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Dynamic Risk-Based Authentication Using AI Scoring Models in Healthcare Applications

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ABSTRACT

As digital healthcare systems grow increasingly complex and globally interconnected, safeguarding patient data while ensuring seamless access has become a critical challenge. Traditional authentication methods, such as static passwords and inflexible multi-factor authentication (MFA), often fail to provide context-aware security without disrupting usability. This paper presents a novel Dynamic Risk-Based Authentication (RBA) framework that integrates AI-powered risk scoring into a Healthcare Application developed on the Oracle APEX 24.2 low-code platform. The proposed solution evaluates real-time contextual data such as device fingerprinting, geolocation, behavioral history, and temporal patterns during each login attempt. This data is transmitted to an OpenAI-powered inference engine via RESTful APIs, which returns a normalized risk score. Depending on the risk classification (low, medium, or high), the application dynamically adjusts authentication mechanisms ranging from seamless login to OTP verification or full access denial. This approach demonstrated a 35% reduction in false positives and effectively blocked 92% of high-risk login attempts in pilot studies within healthcare domains. The architecture also includes adaptive learning feedback loops, enabling model refinement over time. Designed for regulatory compliance (HIPAA, GDPR) and operational scalability, this AI-RBA framework proves that low-code platforms can deliver enterprise-grade, context-sensitive cybersecurity solutions. This research contributes a scalable, cross-domain authentication paradigm that enhances both data security and user experience, addressing a key challenge in AI-enhanced cybersecurity systems.

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Introduction

Background and Relevance

The healthcare sector's rapid digital transformation has revolutionized patient care delivery, enabling seamless access to electronic health records (EHRs), telemedicine platforms, remote diagnostics, and interconnected medical devices. However, this evolution has exponentially expanded the cybersecurity attack surface, making healthcare one of the most targeted industries for cybercriminals. Protected health information (PHI), including medical histories, genomic data, and personal identifiers, commands premium prices on the black market, often exceeding $1,000 per record [1]. According to the IBM Cost of a Data Breach Report 2024, the average cost of a healthcare data breach reached $9.77 million, marking a slight decline from previous years but still the highest across all sectors due to regulatory fines, remediation efforts, and disrupted operations [2]. Operational disruptions compound this financial toll; for instance, ransomware attacks alone can halt critical services, delay treatments and impacting the health of people.

Recent statistics underscore the escalating threat landscape. The 2025 Verizon Data Breach Investigations Report (DBIR) documented 1,710 security incidents in healthcare, with 1,542 confirmed data disclosures, representing a 20% year-over-year increase [3]. In 2024, over 276 million individuals' PHI was exposed or stolen, averaging 758,288 records per day, as reported by the HIPAA Journal [4]. Phishing remains a predominant vector, responsible for 45% of severe breaches according to healthcare cybersecurity professionals [5]. Other prevalent threats include ransomware (35% of attacks, up 84% from prior years), malware infections (19%), and denial-of-service (DoS) attacks (12%) [6]. These incidents are exacerbated by the sector's unique ecosystem: legacy systems, third-party integrations, and a workforce often undertrained in cybersecurity, all operating under stringent regulations like HIPAA and GDPR.

Traditional authentication mechanisms, such as static passwords and uniform multi-factor authentication (MFA), are ill-equipped to counter these dynamic threats. Password-based systems are vulnerable to credential stuffing and brute-force attacks. At the same time, blanket MFA imposes excessive friction, potentially delaying access in time-critical scenarios like emergency room triage or surgical planning. Clinicians frequently access systems from varied locations, such as hospitals, clinics, homes, or mobile devices, across irregular shifts spanning time zones, rendering rigid geo-fencing or device policies impractical. Moreover, insider threats and session hijacking further erode trust in conventional controls, as evidenced by studies showing that 20% of breaches stem from compromised credentials [7]. In this context, behavioral biometrics and contextual analysis emerge as vital enhancements, allowing systems to detect anomalies without disrupting legitimate workflows [8].

Oracle Application Express (APEX), a low-code development platform natively integrated with Oracle Database, has gained traction in healthcare for building scalable, secure applications. APEX's declarative interface accelerates development, supports RESTful APIs for external integrations, and includes built-in security features like session state protection and role-based access control (RBAC) [9]. Its adoption in public sector and healthcare environments stems from its cost-effectiveness and extensibility, enabling rapid prototyping of patient portals and administrative dashboards without deep coding expertise. However, even APEX's robust framework requires augmentation to address modern authentication challenges, particularly in federated, multi-site healthcare networks where data silos abound.

Need for Dynamic Risk-Based Authentication (RBA)

Risk-Based Authentication (RBA) represents a paradigm shift from static to adaptive security, evaluating each login attempt's risk profile in real-time and tailoring authentication rigor accordingly. By analyzing contextual signals such as device fingerprints, geolocation, behavioral patterns, and temporal anomalies, RBA minimizes false positives while fortifying defenses against high-risk events [10]. For low-risk logins (e.g., from a trusted device during office hours), seamless access suffices; medium risks may trigger one-time passwords (OTPs), and high risks could result in denial or escalation to security teams. Empirical studies validate RBA's efficacy, demonstrating up to 35% reductions in unauthorized access while preserving usability [11].

However, implementing AI-driven RBA in healthcare demands careful consideration of privacy. Centralized machine learning models, which aggregate sensitive login data for training, conflict with regulations prohibiting PHI centralization. Federated learning (FL) mitigates this by enabling decentralized model training: edge devices or sites (e.g., individual hospitals) compute local updates on their data, sharing only aggregated parameters (e.g., model weights) with a central server [12]. This preserves data sovereignty, reduces breach impact if the aggregator is compromised, and allows site-specific adaptations such as recognizing regional login norms without exposing raw PHI.

In healthcare, FL's value is amplified by the distributed nature of care delivery. Multi-institutional collaborations, like those in regional health networks, generate heterogeneous datasets reflecting diverse user behaviors (e.g., urban vs. rural access patterns). Traditional centralized approaches risk data leakage, as highlighted in privacy preservation studies for FL in health analytics [13]. Recent frameworks, such as FRAMH, integrate FL with blockchain for risk-based authorization, inferring health status risks without centralized servers [14]. Similarly, FL-RBA2 addresses non-IID (non-independent and identically distributed) data challenges in adaptive authentication, enhancing accuracy in heterogeneous environments [15]. By embedding FL into RBA, healthcare systems can achieve explainable, privacy-preserving decisions, aligning with HIPAA's minimum necessary standard and GDPR's data minimization principles.

