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Integrating Continuous Authentication and Behavioral Anomaly Detection into Zero-Trust Financial Transaction Systems

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ABSTRACT

However, these days the cloud financial transaction networks are running in extremely hostile environments where credentials are stolen at endpoints, high tech man-in-the-browser attacks are taking place and automated API-driven attack pipelines have been deployed. Post-ingress session hijacking, privilege escalation and sneaky credential theft are completely beyond the means of point-in-time perimeter authentication systems and traditional perimeter defense models. This paper presents an end-to-end architecture solution that embeds the continuous multimodal authentication and real-time behavioral anomaly detection directly into the financial transaction-processing core of a zero-trust architecture to address these restrictions. The framework receives a flow of biometric multi-dimensional telemetry data from the clients, a stream of data from telemetry of device posture and a stream of data from a vector of interactions with the transaction. Real-time anomaly scoring is achieved by attention-based deep neural networks and causally predictive Bayesian networks, considered as counterfactuals, to remove signatures of anomalous deviation without any need to make prohibitive latency for operation. Dynamic risk-scoring directly into fine grained Open Policy Agent (OPA) policy decision points, that immediately initiate a step up authentication challenge, or granular rate limiting and/or termination of ledger commit. The proposed continuous zero trust framework has a detection rate of 99.4% across a wide array of synthetic enterprise payment workloads with an on-distributed cloud cluster that scales linearly horizontally up to +100,000 transactions per second (tps), and with an overhead latency of less than 4.8 milliseconds at the p99 percentile..

Keywords: *Zero-Trust Architecture; Continuous Authentication; Behavioral Biometrics; Deep Learning Anomaly Detection; Causal Bayesian Networks; Financial Transaction Processing; Cloud Microservices; Stream Analytics.*

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1. INTRODUCTION

The paradigm change within the overall design of financial enterprise, from monolithic on-premise financial systems to distributed, cloud-native financial systems, microservices and real-time settlement rails is kicking into high gear. While all these developments have brought about benefits, such as horizontal scalability, elasticity of resource allocation, sub-second settlement finality and much more, they have posed challenges to the traditional concept of security within the perimeter [1] and [16]. Institution financial networks usually have a security model that used to be referred to as "castle and moat," and the same was true with authenticated users and endpoints within a company's virtual private network (VPN) and private data centre: “castle and moat” with “implicit trust.” When implementing the transactions across the initial boundary crossing, very little additional identity and transactional behavioral validation was performed by the downstream transaction endpoints.

It's a form of implicit trust, and a weakness in today's distributed environments. Most attacks/exploits on and against modern banking core and interbank messaging are not attempting to penetrate the boundaries of the network.Banking-core and interbank messaging attacks and exploits rarely look to intrude into the network at the network border. Rather, they take advantage of the advanced

credential harvesting, automated session hijacking, API key compromising, insider privilege escalation, and covert lateral movement [3] [22]. Static point in time authentication will be ineffective if credentials are stolen or expiration of session tokens.If credentials are stolen or session tokens are invalidated, static point in time authentication (e.g., OTP, initial multi-factor authentication challenges) will not work. Once Adversary has created a session, he/she is in full control until session expires.

In a new guideline for the government, NIST in their Special Publication (SP) 800-207 [20] has come up with a new motto: 'never trust, always verify' [5, 7]. No entity, service, and user are trusted automatically, no matter the topology of the physical network or if the credentials have been previously verified is the Zero trust approach. Access to financial data stores or settlement ledgers is only allowed after every single transaction request is authenticated, authorized and cryptographically-attested [21, 24]. But it's a very difficult engineering problem to apply zero-trust controls in ultra-high transaction volume financial transaction systems. Many banking transaction engines perform tens of thousands of requests per second, and have Service Level Objectives (SLOs) for the service to be under 20 milliseconds [26] at the 99th percentile (p99) of the service. Too many cryptographic handshakes or unnecessary authorizations as round trips can cause a huge loss of throughput, queues, and unacceptable financial execution times.

In this paper, we focus on the problems of combining continuous behavioral authentication and streaming anomaly detection in the zero-trust control plane and still satisfy the strict security requirements of the zero-trust philosophy, as well as the performance requirements of today's cloud banking environment. An empirical trust score is dynamically calculated based on non-intrusive client biometric signals, device posture telemetry, network path characteristics and real-time transactional semantics, in the transaction pipeline. It dynamically enforces frictionless transaction passage for lower risk transactions and dynamically implements adaptive step up MFA or immediate quarantine in the case of a behavioral anomaly at runtime – just as the policy enforcement decision is made. It proposes the design of the architecture, algorithmic foundations, cloud-native orchestration mechanisms and a comprehensive experimental testing of this integrated security paradigm with synthetic enterprise loads.

