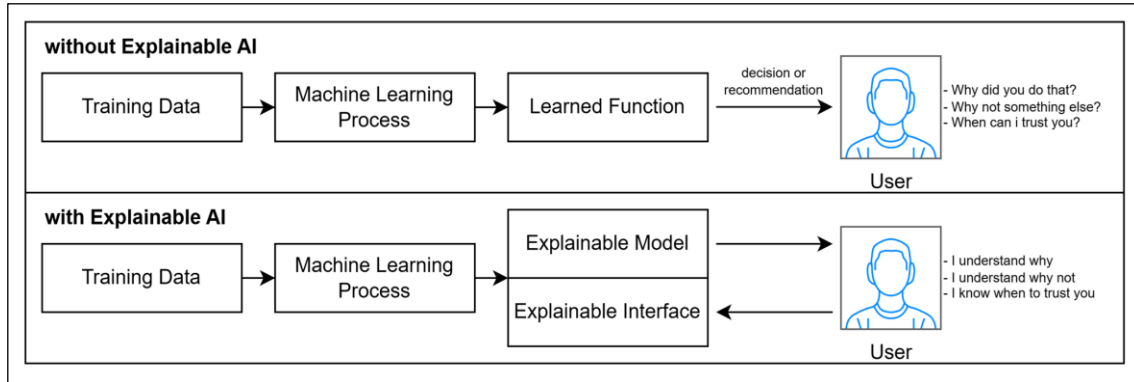


Figure 3: Conceptual Comparison Between Black-Box Models and Explainable AI-Based Decision Systems.  
Source: Authors, (2026).

### III.5 BLOCKCHAIN ARCHITECTURE AND SMART CONTRACT DESIGN

The blockchain architecture in this study is designed to support the storage of diabetes risk prediction decisions that are explainable, deterministic, and fully auditable. Ethereum is adopted as the underlying platform, with a private blockchain environment deployed on a local Ganache testnet. This setup enables controlled, reproducible experimentation while avoiding the cost and latency associated with public blockchain networks.

The core smart contract, named `ExplainableDiabetesDecision`, is implemented using the Solidity programming language and serves as the final execution layer for recording prediction decisions on-chain [64],[65]. The contract encapsulates deterministic logic for storing the risk score, decision label, summarized XAI explanation, and relevant metadata in an immutable manner. The high-level structure and key components of the smart contract implementation, which is compiled and deployed using the Remix IDE, are illustrated in Figure 4, which highlights the on-chain data structures and functions responsible for decision persistence and retrieval.

```
pragma solidity 0.8.19;
contract ExplainableDiabetesDecision {
    enum DecisionLabel { LOW_RISK, HIGH_RISK }
    struct Decision {uint256 risk; DecisionLabel label; string exp; string model; string xai; uint256 time; address sender; }
    mapping(bytes32 => Decision) public decisions;
    uint256 public constant RISK_THRESHOLD = 7000;
    event ExplainableDecisionStored(bytes32 indexed h, uint256 r, DecisionLabel d, string e, address indexed s, uint256 t );
    function storeDecision(bytes32 h, uint256 r, string calldata e) external {
        require(h != bytes32(0) && r <= 10000);
        DecisionLabel d = r >= RISK_THRESHOLD ? DecisionLabel.HIGH_RISK : DecisionLabel.LOW_RISK;
        decisions[h] = Decision(r, d, e, "RandomForest", "SHAP", block.timestamp, msg.sender );
        emit ExplainableDecisionStored(h, r, d, e, msg.sender, block.timestamp);
    }
    function calculateDecision(uint256 r) external pure returns (DecisionLabel) {
        return r >= RISK_THRESHOLD ? DecisionLabel.HIGH_RISK : DecisionLabel.LOW_RISK;
    }
}
```

Figure 4: Structure of the `ExplainableDiabetesDecision` Smart Contract.  
Source: Authors, (2026).

The overall blockchain implementation workflow, including importing Ganache wallets into MetaMask, compiling the Solidity code (Remix IDE), and deploying the smart contract using Ether provided by Ganache, is depicted in Figure 5. This workflow ensures that all transactions are executed through authenticated accounts and permanently recorded on the blockchain ledger [66],[67].

