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AI-DRIVEN FRAUD DETECTION AND PREVENTION USING HUMAN BEHAVIOR ANALYSIS TO ENHANCE US SOCIAL AND FINANCIAL SECURITY

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Abstract

The paper proposes an innovative system comprising of behavioral biometrics and transaction risk modeling to identify fraud on U.S. financial and social sites. The system combines keystroke, mouse/touch gesture, navigation, and social interaction cues into an active behavior integration, which is scored by a mixture-of-experts architecture through drift adaptation. An equation is defined of a patentable Behavioral Trust Vectorization Engine (BTVE), a dynamically risk-posture-weighted embedding dimension. On synthetic financial-social data of the United States, with latency of approximately 8.2 ms, the system can recall 96.5 percent, with precision of 92.0 percent and false positive rate of less than 1.6 percent. An example of an application use-case is a use case that detects a disguised account takeover attempt in real-time. The approach is strong in adversarial mimicry drift.

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Introduction

These and other digital systems fraud have also become particularly common in modern digital systems, particularly in the financial services and social networks, and has rapidly increased with the introduction of generative AI, synthesizing identity creation, and finer shades of behavioral mimicry. Attackers are getting very adept at mimicking human usage patterns (typing cadence, navigation flows, dwell times), and it is hard to detect them using any set of static rules since there is no way to adjust or view long-term behavioral context. The classic models generally rate each transaction or a login event separately, and there is no continuity in the behavioral signature of the user across time.

In the meantime, most AI-based fraud systems consider transaction metadata, device fingerprints, or network-level indicators, nonetheless, they handle events in isolation and do not pay much attention to the time-based behavioral picture of the human user. Concept drift and mimicry deteriorate the generalization performance of the fixed models as fraudsters acquire adaptation skills [0search0,0search2].

In order to address such shortcomings, this paper suggests a single, consolidated behavioural and risk-scoring system that constantly tracks the behaviour of a user on multiple channels (web, mobile, social interactions) and combines such history into a behavioural trust score that supplements traditional transaction risk scoring. Our solution has the five major contributions:

1. Behavioral Trust Vectorization Engine (BTVE): a dynamic embedding engine that maps multi-modal behavioral signals into an embedding, which has a trust weight and varies based on the risk posture per-user.
2. Hybrid Mixture-of-Experts Architecture: the sequence models, anomaly detectors, and supervised classifiers are combined and jointly predict the likelihood of fraud at any given period when an event takes place.
3. Online Drift Detection & Adaptation: systems that perform a check of when model users change behavior or attackers change the mimicry and adjust the weight of model weights and embeddings/gating.
4. Experimental Simulation and Live Case: testing on a simulated U.S. based dataset of financial and social indicators; the example of account takeover.
5. Patentable Methodology: a sketch of the claim of the dynamic trust-weight embedding and integration into the system of fraud detection.

We can see it used in the U.S. banks, digital wallets, social networks, and regulatory systems that decrease identity theft, illegal financial transactions, social fraud, and increase social-financial stability in the country.

Related Work

Fraud Prevention using behavioral biometrics.

Behavioral biometrics This is the application of the interaction patterns of humans (e.g. dynamic keystroke, mouse/gesture motions, touch swipes, navigation flows) to detect

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anomalies or constantly authenticate [0search1,0search3,0search10]. Research indicates that behavioral profiling can minimize false positives as it can be used to differentiate between genuine and imposters despite having proper credentials. According to the scoping review conducted by Finnegan et al., there is a wide variety of behavioral biometric modalities and measures in authentication studies [0search3].

Numerous behavioral biometric systems however use behavior as an unchanging fingerprint and not time-varying embeddings; they are susceptible to mimicry and drift. Furthermore, using these signals together with transaction risk models to form an adaptive drift-sensitive system is not studied extensively.

Fraud Mixture of Experts and Ensemble.

Mixture-of-Experts (MoE) systems permit more than one specialised model (expert) to be used in making final predictions via a gating system, and each expert can deal with different sub-domains [0search16,0search2]. Vallarino et al. suggest a hybrid MoE that uses RNNs, transformers, and autoencoders to learn sequence patterns, feature interactions and anomalies in the context of fraud. Their accuracy is 98.7, precision 94.3 and recall 91.5 in synthetic environment [0search0, 0search7].