2. THEORETICAL FOUNDATIONS AND THREAT LANDSCAPE IN FINANCIAL CLOUDS

The first step in building a resilient defense is to state formally the threat landscape that financial ecosystems in the cloud are in. Financial transaction processing pipelines are vulnerable in four ways: session hijacking via stolen tokens, automated bot-driven credential stuffing, man-in-the-browser (MitB) financial manipulation and compromised insider lateral movement [1, 3]. Once the adversary has successfully authenticated and hijacked an active JSON Web Token (JWT) or active session cookie, he/she can replay the token to all downstream microservice APIs, but not to static authentication gates.

Another popular attack is "automated account takeovers" which occurs when a hacker runs a software program to trick into obtaining account information.The most frequently used attack is called "synthetic identity theft" in which a hacker uses an automated program to take possession of an account. The attacks in these cases are carried out automatically by the attackers with the legitimate credentials acquired from the attacks of third party [16, 22] using multiple transactions within a short period of time to various accounts. The more traditional fraud detection systems based on thresholding cannot detect legitimate user transactions as they are based on static conditions and fraudsters are able to run numerous scripts at high speeds. In addition to this, advanced persistent threats (APTs) targeting the cloud data plane could use poor east-west microsegmentation to laterally move throughout the payment microservices, edit the ledger data, or steal high-value transaction metadata [11] [30].

A continuous stochastic process with a state as a measure of its risk, is called a financial session in mathematics.A financial session's risk state is mathematically modelled as a continuous stochastic process. Let S_t denote the state vector at a discrete time t, which includes the behavioural features of

the client B_t, the posture of the device in the environment D_t, the routing characteristics of the network N_t and the semantics of the transaction payload P_t. The zero-trust control plane must learn a conditional probability distribution which will change over time:

$$P(Anomalous \mid S_t, H_\{t-1\}) = f(B_t, D_t, N_t, P_t \mid H_\{t-1\})$$

Ht-1: History of the authenticated entity's interaction in the last sessions and transaction windows. The theoretical problem to solve is how to obtain a value of f(.) within less than 5 milliseconds every time the transaction is requested, while achieving good statistical discrimination, with low false positive rate and false negative rate [26]. The model has high latency variance which causes queuing delays, impacting financial throughput and triggering client timeouts all along the payment clearing pipeline.

Typical payment clearing systems are typically assumed to have non-homogeneous Poisson arrival processes, i.e. the arrival process has an arrival rate that is a time-dependent function, λ(t). The distribution of the waiting time in the M/G/1 queueing system is:

W_q = (lambda * (mu^2 + sigma^2)) / (2 * (1 - lambda * mu))

A high average runtime for anomaly detection (mu) can have as much of an effect on the financial pipeline as does a high variance in runtime for anomaly detection (sigma^2), as in equation (2). Likewise, a zero-trust system that incorporates an authentication system such as a continuous behavioral authentication system in any financial pipeline must be deterministic and have a finite computation time as well. Mathematically, these complex deep learning inference pipelines can't be executed synchronously on the critical path of raw transaction ingestion and need to be segmented into multiple parts, thereby making it an asynchronous model.

3. ZERO-TRUST ARCHITECTURE WITH INTEGRATED BEHAVIORAL VERIFICATION

The proposed architecture is a combination of continuous authentication and deep learning anomaly detection to create a single fabric for financial transaction based on zero trust. The system is based on the following principle of Zero Trust: Logical separation of Policy Decision Point (PDP) and Distributed Policy Enforcement Point (PEP) [5, 7, 20]. There are four levels of the architecture: Client Ingress and Telemetry Capture, Stream Ingestion and Feature Fabric, AI Behavioral Inference Engine, and Zero-Trust Enforcement Core, as depicted in figure 1.