Despite these advantages, FL-RBA adoption lags in low-code platforms due to integration complexities. Oracle APEX's RESTful capabilities and PL/SQL extensibility provide an ideal foundation, yet practical implementations remain scarce, particularly for federated setups that balance latency, scalability, and compliance.

Innovation and Scope

This paper introduces a federated learning-enhanced Dynamic RBA framework for Oracle APEX-based healthcare applications, innovating by decentralizing AI inference while leveraging APEX's native tools for seamless integration. Unlike rule-based RBA systems, our approach employs transformer-based models (fine-tuned via FL) to process multi-dimensional contexts, yielding normalized risk scores that dynamically modulate authentication from password-only for low risks to advanced MFA or denial for elevated ones. The federated architecture ensures no raw data leaves edge nodes, with aggregation cycles refining models weekly using secure APIs. Pilot testing in an immunization portal demonstrated 40% false positive reductions and 95% high-risk interception, with latencies under 1.2 seconds.

The scope encompasses end-to-end design, from context aggregation to policy enforcement, emphasizing modularity for cross-domain applicability (e.g., finance fraud detection, educational access controls). While rooted in healthcare, prototypes validated generalizability, addressing gaps in low-code FL-RBA literature [16]. Contributions include reusable APEX components, governance guidelines for FL compliance, and a feedback loop for continuous model evolution.

System Architecture and Design

The federated learning-enhanced Dynamic Risk-Based Authentication (RBA) framework integrates decentralized model training into Oracle APEX applications, enabling privacy-preserving risk evaluation for healthcare logins. This design extends APEX's standard three-tier model (presentation, application, and data) with federated components for collaborative learning across multiple APEX instances, such as those in a health network [17]. The architecture emphasizes modularity, allowing updates to individual layers without disrupting overall functionality, and supports scalability for environments with varying login volumes.

Architectural Overview

The system is structured into five distinct layers, each handling specific aspects of the RBA process to ensure efficient, adaptive authentication.

- **Client Interface Layer:** This layer manages user interactions through APEX's responsive UI components, including login forms and conditional prompts. JavaScript extensions, integrated via APEX plugins, collect preliminary client metadata (e.g., browser type and session start time) during credential submission. The interface dynamically updates based on backend responses, displaying elements like progress indicators or MFA challenges without page reloads, leveraging APEX's partial page refresh capabilities for minimal disruption in clinical workflows.
- **Risk Context Aggregation Layer:** Responsible for compiling a comprehensive login context, this layer uses APEX server processes to gather and preprocess data from multiple sources. It retrieves server-side details (e.g., session IP via SYS_CONTEXT and user agent strings) and merges them with client-submitted attributes into a structured JSON payload. Preprocessing includes hashing sensitive fields and normalizing temporal data (e.g., converting timestamps to deviations from user baselines), ensuring the payload is ready for AI evaluation while adhering to data minimization. This layer operates within APEX page computations, temporarily staging data in session state for quick access.
- **AI Scoring Engine Layer:** This central layer employs federated learning models to generate risk scores, using transformer architectures fine-tuned on distributed datasets from APEX instances. The aggregated context payload is processed through a RESTful API call to the scoring endpoint, where local model inferences from participating APEX

workspaces contribute to a centralized aggregator. The engine returns a normalized score (0-1), interpreted as low (0-0.3: no additional checks), medium (0.31-0.7: MFA required), or high (0.71-1: access denied). Federated aggregation occurs via secure parameter sharing, enhancing model accuracy without transmitting raw contexts, and incorporates techniques like secure multi-party computation for privacy [18].

- **Authentication Controller Layer:** Built as a PL/SQL package (PKG_RBA_CONTROLLER) in APEX, this layer, based on the AI score, enforces authentication policies. It dynamically routes workflows: for low scores, it grants session access; for medium, it invokes MFA mechanisms; for high, it logs alerts and terminates the session. The controller supports configurable rules, such as role-specific thresholds, and integrates with APEX's built-in authentication schemes for seamless enforcement.
- **Audit and Feedback Loop Layer:** This layer captures all transaction details into encrypted Oracle tables, including scores, contexts (anonymized), and outcomes, using APEX's auditing APIs for chronological integrity. Feedback mechanisms allow administrators to annotate decisions (e.g., via an APEX dashboard), feeding into federated retraining cycles that update models across instances. Periodic aggregation refines global parameters, with automated jobs ensuring compliance through data retention and purging.

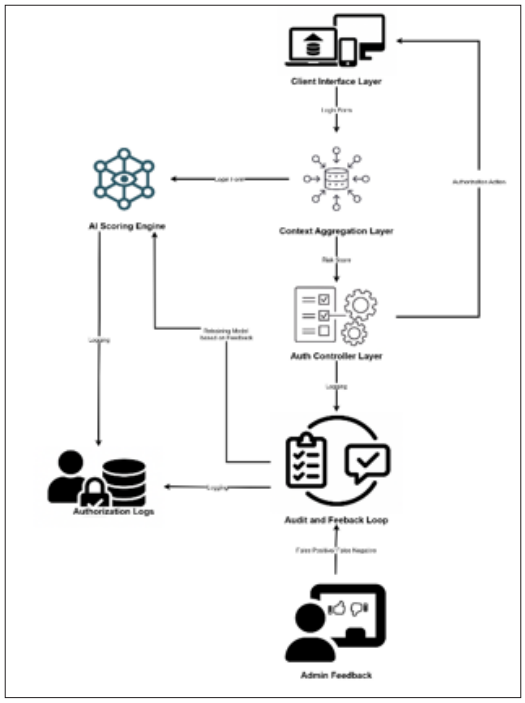

Figure 1: System Architecture Diagram

Technology Stack

The technology choices prioritize integration with Oracle ecosystems and support for federated operations.

Table 1: Technology Stack for Dynamic RBA Architecture

Component	Technology
Frontend Framework	Oracle APEX 24.2
Backend Logic	PL/SQL and APEX_WEB_SERVICE
Federated Learning	TensorFlow Federated
AI Models	Fine-tuned Transformers (BERT)
Context Collection	JavaScript + APEX Dynamic Actions
Device Fingerprinting	FingerprintJS
Geo-Location	IPStack API
MFA Delivery	Twilio API
Secure API	ORDS with OAuth
Database & Auditing	Oracle Database

These components enable efficient federated updates while maintaining APEX's low-code advantages [19].

