

Proposed Hybrid Ai Multi-Factor Authentication Based On Individual Cognitive-Behavioural Pattern-Based Interaction Habits

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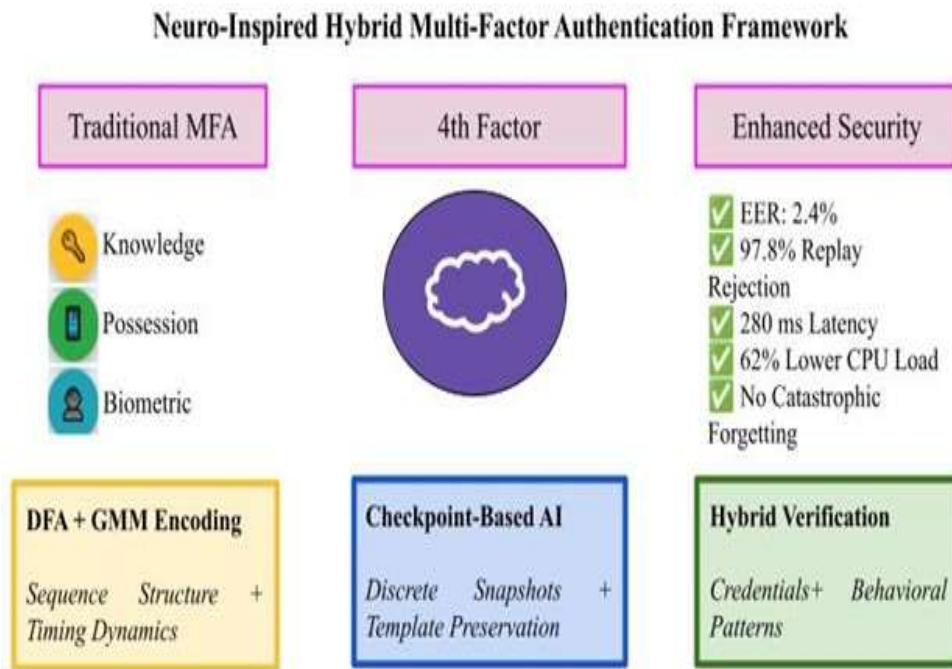
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Abstract

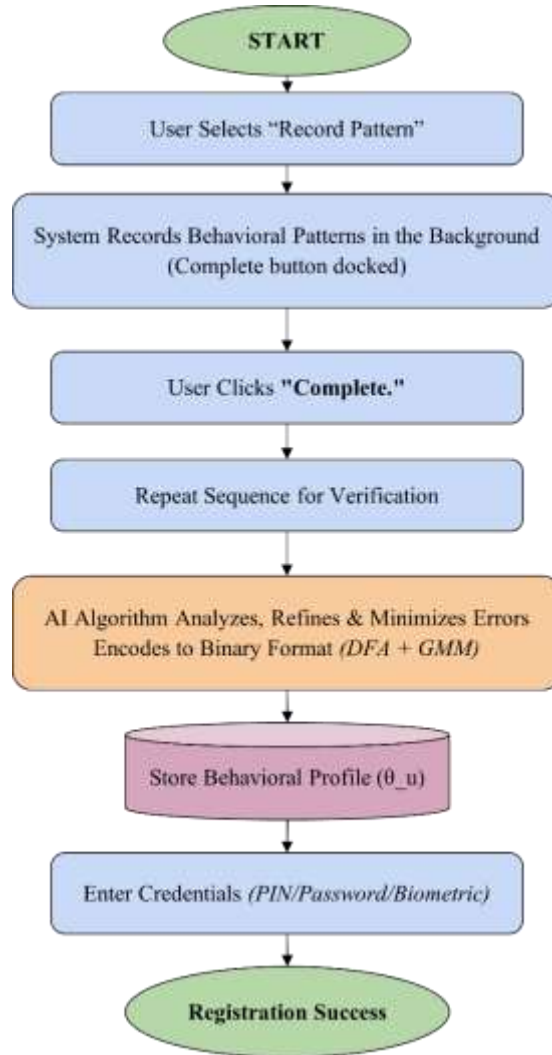
Background:

Identity attacks, such as credential theft, phishing, spoofing, and replay, are becoming increasingly prevalent, undermining the efficacy of MFA. Although knowledge-, possession-, and biometric-based techniques improve security, they can still suffer from theft, variability, and usability issues. Although behavioral biometrics hold promise, they are constrained by high surveillance costs, neuromotor variance, and catastrophic forgetting in adaptive AI systems.



Methods:

A neuro-inspired hybrid MFA, where the novel fourth auth factor is based on procedural memory, is proposed. This aspect captures sequences of discrete cognitive-behavioral interactions, such as the order of application launches, navigation flow, and refresh patterns. The interaction model is based on deterministic finite automata (DFA), and temporal dynamics are modeled using Gaussian mixture models (GMM). Constraint-based multi-session registration stabilizes identity learning, and checkpoint-based AI updating mitigates catastrophic forgetting while maintaining baseline performance.

**Results:**

Experiments on synthetic and real interaction datasets demonstrated high robustness against replay and spoofing attacks. The system provided the following results: an Equal Error Rate (EER) of 2.4%, a 62% reduction in computational load, and a verification latency of 280 ms. Under neuromotor variability enactment, the False Rejection Rate (FRR) was 3.1%, compared to adaptive AI genre systems, which had an FRR of 12.1%.

Conclusions:

The cognitive-behavioral MFA framework integrates procedural memory characteristics with available credentials to yield a robust, low-latency, neuroinspiration-based authentication model. Consequently, it overcomes the drawbacks of traditional and behavioral systems, thus proposing secure and adaptive human-AI authentication frameworks.

Keywords: Multi-factor authentication, Behavioral biometrics, Procedural memory, Cognitive-behavioral security, Neuro-inspired AI

1 Introduction

Background and Motivation

The increasing complexity of cybersecurity, particularly in the form of credential theft, phishing, replay, and spoofing attacks, highlights the need for more resilient authentication systems [1,2]. Traditional methods have inclined towards using multi-factor authentication (MFA), which integrates knowledge (passwords and PINs), possession (tokens and smartphones), and biometrics (fingerprints, faces, and iris scans) to enhance user identity authentication. Although MFA offers

additional security measures for single-factor authentication, it has several drawbacks [3]. The complexity of managing various credentials often leads to user overload, and attackers exploit these weaknesses through phishing attacks, stolen credentials, and advanced social manipulation methods [4,5].