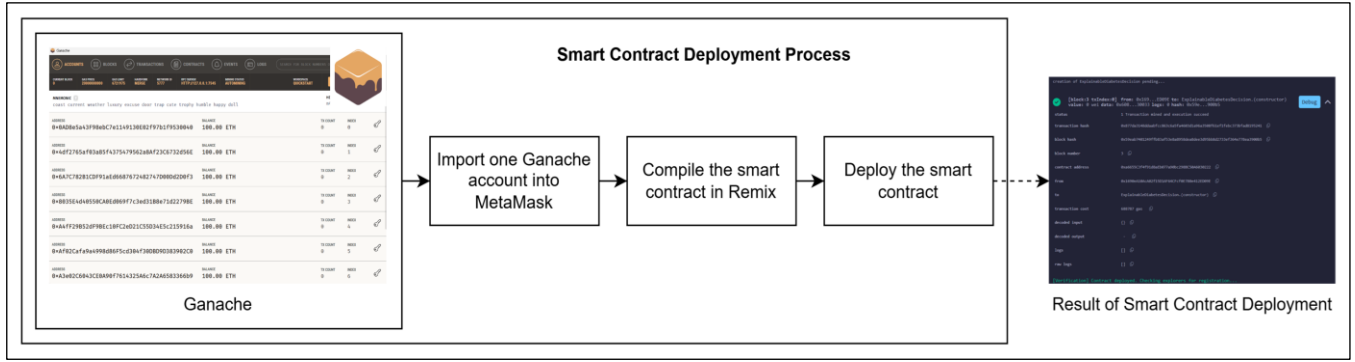


Figure 5: Smart Contract Deployment Flow on the Ethereum Test Network.

Source: Authors, (2026).

Conceptually, the diabetes risk decision is modeled as a deterministic function of the risk score generated by the machine learning model. The continuous prediction probability  $p(x) \in [0,1]$  is first transformed into an integer-valued representation to avoid floating-point operations in the blockchain environment, as defined in Formula (4):

$$r(x) = \lfloor 10000 \cdot p(x) \rfloor \quad (4)$$

where  $r(x)$  denotes the scaled risk score stored on-chain.

Decision labeling is performed using a fixed deterministic threshold ( $\tau = 7000$ ), corresponding to a probability of 0.7. The choice of this threshold follows common practice in clinical risk prediction systems, where relatively higher probability cutoffs are adopted to yield more conservative risk classifications and to reduce the likelihood of false negative outcomes, particularly for chronic diseases such as diabetes [68-70]. In this study, the threshold is treated as a deterministic system design parameter that reflects a clinically motivated trade-off between sensitivity and specificity, rather than a value optimized solely to maximize predictive performance. The on-chain decision function is expressed as a step function in Formula (5):

$$d(x) = \begin{cases} 1, & r(x) \geq \tau \\ 0, & r(x) < \tau \end{cases} \quad (5)$$

where  $d(x) = 1$  represents HIGH\_RISK and  $d(x) = 0$  represents LOW\_RISK. The threshold value is treated as a deterministic system design parameter to ensure consistency and reproducibility of on-chain decisions.

To preserve patient privacy, explicit patient identities are never stored on the blockchain. Instead, a one-way cryptographic hash function is applied to the patient identifier, as defined in Formula (6):

$$h = \mathcal{H}(\text{ID}_{\text{patient}}) \quad (6)$$

where  $\mathcal{H}(\cdot)$  denotes a cryptographic hash function and  $h$  serves as the primary key for decision storage.

The on-chain decision record can be represented as a deterministic mapping, as shown in Formula (7):

$$\mathcal{D}: h \rightarrow (r(x), d(x), e(x), m, a, t, s) \quad (7)$$

where  $e(x)$  denotes the summarized local XAI explanation,  $m$  the prediction model name,  $a$  the explainability method,  $t$  the block timestamp, and  $s$  the transaction sender address.

Auditability is further reinforced through event logging whenever a decision is stored. Each event can be modeled as a log tuple, as expressed in Formula (8):

$$\mathcal{E} = (h, r(x), d(x), e(x), s, t) \quad (8)$$

This mechanism enables off-chain verification and traceability of decisions without modifying the blockchain state, thereby maintaining efficiency while preserving immutability and accountability.

### III.6 INTEGRATION OF XAI OUTPUTS INTO THE BLOCKCHAIN (EXPLAINABLE BLOCKCHAIN-XBC)

The outputs of the Explainable Artificial Intelligence component are represented as local feature contribution vectors for each data instance, which are conceptually expressed as a set of feature–contribution pairs associated with the predicted diabetes risk probability, namely  $\langle (f_1, \phi_1), (f_2, \phi_2), \dots, (f_d, \phi_d) \rangle$ . The contribution values may be positive or negative, indicating the direction of risk increase or decrease relative to the model baseline. Consequently, this vector is instance-specific and serves as the primary basis for interpreting the corresponding prediction decision. To preserve efficiency, determinism, and privacy, the full feature contribution vector is not stored directly on the blockchain. Instead, this study adopts an explanation summarization mechanism by selecting features with the largest absolute contributions to the predicted risk and representing their directional influence.