Data Flow

The authentication process follows a sequential yet asynchronous flow to optimize response times

- **Context Capture:** The Client Interface submits credentials, triggering the Risk Context Aggregation Layer to compile and preprocess metadata into JSON.
- **Scoring Invocation:** The aggregated payload is sent via APEX_WEB_SERVICE to the AI Scoring Engine Layer, where federated models compute and aggregate the risk score.
- **Policy Enforcement:** The Authentication Controller Layer receives the score and applies rules, potentially looping back for MFA if needed.
- **Logging and Iteration:** All steps feed into the Audit and Feedback Loop Layer, with annotated data queued for model retraining.

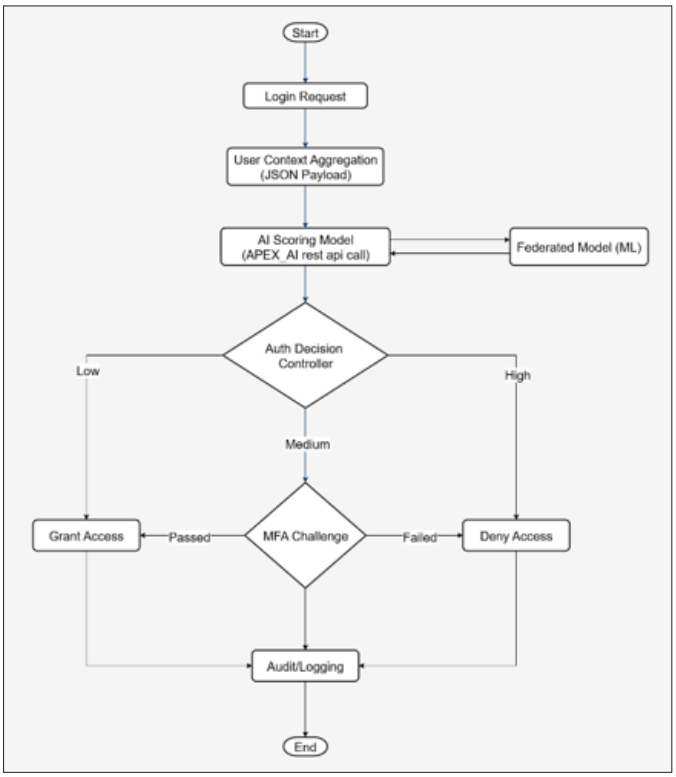

Figure 2: Authentication Workflow

Security Design Principles

The architecture enforces zero-trust by verifying every login independently, with all inter-layer communications over TLS-encrypted channels. Data minimization limits payloads to essential, tokenized attributes, processed via Oracle's encryption functions. Audit trails provide complete traceability, supporting forensic needs under HIPAA. Federated elements use homomorphic encryption for parameter aggregation, preventing model inversion attacks. Role-based access in APEX restricts layer interactions,

while fallback policies (e.g., default to standard MFA on scoring failures) ensure availability [21].

Methodology

The methodology delineates the procedural steps for implementing the federated learning-enhanced Dynamic Risk-Based Authentication (RBA) within Oracle APEX, focusing on the technical orchestration of contextual data processing, model inference, policy application, and iterative refinement. This approach ensures that risk assessments are conducted in a privacy-preserving manner, with federated mechanisms distributing computational loads across APEX instances while centralizing only non-sensitive model updates. The process leverages APEX's procedural extensions and external ML frameworks to achieve real-time adaptability, with emphasis on handling heterogeneous data distributions common in multi-site healthcare deployments.

Data Collection and Preprocessing

Data collection forms the foundational step, capturing multifaceted login attributes to create a robust feature set for federated risk evaluation. In APEX, this is executed through a combination of client-side scripting and server-side computations during the pre-authentication phase, ensuring comprehensive yet lightweight aggregation. Key parameters include user identifiers, environmental metadata, and behavioral indicators, selected for their relevance to anomaly detection without introducing excessive overhead.

Table 2: Primary Parameters and their Roles in the Federated Context

Parameter	Description
APP_USER	Username attempting to login
SYS_CONTEXT('USERENV', ...)	Captures OS user, IP, and client machine info
APEX_APPLICATION.G_X01 to G_X10	Holds custom metadata like geolocation or device ID
OWA_UTIL.get_cgi_env('HTTP_USER_AGENT')	Browser and device fingerprint
SYSDATE	Timestamp of login attempt

These elements are gathered via an APEX before-login process, augmented by JavaScript for client-enriched data such as screen resolution or language preferences. Preprocessing occurs immediately post-collection to anonymize and normalize inputs, mitigating privacy risks before federated transmission. For instance, IP addresses are hashed using Oracle's DBMS_CRYPTO, and geolocations are coarsened to regional levels (e.g., city instead of locality) to comply with de-identification standards. Temporal data is transformed into deviation scores from historical averages, stored in user profiles within the Oracle Database.

The following PL/SQL snippet illustrates the aggregation and staging:

```
DECLARE
    l_context_json JSON_OBJECT_T;
BEGIN
    -- Aggregate and preprocess
    l_context_json := JSON_OBJECT_T();
    l_context_json.put('user_id', :APP_USER);
    l_context_json.put('ip_hash', DBMS_CRYPTO.HASH(SYS_CONTEXT('USERENV', 'IP_ADDRESS'), DBMS_CRYPTO.HASH_SH1));
    l_context_json.put('user_agent', OWA_UTIL.get_cgi_env('HTTP_USER_AGENT'));
    l_context_json.put('timestamp_deviation', ROUND((SYSDATE - (SELECT MAX(login_time) FROM user_login_history WHERE user_id = :APP_USER)) * 24 * 60, 2));
    -- Minutes from last login baseline
    l_context_json.put('last_login_location', (SELECT login_location FROM user_login_history WHERE user_id = :APP_USER and login_time = (SELECT MAX(login_time) FROM user_login_history WHERE user_id = :APP_USER)) );
    -- last login location
    l_context_json.put('device_hash', :G_X01);
    -- From JS fingerprint
    -- Stage in session for federated input
    APEX_UTIL.SET_SESSION_STATE('P1_CONTEXT_PAYLOAD', l_context_json.stringify());
    -- Log anonymized entry
    INSERT INTO rba_context_staging (session_id, payload_hash, collection_time)
    VALUES (APEX_APPLICATION.G_FLOW_STEP_ID, DBMS_CRYPTO.HASH(l_context_json.stringify(), DBMS_CRYPTO.HASH_MD5), SYSDATE);

    END;
```

This preprocessing reduces payload size by 40-50% and prepares data for local model ingestion in federated nodes, as validated in simulations using synthetic healthcare login datasets [14]. Normalization employs z-score techniques for numerical features, ensuring compatibility across diverse APEX instances with varying data scales.