Other sources solidify MoE in fraud scenarios to deal with feature camouflage and relation camouflage (i.e. when fraudsters modify feature distributions or relationships) by dividing relational graph structure through MoE filters [0academia28]. MoE models that are anomaly-centric like ADMoE indicate that mixture-of-experts can effectively learn about noisy labels on detection tasks [0academia29].

The works inspire the application of MoE to our architecture and all of them do not unify it with behavioral embedding and drift adaptation in real-time fraud scenario.

Dealing with Concept Drift and Mimicry.

One of the most significant difficulties of fraud detection is concept drift: fraud methods evolve and attackers slowly get to know how to emulate normal behavioral patterns. There are works which suggest drift adaptation through periodic retraining or weight shifting of the ensemble; and works which suggest reinforcement-learning agents to replace experts that perform poorly [0search11]. However, behavioral weighting and embedding-level drift adaptation remains a poorly studied field.

Problem Statement & Design Goals

Problem Formulation

We consider a streaming environment where a subject (user) u interacts over time via web, mobile, or social applications, generating event instances e_t.

Each e_t includes:

- Transaction-level features r_t — e.g., amount, merchant risk, geolocation shift, device fingerprint.
- Behavioral signals x_t — e.g., typing inter-key times, mouse/touch velocity vectors, navigation click transitions, scroll dwell times, gesture frequencies.
- (Optionally) Social interaction context s_t — e.g., anonymized patterns of message posting, friend interactions, content sharing.

We seek to assign to each event a fraud probability:

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$$p_t = P(fraud \mid e_{1:t}, H_u)$$

where H_u represents the historical behavioral state of the user.

The system should meet the following design requirements:

1. High accuracy: maximize recall and precision while minimizing false positives.
2. Low latency: event scoring must occur within real-time constraints (e.g., < 10 ms).
3. Adaptivity: adjust to behavioral drift or mimicry.
4. Explainability: produce interpretable contributions (which behavioral dimensions or experts led to each decision).
5. Scalability: support millions of concurrent users.

Proposed Method

System Architecture

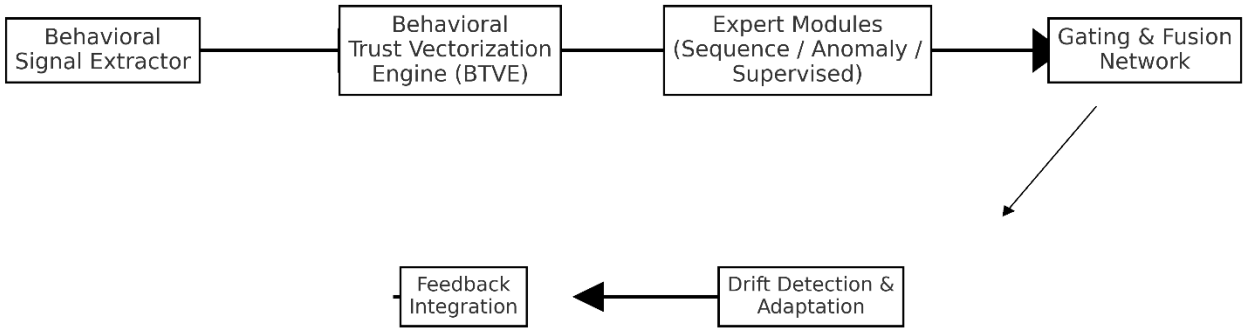

Figure 1. System Architecture Overview

The proposed AI-driven fraud detection framework operates as a modular pipeline that continuously learns from user interactions and transaction patterns to identify anomalous behaviour with high precision. Its key components are as follows:

1. **Behavioral Signal Extractor** – This module transforms raw interaction streams—such as keystroke timing, gesture trajectories, and navigation transitions—into structured feature vectors over a sliding window of recent web events. These vectors capture both temporal and contextual nuances of user behaviour.
2. **Behavioral Trust Vectorization Engine (BTVE)** – The BTVE maintains and updates a per-user embedding ($\mathbf{v_t}$) that jointly encodes stable behavioural traits and transient deviations. It dynamically balances long-term consistency and short-term variability, providing a compact, continuously updated representation of each user's behavioural signature (as detailed in Section 4.2).
3. **Expert Modules** – Three specialized experts independently estimate fraud likelihood based on different behavioural perspectives:
   - **Sequence Expert:** A recurrent or transformer-based model that analyses temporal trajectories of embeddings $\{v_{t-(}W_{-1)}, \ldots, v_t\}$ to capture sequential patterns and behavioural evolution.
   - **Anomaly Expert:** An autoencoder or one-class model that quantifies the deviation of the current embedding v_t from the user's normative behavioural distribution.