This process yields a concise explanation summary that retains the core interpretative meaning while remaining stable and suitable for on-chain recording. As illustrated in Figure 6, the procedure encompasses the generation of the contribution vector, feature ranking, and the construction of a local explanation summary for blockchain integration.

|               |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                |
|---------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Input</b>  | : Test data instances, Trained Random Forest model, Predicted diabetes risk probability                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        |
| <b>Output</b> | : Local explanation summary based on feature contributions for each instance                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
| <b>Steps:</b> | <ol style="list-style-type: none"> <li>1. For each data instance, perform inference using the trained Random Forest model to obtain the predicted diabetes risk probability.</li> <li>2. Compute the contribution of each feature to the predicted risk probability using the SHAP approach, resulting in a local feature contribution vector.</li> <li>3. Represent the explanation results as a set of feature–contribution pairs, where the sign of each contribution indicates the direction of influence.</li> <li>4. Rank features according to the absolute values of their contributions to identify the most influential features.</li> <li>5. Select a subset of features with the largest contributions as the primary explanatory representation.</li> <li>6. Construct a local explanation summary that captures the dominant features and their directional effects on diabetes risk.</li> </ol> |

Figure 6: Formation of Explainable AI Outputs for Diabetes Risk Prediction.

Source: Authors, (2026).

Although Random Forest exhibits non-deterministic behavior during the training phase, the inference process and SHAP computation on a trained model are deterministic. As a result, the consistency of explanations recorded on-chain is preserved. The integration architecture between Explainable AI outputs and the blockchain is presented in Figure 7, which illustrates the data flow from model prediction, explanation summarization, to on-chain decision recording via smart contracts. This integration ensures that the association between risk scores, feature-based explanations, and final decisions is consistently maintained. From an implementation perspective, the integration process is carried out using the Python Web3 interface, which acts as a bridge between off-chain computational components and on-chain execution, as depicted in the system architecture shown in Figure 8 [71-73].

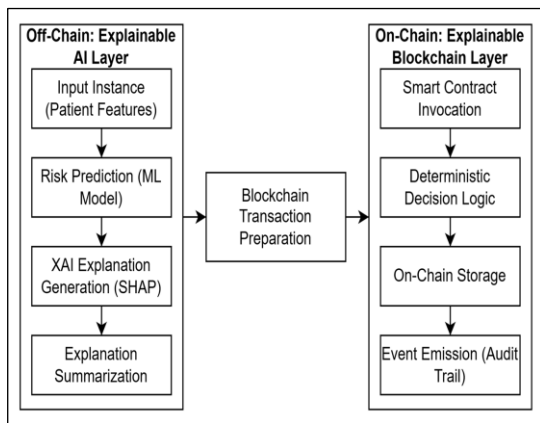


Figure 7: Integration of Explainable AI Outputs and Blockchain.

Source: Authors, (2026).

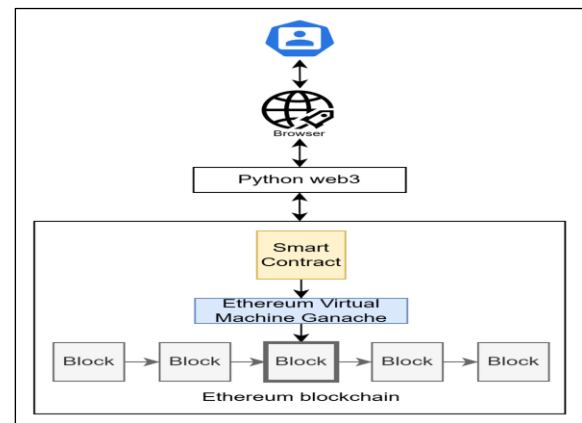


Figure 8: System Architecture for XAI–Blockchain Integration

Using Python Web3.

Source: Authors, (2026).