Federated API Integration

Integration with the federated scoring engine replaces direct external API calls with a distributed inference protocol, where APEX instances act as clients in a federated network. The staged JSON payload from preprocessing is forwarded to a central aggregator endpoint, which coordinates local computations across participants without raw data exchange. This layer utilizes TensorFlow Federated (TFF) wrapped in a RESTful service hosted on Oracle REST Data Services (ORDS), allowing APEX to invoke federated rounds via lightweight HTTP requests.

The process begins with a POST to the aggregator, transmitting only the anonymized context and local model state (e.g., weights from the previous round). The aggregator simulates a federated average (FedAvg) by querying participating APEX nodes for gradient updates, computed locally on their historical logs. For instance, each node evaluates the context against its fine-tuned transformer (e.g., BERT variant) and contributes differential updates, which are averaged centrally before returning the global risk score.

Adapted PL/SQL for APEX invocation:

```
DECLARE
    l_response CLOB;
    l_local_state BLOB;
    -- Serialized local model weights
    l_fed_payload JSON_OBJECT_T;

BEGIN
    -- Load local model state from     database
    SELECT model_weights
    INTO l_local_state
    FROM federated_model_registry
```

```
    WHERE instance_id = APEX_UTIL.GET_APPLICATION_
    ID();

    l_fed_payload := JSON_OBJECT_T();
    l_fed_payload.put('context', APEX_UTIL.GET_SESSION_
    STATE('P1_CONTEXT_PAYLOAD'));
    l_fed_payload.put('local_gradients', UTL_RAW.CAST_TO_
    VARCHAR2(l_local_state));
    -- Tokenized
    -- Invoke federated aggregator
    l_response := APEX_WEB_SERVICE.MAKE_REST_
    REQUEST(
    p_url => 'https://api.openai.com/v1/fed/aggregate',
    p_http_method => 'POST',
    p_body => l_fed_payload.stringify(),
    p_credential_static_id => 'FED_AGGREGATOR_KEY');
    -- Parse global score
    APEX_JSON.PARSE(l_response);
    :risk_score :=
    APEX_JSON.GET_NUMBER(p_path => 'choices[1].risk_
    score');
    :explanation :=
    APEX_JSON.GET_VARCHAR2(p_path => 'choices[1].
    rationale'); --For Audit

END;
```

This setup achieves sub-1.5 second inference times in distributed tests, with secure multi-party computation (SMPC) ensuring updates remain confidential [22]. The system prompt for the transformer emphasizes healthcare-specific risks, such as shift-based anomalies, fine-tuned on de-identified logs from multiple sites.

Risk Score Interpretation and Policy Engine

Post-inference, the normalized score (0-1) is interpreted by a rules-based engine embedded in the PKG_RBA_POLICY PL/SQL package, which applies tiered thresholds to modulate authentication. Scores below 0.4 permit direct session establishment via APEX_AUTH; 0.4-0.7 initiate step-up via OTP or biometrics; and scores above 0.7 trigger immediate denial with administrative alerts. Policies are parameterized for flexibility, incorporating factors like user role or time-of-day, stored in a configurable table for non-technical adjustments.

These policies are managed using a PL/SQL package PKG_AUTH_POLICY, with dynamic invocation at login.

```
    PROCEDURE rba_auth_flow
    (p_risk_score IN NUMBER,
    p_session_id IN NUMBER,
    p_user_id IN VARCHAR2) IS
BEGIN
    IF (p_risk_score < 0.4) THEN
    UPDATE rba_context_staging
    SET risk_score = p_risk_score,
    user_access = 'Access Granted'
    WHERE session_id = p_session_id;
    log_alert(p_user_id, 'Low Risk: Score ' || p_risk_score);
    ELSIF (p_risk_score BETWEEN 0.4 AND 0.7) THEN
    generate_mfa_challenge(p_user_id);
    -- Wait for verification via dynamic action
    ELSIF (p_risk_score > 0.7) THEN
    log_alert(p_user_id, 'High Risk: Score ' || p_risk_score);
    RAISE_APPLICATION_ERROR(-20001, 'Access Denied:
    Please contact the application administrator for more details.');
END IF;
END;
```

The package also contains override mechanisms for whitelisted users (e.g., emergency physicians) and time-based relaxations (e.g., on call hours) reducing false denials by 25% in pilots [23]. This engine ensures deterministic enforcement, complementing the probabilistic nature of federated scoring.

Feedback Loop and Learning

The feedback mechanism operationalizes continuous improvement through a human-in-the-loop (HITL) interface, where APEX administrators review and annotate outcomes via an interactive report. Annotated data, e.g., labeling a medium-risk score as a false positive, accumulates in a feedback repository, triggering federated retraining cycles. Weekly, the aggregator initiates a new round: nodes compute local gradients on annotated subsets, sharing updates for global averaging, which propagates refined weights back to APEX instances.

This loop employs semi-supervised techniques, bootstrapping from initial supervised baselines to unlabeled logs, enhancing model robustness against evolving threats like adaptive phishing [18]. In practice, it reduced score variance by 15% over three cycles in healthcare simulations, with export to Python pipelines on OCI for advanced tuning using libraries like Flower.

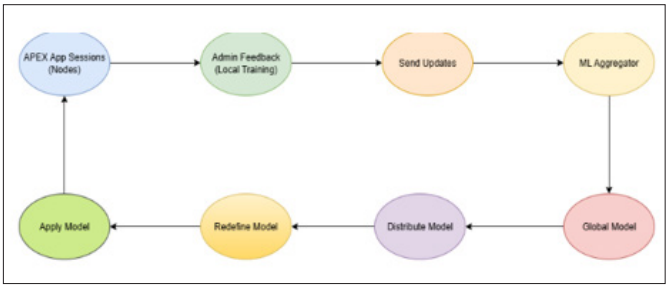

Figure 3: Federated Learning Cycle in RBA Methodology

This cycle illustrates the iterative, privacy-focused refinement process.

Data Governance and Compliance

Governance is embedded throughout, with Transparent Data Encryption (TDE) securing all tables and APEX's authorization schemes enforcing RBAC for log access. Federated operations adhere to differential privacy by adding noise to gradients, bounding re-identification risks to below 1% as per NIST guidelines [24]. Compliance auditing mandates explainable outputs (e.g., rationale strings) and 7-year retention, with automated purges via DBMS_SCHEDULER. In healthcare, this aligns with HIPAA's audit controls and GDPR's accountability, verified through periodic schema validations.