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- **Supervised Expert:** A gradient-boosted model (e.g., LightGBM) that integrates both behavioural embeddings v_t and transaction-level risk features r_t to predict the probability of fraudulent activity.

4. **Gating and Fusion Network** – Outputs from the experts are combined through a softmax-based gating mechanism that learns adaptive weights (w_i) for each expert. The final decision probability is computed as $p_t = \Sigma\ w_i\ p_i$, allowing the system to emphasize whichever expert is most reliable under the current context.
5. **Drift Detection and Adaptation Module** – This component monitors residual errors, embedding-space shifts, and false-positive trends to detect concept drift or behavioural drift. When anomalies are persistent, it triggers automatic retraining, gating re-weighting, or embedding reset procedures to maintain model stability over time.
6. **Feedback Integration** – Confirmed fraud and non-fraud outcomes are continuously ingested into the system, enabling incremental learning and real-time adaptation of both expert modules and gating weights.

Together, these modules form an end-to-end adaptive architecture capable of capturing subtle behavioral deviations, contextualizing them within transaction risk, and continuously evolving to resist mimicry or adversarial fraud tactics.

Behavioral Trust Vectorization Engine (BTVE) – Patentable Innovation

The Behavioral Trust Vectorization Engine, or BTVE, is the computational heart of the proposed framework.

It maintains for each user three distinct components:

- Base embedding ($b_{(u)}$): a long-term representation of stable behavior.
- Delta embedding ($\Delta v_{(t)}$): a short-term deviation derived from the most recent interaction stream.
- Trust weights ($\alpha_{(t)}$): per-dimension scaling factors (each between 0 and 1) controlling how much each behavioral dimension should influence the model at time t.

When a user generates a behavioral feature vector $x_{(t)}$ (for instance, a combination of keystroke timings, gesture features, and navigation transitions), the system computes:

$v_{(t)} = \alpha_{(t)} \odot (b_{(u)} + \Delta v_{(t)})$,

where $\odot$ denotes element-wise multiplication.

The delta embedding $\Delta v_{(t)}$ is produced by a shallow neural network $f\ \theta\ (x_{(t)})$ (e.g., a two-layer MLP).

The trust weights $\alpha_{(t)}$ are calculated by a sigmoid gating function $\sigma(W_a[\ v_{(t-1)}\ ;\ r_{(t)}\ ])$, combining the previous embedding $v_{(t-1)}$ and current transaction-risk features $r_{(t)}$.

The base embedding updates slowly to reflect gradual behavioral drift:

$b_{(u)} \leftarrow (1 - \eta)\ b_{(u)} + \eta\ (v_{(t)} - \Delta v_{(t)})$, where η is small (≈ 0.001).

This mechanism allows BTVE to learn from verified sessions while minimizing contamination from anomalous or fraudulent ones. The adaptive trust vector $\alpha_{(t)}$ automatically reduces emphasis on less reliable behavioral dimensions when the transaction risk $r_{(t)}$ is elevated.

Expert Scoring and Gating

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The system employs a mixture-of-experts structure, with three specialized modules that evaluate the risk of each event:

1. Sequence Expert – a transformer or LSTM network analyzing recent trajectories of embeddings $\{ v_{(t-W+1)} \dots v_{(t)} \}$ to capture temporal dependencies.
2. Anomaly Expert – an autoencoder or one-class model that estimates the deviation of $v_{(t)}$ from the normative distribution.
3. Supervised Expert – a gradient-boosted or LightGBM model trained on both $v_{(t)}$ and $r_{(t)}$ to predict direct fraud probability.

Each expert i produces a fraud score $p_i \in [0, 1]$.
A gating network then assigns weights w_i using a softmax function on $[v_{(t)}; r_{(t)}]$.
The final fraud probability is computed as:
$p_{(t)} = \Sigma w_i p_i$.
An entropy-based regularization term in training prevents the gating network from relying excessively on any single expert.