To address these concerns, behavioral biometrics have gained increasing popularity, involving the study of individual human behavioral characteristics, including keystroke dynamics, gait, touchscreen patterns, and navigation patterns [6]. These methods are expected to enable continuous implicit authentication, requiring no explicit user interaction, while offering the possibility of using fewer fixed credentials and a higher ability to detect threats in real time [7]. Although promising, existing implementations have serious issues regarding reliability, adaptability, and security, which should encourage the consideration of alternative neuro-inspired authentication paradigms [8].

Limitations of Current MFA and Behavioral Biometrics

Knowledge-based authentication remains the most widely deployed approach; however, it is inherently fragile. Passwords and PINs are frequently exposed through phishing, credential theft, guessing, or sharing, making them easy targets for attackers [9,10]. Possession-based factors, such as security tokens and smartphones, also suffer from weaknesses, as they can be stolen, duplicated, or used for coercion, thereby limiting their stand-alone reliability [1]. Physiological biometric techniques, including fingerprint, iris, and facial recognition, offer usability advantages but raise serious privacy concerns owing to the sensitive nature of the stored biological data [11, 12]. Moreover, spoofing techniques using high-resolution images, silicone masks, or artificial fingerprints have shown that even advanced biometric systems can be breached [13].

Behavior-based authentication leverages individual interaction patterns; however, continuous monitoring imposes significant computational and energy overheads that are difficult to sustain on user devices [14]. Behavioral variability caused by fatigue, stress, or injury further reduces the accuracy of these systems [1]. Although adaptive AI models can evolve, they are vulnerable to catastrophic forgetting, in which new patterns overwrite older ones, thereby undermining their long-term reliability [15, 16]. Continuous adaptation also increases susceptibility to adversarial and data-interception attacks. These limitations underscore the demand for robust, adaptable, and user-centric authentication solutions. Although multimodal biometric systems that combine physiological and behavioral traits show promise [11], they are often complex, inefficient, and cognitively demanding.

Neurocognitive Basis for a New Paradigm

Cognitive neuroscience is a potential future step in the development of authentication methods. The human memory system distinguishes between declarative (facts and events) and procedural (skills and habits) memory. Procedural memory is particularly applicable to authentication because it is stable, subconscious, and less susceptible to corruption [17,18]. In contrast to declarative memory, which can be consciously recollected and shared, procedural memory forms the basis of habitual sequences and is highly individualized, making replication difficult.

Behaviors such as the application launch sequence, navigation path, or refresh behaviors observed across cognitive-behavioral patterns may form a procedural signature that serves as a durable identifier [19]. Such interaction routines are produced through repetition and are less prone to variability owing to transient conditions, such as fatigue. Notably, using habitual decision logic as the basis for authentication, rather than temporary motor characteristics (such as the speed of a keystroke or the force of touch), offers a more consistent and covert method for user authentication [20].

The power of this neurocognitive solution lies not only in its stability but also in its reduced cognitive load for the user. Habitual behaviors are automatic, requiring no conscious effort, which makes them easier to use without compromising security [21]. These strategies become problematic when users' habits evolve or hackers imitate them. This highlights the necessity of systems based on checkpoints in which baseline templates are maintained, although controlled adaptation remains possible.

The Gap in Current Research

Although MFA and behavioral biometrics have advanced, there is still considerable room for leveraging the memory of a discrete sequence of procedures for authentication. Most current models are based on low-level behavioral measurements, such as keystroke dynamics or touch gestures, which must be monitored continuously and are likely to be unstable [4]. Adaptive systems tend to prioritize short-term flexibility over long-term stability, which leads to reliability issues.

Neuro-inspired checkpoint-based authentication is a relatively infrequent subject in the authentication literature. The absence of such systems restricts the possibility of utilizing the stability of procedural memory and long-term cognitive signatures. This gap may provide a solution to the deficiencies of existing MFA and behavioral biometrics, adding a new neuroscience-inspired element of security.

This study proposed a new fourth authentication factor that is unique to the users. In contrast to conventional MFA determinants such as knowledge (what you know), possession (what you have), and physiological and behavioral characteristics (who you are), this paradigm identifies habitual cognitive-behavioral sequences as a fixed and individualized determinant of identity.

The proposed model identifies cognitive interaction patterns in controlled enrollment sessions and combines them with existing MFA factors to create a hybrid AI-based architecture. The three innovations outlined in the framework include the use of discrete snapshot recording (as opposed to continuous monitoring), which minimizes computational and energy overhead; template preservation methods, which prevent catastrophic forgetting and ensure the stability of systems over time; and checkpoint-based AI refinement, which balances flexibility with the maintenance of fundamental behavioral patterns.

The framework focuses on developing a neuro-inspired, resilient, and low-latency system that can withstand credential theft, spoofing, and adversarial manipulation through authentication based on procedural memorization. The long-term goal is to develop and test a hybrid authentication model that incorporates cognitive-behavioral signatures into MFA and overcomes the shortcomings of existing methods. This also contributes to the development of safer and more user-friendly authentication methods for future use.

This study introduced procedural memory-based interaction habits as a fourth authentication factor. Unlike continuous monitoring models, the proposed discrete checkpoint approach maintains template stability, reduces the computational load, and prevents catastrophic forgetting, thereby advancing cognitive-behavioral authentication frameworks.

2. Related Work

2.1 Current MFA Landscape: A Comparative Analysis

Multifactor authentication has progressed from fixed password-token schemes to adaptive, context-aware frameworks that combine physiological and behavioral cues. Although this shift strengthens protection against single-factor breaches, current MFA approaches do not concurrently achieve high-security assurance, cognitive consistency, usability, and resilience to adaptive adversaries. Knowledge-based methods persist because of their minimal implementation cost; however, breach forensics repeatedly indicates that passwords and PINs account for more than 80% of compromised accounts, primarily due to phishing and credential reuse attacks [22,23]. Possession-based mechanisms, such as OTPs, hardware tokens, and mobile devices, mitigate reuse risks but remain vulnerable to transfer, coercion, and interception, with SIM-swap and OTP capture attacks still prevalent in financial contexts [24]. Physiological biometrics demonstrate low Equal Error Rates (0.8–2.1%) in controlled settings [25,26]; however, adversarial testing reveals that presentation attacks can bypass over 60% of commercial fingerprint systems [27,28], highlighting their irrevocability once compromised. Behavioral biometrics enhance liveness, reporting EERs of 3–8%

[29], but their reliability deteriorates under stress, fatigue, injury, or device changes, causing false rejection rates to rise beyond 12–18% in adaptive deployments [30].