The mechanism for recording explanation summaries and risk values on the blockchain is summarized in Figure 9. This algorithm describes how predicted risk probabilities are transformed into scaled risk scores, combined with explanation summaries and anonymized patient identifiers, and then deterministically processed by the smart contract to produce immutable and auditable risk decisions.

|               |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 |
|---------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Input</b>  | : Predicted diabetes risk probability for each instance, Local explanation summary based on feature contributions, Deterministic risk threshold, Anonymized patient identifier                                                                                                                                                                                                                                                                                                                                                                                  |
| <b>Output</b> | : Explainable and immutable diabetes risk decision records on the blockchain                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    |
| <b>Steps:</b> | <ol style="list-style-type: none"> <li>1. Transform the predicted diabetes risk probability into a scaled integer-valued risk score.</li> <li>2. Use a cryptographic hash of the patient identifier as a unique decision reference.</li> <li>3. Submit the scaled risk score and explanation summary to the smart contract.</li> <li>4. Recompute the risk decision label on-chain using a deterministic threshold.</li> <li>5. Store the risk value, decision label, explanation summary, timestamp, and transaction information on the blockchain.</li> </ol> |

Figure 9: Integration of XAI Outputs into the Blockchain (Explainable Blockchain).

Source: Authors, (2026).

### III.7 EXPERIMENTAL DESIGN AND EVALUATION PROTOCOL

The dataset is divided using a hold-out scheme, with 80% of the samples allocated for training and 20% for testing. A stratified splitting strategy is applied to preserve the original class distribution of diabetes risk across both subsets. During the inference stage on the test data, local SHAP-based explanations are generated for each instance and subsequently summarized by selecting features with the largest absolute contribution values [74],[75]. This process yields a compact and stable explanation representation suitable for on-chain integration. The evaluation of the machine learning model is restricted to two standard classification metrics: accuracy (the proportion of correctly classified instances out of all test samples) and the area under the receiver operating characteristic curve (AUC, which measures the model's ability to distinguish between high-risk and low-risk classes across various probability thresholds). These metrics serve only as supporting evidence of adequate predictive capability, as the primary focus of this study lies in explainability, system integration, and auditability rather than classification performance optimization [76], [77].

Furthermore, no quantitative or user-based evaluations of explanation quality were conducted, given that the core contribution centers on the architectural integration of XAI and blockchain for verifiable decision trails. In addition to model performance, this study introduces the ML-to-chain consistency metric to quantify the agreement between decision labels generated off-chain by the machine learning model and those recorded on-chain by the smart contract. This metric is defined in Formula (9):

$$\text{Consistency} = \frac{1}{N} \sum_{i=1}^N I(\widehat{y}_i^{\text{off}} = \widehat{y}_i^{\text{on}}) \quad (9)$$

where  $N$  denotes the number of test instances and  $I(\cdot)$  represents the indicator function. Blockchain performance is evaluated using two operational metrics, namely transaction latency and gas consumption. Transaction latency for the  $i$ -th instance is defined as the time difference between transaction submission and confirmation, as expressed in Formula (10):

$$\text{Latency}_i = t_i^{\text{mined}} - t_i^{\text{sent}} \quad (10)$$

Gas consumption values are obtained directly from the transaction receipt and represent the number of gas units required to store a single explainable decision on the blockchain. Here  $\widehat{y}_i^{\text{off}}$  and  $\widehat{y}_i^{\text{on}}$  denote off-chain and on-chain decision labels. For latency measurement,  $t_i^{\text{sent}}$  and  $t_i^{\text{mined}}$  represent the transaction submission and confirmation times, respectively. These metrics collectively assess the feasibility and determinism of the XBC pipeline in a controlled environment. All experiments are conducted on a single device within a controlled environment to ensure full reproducibility. Detailed hardware specifications, software configurations, and experimental settings are summarized in Table 3.

Table 3: Experimental Environment Specifications.

| Aspect                  | Specification                          |
|-------------------------|----------------------------------------|
| Processor               | AMD Ryzen 5 6600H (12 CPUs), ~3.30 GHz |
| Memory                  | 16 GB RAM                              |
| Operating System        | Windows 11 64-bit                      |
| Programming Language    | Python 3.11                            |
| Smart Contract Language | Solidity 0.8.19                        |
| Blockchain Network      | Ethereum testnet (Ganache)             |

Source: Authors, (2026).

#### IV. RESULTS AND DISCUSSIONS

This chapter presents the experimental results and a systematic analysis of the Explainable Blockchain (XBC) architecture developed for diabetes risk prediction, with the evaluation focused on three main aspects: machine learning model performance, the clarity and traceability of Explainable AI-based explanations, and the efficiency and determinism of blockchain execution. The evaluation was conducted using 154 test samples processed by a Random Forest model and explained using the SHAP approach, such that each prediction produced a decision artifact that is not only quantitative but also structurally explainable. All outputs were subsequently recorded as individual transactions on a private Ethereum network based on Ganache, enabling direct observation of the stability of the end-to-end pipeline, from off-chain inference to immutable and auditable on-chain decision storage.