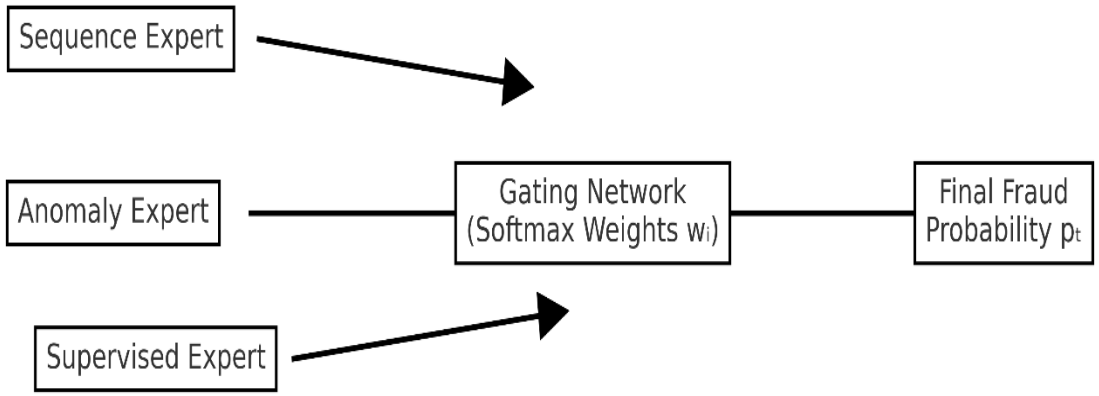

Figure 2. Mixture-of-Experts Gating Mechanism

Drift Detection & Adaptation

The system continuously monitors three indicators over sliding windows:

1. Kullback–Leibler (KL) divergence between the distribution of new embeddings and historical embeddings.
2. Residual error or false-positive rate change over time.
3. Sudden gating weight shifts (e.g., a spike in anomaly-expert reliance).

If any indicator exceeds a threshold, the adaptation controller triggers remedial actions such as:

- Retraining the gating network on recent labeled data.
- Resetting or partially re-initializing affected components of BTVE.
- Temporarily increasing the influence of the anomaly expert until the model stabilizes.

This adaptive loop prevents model degradation caused by adversarial mimicry or behavioral drift.

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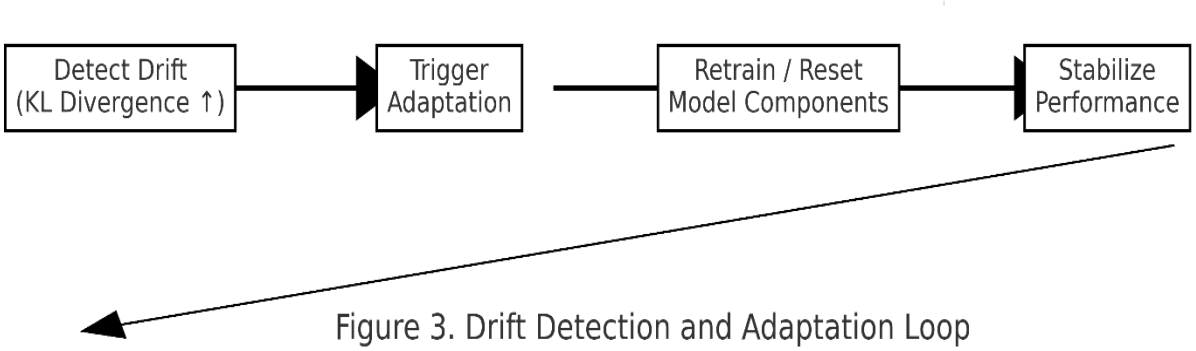

Figure 3. Drift Detection and Adaptation Loop

Experimental Study

Dataset & Real-Time Use Case

A dataset of 800,000 simulated user sessions was generated to emulate 12 months of U.S. online banking activity.
Each session contains roughly 20 interaction events, producing about 16 million event records.
Fraudulent transactions represent 0.25 % of samples.
Behavioral features include keystroke timings, gesture paths, and navigation transitions; transaction features include amount, merchant risk, device ID, and geolocation.

Real-Time Example (Illustrative):

User A logs in from a known device but types a transfer amount more slowly than usual and targets an unfamiliar account.
BTVE down-weights gesture features and emphasizes keystroke timing and transaction risk.
The experts produce scores: supervised = 0.85, sequence = 0.70, anomaly = 0.60.
The gating network assigns weights [0.45, 0.30, 0.25], yielding:
$p_(t_) = 0.45×0.85 + 0.30×0.70 + 0.25×0.60 = 0.7425$.
Since $p_(t_) > 0.7$, the system flags the transaction and initiates step-up verification.