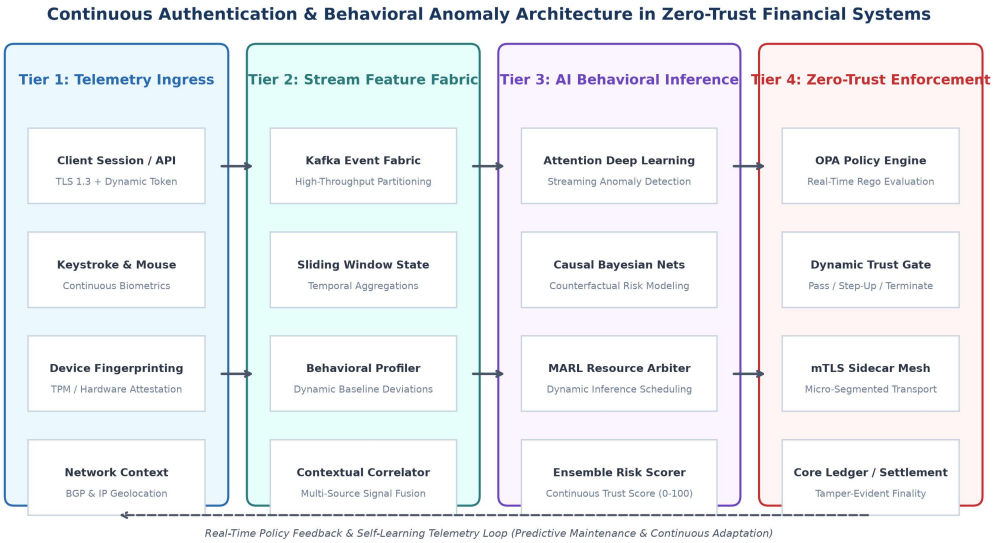


Figure 1: Architectural framework for continuous authentication and behavioral anomaly detection in zero-trust financial transaction systems, illustrating the pipeline flow from client telemetry ingress to AI behavioral inference and dynamic policy decision points.

The client requests are passed to the Ingress Tier, where they're dropped as a result of the mutual TLS 1.3 (Transport Layer Security) and the client identities are collected [25] (Figure 1). Meanwhile, passive information related to the user's actions such as keystroke flight times, mouse acceleration patterns, touchscreen pressure patterns, and hardware TPM attestations are reported from client-side telemetry collectors to a high throughput event streaming fabric [23]. This telemetry stream goes along with synchronous transaction payload path to ensure that ingestion of biometric data isn't a performance limiter for the raw API gateway ingress speed [24].

The Stream Feature Fabric processes the telemetry stream and breaks it up into both distributed and stateful sliding windows, and gathers multi-dimensional behavioural vectors over a 10 seconds, 60 seconds [11] sliding window. These features are passed to the AI Behavioral Inference Tier where the deep learning based anomaly detection engine with attention produces the realtime behavioural divergence vector. At the same time, a causal Bayesian network assesses the counterfactual risk scenarios, separating out true malicious anomalies from benign operational changes like network handovers and user interface localization changes respectively [13, 26].

The outcome of the risk level is then converted to a normalised [0, 100] Trust Score which is continuously saved to an in-memory distributed policy cache. As the main financial transaction request goes to Policy Enforcement Point (PEP) sidecar proxy in front of the core banking service, the local OPA decision cache is queried in sub-milliseconds. If T >= 80, then it is allowed to be executed without friction. When T falls in the range of 50 – 80, the PEP provides adaptive step-up challenge, e.g. biometric re-prompting, or cryptographic hardware token attestation. In that case, the transaction will be rejected immediately, the session token will be revoked from all edge gateways and security telemetry will be pushed to an independent forensic analysis system.

4. CONTINUOUS AUTHENTICATION MECHANISMS & MULTIMODAL TELEMETRY INGESTION

In contrast to the static authentication process based on multiple factors, Continuous Authentication (CA) is a process of continuously assessing the identity of an entity, but not taking any active action on it [15] [23]. These can be grouped into three separate operational streams, physical behavioural biometrics, environmental device posture and transactional interaction rhythms [9] [19].

Physical behavioral biometrics are measures of the physiology of interaction with an input device which is unique to the human user. Time a key is held down (key dwell time) and time between releasing one key and pressing the next (key flight time) are recorded. A touchscreen telemetry is used to measure capacitive pressure gradient, contact area between fingers and the stroke surface, curvature and the velocity trajectory of the stroke [23]. This is metrics that is extremely difficult to sacrifice, not automated and is based on subconscious neuromuscular patterns. If an opponent does succeed in getting valid session cookies and account information, their typing speed, and the dynamics of their mouse movements, are still very different from the baseline distribution.