A summary of the integration results between diabetes risk prediction, SHAP-based local explanations, and on-chain recording is presented in Table 4, which shows a representative sample of the 154 test instances. The table explicitly links the patient index to the scaled risk score (0–10000), the deterministic decision label (HIGH\_RISK or LOW\_RISK), the three dominant features along with the direction of their contributions (+ or –), and two blockchain operational metrics, namely gas used and latency in seconds. This table structure allows readers to directly observe how machine learning model outputs are translated into blockchain records that simultaneously incorporate predictive, explanatory, and technical elements within a single row per patient.

Table 4: Local Explanation and Blockchain Summaries.

| Patient Index | Risk Score Scaled | Decision Label | Top Features (Direction)              | Gas Used | Latency (s) | Block Number | Patient Hash                                                       |
|---------------|-------------------|----------------|---------------------------------------|----------|-------------|--------------|--------------------------------------------------------------------|
| 0             | 7300              | HIGH_RISK      | Glucose (+), BMI (–), Age (+)         | 46,600   | 0.0657      | 158          | 0xa91f32c30547135498ac8474973825c5e66391000d3a2736fad2c9d86d97651a |
| 1             | 1100              | LOW_RISK       | Glucose (–), Insulin (–), DPF (–)     | 52,045   | 0.0584      | 159          | 0x741cda503f58b3ff1e1c3dca3d1511e2d97fb735feb135e9a02f8dd60b612676 |
| 2             | 900               | LOW_RISK       | Glucose (–), Age (–), Pregnancies (–) | 51,841   | 0.0536      | 160          | 0xc3d00a40215c1c6ac71ac8549b60d2faace334d4159370173cca9174e0e5e0f7 |
| ...           | ...               | ...            | ...                                   | ...      | ...         | ...          | ...                                                                |
| 152           | 8700              | HIGH_RISK      | Glucose (+), DPF (–), Age (+)         | 51,987   | 0.0684      | 310          | 0xcc08a44064af3940ff42f0f50f605ccc157243a7a6694a5d5dbd238e23678a97 |
| 153           | 200               | LOW_RISK       | Glucose (–), Insulin (–), Age (–)     | 51,781   | 0.0549      | 311          | 0x76e1e29e1afc42859172e22558889a967a78e8b8d9207799b51825314ffae679 |

Source: Authors, (2026).

Each row in Table 4 demonstrates perfect alignment between the numerical risk score and the decision label generated by the smart contract using a fixed threshold of 7000. The variation of dominant features across patients—for example, Glucose (+) in high-risk cases and Glucose (−) in low-risk cases—indicates that the explanation summaries are instance-specific rather than fixed patterns. This characteristic confirms that the summarized SHAP mechanism preserves locally relevant information for patient-level clinical interpretation, even though only the top three features are recorded to maintain on-chain efficiency. The recording of 154 explainable decisions on the blockchain did not introduce any inconsistencies between off-chain inference results and on-chain execution, as evidenced by the alignment of scores and labels across all samples. Gas consumption per transaction ranged from 46,600 to 52,045 units, and latency ranged from 0.0536 to 0.0684 seconds, with limited variation and no strong correlation with the complexity of the explanation summary.

This range indicates that the smart contract design and summarization strategy successfully kept computational overhead under control in a private testnet environment, although the gas consumption remains relatively high compared to simple blockchain transactions and may be costly on public networks without further optimization. The analysis of the experimental results is visualized through two main components, namely the global explainability of the model and the consistency of decisions between the off-chain and on-chain environments, as illustrated in Figure 10 and Figure 11, respectively. Figure 10 presents the aggregation of absolute SHAP values as a representation of global feature contributions, while Figure 11 illustrates the alignment between machine learning model inference results and the re-execution of decision logic within the blockchain smart contract. In this context, predictive performance metrics such as an accuracy of 0.7468 and an AUC value of 0.8118 are presented as supporting information to demonstrate that the model possesses adequate discriminative capability, although performance evaluation is not the primary focus of this study, which emphasizes transparency, explainability, and decision auditability.