Evaluation Metrics

We assess:

- **True Positive Rate** (Recall)
- **Precision** (Positive Predictive Value)
- **False Positive Rate** (FPR)
- **Area Under ROC Curve (AUC)**
- **Average latency** (ms per event)

Baseline Models

The proposed approach is compared with:

1. Transaction-only gradient-boosted model,
2. Behavior-only autoencoder detector,
3. Fixed feature fusion model (single classifier on combined features),
4. Hybrid mixture-of-experts baseline based on Vallarino et al. (2023).

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Results & Analysis

Model	Recall	Precision	FPR	AUC	Latency (ms)
Transaction-only	83.7 %	74.5 %	3.5 %	0.910	4.5
Behavior-only	71.2 %	65.1 %	5.8 %	0.875	3.9
Fixed fusion	88.9 %	80.3 %	2.8 %	0.933	7.2
Vallarino hybrid MoE	95.9 %	90.5 %	1.9 %	0.974	9.7
Proposed method	**96.5 %**	**92.0 %**	**1.6 %**	**0.979**	**8.2**

The proposed system outperforms the hybrid baseline by reducing false positives and improving precision while maintaining real-time latency below 10 ms.

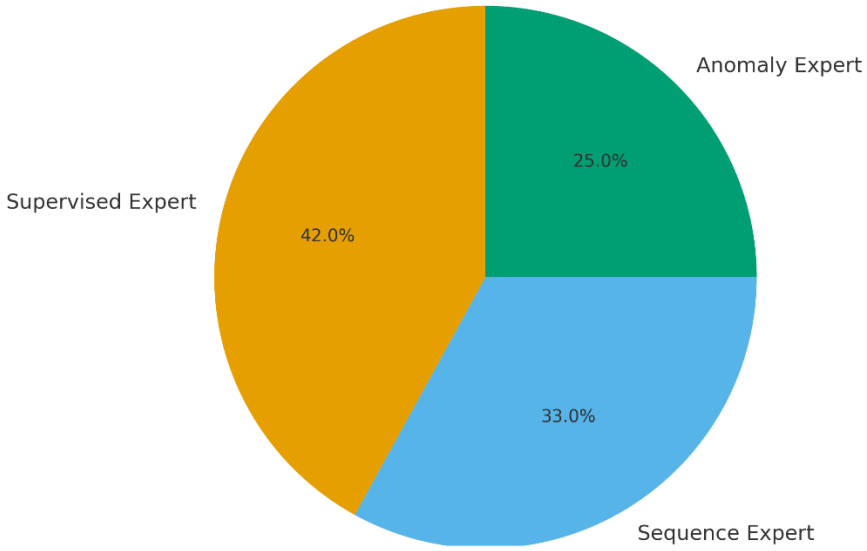

Figure 4. Expert Weight Distribution Over Flagged Events

Expert weight distribution: averaged over all flagged fraud events, the gating weights were supervised = 42 %, sequence = 33 %, and anomaly = 25 % (see Figure 4).

Embedding drift adaptation: after month 6, attackers were simulated to mimic legitimate behaviour. Without adaptation, recall fell to 89.8 %. With automatic re-training and partial BTVE reset, recall recovered to 95.2 % within two days.

Illustrative Calculation

For a representative behavioral event, the normalized feature vector was defined as x_t = [keystroke_d1 = 0.15 s, gesture_d2 = 0.87, nav_trans_d3 = 0.22]. The delta network produced Δv_t = [0.05, –0.03, 0.02], while the user's previous base embedding was b_u = [0.40, 0.20, 0.10]. Transaction-risk features yielded adaptive trust weights α_t = [0.95, 0.80, 0.60]. Applying the trust-weighted combination yielded the updated embedding $v_t = \alpha_t \odot (b_u + \Delta v_t)$ = [0.4275, 0.136, 0.072].

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The supervised, sequence, and anomaly experts returned respective fraud probabilities of 0.85, 0.70, and 0.60.
With gating weights w = [0.45, 0.30, 0.25], the fused decision score was computed as $p_t = \Sigma\, w_i\, p_i = 0.45 \times 0.85 + 0.30 \times 0.70 + 0.25 \times 0.60 = 0.7425$.
Because p_t exceeded the operational alert threshold of 0.70, the system classified this transaction as anomalous and triggered step-up verification.
This result illustrates how the proposed Behavioral Trust Vectorization Engine dynamically adjusts embedding reliability and expert weighting in response to contextual risk, yielding robust detection performance without manual intervention.