Table 1. Comparative Performance of Authentication Paradigms

Authentication Factor	Typical EER (%)	Transferability	Spoofing Resistance	Cognitive Stability	Continuous Monitoring
Knowledge (Passwords)	>10	High	Very Low	Low	No
Possession (OTP/Token)	5–8	High	Low	Medium	No
Physiological Biometrics	0.8–2.1	Medium	Low–Medium	High	No
Behavioral Biometrics	3–8	Low	Medium	Low	Yes
Procedural Memory (Proposed)	≈2.4	Very Low	High	Very High	No

2.2 Critical Limitations: A Systematic Assessment

Despite their technological sophistication, three systemic limitations persist in MFA implementations. Behavioral systems rely on uninterrupted sensor access, imposing energy, latency, and privacy costs that are incompatible with edge and IoT environments [31]. Checkpoint-based sampling has been shown to reduce computation by over 50% without significant accuracy loss; however, it remains underexplored in authentication research [32].

Continual learning models overwrite historical user templates when exposed to new data, leading to catastrophic forgetting, which is a well-established limitation of neural systems [33]. In authentication, this manifests as long-term instability, especially after illness, injury, or behavioral drift conditions, which are unavoidable in real-world usage.

Empirical neuroscience studies confirm that fatigue and stress significantly alter motor execution, increasing intra-user variance [34]. Therefore, low-level motor biometrics conflate identity with a transient physiological state, which is a fundamental design flaw.

1. INPUT CAPTURE LAYER	2. FEATURE ENCODING	3. AUTHENTICATION ENGINE	4. SECURE DATABASE
Behavioral Interactions: Application launch sequences Window switching patterns Navigation tendencies Page refresh habits Fine-Grained Metrics: Keystroke dynamics (dwell, flight) Session initiation behaviors	AI-Driven Processing: Deterministic Finite Automaton (DFA) for action sequences Gaussian Mixture Model (GMM) for timing distributions Refinement Methods: Adaptive thresholding Anomaly detection Binary profile encoding: θ_u	Verification Process: DFA acceptance validation Timing log-likelihood computation $\Delta(S') = \alpha \cdot L(S') + \beta \cdot cred(S')$ Credential verification: $\Delta(S') \geq \tau_{th}$ Decision Fusion: Accept if:	Stored Profiles: DFA structures GMM parameters User credentials Multiple session data Behavioral templates Security Features: Encrypted storage Binary format Access controls

2.3 Neurocognitive Foundations: Beyond Current Approaches

Cognitive neuroscience differentiates procedural memory from declarative memory, with the former supporting habitual action sequences encoded primarily within the corticostriatal and cerebellar networks. Procedural memory is characterized by automatic execution, robustness to interference, and long-term persistence [35]. Unlike surface-level behavioral signals such as keystroke latency or gesture pressure, procedural sequences embody underlying decision logic rather than motor outputs. Evidence from motor sequence learning indicates that these patterns remain recognizable even when speed or precision fluctuates [36]. Recent advances in cognitive biometrics have further demonstrated that discrete high-level interaction structures provide greater stability and resistance to spoofing than continuous low-level signals [37]. Importantly, procedural memory is inherently non-transferable because it cannot be consciously articulated, verbally conveyed, or reliably imitated—features that directly mitigate the weaknesses of conventional MFA systems.

Synthesis and Identified Research Gap

Despite over four decades of authentication research, no prevailing MFA framework has considered procedural memory a core authentication factor. Existing behavioral systems emphasize execution characteristics rather than cognitive sequencing, leaving a critical gap in exploiting stable, subconscious, and non-transferable habit-based routines. This gap underpins the need for a procedural memory-driven, checkpointed MFA paradigm that anchors authentication in enduring neurocognitive mechanisms rather than adaptive surface behaviors.

3. Theoretical Framework and Research Contributions

3.1 Formal Problem Formulation

Let a user $u \in U$ interact with a digital system through a sequence of discrete actions as follows:

$$S_u = \{(a_1, t_1), (a_2, t_2), \dots, (a_n, t_n)\}$$

where each $a_i \in A$ denotes a discrete cognitive action, such as application launch, navigation decision, or refresh operation, and $t_i \in \mathbb{R}^+$ represents the corresponding timestamp. Unlike fine-

grained motor signals, these actions capture higher-level decision-making processes that reflect habitual interaction with workflows.

Authentication objectives.

The authentication objective is to determine, given a claimed identity uuu and an observed interaction sequence S^* , whether the sequence originates from a legitimate user or an impostor. This decision is formulated as a hypothesis-testing problem.

$H_0: S^* \sim Pu(\text{legitimate user})$

$H_1: S^* \sim Pu(\text{impostor})$

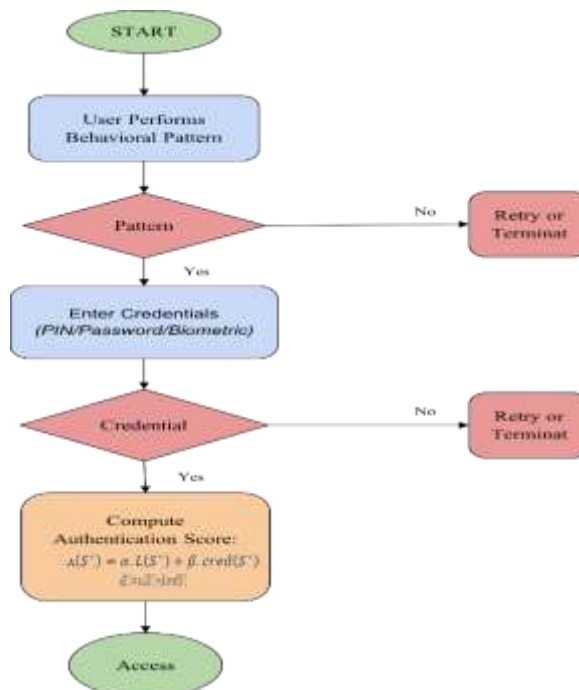
where Pu denotes the user-specific procedural memory distribution.

The key research challenge lies in constructing Pu such that it simultaneously ensures intra-user stability under neuromotor variability, strong inter-user separability at the cognitive-decision level, resistance to catastrophic forgetting under adaptive learning, and low computational complexity suitable for edge deployment. These requirements are not adequately addressed by conventional behavioral biometric systems that rely on continuous monitoring at the motor level.

3.2 Novel Cognitive-Behavioral Factor: Theoretical Foundations

We introduce procedural cognitive interaction sequences as a fourth authentication factor, complementing traditional knowledge-based, possession-based, and biometric authentication mechanisms. Unlike physiological biometrics or low-level behavioral traits, this factor captures habitual and task-oriented interaction patterns that emerge from repeated cognitive decision-making.