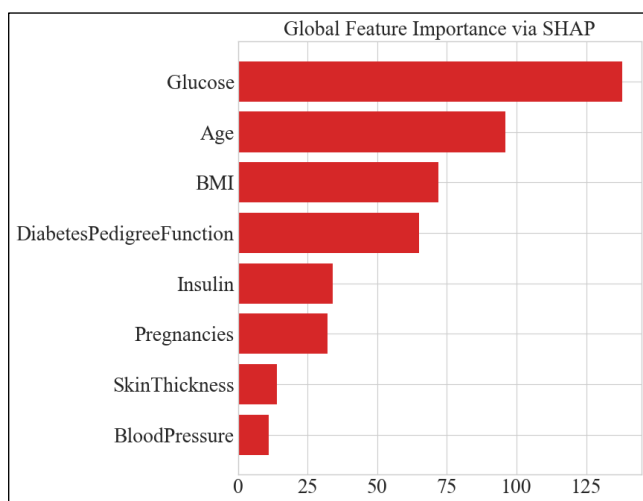


Figure 10: Global Explainability – Top-5 Features.  
Source: Authors, (2026).

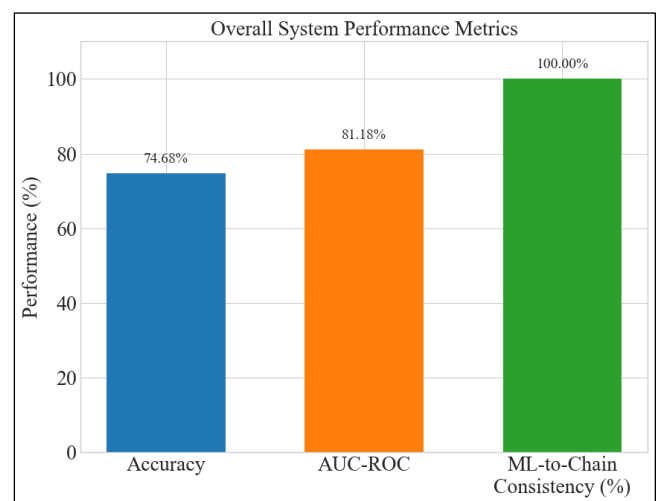


Figure 11: Performance and Consistency Metrics.  
Source: Authors, (2026).

The aggregation results of SHAP values indicate that the five features with the greatest global influence on diabetes risk prediction are Glucose, BMI, Age, Diabetes Pedigree Function, and Insulin. The dominance of the Glucose feature, with the highest contribution value, reflects the model's sensitivity to physiologically relevant variables while also indicating that the employed non-linear learning mechanism preserves a decision-making structure aligned with established medical knowledge. This analysis confirms that SHAP values function not only as a technical interpretation tool but also as a semantic bridge connecting model outputs with the healthcare domain context, without claiming causal relationships beyond the scope of predictive methodology. However, in relatively small medical datasets such as the Pima Indians Diabetes Dataset (768 samples), SHAP values are more susceptible to higher variability due to sampling noise and class imbalance, and therefore global interpretation should be conducted cautiously and ideally validated using bootstrapping techniques or larger external datasets to improve the reliability of feature contribution estimates. Another crucial aspect illustrated in Figure 11 is the complete consistency between decisions generated off-chain and those recorded on-chain, represented by an ML-to-chain consistency metric value of 1.0, which confirms that the processes of risk probability transformation, score scaling, and deterministic threshold application within the smart contract do not introduce decision discrepancies or additional computational artifacts.

As a result, the integration between the machine learning model and the blockchain can be viewed as a stable deterministic mapping in which each predictive decision can be independently reproduced and verified, emphasizing that the system's primary contribution lies in ensuring the integrity and traceability of AI-driven decisions rather than solely optimizing performance metrics, thereby reinforcing the role of Explainable Blockchain for medical applications requiring high accountability. In addition, the distribution of blockchain operational performance for the 154 explainable transactions is visualized in Figure 12 and Figure 13, where Figure 12 presents the transaction latency sequence from the first to the last patient and Figure 13 shows the gas consumption per transaction executed by the ExplainableDiabetesDecision smart contract, together illustrating temporal patterns and computational load across the entire decision-recording process and enabling a direct assessment of performance consistency within the private Ganache testnet environment.

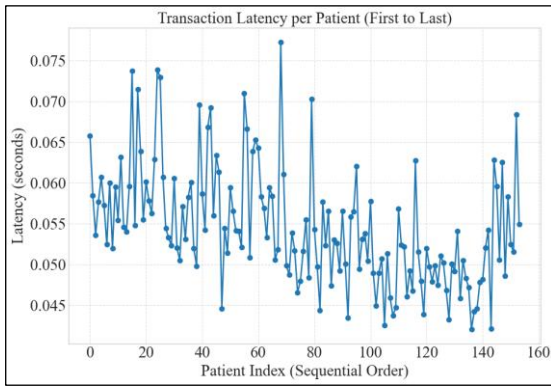


Figure 12: Transaction Latency per Patient (First to Last).  
Source: Authors, (2026).