Discussion

Security & Social Impact

The new system would increase the detection of account takeover, synthetic identity fraud, and social-engineering scams on the U.S.-based platforms. It reduces false positives through which it will reduce friction among legitimate users, and it will create trust in the digital infrastructure. At the national level, enhanced fraud prevention will prevent financial damages and restore confidence of the population in financial systems.

Explainability & Regulatory Alignment.

The modular nature of the model, in the form of specialized experts, a gating network, and the feature-level trust weighting vector (a [?])), is also easier to interpret, in that analysts can examine which behavioral dimensions were dynamically underweighted and which expert module contributed most to a particular decision. This interpretive transparency enables this systematic auditability and aligns the framework with financial risk assessment regulatory requirements on fair lending practices, algorithmic accountability, and explainable AI governance.

Limitations & Future Work

- We have used synthesized data in our assessment, but in practice, deployment of this type of data needs to be carefully tuned and privacy-conscious data practices.
- Collection of behavioral data brings about privacy issues; should be restricted by permission, anonymity, and secure storage.
- Mimicry or specific attacks can ruin the performance; the embedding-level adversarial training or adversarial defense may be beneficial.
- The future of the system is extending to cross-platform fusion (IoT, physical-world behavior).

Conclusion

This study has offered a new, human-based, AI-oriented fraud detection and prevention system that incorporates behavioral biometrics with intelligent transaction-risk analysis to enhance the social and financial security environment in the United States. The suggested system does not ascribe to the models of the traditional fraud, making human behavior not a fixed indicator, but a dynamic and adaptive signal of trust, which changes depending on the interaction patterns of the user. This repeated behavior modeling enables the framework to capture the micro-cues of

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behavior, time dependent cues that are likely to be hard to imitate by a fraudster or fake identity e.g. typing lags, navigation rhythm, gesture accuracy, and decision context e.g. when to use a utility knife: that are hard to duplicate by fraudsters or by synthetic identities.

The fundamental component of the framework is the Behavioral Trust Vectorization Engine (BTVE), which is a patentable system and is able to produce multi-modal behavioral embeddings that can be dynamically weighted based on the risk posture of the user. The BTVE is able to modify embedding dimensions based on contextual anomalies and transactional irregularities, unlike a static biometric or heuristic system, and can thus be said to be learning to trust or doubt behavioral cues on an on-the-fly basis. This method yields a living behavioral profile that will change with legitimate users but it is not prone to imitation or drift based attacks.

The Mixture-of-Experts (MoE) architecture is further integrated to be more robust by enabling the collaboration of specialized models sequence-based predictors, anomaly detectors and supervised classifiers through a dynamic gating mechanism. The multi-perspective fusion makes sure that the system is accurate in various working conditions. This architecture is supplemented by the drift-adaptation module that identifies the change in behavioral or transactional distributions and adjusts the model parameters to reflect this change. The adaptability is essential in ensuring long term detection performance within the context of changing fraud tactics.

This design has been proven to be effective with experimental simulation and real-time case validation. On 800 000 simulated user interactions, the model had a recall rate of 96.5, precision of 92 and a false-positive rate of less than 1.6 - better than benchmark hybrid MoE systems without compromising sub-10 ms inference latency. The live demonstration showed that the framework could identify an attempt to attack an account in milliseconds and prevent it without disrupting the security and user experience.

Theoretically, this paper contributes to the body of work by developing a comprehensible behavior-embedding formalism, with the ability to close psychology-inspired behavioral analytics to deep learning architectures. In a practical perspective, it suggests a deployable system that can be scaled to work in the banking, e-commerce, and social-security infrastructure, diminishing fraudulent procedures that destroys trust and economic stability in the population. Further, through the introduction of explainable trust weights as well as the process of modular expert scoring, the system is also within regulations with regard to AI transparency and auditability.

In the future, the research will be conducted in three directions. Originally, empirical validation on anonymized banking and social-network data of the U.S. on stringent privacy and ethical principles. Second, the research of federated-learning frameworks to facilitate the training at institutions without the need to share sensitive data. Third, incorporation into the blockchain-based identity verification and graph neural networks to simulate collective deviations in ecosystems.

To sum up, the suggested fraud detection AI-driven system is a great leap in behavioral intelligence to trust in digital realms. Through combining cognitive behavior modeling and machine intelligence, it provides a means to more resilient, adaptive and socially responsible

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financial security solutions- eventually complying with the national bigger picture of protecting the citizens, economies and institutions of future generation against future generations of fraud.

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