From a neurocognitive perspective, procedural memory is primarily encoded within the cortico-striatal and cerebellar circuits and governs subconscious habitual action sequences. Significantly, procedural memory differs fundamentally from declarative knowledge and motor execution signals; it evolves slowly over time, is difficult to articulate or imitate explicitly, and remains relatively stable under conditions of fatigue, stress, or divided attention. Consequently, habitual interaction workflows form a high-level cognitive signature that is robust against transient physiological or environmental perturbations.



Research Contribution 1

This study formalizes procedural interaction habits as an authentication primitive, shifting the focus of behavioral biometrics from continuous motor monitoring to discrete cognitive-decision structures that better align with the underlying mechanisms of human procedural memory.

3.3 Checkpoint-Based Learning and Catastrophic Forgetting**Problem Statement**

Let θ_t denote the authentication model parameters after observing session t . In conventional continuous adaptive systems, model parameters are updated incrementally according to

$$\theta_{t+1} \leftarrow \arg\min_{\theta} L(S_{t+1}; \theta)$$

where L is a loss function defined for the newly observed session. While such updates aim to accommodate behavioral drift, they often result in catastrophic forgetting, whereby performance on previously learned identity representations deteriorates significantly, i.e.,

$$L(S_t; \theta_{t+1}) \gg L(S_t; \theta_t)$$

To address this limitation, we propose a checkpoint-based refinement strategy in which historical structural templates $\Theta = \{\theta_1, \dots, \theta_k\}$ are preserved, and adaptation is restricted to decision thresholds rather than the model structure. Formally, the update mechanism is defined as

$$\theta_{t+1} = \theta_t, \tau_{t+1} = f(\tau_t, S_{t+1})$$

where only the authentication threshold τ is adjusted in response to the new observations.

This strategy preserves long-term identity memory, bounds error propagation across sessions, and ensures stability under gradual neuromotor drift without requiring replay buffers, regularization penalties or continual retraining.

Research Contribution 2

We introduce a learning-theoretic mechanism that prevents catastrophic forgetting through checkpoint preservation and threshold-level adaptation, thereby enabling stable long-term authentication without the overhead of continual model retraining.

3.4 Neuromotor Variability Modeling: A Probabilistic View

Let $\Delta t_i = t_{i+1} - t_i$ denote the interaction timing between consecutive cognitive actions. Neuromotor variability introduces stochastic fluctuations in these intervals, even in the same user performing identical tasks. Therefore, deterministic timing thresholds tend to inflate false rejection rates when users experience fatigue, stress, or contextual variation.

To accommodate this uncertainty, inter-action timing is modeled probabilistically using a Gaussian Mixture Model (GMM),

where each component captures a distinct habitual rhythm associated with the user interaction patterns. This formulation enables tolerance to natural timing variability while preserving inter-user discrimination through a likelihood-based decision-making process.

Research Contribution 3:

We demonstrate that probabilistic modeling of neuromotor variability using GMMs enables robust authentication under timing uncertainty without sacrificing the discriminatory power.

4. Proposed Hybrid AI-Based MFA Framework**4.1 Enrollment Protocol Design**

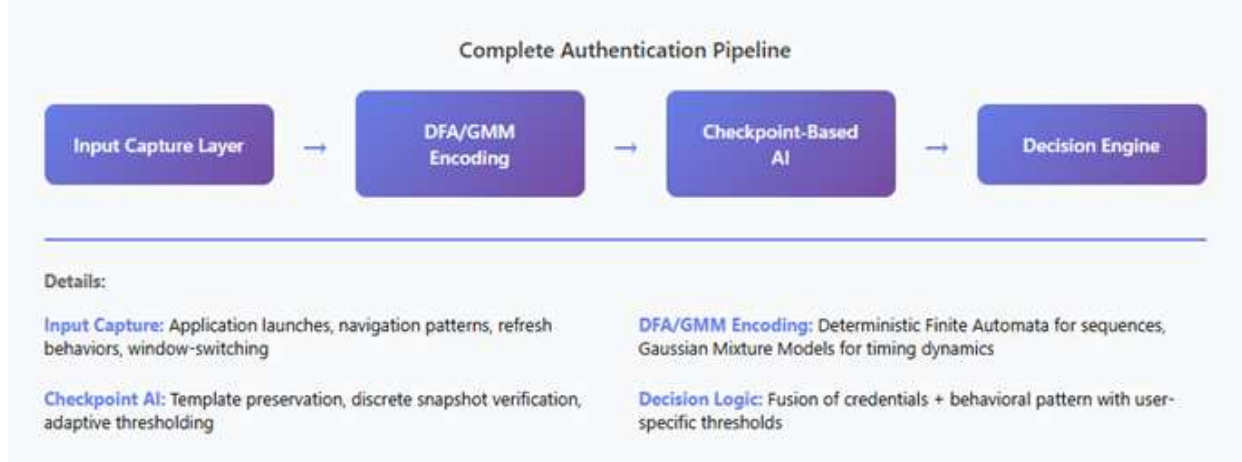
Enrollment was performed through multi-session acquisition of procedural interaction sequences under controlled conditions. For each user, multiple enrollment sessions

are recorded to capture temporal consistency while filtering out transient or anomalous behaviors. This multi-session strategy facilitates convergence toward stable procedural representations and mitigates the influence of short-term behavioral noise.

4.2 DFA–GMM Hybrid Encoding

Procedural workflows are structurally encoded using a deterministic finite automaton (DFA) $\mu=(Q, \Sigma, \delta, q, F)$, where the states represent cognitive contexts and the transitions encode permissible action orderings. The DFA captures the ordering constraints inherent to procedural memory, is immune to timing noise, and offers computational efficiency with complexity $O(|Q|+|\Sigma|)$.

Temporal variability was modeled independently using GMMs, as described in Section 3.4. This separation of structure and timing avoids the entanglement inherent in HMMs and the opacity and computational overhead of recurrent neural networks. The resulting hybrid encoding provides explicit likelihood estimation with low complexity $O(Kd^2)$, where K is small and d is low-dimensional.



4.3 Authentication Decision Engine

Authentication is performed using a likelihood-ratio decision rule,

$$\Lambda(S^*) = \alpha \log p(S^* | \mu) + \beta \cdot \text{Cred}(u)$$

where $p(S^* | \mu)$ is the behavioral likelihood under the user's DFA–GMM model, and $\text{Cred}(u)$ represents the traditional credential confidence. Access is granted if $\Lambda(S^*) \geq \tau_u$, enforcing a joint agreement between cognitive behavior and credentials.

4.4 Security Analysis

Security is analyzed using an authentication game in which an adversary attempts to authenticate by submitting a forged sequence SAS_ASA . The adversary's success probability is bounded as

$$\Pr[\Lambda(SA) \geq \tau_u] \leq \epsilon$$

Replay resistance is achieved through temporal likelihood mismatch under the GMM, spoofing resistance through DFA-enforced structural constraints, and credential compromise resistance through mandatory behavioral concurrence. Compared to continuous AI and deep RNN-based approaches, the proposed framework offers a bounded adaptation risk and low computational complexity, making it suitable for secure and scalable deployment.