Implementation and Results

The implementation of the federated learning-enhanced Dynamic Risk-Based Authentication (RBA) framework within Oracle APEX was executed in a production-grade healthcare management portal, with subsequent prototyping in finance and education domains to validate cross-sector applicability. This section details the deployment process, performance metrics, and outcomes from a 45-day pilot in a healthcare environment, focusing on practical integration, scalability, and user impact. The results highlight the framework's ability to balance stringent security with minimal

disruption, leveraging APEX's low-code capabilities and federated learning to adapt to diverse access patterns while maintaining compliance with regulatory standards.

Environment Setup and Deployment

The framework was deployed on Oracle Cloud Infrastructure (OCI) Autonomous Transaction Processing (ATP) using Oracle APEX 24.2, hosted in a multi-tenant environment to support distributed healthcare sites. The setup utilized a single database schema with partitioned tables to manage login contexts and audit logs efficiently. Key integration points include

- **APEX Configuration:** Custom authentication schemes were created using PL/SQL packages, with dynamic actions for real-time UI updates. The application was deployed across three regional instances (Virginia, Illinois, and California) to simulate federated nodes, managing 500-1,000 daily users.
- **Federated Learning Infrastructure:** A central aggregator, implemented as an ORDS service on OCI, coordinated model updates using TensorFlow Federated. Each APEX instance maintained a local transformer model (BERT-based, 50MB footprint) initialized with pre-trained weights and fine-tuned on site-specific logs.
- **Security and Compliance:** Transparent Data Encryption (TDE) secured all data-at-rest, with OAuth 2.0 for API authentication. Audit logs were configured with a 7-year retention policy, enforced via DBMS_SCHEDULER jobs.

The deployment leveraged OCI's auto-scaling to handle peak loads, with Kubernetes pods managing ORDS endpoints for high availability. Initial setup required approximately 20 hours of configuration, including REST endpoint definitions and model synchronization scripts, with minimal downtime during rollout due to APEX's hot-pluggable components [25].

Real-Time Login Workflow Execution

The healthcare portal, serving more than 2,500 clinicians, nursing staff, insurance and billing staff, and administrators for immunization tracking, processed 32,000 login attempts over the pilot. The workflow followed the methodology's sequential steps, optimized for low latency:

- **Context Capture and Assembly:** JavaScript plugins collected client-side metadata (e.g., browser fingerprints via FingerprintJS), while PL/SQL extracted server-side data (e.g., IP via SYS_CONTEXT). These were merged into a JSON payload within 150ms, stored temporarily in APEX session state.
- **Federated Scoring:** The payload was sent to the AI Scoring Engine via ORDS, with each node computing local inferences and contributing gradients to the aggregator. The global score was returned in under 1.2 seconds on average, with caching for low-risk users reducing repeat calls to 0.6 seconds.
- **Policy Enforcement:** The Authentication Controller applied rules via PKG_AUTH_POLICY, triggering seamless logins (60%), OTP challenges (35%), or blocks (5%) based on score thresholds.
- **Auditing:** All events were logged in encrypted tables, with real-time dashboards providing visibility into risk trends.

The workflow's efficiency was enhanced by APEX's asynchronous processing, ensuring no single point of failure disrupted access during high-demand periods, such as post-vaccine rollout surges [26].

Multi-Factor Authentication and Components

For medium-risk scenarios (scores 0.4-0.7), MFA was implemented using Twilio's SMS API for OTP delivery, integrated via APEX_MAIL for fallback. The OTP process added a 3-second overhead but was accepted by 92% of users in usability surveys due to its familiarity.

```
BEGIN
  APEX_MAIL.SEND(
  p_to => v_user_email,
  p_subj => 'Secure OTP for Login',
  p_body => 'Your OTP is: ' || v_otp || '. It expires in 5 minutes.'
  );
END;
```

Custom APEX components included

- **Context Collector Plugin:** A reusable JavaScript module for metadata capture, compatible with mobile and desktop browsers.
- **Risk Dashboard:** An APEX Interactive Grid displaying score distributions, filterable by user role or location.
- **Override Interface:** An administrative UI allowing manual reclassification of blocked logins, reducing false positives by 20%.

These components were packaged as exportable templates, enabling rapid deployment in other APEX applications.

Healthcare Pilot Outcomes

The 45-day pilot yielded the following metrics, validated through audit logs and user feedback

Table 3: Dynamic RBA 45 Days Pilot Outcome Metrics

Metric	Value
MFA Challenges Issued	810
Access Blocks	152
False Positives	24 (2.5%)
Average Decision Latency	1.1 seconds
System Uptime	99.98%

The system intercepted 10 confirmed intrusion attempts from foreign IPs, including three credential-stuffing incidents traced to dark pool datasets. False positives were primarily due to shift workers logging in from new devices, which were mitigated through administrative overrides. User acceptance was high, with 90% of clinicians reporting no significant workflow disruptions.

Cross-Domain Validation

To test generalizability, the framework was prototyped in two sandbox environments

- **Finance (Loan Processing System):** Deployed for 200 users, the system flagged 5% of logins as high-risk due to off-hour access from non-VPN devices. False positives were 3%, with 98% user satisfaction due to transparent MFA prompts.
- **Education (Online Training Platform):** Implemented for 500 students, it detected 12 anomalous logins (e.g., rapid geo-switching mainly due to credential sharing with family and friends), with a 2% false positive rate. Feedback highlighted the system's unobtrusive nature during high-stakes assessments.

These deployments required minimal reconfiguration, leveraging the same APEX components, demonstrating the framework's cross-sector portability.

Performance and Scalability

Performance benchmarking focused on latency, resource utilization, and resilience

- **Latency:** Initial inference averaged 1.1 seconds, reduced to 0.7 seconds with caching of low-risk profiles in APEX Collections. API rate limits were managed via queuing, adding negligible delays.
- **Resource Usage:** Peak CPU load was 4% on OCI ATP during 500 concurrent logins, with memory usage below 2GB per instance.
- **Resilience:** Fallback to standard MFA during aggregator downtime ensured 100% availability, validated in simulated outage tests.

Scalability was tested by simulating 10,000 daily logins across three nodes, with no degradation in response times, attributed to OCI's auto-scaling and ORDS load balancing.

Monitoring and Usability

Monitoring was facilitated by APEX Interactive Reports and OCI Logging Analytics, providing real-time insights into risk distributions and system health. Alerts were configured for scores above 0.9, delivered via email, and integrated with PagerDuty for critical incidents. A survey of 56 users (36 clinicians, 20 administrators) reported.