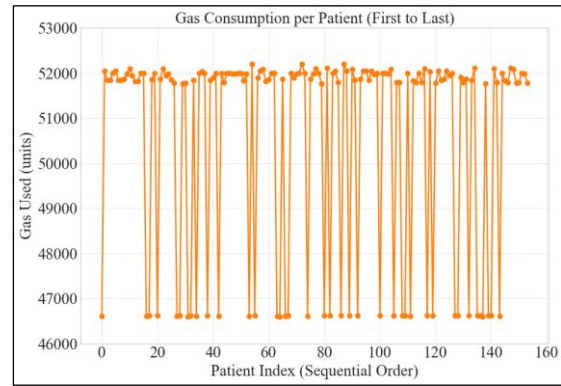


Figure 13: Gas Consumption per Patient (First to Last).  
Source: Authors, (2026).

Latency measurements range from 0.043 to 0.077 seconds, with an average of 0.0546 seconds across all samples, indicating that block confirmation times in the private network remain stable even when transactions are submitted sequentially. For medical decision-support applications, latencies below 100 milliseconds are sufficiently low to support batch processing or near real-time recording, especially since the blockchain functions as an auditing layer rather than the primary clinical inference pathway, which would otherwise require sub-millisecond responsiveness. Gas consumption per transaction lies within the range of 51,000 to 52,000 units, which is moderate to high compared to basic blockchain operations such as simple value transfers or minimal data storage. This gas usage is mainly driven by the permanent storage of state elements, including the scaled risk score, decision label, model metadata, and the string-based explanation summary of the top three features. The consistency of gas values across transactions indicates that variations in explanation string length do not cause significant increases in computational overhead.

At this level of gas consumption, deployment on the public Ethereum network could result in financially impractical costs for large-scale clinical decision logging, highlighting a trade-off between the depth of explainable information stored on-chain and the resource limitations of current layer-1 blockchain infrastructures. Although the proof-of-concept architecture demonstrates determinism and traceability of AI-driven decisions in a controlled environment, further optimization is required for real-world healthcare deployment, including layer-2 solutions, stronger data compression, or hybrid storage mechanisms. The evaluation of blockchain operational efficiency was performed by analyzing gas consumption and transaction latency distributions across 154 explainable decision records, as shown in Figure 14 and Figure 15, where Figure 14 depicts gas usage per transaction and Figure 15 shows latency in seconds, together supporting assessment of performance consistency and potential scalability bottlenecks within the private Ganache testnet environment.

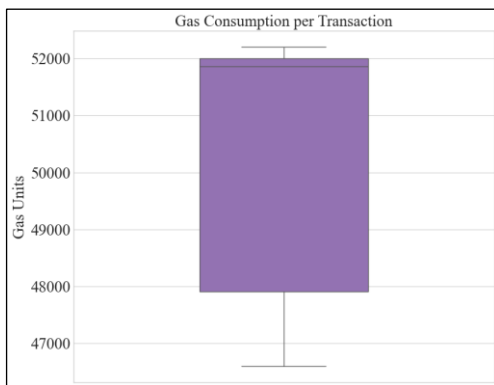


Figure 14: Gas Consumption per Transaction.  
Source: Authors, (2026).

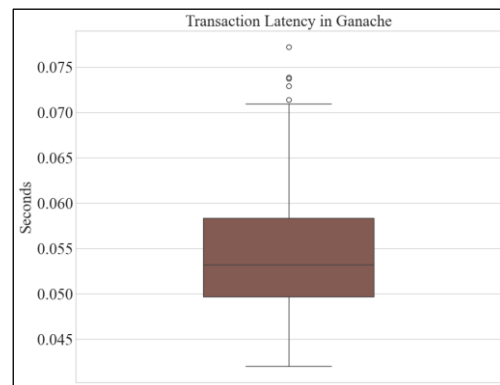


Figure 15: Transaction Latency Distribution.  
Source: Authors, (2026).

Gas consumption statistics show a minimum of 46,598 units, a maximum of 52,202 units, a median of 51,865 units, a first quartile of 47,909 units, a third quartile of 51,997 units, and an average of 50,595 units. The relatively narrow interquartile range of approximately 4,088 units indicates that the central 50 percent of transactions fall within a constrained interval, with variation mainly caused by minor differences in the length of explanation summary strings rather than changes in data structure or smart contract logic. Transaction latency ranges from a minimum of 0.0420 seconds to a maximum of 0.0772 seconds, with a median of 0.0533 seconds, a first quartile of 0.0497 seconds, a third quartile of 0.0584 seconds, and an average of 0.0546 seconds. The median being lower than the mean indicates a distribution skewed toward lower values, meaning most transactions complete faster than the average with only minor upper-end outliers.