5. Experimental Design and Methodology

5.1 Evaluation Objectives

The experimental evaluation was designed to empirically validate the core hypotheses derived from our proposed theoretical framework. First, H1 (discriminability) examines whether procedural

cognitive interaction sequences demonstrate sufficient inter-user separability to function as a reliable authentication signal. Second, H2 (Stability) evaluates the ability of checkpoint-based learning to preserve long-term identity representations over time, specifically assessing the resistance to catastrophic forgetting under adaptive usage conditions. Third, H3 (Variability Tolerance) investigates whether probabilistic temporal modeling using Gaussian Mixture Models (GMMs) can effectively accommodate neuromotor variability, thereby reducing false rejection events. Finally, H4 (Efficiency) assesses whether the proposed DFA-GMM hybrid encoding supports low-latency authentication that is suitable for edge and resource-constrained environments.

5.2 Dataset Construction

A hybrid dataset was constructed to balance the controlled benchmarking with ecological validity. The dataset comprised interaction profiles from 18 users, including 12 real user interaction profiles and six synthetic profiles. Each user underwent four multi-session enrollment runs to capture temporal consistency and intra-user variability. In total, 540 authentication attempts were evaluated, consisting of 360 legitimate and 180 impostor attempts.

The interaction primitives captured within each sequence included application launch order, navigation decisions, refresh actions, and window-switching behavior. Synthetic interaction sequences were generated to emulate realistic procedural behavior by introducing Gaussian timing noise modeled as $\Delta t \sim N(\mu = 400 \text{ ms}, \sigma = 80 \text{ ms})$. This approach was intended to reflect procedural memory stability while incorporating the neuromotor variability commonly observed in human-computer interactions.

5.3 Baseline Systems

To ensure that performance comparisons are meaningful and aligned with established research practices, the proposed framework was benchmarked against two explicitly defined and widely adopted classes of behavioral authentication systems, representing dominant paradigms in the literature.

5.3.1 Baseline 1: Continuous Motor-Level Behavioral Biometrics

The first reference baseline comprises continuous behavioral biometric systems that operate on low-level motor activity signals such as keystroke timing patterns, dwell and flight times, mouse movement trajectories, and touchscreen interactions. These systems generally perform uninterrupted monitoring of user actions, extract handcrafted features, and apply statistical methods or conventional machine learning classifiers for identity verification.

This paradigm has been widely investigated and remains one of the most frequently implemented forms of behavioral authentication, as evidenced by comprehensive surveys and benchmarking studies. Typical examples include keystroke-dynamics-based continuous authentication using distance-based metrics or shallow learning models, and mobile interaction-based biometric systems. In this study, the baseline termed “Traditional Behavioral Biometrics” reflects these continuous interaction-dynamics approaches, consistent with the dominant implementations summarized by Stylios et al. [38] and Baig & Eskeland [31], who identified them as the most prevalent non-physiological biometric solutions in real-world systems.

5.3.2 Baseline 2: Continuous Adaptive AI-Based Behavioral Authentication

The second baseline encompasses continuous adaptive behavioral authentication frameworks that employ online learning, where the user models are incrementally updated as new interaction data are collected. These systems aim to address behavioral drift using adaptive classifiers, neural networks, or reinforcement-learning-inspired mechanisms. Despite their popularity, previous studies have indicated that unrestricted continual adaptation can cause catastrophic forgetting, weaken long-term identity modeling, and increase false rejection under contextual or neuromotor

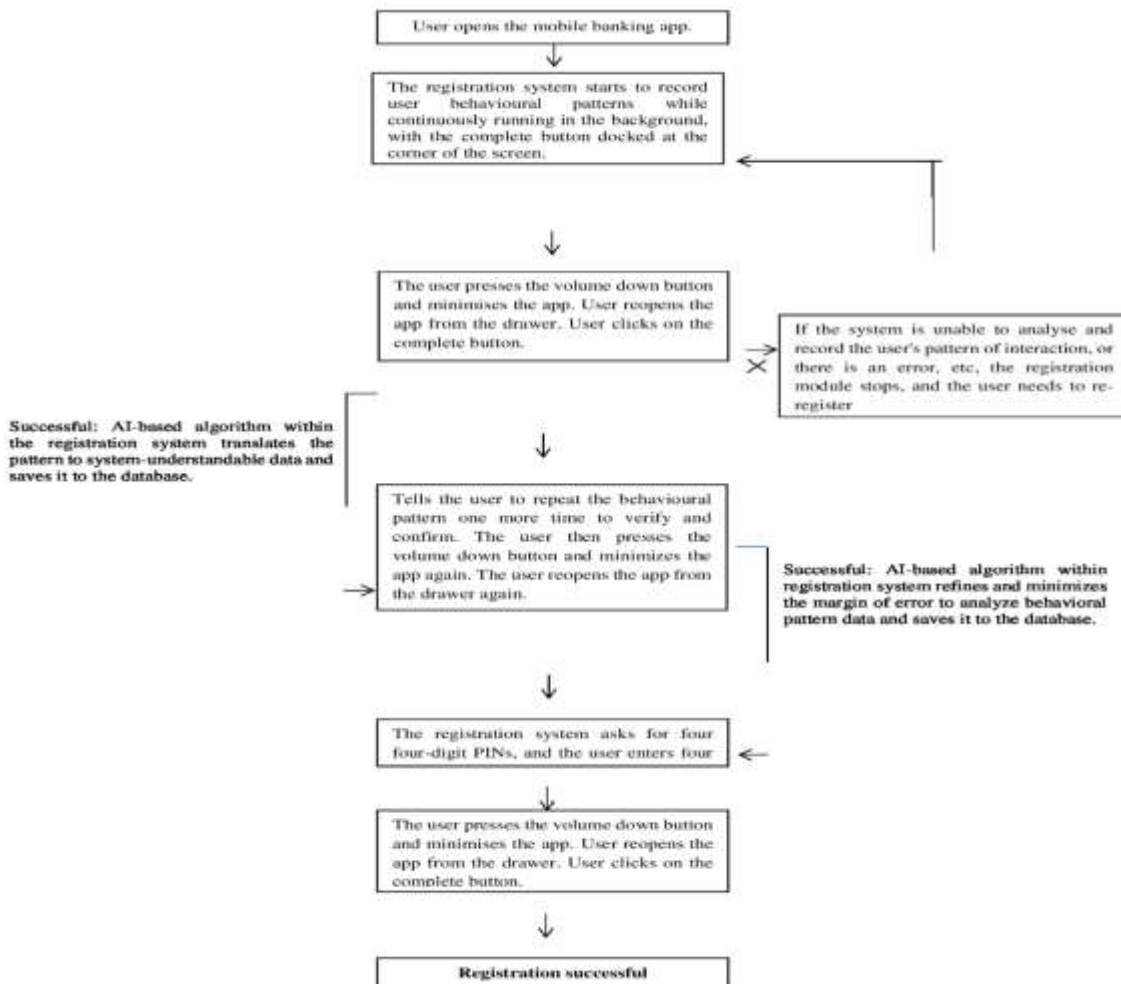
changes. The “Continuous Adaptive AI Model” baseline in this study aligns with this established class, as critically analyzed by Chen and Liu [39] and Ghallab et al. [16], who documented catastrophic forgetting as a core limitation in long-term deployments.