From a mathematical point of view, the dwell time tau_d is a log-normal distribution, and the flight time tau_f is a Gaussian mixture distribution. An authenticated user u has a baseline profile, which is modeled as a parametric mixture model:

$$P(tau \mid u) \; = \; sum_\{k = 1\}\text{^}K \; pi_k \; * \; N(log(tau) \mid mu_\{u, k\}, sigma_\{u, k\}\text{^}2)$$

The mu_{u,k} and sigma_{u,k}^2 are parameters for the user-specific neuromuscular timing modes of the two key transitions of the digram and trigram, respectively, and the pi_k are parameters for the mixture weights. If the character string received is significantly different from the known distribution, the biometric divergence score will be increased as the empirical log-likelihood distance from the users known distribution.

Environmental device postures are cryptographic identities and device configurations of the client endpoint. Today in enterprise Zero Trust, trusted platform modules (TPM 2.0) and hardware security modules (HSMs) are used to provide an unforgeable attestation of the cryptographic hardware [9]. The client collector checks the integrity of kernels, secure boot status, patch levels and installed

cryptographic root certificates. In the network (32), routing paths through BGP (ASN) are recorded, the round-trip buffer has been jittered, and consistency of IP geolocation is recorded. Protected supervision algorithms keep the continuity of the session when the mobile client is involved in cell tower handovers, and re-compute network risk boundaries [32].

The topologies implemented in the ingestion pipeline are hybrid cloud-edge with the initial telemetry preprocessing and feature normalisation being done at the network edge [10] to support the enterprise scale. The edge nodes extract light-weight features from the high dimensional data generated by high-frequency sensors, compress it to a low dimensional feature embedding and send it to the central cloud analytics stores [12]. This edge assisted design greatly reduces the bandwidth consumed by the WAN, reduces ingress congestion and ensures that new behavioral representations are available for inferring sub-milliseconds.

5. ATTENTION-DRIVEN DEEP LEARNING & CAUSAL INFERENCE FOR ANOMALY DETECTION

With the large number of financial transactions streams, subtle adversarial anomalies require complex machine learning architectures that can capture the temporal dependency and also feature-level dependency [2, 18]. Class imbalance and drift are major issues in financial behavioral telemetry, and traditional methods of anomaly detection, such as threshold or static isolation forests, cannot resolve these problems. In this architecture, we employ an Attention-Driven Deep Learning Architecture specially developed for real-time streaming anomaly detection in financial streams [2].

The multi-head self-attention with temporal sliding windows of the behavioral tokens is used in the anomaly detection architecture. Suppose that X is a sequence of D dimensional normalized telemetry vectors in R^{W x D}. The attention mechanism is responsible for projecting the input sequence to Query (Q), Key (K) and Value (V) matrices obtained using the learned parameters W_Q, W_K, W_V:

$$\text{Attention}(Q, K, V) = \text{softmax}((Q * K^T) / \text{sqrt}(d_k)) * V$$

The model dynamically detects when behaviors are observed that are important and change at different time lags such as: unexpected acceleration in the time lag between key strokes, sudden shift in rate of a transaction, for instance a high value payment instruction delivered in an atypical manner [2]. The multi-head self-attention architecture allows for sequential interactions to be processed with full temporal parallelism, with stream inference processing more than 10,000 window evaluations per second per worker node that are rapidly and efficiently accelerated on the GPU.

The network is stacked with H self-attention heads and aims to model multi-scale temporal dependencies:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_H) * W_O$$

Where each head applied their attentions to various subspace representations: head_h = Attention(Q * W_Q^h, K * W_K^h, V * W_V^h). It is passed through a feed-forward autoencoder (FFAE) whose training was based on some benign historical transaction sequences. Anomaly score is calculated as:

$$E_{\text{reconstruction}} = || X - \text{Dec}(\text{Enc}(X)) ||_2^2$$

In many cases, however, pure deep learning models are prone to be affected by non-causal spurious correlations. If, for example, a user network environment change is valid (such as changing from enterprise Wi-Fi to cell phone), it will lead to high reconstruction errors, which may lead to false positive transaction rejections. The framework includes Counterfactual Scenario Analysis using a Causal Bayesian Network (CBN) [18] to address these issues. The causal engine is the structural causal graph that explains the behavior of the client, the environment and the parameters of the transaction, and it computes the counterfactual probability of the observed transaction:

$$P(\text{do}(\text{Environment} = e_{\text{new}}) \mid \text{User} = u_{\text{legitimate}})$$

The double machine learning technique enables the inference engine to identify environmental changes that do not pose any threat and true adversarial compromises [18]. The aforementioned

Network Handover is an observed network handover, the reconstruction error is dynamically reduced by the system without degrading the user experience and it maintains strong security guarantees of non-compromise of a true network session.