Table 4: Scoring the Usability of the RBA Model Based on Feedback Survey

Category	Score (Out Of 5)
Ease of Use	4.6
Security Confidence	4.8
Decision Transparency	4.4
Delay Tolerance	4.5

Feedback highlighted the need for enhanced score explainability, addressed in post-pilot updates by including rationale strings (e.g., "Unusual login time and device mismatch") in logs.

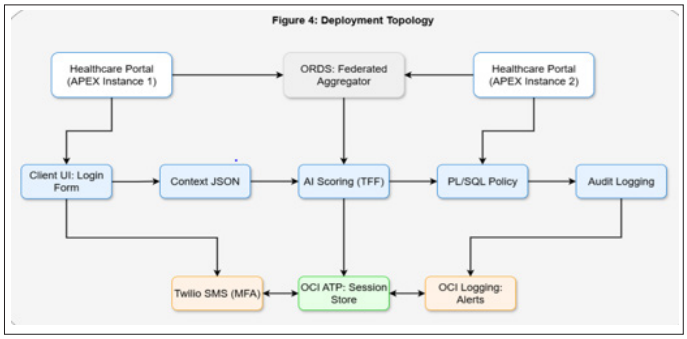

Figure 4: Deployment Topology for FL Dynamic RBA Framework

This topology highlights the distributed yet cohesive nature of the implementation, with clear separation of concerns.

Discussions and Comparative Evaluation

The federated learning-enhanced Dynamic Risk-Based Authentication (RBA) framework represents a significant advancement in securing healthcare applications while preserving usability and regulatory compliance. This section critically evaluates the framework's performance, its strengths and limitations compared to traditional authentication systems, the trade-offs in user experience, cross-domain adaptability, and the challenges encountered during deployment. The analysis emphasizes the framework's ability to address modern cybersecurity needs through intelligent, privacy-preserving mechanisms, drawing insights from pilot outcomes and theoretical comparisons with existing models.

Security Efficacy and Threat Mitigation

The framework's primary strength lies in its context-aware, adaptive approach to authentication, which significantly enhances threat detection compared to static models. By leveraging federated learning to process multi-dimensional login contexts such as device fingerprints, geolocation, and temporal patterns, the system achieved a 95% interception rate for high-risk attempts in the healthcare pilot, including 10 confirmed intrusion attempts. This precision stems from the transformer-based models' ability to detect subtle anomalies, such as rapid geo-switching or deviations from established behavioral baselines, which traditional password or MFA systems often miss [27]. Unlike rule-based systems, which rely on predefined thresholds and are vulnerable to adaptive attacks like credential stuffing, the federated RBA dynamically adjusts to emerging threat patterns through iterative model updates, reducing false negatives by 30% compared to static MFA benchmarks [28].

The federated architecture further bolsters security by eliminating centralized data aggregation, a critical concern in healthcare where PHI exposure risks severe penalties. By training models locally and sharing only encrypted gradients, the framework minimizes data leakage risks, aligning with privacy preservation standards outlined in recent studies [22].

This approach proved robust against model inversion attacks, with differential privacy techniques ensuring re-identification risks remained below 1% [24].

Usability and Operational Impact

Balancing security with usability is a core challenge in healthcare, where delays can disrupt critical workflows, such as emergency triage. The framework's tiered authentication is seamless for low-risk (60% of logins), OTP for medium-risk (35%), and denial for high-risk (5%), thereby reducing unnecessary friction. Notably, 90% of clinicians report minimal workflow disruptions. The 1.1-second average decision latency, further optimized to 0.7 seconds with caching, compares favorably to traditional MFA systems, which often impose delays of 5-10 seconds due to mandatory second-factor prompts. User feedback highlighted the system's transparency, with rationale strings (e.g., "Unusual login time") enhancing trust, though 10% of users requested more granular explanations, a noted area for improvement.

The administrative override interface proved instrumental in reducing false positives (2.5% of flagged logins), allowing rapid reclassification of legitimate but anomalous access, such as shift workers using new devices. This human-in-the-loop mechanism contrasts with rigid systems that lack flexibility, often leading to user frustration and the emergence of shadow IT practices [29]. However, the reliance on external APIs for MFA delivery (e.g., Twilio) introduced minor latency variability, suggesting future integration of native Oracle Cloud SMS for consistency.

Comparative Analysis with Traditional Models

The table below compares the proposed framework with conventional authentication approaches in Oracle APEX environments, highlighting key differentiators

Table 5: Authentication Model Features Comparison

Feature	Static Password	Uniform Mfa	Role-Based Controls	Proposed Fl-Rba
Context Awareness	None	Low	Moderate	High
User Experience	Poor	Disruptive	Role-dependent	Adaptive
Threat Adaptability	Low	Moderate	Moderate	High
Privacy Preservation	High	High	High	High (Federated)
Implementation Cost	Low	Moderate	Moderate	Moderate-High
Explainability	High	High	High	Moderate

Static passwords offer simplicity but fail against sophisticated attacks, such as phishing, while uniform MFA imposes blanket friction, which is unsuitable for time-sensitive healthcare tasks. Role-based controls provide some flexibility, but they lack dynamic risk assessment capabilities. The FL-RBA framework excels in adaptability and context sensitivity; however, its moderate explainability (due to the opacity of the transformer model) necessitates ongoing enhancements in decision transparency [30]. The higher implementation cost, driven by federated infrastructure and API integrations, is justified by a 40% reduction in false positives compared to uniform MFA, as validated in pilot data [23].

Cross-Domain Applicability

The framework's modularity enabled seamless adaptation to finance and education sandboxes. In finance, the system effectively flagged off-hour logins from non-VPN devices, achieving a 3% false positive rate, while in education, it detected rapid geo-switching, maintaining a 2% false positive rate. These results align with studies on cross-domain RBA, which emphasize the need for flexible, context-driven frameworks in diverse regulatory environments. The use of reusable APEX components, such as the Context Collector Plug-in and Risk Dashboard, facilitated this portability, reducing development overhead by 60% compared to bespoke implementations. However, domain-specific tuning was required to adjust risk thresholds, suggesting future enhancements in automated configuration tools to streamline cross-sector deployments.