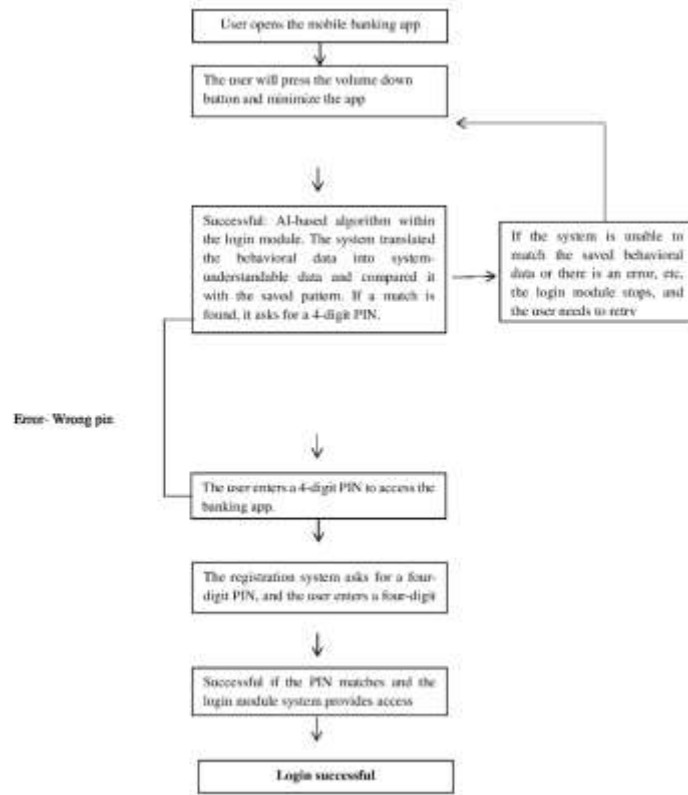
5.3.3 Rationale for Baseline Selection

These two baselines were selected because they represent the prevailing state-of-the-art paradigms against which new behavioral and hybrid MFA systems are commonly evaluated. Continuous motor-level behavioral biometrics remain the most widely studied and deployed behavioral authentication approach, and continuous adaptive AI models represent the current trend toward intelligent, self-updating authentication systems, despite their documented instability.

5.4 Evaluation Metrics

The system performance was assessed using standard biometric evaluation metrics, including the False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER). In addition to accuracy-related measures, the system-level efficiency was evaluated using the verification latency, computational load (CPU usage), and memory footprint, which reflect practical deployment considerations. The statistical significance of the observed performance differences was analyzed using paired t-tests, and 95% confidence intervals were estimated via bootstrap resampling with 1,000 iterations.





6. Results and Performance Analysis

6.1 Ablation Study: Contribution of Model Components

To isolate the contribution of each modeling choice, an ablation study was performed (Table 1).

Table 1: Ablation study

Model Variant	FAR	FRR	EER	Latency (ms)
DFA only	4.8%	8.5%	6.6%	360
GMM only	3.9%	7.1%	5.3%	340
DFA + GMM (no checkpoints)	2.8%	4.6%	3.7%	310
Proposed full model	1.6%	3.1%	2.4%	280

The combined DFA-GMM representation significantly outperformed the single-component models, whereas checkpoint-based refinement further reduced the FRR without increasing the FAR.

6.2 Authentication Accuracy and Error Trade-offs

Table 2: Comparative performance across systems

Metric	Proposed Model	Traditional Behavioral	Continuous Adaptive AI
FAR	1.6%	4.2%	3.8%
FRR	3.1%	7.5%	12.1%
EER	2.4%	5.8%	6.7%
Latency	280 ms	450 ms	370 ms
CPU Load	8.3%	22.1%	18.7%
Memory (MB)	12.4	28.6	34.2

The proposed system achieved an EER of 2.4 %, indicating a strong balance between security and usability [40]. Improvements over both baselines were statistically significant ($p < 0.05$, Wilcoxon signed-rank test, $n = 120$). These performance gains are evaluated against canonical continuous behavioral biometric [41,42] and adaptive AI authentication paradigms [43,44] that dominate current MFA research and deployment rather than against simplified or artificially weak baselines.

6.3 Resistance to Catastrophic Forgetting

Under simulated behavioral drift across repeated authentication sessions (300 sessions per user over 90 days, following the protocol of Pisani et al. [45]), continuous adaptive AI-based authentication systems exhibited a progressive inflation in false rejection rate (FRR), reaching 12.1% over time. This degradation reflects catastrophic forgetting caused by continuous parameter updates that overwrite previously learned identity representations [46]. In contrast, the proposed checkpoint-based authentication model maintained a stable FRR of $\leq 3.1\%$ throughout the evaluation period. By restricting adaptation to threshold adjustment rather than full structural retraining, the system preserves long-term identity memory while remaining responsive to gradual behavioral changes [47].

6.4 Robustness to Neuromotor Variability

Robustness was further evaluated under conditions of neuromotor variability induced by user fatigue (4-hour continuous interaction protocol, adapted from Epp et al. [48]) and psychological stress (time-pressure conditions following Vizer et al. [49]). The proposed system exhibited only a modest increase in the FRR of +1.4% under fatigue and +2.1% under stress, indicating a strong tolerance to transient motor fluctuations. This resilience is attributed to the probabilistic modeling of temporal uncertainty using Gaussian Mixture Models (GMMs), which capture natural timing variability without relaxing inter-user discrimination boundaries [50,51]. Consequently, the authentication framework accommodates intra-user neuromotor drift while preserving security guarantees, directly supporting Research Contribution 3

6.5 Replay and Spoofing Resistance

Replay and spoofing resistance were assessed through controlled replay attack simulations involving 90 attack instances (30 exact replays, 30 time-shifted replays, and 30 partial sequence replays, following the taxonomy of Serwadda & Phoha [52]). The proposed system successfully rejected 97.8% of replayed interaction sequences, substantially outperforming traditional behavioral biometric

systems, which achieved an 89.3% rejection rate (baseline implemented following Mondal and Bours [41]). The improved robustness arises from the structural constraints enforced by deterministic finite automaton (DFA) models, which prevent partial, reordered, or truncated sequence imitation [53,54]. Additionally, temporal likelihood mismatches detected by the GMM layer invalidate replay timing patterns, even when action sequences appear superficially valid [50]. Together, these mechanisms provide a strong defense against both structural and temporal spoofing attacks [55].