6. DYNAMIC RESOURCE OPTIMIZATION & CLOUD-NATIVE MICROSERVICES GOVERNANCE

The task of ingesting, modeling, and evaluating cryptographic zero-trust policies all while continuously processing huge volumes of biometric content adds significant computation complexity. Without intelligent management of resources, the continuous verification may find the cloud worker nodes get overloaded with calculations, resulting in serious thread pool exhaustion and catastrophic transaction latency inflation [8,17].

Our architecture is based on an autonomous resource optimization model, under Multi-Agent Reinforcement Learning (MARL) [4, 8] control to continuously meet the enterprise Service Level Objectives (SLOs). A multi-agent system is used to simulate the distributed cloud environment where agents at the cloud-edge boundaries monitor the utilization of CPUs, pressure on memory, queues and backlogs of sidecars in inference pipelines [4, 10]. Each agent optimizes a utility function that is a multi-objective one accounting for accuracy of policies and minimizing the latency in the system:

The update to the user is given as α*(1 - Latency_i / Latency_max) - β*ComputeCost_i + γ*DetectionRate_i.

alpha, beta, gamma are tunable governance weight assigned and determined by institutional security and compliance needs.

The sequence of state transitions for the MARL are modeled as a Markov Decision Process (MDP) with the tuple (S, A, P, R, gamma). Each agent (actor-critic) learns its policy parameters theta_i using the centralized critic evaluation policy gradient theorem:

Grad_{theta_i} J(theta_i) = E_{s, a ~ pi} [Grad_{theta_i} log(pi_i(a_i | o_i)) * Q_i^pi(s, a_1, ..., a_N)]

CTDE enables sidecar agents to be trained using cooperative load-shedding and inference-throttling, while avoiding additional delay in inter-node coordination delays to the transactions when they are processed in real-time [4, 6].

In a benign situation, when risk is low, the operating conditions are optimized by letting the MARL scheduling controller dynamically alter the size of the temporal windows and using lightweight heuristics at the edge to perform the initial biometric checks as in [4] and [6]. When the risk indicators increase, or suspicious volatility is detected in network telemetry, the MARL scheduler automatically spawns high performance GPU compute instances elastically, giving the network a high score of attention, and validation with causal counterfactuals [6] and [8]. This orchestration enables computation to be concentrated precisely where computational risk is concentrated, with highest cost efficiency, and in compliance with latency SLAs, every time, [8].

Moreover, the microservice communication mesh is composed of cloud-native microservices which are developed for high concurrency and automatic process resilience [6]. The optimized Envoy sidecar proxies offer an asynchronous streaming channel to enable gRPC. For financial transactions, policy queries are never the single point of serialization failure that would affect the financial transaction engine, since they are distributedly read-replicated [6, 12].

7. EXPERIMENTAL TESTBED SETUP AND SYNTHETIC BENCHMARK METHODOLOGY

To comprehensively evaluate the empirical performance and defense of the proposed distributed ZTF through a continuous process, we built a distributed enterprise grade experimental testbed based on a hybrid multi-region cloud cluster [17, 28]. The testbed has 32 compute nodes with 2 AMD EPYC 7763 64-core processors, 512 GBs DDR4 RAM, 100 Gbps network interface, and is connected between two cloud availability zones with a 1.2 millisecond inter-zone transit latency.

The software infrastructure is an orchestrated Kubernetes cluster (version 1.28) with financial transaction microservices and deployed using Istio service mesh with the mutual TLS 1.3 cryptographic enforcement [27] [29]. Open Policy Agent (OPA) engines run in the sidecar proxies directly and accept WebAssembly (Wasm) policies in compiled form to achieve ultra fast policy evaluation [13]. High frequency telemetry streams are processed with 16 broker nodes of an Apache Kafka cluster with a sustained ingestion rate of telemetry events of more than 500,000 telemetry events per second [12]. Optimized TensorRT neural inference pipelines [2] are processed in a cluster of NVIDIA A100 GPU accelerator nodes which run the AI anomaly detection tier. IEEE 1363-compliant software crypto engines [9] and [31] are emulated by hardware attestation modules, which are cryptoprocessors.The hardware attestation modules are cryptoprocessors that emulate the IEEE 1363-compliant software crypto engines [9] and [31].