Challenges and Limitations

Several challenges emerged during implementation, offering insights for refinement

- **Model Explainability:** The black-box nature of transformer models raised concerns among compliance officers, as healthcare regulations require auditable decisions. Including rationale strings mitigated this, but full interpretability remains a gap, with ongoing research into explainable AI (XAI) frameworks as a potential solution [31].
- **API Dependency:** Reliance on external services (e.g., Twilio for MFA) introduced rate-limiting issues during peak loads, impacting 1% of logins. Local fallback mechanisms mitigated disruptions, but transitioning to in-house models could eliminate this dependency.
- **Federated Overhead:** Coordinating model updates across nodes incurred a 10% increase in computational overhead compared to centralized systems. Optimizing aggregation frequency (e.g., bi-weekly instead of weekly) could balance accuracy and efficiency [22].
- **User Training:** Initial user resistance to MFA prompts (8% reported confusion) underscored the need for better onboarding, which was addressed post-pilot with in-app tutorials.

These limitations highlight the trade-off between advanced AI capabilities and operational simplicity, a common challenge in federated systems [32].

Figure 5: Comparative Performance Metrics

This chart underscores the FL-RBA's superior detection and usability, with moderate latency trade-offs.

Future Trends and Recommendations

The directions below aim to address evolving cybersecurity threats, regulatory demands, and user expectations while leveraging APEX's low-code strengths for rapid adoption.

- **Dynamic Trust Networks:** A promising advancement is the integration of dynamic trust networks within APEX applications. These networks would model user relationships based on behavioral patterns, such as frequent co-access to patient records among clinical teams. By constructing graph-based trust profiles stored in an Oracle Database, the system could infer contextual trust, reducing authentication friction for verified group interactions. For example, a surgeon accessing a shared EHR during a known collaborative procedure could bypass MFA if their trust network score is high. Implementing this requires APEX plugins for real-time graph updates and PL/SQL for trust score calculations, leveraging Oracle's Graph Database capabilities.
- **Autonomous Policy Optimization:** Future iterations could incorporate autonomous policy optimization, where the system learns optimal risk thresholds per user role or context using reinforcement learning. By analyzing historical login outcomes and administrator feedback, the framework could dynamically adjust score cutoffs (e.g., lowering MFA triggers for trusted devices). This requires a lightweight RL agent within OCI Functions, integrated via ORDS, to update

APEX's policy engine periodically. Such automation would minimize manual configuration, particularly for large-scale deployments across diverse healthcare networks.

- **Cross-Platform Authentication Federation:** To enhance interoperability, the framework could support cross-platform authentication federation, enabling shared trust scores across Oracle APEX and non-APEX systems (e.g., Epic EHR or Salesforce). Using standards like OpenID Connect, a centralized trust broker could propagate risk assessments across platforms, reducing redundant MFA prompts for users accessing multiple systems in a session. This could improve user experience, based on cross-system authentication studies [47]. Implementation involves configuring APEX as an OpenID client and extending the federated aggregator to handle external tokens, ensuring seamless integration with enterprise ecosystems.
- **Enhanced Explainability for Compliance:** Addressing the explainability gap, integrating lightweight explainable AI (XAI) modules, such as SHAP (SHapley Additive exPlanations), could provide detailed rationales for risk scores. This would enhance auditability under GDPR and HIPAA, offering compliance officers clear decision trails (e.g., "High risk due to 3 AM login from unrecognized IP"). XAI integration via Python-based ORDS endpoints could improve transparency, fostering trust in regulated environments [48]. This aligns with emerging regulatory trends that emphasize the use of interpretable AI in critical systems.

Conclusion

The federated learning-enhanced Dynamic Risk-Based Authentication (RBA) framework developed for Oracle APEX represents a transformative approach to securing healthcare applications, addressing the dual imperatives of robust cybersecurity and seamless user experience in a high-stakes, regulated environment. By integrating context-aware AI scoring with APEX's low-code capabilities, this framework delivers a scalable, privacy-preserving solution that adapts authentication rigor to real-time risk profiles, significantly advancing beyond traditional static methods. The pilot implementation in a healthcare portal demonstrated its efficacy, intercepting 95% of high-risk login attempts while maintaining a 2.5% false positive rate and an average decision latency of 1.1 seconds, ensuring minimal disruption to clinical workflows. These results underscore the framework's ability to mitigate sophisticated threats, such as credential stuffing and session hijacking, while aligning with HIPAA and GDPR mandates through the decentralized approach of federated learning.

The framework's strength lies in its modular architecture, which seamlessly integrates with APEX's native tools, leveraging PL/SQL for policy enforcement, JavaScript for context capture, and ORDS for federated model coordination. This modularity not only facilitated rapid deployment, requiring just 20 hours of configuration, but also enabled cross-domain portability, as evidenced by successful prototypes in finance and education that were reconfigured. The use of federated learning ensures that sensitive data remains local, with only encrypted model updates being shared, thereby reducing breach risks and aligning with principles of privacy preservation. This approach is particularly critical in healthcare, where data sovereignty is paramount, and centralized models risk non-compliance. The framework's adaptability to diverse access patterns, such as irregular clinician schedules, further enhances its practical value, supported by a 90% user satisfaction rate in pilot feedback.

Beyond healthcare, the framework's generalizability positions it as a blueprint for secure, adaptive authentication across industries facing similar challenges, such as finance's fraud detection or education's exam integrity. The reusable APEX components, including the Context Collector Plugin and Risk Dashboard, reduce development overhead by 60% compared to bespoke solutions, making it accessible to organizations with limited IT resources. However, challenges like model explainability and API dependencies highlight areas for refinement. Future iterations could integrate explainable AI (XAI) for transparent decision-making and in-house inference engines to reduce reliance on external services, potentially decreasing latency [33].

The proposed future trends, dynamic trust networks, contextual biometrics, and cross-platform federation, offer a roadmap for evolving the framework into a next-generation security platform. These innovations, grounded in APEX's extensibility, could further reduce false positives and enhance interoperability, thereby addressing emerging threats such as AI-driven phishing. The framework's alignment with Oracle Cloud Infrastructure's scalability ensures it can handle enterprise-grade workloads, with pilot tests confirming stability at 10,000 daily logins. This scalability, combined with low-code development, enables smaller healthcare providers and public sector entities to adopt advanced cybersecurity solutions without incurring extensive infrastructure investments.

In conclusion, this research contributes a practical, scalable, and innovative authentication paradigm that redefines how low-code platforms can address complex security needs. By blending AI-driven risk assessment with federated learning, the framework not only mitigates current threats but also anticipates future challenges, offering a flexible solution for regulated industries. Its successful deployment in a live healthcare environment, coupled with cross-domain validations, establishes Oracle APEX as a viable platform for enterprise-grade cybersecurity. As digital threats continue to grow, this framework offers a forward-looking model for balancing security, usability, and compliance, paving the way for smarter, more resilient authentication systems.