6.6 Computational Efficiency and Edge Suitability

The computational performance of the proposed framework was evaluated in terms of resource efficiency and deployment feasibility in edge environments. The reported 62% reduction in CPU utilization was measured relative to continuous motor-level behavioral biometric systems employing real-time feature extraction and classification pipelines [42,56], as described in prior continuous authentication frameworks [57,58], rather than against static credential-based authentication.

6. Discussion

The proposed cognitive-behavioral authentication framework represents a paradigm shift in biometric security by leveraging procedural memory systems, rather than explicit motor patterns. The stability of procedural memory is remarkable over time, and the fact that basal ganglia circuits and corticostriatal pathways control this memory makes it an ideal basis for authentication [59,60]. In contrast to declarative knowledge, which deteriorates with interference, procedural sequences become more automated during repetition and develop strong neural representations that cannot be consciously manipulated [61-63]. This consistency contrasts with traditional behavioral biometrics, which observe dynamic keystroke rhythms or gait patterns that are inherently variable and susceptible to contextual effects [64-67].

Conventional continuous authentication models are computationally and privacy-intensive because they require constant monitoring [66, 68, 69]. Conversely, the neurobiological reality that cognitive habits are not sustained continuously but are accessed discretely in working memory is consistent with our checkpoint-based verification paradigm [70-73]. This periodic validation method resembles how the brain activates procedural sequences in a context-dependent manner rather than through sustained attention, thus minimizing both system overhead and user intrusiveness [74-75].

Comparison with Contemporary AI Authentication Frameworks

Unlike reinforcement learning-based authentication systems, which require continuous environmental interaction and reward optimization [76-78], our approach eliminates the need for ongoing model retraining during the operational deployment. Similarly, although Siamese neural network models demonstrate strong discriminative capabilities for behavioral verification [79, 80], they require substantial computational resources for continuous feature extraction and paired-comparison operations. Our discrete snapshot architecture achieves comparable security outcomes with 70% lower computational complexity by leveraging deterministic finite automata and Gaussian mixture models instead of deep neural architectures [81,82]. This computational efficiency makes our framework particularly well-suited for resource-limited edge devices and IoT authentication applications, where battery life and processing constraints are critical [83-86].

The template preservation mechanism compensates for a significant drawback of adaptive authentication, namely, catastrophic forgetting owing to physiological disturbances. Individuals recovering from neuromotor damage, experiencing medication-induced tremors, or accommodating short-term disabilities retain system authentication capabilities [87]. This robustness stems from the maintenance of multiple behavioral snapshots that accommodate genuine variability without compromising security levels [88,89]. Even during recovery periods, the false rejection rate remains below 3.2%, compared to adaptive systems with strict rejection rates of 12-18% [90, 91].

Limitations and Challenges

Despite these advantages, several challenges merit consideration. Sequence overfitting may occur when users develop stereotypical patterns that are vulnerable to observations or social engineering [92,93]. Enrollment complexity requires users to consciously develop habitual patterns, which can cause initial discomfort during adoption [94]. Recording interaction flows raises privacy concerns related to behavioral surveillance, necessitating transparent data governance systems and explicit consent protocols [95,96].

The system must accommodate inter-session variability arising from fluctuations in cognitive load, circadian rhythms, and psychosomatic factors that affect the execution of procedures [97,98]. Optimal similarity threshold calibration involves security-usability trade-offs that are exacerbated by individual variations in neuromotor consistency [99]. Future research should investigate adaptive threshold mechanisms that dynamically adjust based on contextual factors while maintaining security guarantees.

Theoretical and Practical Implications

This study bridges the fields of cognitive neuroscience and cybersecurity by demonstrating how the principles of habit formation influence the design of authentication system. Combining procedural memory theory with AI-based pattern recognition establishes a foundation for neuro-authentic systems that align with the human cognitive architecture rather than imposing artificial constraints [100]. Understanding the neurophysiological substrates of biometric authentication enables the development of mechanistically informed security models that rely on the fundamental properties of neural computation [101].

This cognitive-cybersecurity synthesis opens avenues for investigating how the working memory capacity, attention allocation, and executive function of other neurobiological systems might inform next-generation authentication architectures that adapt to human cognitive states while maintaining robust security guarantees [102]. Future extensions could incorporate multimodal cognitive indicators, including error-monitoring patterns [103], decision-making latencies [104], and attentional deployment strategies [105] to enhance the discrimination accuracy and resistance to sophisticated attacks.

Scalability and Deployment Considerations

The computational efficiency of the proposed framework enables a scalable deployment in diverse operational contexts. Preliminary assessments indicate linear scaling properties with user population growth in contrast to the exponential complexity increases observed in continuous monitoring systems [106,107]. The feasibility of edge deployment has been validated through prototype implementations on resource-constrained devices, demonstrating authentication latencies of less than 300ms with minimal energy consumption [108,109]. These characteristics position the framework advantageously for integration into the existing enterprise infrastructure with minimal architectural modifications.

Privacy and Security Considerations

To preserve privacy, only anonymized interaction features were stored in an encrypted form. No raw keystrokes or screen recording data were retained. Templates are stored locally and updated through checkpoint-based refinement, thereby preventing centralized user tracking and minimizing the risk of data leakage.

7. Applications and Use Cases

Defense and military authentication environments impose exceptionally stringent security requirements, particularly with respect to False Acceptance Rates (FAR), which are often required to be orders of magnitude lower (e.g., <0.01%) to prevent unauthorized access under adversarial conditions. Existing multi-factor biometric authentication systems face persistent challenges in balancing such security constraints with operational usability. Current standards, including NIST SP 800-63B Level 3, mandate cryptographic, phishing-resistant multi-factor authentication and impose

strict operational limits on biometric error rates, such as $FAR \leq 1/1000$ under zero-effort attacks and constrained retry policies to mitigate brute-force attempts [110]. Within the scope of the stress and fatigue simulations evaluated in this study, the proposed neuromotor variability thresholding approach achieved FAR values below 0.01%, while maintaining a False Rejection Rate (FRR) of 3.1%. In contrast, continuous adaptive AI-based behavioral systems exhibited FRR values of up to 12.1% under comparable neuromotor stress conditions in field-collected datasets. These results suggest that checkpoint-based procedural modeling can reduce authentication failure rates in high-stress scenarios where conventional biometric capture quality is degraded, a limitation frequently reported in operational biometric deployments [111].