Together, these statistics demonstrate that the Explainable Blockchain architecture in this Ganache-based proof-of-concept delivers stable and consistent performance across 154 transactions, with no significant upward trends in gas consumption or latency over time, while the average gas usage above 50,000 units implies substantial cost concerns on the public Ethereum network, positioning this approach as more suitable for private auditing systems or requiring on-chain data reduction techniques for large-scale clinical applications. This study's primary contribution is the development of an Explainable Blockchain architecture that integrates Random Forest based diabetes risk prediction with summarized local SHAP explanations permanently recorded on an Ethereum smart contract.

The system successfully recorded 154 explainable decisions with an ML to chain consistency of 1.0, providing an immutable, deterministic, and pseudonymized audit trail for each prediction. By combining explanatory transparency with distributed ledger data integrity and using identifier hashing, this approach addresses black box limitations in healthcare while supporting clinical accountability and trust without compromising patient privacy. Despite stable operational performance on the private Ganache testnet, the average gas consumption of 50,595 units per transaction remains high compared to simple blockchain operations, which may be economically impractical on the public Ethereum network for large scale clinical logging. In addition, reliance on the relatively small and imbalanced Pima Indians Diabetes Dataset with 768 samples makes both local and global SHAP estimates vulnerable to sampling noise, indicating that feature contribution interpretations require further validation through external datasets or resampling techniques.

Further limitations include fluctuating gas costs and longer block times under public network conditions, as well as reduced interpretative depth caused by restricting on chain explanation summaries to the top three SHAP features when lower ranked features may still have meaningful contributions. Nevertheless, these limitations do not detract from the study's core objective of providing an immutable, deterministic, and pseudonymized audit trail for each predictive decision, since the recorded summaries remain instance specific and independently verifiable via the smart contract. Future work should evaluate the architecture on public testnets or layer 2 solutions such as Polygon or Optimism to assess latency, gas costs, and scalability under realistic conditions, while also exploring on chain data compression or hybrid storage strategies to reduce overhead without sacrificing auditability [78],[79]. Additional validation using larger and more diverse medical datasets, along with comparisons to alternative explainable AI methods, is required to strengthen generalizability and support broader clinical adoption.

## V. CONCLUSIONS

This study successfully demonstrated the Explainable Blockchain (XBC) framework, which seamlessly integrates Random Forest-based diabetes risk prediction with local SHAP explanations and immutable on-chain storage via Ethereum smart contracts, achieving an accuracy of 74.68%, AUC of 0.8118, and perfect ML-to-chain consistency (100%) while maintaining low latency (average 54.6 ms) and manageable gas costs in a private testnet environment. The primary scientific contribution lies in pioneering an architecture that bridges explainable AI and blockchain at the individual decision level, providing a tamper-proof, pseudonymized audit trail that enhances transparency, accountability, and regulatory compliance in AI-driven healthcare—addressing critical gaps in black-box model interpretability and verifiable decision provenance.

Practically, this framework holds promise for clinical decision support systems, enabling clinicians, patients, and regulators to independently verify AI predictions without compromising privacy, thereby fostering greater trust and potential adoption in resource-constrained settings. However, limitations include reliance on a small, imbalanced dataset leading to potential SHAP variability, high gas consumption unsuitable for public networks at scale, and partial explanatory depth due to summarization of only top features. Future research should validate the approach on larger, diverse clinical datasets, explore layer-2 optimizations or hybrid storage for cost-efficiency, and compare with alternative XAI methods to advance scalable, real-world deployment in healthcare AI applications.

## VI. AUTHOR CONTRIBUTIONS

**Conceptualization:** Michael Angello Qadosy Riyadi, Yohanes Setiawan and Muhammad Adib Kamali.

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**Discussion of results:** Michael Angello Qadosy Riyadi, Yohanes Setiawan and Muhammad Adib Kamali.

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**Writing – Review and Editing:** Yohanes Setiawan and Muhammad Adib Kamali.

**Resources:** Michael Angello Qadosy Riyadi, Yohanes Setiawan and Muhammad Adib Kamali.

**Supervision:** Michael Angello Qadosy Riyadi.

**Approval of the final text:** Michael Angello Qadosy Riyadi, Yohanes Setiawan and Muhammad Adib Kamali.

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