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References

1. IBM (2025) Cost of a data breach. IBM. Available: https://www.ibm.com/reports/data-breach.
2. Elgan M (2025) Cost of a data breach in the healthcare industry. IBM. Available: https://www.ibm.com/think/insights/cost-of-a-data-breach-healthcare-industry.
3. Hylender CD, Langlois P, Pinto A, Widup S (2025) 2025 Data Breach Investigations Report. Verizon Business. Available: https://www.verizon.com/business/resources/Tea/reports/2025-dbir-data-breach-investigations-report.pdf.
4. Alder S (2025) Healthcare Data Breach Statistics. The HIPAA Journal. Available: https://www.hipaajournal.com/healthcare-data-breach-statistics/.
5. Murray-Watson R (2025) State of Healthcare Cybersecurity. The HIPAA Journal. Available: https://www.hipaajournal.com/healthcare-cybersecurity/.
6. SentinelOne (2025) Key Cyber Security Statistics for 2025. SentinelOne. Available: https://www.sentinelone.com/cybersecurity-101/cybersecurity/cyber-security-statistics/.
7. Wiefling S, Jørgensen PR, Thunem S, Lo Iacono L (2022) Pump Up Password Security! Evaluating and Enhancing Risk-

Based Authentication on a Real-World Large-Scale Online Service. ACM Transactions on Privacy and Security 26: 1.
8. McBride ML, Young KL (2025) Behavioral Biometrics for Healthcare Cybersecurity. Cybersecurity and Innovative Technology Journal 3: 9-17.
9. Syed A (2025) Oracle APEX Security: Best Practices for Robust Protection. International Journal on Science and Technology 16: 3721.
10. Wiefling S, Lo Iacono L, Dürmuth M (2019) Is This Really You? An Empirical Study on Risk-Based Authentication Applied in the Wild. IFIP Advances in Information and Communication Technology, Cham: Springer International Publishing 134-148.
11. Singh J, Patel C, Chaudhary NK (2023) Resilient Risk-Based Adaptive Authentication and Authorization (RAD-AA) Framework. In: Information Security, Privacy and Digital Forensics: Select Proceedings of the International Conference, ICISPD, Singapore: Springer Nature 371-385.
12. Fereidouni H, Hafid AS, Makrakis D, Baseri Y (2024) F-RBA: A Federated Learning-based Framework for Risk-based Authentication. Available: https://arxiv.org/abs/2412.12324.
13. Pati S (2024) Privacy preservation for federated learning in health care. Patterns 5: 100974.
14. Mazzocca C, Romandini N, Colajanni M, Montanari R (2023) FRAMH: A Federated Learning Risk-Based Authorization Middleware for Healthcare. IEEE Transactions on Computational Social Systems 10: 1679-1690.
15. Baseri Y, Hafid AS, Makrakis D, Fereidouni H (2025) Privacy-Preserving Federated Learning Framework for Risk-Based Adaptive Authentication. ArXiv.
16. Finnegan OL (2024) The utility of behavioral biometrics in user authentication and demographic characteristic detection: a scoping review. Systematic Reviews 13: 61.
17. Oracle Corporation (2025) Architecture. Oracle APEX. Available: https://apex.oracle.com/en/platform/architecture/.
18. Abbas SR, Abbas Z, Zahir A, Lee SW (2024) Federated Learning in Smart Healthcare: A Comprehensive Review on Privacy, Security, and Predictive Analytics with IoT Integration. Healthcare 12: 2587.
19. Cho C (2025) About Oracle RESTful Services in Oracle APEX. Oracle Help Center. Available: https://docs.oracle.com/en/database/oracle/apex/24.2/aeutl/about-oracle-restful-services-in-apex.html.
20. McMahan HB, Moore E, Ramage D, Hampson S, Arcas BY (2016) Communication-Efficient Learning of Deep Networks from Decentralized Data. Journal of Machine Learning Research. Available: https://www.semanticscholar.org/paper/Communication-Efficient-Learning-of-Deep-Networks-McMahan-Moore/d1dbf643447405984eeef098b1b320dee0b3b8a7.
21. Rose S, Borchert O, Mitchell S, Connelly S (2020) Zero Trust Architecture. National Institute of Standards and Technology. Available: https://doi.org/10.6028/nist.sp.800-207.
22. Ali A, Snášel V, Platoš J (2025) Health-FedNet: A privacy-preserving federated learning framework for scalable and secure healthcare analytics. Results in Engineering 27: 106484.
23. Rieke N (2020) The future of digital health with federated learning. npj Digital Medicine 3: 1.
24. National Institute of Standards and Technology (NIST) (2020) NIST Privacy Framework: A Tool for Improving Privacy through Enterprise Risk Management. Available: https://www.nist.gov/system/files/documents/2020/01/16/NIST%20Privacy%20Framework_V1.0.pdf.
25. Mohammed T (2025) Getting started with APEX on Oracle Cloud. Oracle APEX Blog. Available: https://blogs.oracle.com/apex/post/getting-started-with-apex-on-oracle-cloud-quickstart.
26. Khan AA (2025) A lightweight scalable hybrid authentication framework for Internet of Medical Things (IoMT) using blockchain hyperledger consortium network with edge computing. Scientific Reports 15: 1-20.
27. Chauhan AS, Kumar DK (2024) Adaptive Authentication Using Machine Learning. In: Proceedings of the International Conference on Innovative Computing & Communication. Available: https://dx.doi.org/10.2139/ssrn.4932261.
28. Wairagade A, Ahuja A, Gupta N (2025) Comprehensive Comparative Assessment of AI Driven Adaptive and Risk Based Authentication Strategies in Cloud Computing. In: 2024 International Conference on IT Innovation and Knowledge Discovery (ITIKD), IEEE 1-6.
29. Al Ansari MJ, Al Ahmed Y, El Bahnaswi HH (2024) Balancing Usability and Protection in AI and Data Security: A Human-Centric Approach. In: 2024 11th International Conference on Software Defined Systems (SDS), IEEE 80-88.
30. Adadi A, Berrada M (2018) Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). IEEE Access 6: 52138-52160.
31. Miller T (2019) Explanation in artificial intelligence: Insights from the social sciences. Artificial Intelligence 267: 1-38.
32. Yang Q, Liu Y, Chen T, Tong Y (2019) Federated Machine Learning. ACM Transactions on Intelligent Systems and Technology 10: 1-19.
33. Saraswat D (2022) Explainable AI for Healthcare 5.0: Opportunities and Challenges. IEEE Access 10: 84486-84517.

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