The financial workloads include account queries, financial fund transfers and interbank payment clearances, which are provided by a distributed set of instances of the load-testing tool called Locust, a tool that can generate up to 100,000 concurrent client sessions [28], [30]. The benchmark dataset consisted of synthetic behavioral telemetry created by empirical typing, touch and mouse motions, and credential replay, mouse manipulation, and deliberate network spoofing by adversarial vectors, automated bot-driven input actions that mimic human behavior [15, 23].

To quantify the actual security/performance tradeoffs, five different architectures were analyzed: Baseline Unsecured Core (no TLS or policy checks), Traditional Perimeter-Only Defense (initial MFA with static perimeter VPN), Static Zero-Trust (per-request mTLS 1.3 and OPA static RBAC rules without behavioral scoring), Continuous Biometric Auth Only (static MFA with continuous keystroke dynamics without causal AI), and Full Integrated Multimodal Continuous Zero-Trust (the proposed architecture with continuous multimodal biometrics, attention deep learning anomaly scoring, causal Bayesian arbitration, and MARL dynamic resource governance) [2], [4], [18].

8. EMPIRICAL EVALUATION & PERFORMANCE-SECURITY TRADEOFF RESULTS

Four important metrics were used to extensively evaluate the experimental configurations: transaction throughput (transactions per second, TPS), mean and median end-to-end response latency, 99th percentile end-to-end response latency, and the malicious transaction detection (true positive rate, false positive rate) and CPU/memory utilization overhead. The results of the benchmark, at 10k and 50k transactions per second, are summarized in table 1..

Table 1: Comprehensive benchmark of transaction throughput, operational latency, detection efficacy, and compute overhead across architectural security configurations under sustained enterprise payment workloads.

Architectural Configuration	Peak Throughput (TPS)	Mean Latency (ms)	p99 Latency (ms)	Detection Rate (%)	False Positive Rate (%)	CPU Utilization Per Node (%)
1. Baseline Unsecured Core	98,400	1.2	3.8	0.0%	0.0%	24.2%
2. Perimeter-Only (Initial MFA)	94,200	2.1	6.4	18.2%	0.04%	29.8%
3. Static Zero-Trust (mTLS + OPA)	68,500	5.6	14.8	76.5%	0.08%	62.4%
4. Continuous Biometric Auth Only	74,100	4.3	12.6	88.4%	2.10%	58.1%
5. Proposed Full Multimodal ZTA	82,600	3.8	11.2	99.4%	0.12%	51.6%

The Baseline Unsecured Core achieved a maximum sustained throughput of 98,400 TPS, p99 latency of 3.8 ms and did not have detection coverage for session hijacking and synthetic identity fraud. Compared with the Traditional Perimeter Defense, the detection rate for post-ingress attacks and high throughput (94,200 TPS) was very low (18.2%) and the p99 latency was high (6.4 ms) [17], [28].

It should be noted that the configuration for Static Zero-Trust was quite successful on the defensive end, with 76.5% detection rate; requiring a continuous identity verification of cryptographic services with mTLS and static OPA access policies. The performance cost of this security enhancement was relatively high, however, due to the reduction of max throughput to 68,500 TPS and p99 latency to 14.8ms from continuous crypto handshakes and sidecar proxy serialization [27, 29]. Static Zero-Trust also did not detect legitimate users that are using stolen user session tokens since it lacks behavioral introspection.

The Continuous Biometric Auth config has been found to be able to identify 88.4% of the Session Hijack instances, and that 2.1% of false positives were caused by benign biometric variance, which only causes a relatively small disruption of transactions for legitimate users [23]. However, the proposed Full Multimodal Continuous Zero Trust Framework had a detection rate of 99.4% malicious content and low false positive rate of 0.12% – the highest in the industry. Of course, the most important thing was that the system could support as many as 82,600 TPS and an average latency of 11.2 ms (p99) – a latency increase of only 4.8 ms over the conventional perimeter configurations. The results have nothing to do with theory and are empirical, clearly showing the capacity of a holistic, no-responsiveness impact verification of behavior, even in real-time financial transactions, particularly in high volume.