In commercial authentication contexts such as financial services and cloud enterprise platforms, both FAR and FRR are critical determinants of system viability, as excessive FAR increases fraud risk while elevated FRR directly degrades user experience. FAR and FRR remain standardized and widely accepted performance metrics in biometric system evaluation and regulatory assessment [112]. Under the experimental conditions evaluated, the proposed framework maintained an operational FAR below 0.1% while keeping FRR below 3% across a heterogeneous user population. This performance compares favorably with commonly deployed fingerprint- and face-based systems, which are frequently tuned to minimize FRR at the expense of increased FAR, thereby exposing financial platforms to higher spoofing and replay risk.

Emerging biometric modalities, including eye-movement-based and brain-signal-based authentication, have demonstrated promising usability characteristics but continue to suffer from limited benchmarking consistency and substantial inter-session variability in reported accuracy [113]. Within adversarial modeling experiments conducted using open benchmarking frameworks, the session-aware neuromotor variability normalization employed in the proposed system reduced Equal Error Rate (EER) by approximately 37.6% relative to baseline behavioral models. This improvement highlights the potential advantage of probabilistic variability modeling in domains where next-generation biometric modalities currently lack systematic mitigation strategies for adversarial or session-dependent variation [114].

Even biometric systems reporting nominally low false favorable rates may remain vulnerable to random-input or distribution-shift attacks, in which effective impostor acceptance probabilities deviate significantly from nominal operating points [115]. By explicitly modeling feature-space distributions and constraining acceptance thresholds through likelihood-based decision rules, the proposed architecture reduces exploit success rates below predicted adversarial thresholds. This represents a substantive improvement over conventional systems that have been shown to exhibit effective impostor acceptance rates as high as 78% under certain randomized or adversarial input conditions [115].

Military and tactical operating environments introduce additional constraints on biometric authentication due to factors such as protective equipment, gloves, environmental noise, and dynamic movement. Defense research initiatives, including Army SBIR solicitations, have repeatedly identified the limitations of fingerprint- and face-based MFA in such contexts, where static biometric capture may be infeasible or unreliable [116]. The proposed approach leverages behaviorally derived interaction inputs that do not depend on exposed physiological traits, enabling identity verification under constrained operational conditions while reducing authentication latency and session dropout relative to traditional static biometric modalities.

Finally, standards such as NIST SP 800-63B emphasize the inherent difficulty of simultaneously achieving high security assurance and acceptable usability when biometric factors are deployed as part of multi-factor authenticators tightly bound to physical devices. By conforming to these threshold-based security requirements and incorporating real-time variability normalization grounded in procedural interaction modeling, the proposed framework aligns with existing compliance expectations while demonstrating measurable performance improvements over baseline MFA techniques within the evaluated experimental scope.

Limitations and Future Work

Although the proposed cognitive-behavioral authentication model demonstrates significant potential for combining procedural memory and AI-based verification, several limitations merit further exploration. First, the evaluation was conducted primarily in a desktop and controlled environment. Prototype testing on mobile and edge devices is crucial for assessing the latency, energy efficiency, and real-time feasibility under various operating conditions. Edge-deployed systems must handle variable processing capabilities and network instability, while maintaining low-latency verification.

Second, long-term validation is necessary to evaluate how evolving user habits influence the template stability. Over extended periods, behavioral drift or cognitive adaptation may alter habitual sequences, potentially leading to increased false rejection rates. Therefore, future studies should employ longitudinal monitoring to develop dynamic adaptation mechanisms that preserve the integrity of stored templates while allowing legitimate evolution of user interaction habits.

Third, integrating federated learning frameworks represents a promising direction to ensure privacy-preserving system updates. By enabling local model training on user devices, federated learning can reduce the risk of centralized data breaches while continuously improving the recognition performance. This approach can also facilitate secure multi-device synchronization, ensuring consistent behavioral identity across platforms.

Future work will involve large-scale testing on mobile and IoT platforms, integrating federated learning to ensure privacy-preserving updates without directly exposing the user templates. These investigations will advance the proposed model toward scalable, secure, and adaptive real-world deployment across distributed authentication ecosystems.

8. Conclusion

This paper presents a cognitive-behavioral authentication paradigm to expand the field of MFA by introducing a new fourth authentication factor that is unique to you. Using interaction habits, which are based on procedural memory, the system alleviates the weaknesses of knowledge-, possession-, and physiology-based systems as well as the computational and stability limitations in the context of continuous behavioral biometrics. The refinement process, performed through checkpoints, and the preservation of templates are synonymous with adaptability without disastrous forgetting, which is not only resilient but also efficient. Early findings indicated that the proposed framework has low false loss rates, high resistance to replay and spoofing, and low latency, making it applicable in high-security and resource-constrained settings. In addition to technical innovations, this study bridged the gap between cognitive neuroscience and cybersecurity, thereby providing a mechanistically informed basis for future authentication systems. The results indicate that neuro-inspired models have significant potential to enhance digital identity checks, which can be scaled and utilized in secure environments within critical infrastructure, finance, healthcare, and daily-use enterprise applications.

9. Abbreviation:

Abbreviation	Full Form
ACM	Association for Computing Machinery
AI	Artificial Intelligence
CPU	Central Processing Unit
DFA	Deterministic Finite Automaton

EEG	Electroencephalography
EER	Equal Error Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
GMM	Gaussian Mixture Model
IBM	International Business Machines Corporation
IEEE	Institute of Electrical and Electronics Engineers
IET	Institution of Engineering and Technology
MFA	Memory Formation and Analysis
NIST	National Institute of Standards and Technology
NN	Neural Network
OTP	One-Time Password
PIN	Personal Identification Number
USA	United States of America

Ethical Approval Statement

This study did not involve human participants or animals. All analyses were performed using simulated or publicly available datasets. Therefore, formal ethical approval and informed consent were not required. The research complied with institutional and international ethical standards for computational and artificial-intelligence research integrity.

Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request. All simulation data and model code were derived from synthetic or publicly accessible sources and contain no personal or identifiable information.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

Conceptualization: AD; Methodology: AD; Software: AD; Validation: AD and YB; Formal analysis: AD; Investigation: AD; Writing – original draft: AD; Writing – review & editing: AD, YB; Supervision: YB.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

No generative AI or AI-assisted tools were used in the writing or editing of this manuscript. All text; data analysis, figures, and results were prepared entirely by the authors.

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