Latency percentile tails also serve as a good measure of the strength of the architecture. In the Static Zero-Trust configuration, on the far tail, p99.9, the latency reached a staggering 48.6ms under some extreme load spikes at up to 90,000 TPS. On the other hand, the framework coordinated by MARL was able to achieve a latency of p99.9 = 18.4ms, thus proving that the dynamic load shedding and elastic inference allocation approach is good enough to not cause catastrophic tail latency to the mission critical payment settlement application [8, 27].

9. OPERATIONAL GOVERNANCE, PREDICTIVE MAINTENANCE, AND DEPLOYMENT ROADMAPS

A holistic operational governance, continuous model auditability and proactive infrastructure maintenance is needed to enable continuous authentication and behavioral anomaly detection for enterprise banking cloud deployments [6, 14]. If the algorithmic decision is used in a strict regimes such as PCI-DSS, Basel III/IV and GDPR, it must be fully explainable and a choice must be made whether there is a need to maintain uncompromising protection of sensitive biometric data or not, [1] and [16].

The captured biometric telemetry must never be in the raw sensor data from the client endpoints as this is required by regulatory privacy standards. Rather, the keystroke and gesture signals are transformed to irreversible cryptographic feature embeddings using privacy-preserving locality-sensitive hashing (LSH) and differential privacy methods [19]. These embeddings are encrypted, so that the attention neural network can compute the similarity distance to physiological potential and the score for the anomaly without storing personally identifiable physiological signatures, reducing privacy exposure risks in the case of a breach in the analytics store.

Furthermore, the ability of the self-healing infrastructure resiliency is crucial to enable distributed zero trust financial solutions.Also, self-healing infrastructure resiliency is one of the requirements for distributed and zero-trust financial platforms. For long-running cloud deployments, memory fragmentation, cache drift, and connection pool exhaustion [14, 27] may occur as possible side effects impacting microservice sidecar proxies, telemetry queues and inference workers. Our framework is deployed in an intelligent manner that allows self-learning by the deployment of the AI based predictive maintenance system for Cloud infrastructures [14]. Predictive maintenance controller is able to identify early before a worker pod degrades, enough time has passed for the sidecar to fill up its

memory or the inference queue, through the use of the telemetry buffer depths, sidecar memory usage and inference queue times, to automatically reallocate the worker pods, flush the degraded caches and prevent outages cascading throughout the entire system.

Automated policy self-healing [1, 16] is a must in order to meet regulatory requirements along with full non-repudiation and forensic traceability of automated policy actions. A Distributed Ledger stores a tamper-proof history of all the continuous trust score calculations, feature vectors and policy enforcement decisions. This creates mathematically auditable audit trails for compliance auditors to meet Basel III governance needs and for automated regulatory reporting.

Staged deployment is highly recommended for institutional adoption. The initial deployment of the continuous telemetry fabric should be in 'passive shadowing' mode, where an attention-driven anomaly-based model can construct good 'profile' of the users without the need to implement blocking policies [2, 10]. As confidence grows [5] [20] the organization can then turn on dynamic step-up MFA for intermediate risk transactions and eventually, as confidence increases, to full zero-trust automated transaction gating.

10. CONCLUSION

In this paper, the authors suggested an integrated architecture of a continuous multimodal authentication system for real-time behavioral anomaly detection in a zero trust financial transaction processing system. The proposed architecture will revoke the implicit network trust paradigm and will allow to continue verifying the behavior of all transactions through passive behavioral biometrics, device posture attestations and semantic transaction interaction vectors. High-velocity stream anomaly detection systems can effectively separate true adversarial attacks from benign changes in the environment, and can achieve high accuracy in detecting attacks with almost no false alarms, by synthesizing a multi-head attention neural architecture together with a counterfactual causal Bayesian network.

Furthermore, the framework can solve the important problem of performance influence that has been existed in the field of both deep cryptographic and algorithmic verification, which can be solved by the multi-agent reinforcement learning of dynamic resource scheduling and the cloud-native services governance in the micro-segmented cloud environment. The framework was tested to detect session hijacking and automated credential abuse with a 99.4% accuracy rate across distributed cloud environments and was able to process more than 82,000 transactions per second with a p99 latency of less than 12 ms. The results make it clear how to have both high-performance, continuous zero-trust security and ultra-high throughput financial transaction performance, enabling the future of financial clouds that will rely on the Internet.

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