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Engineering Trust

Scalable, Intelligent, and Secure Financial Systems with Blockchain and AI

November 8-10, 2026

Nashville, Tennessee

Edited by

Ali Emdad, Ph.D.

Conference Chair

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Welcome from the Conference Chair

Welcome to the 7th National HBCU Blockchain, FinTech & AI Conference, held November 8-10, 2026, at the Margaritaville Hotel in Nashville, Tennessee. Organized by Morgan State University's National FinTech Center, the conference brings together faculty, researchers, students, industry leaders, and practitioners committed to advancing education, research, and innovation in emerging financial technologies.

This year's theme, "Engineering Trust: Scalable, Intelligent, and Secure Financial Systems with Blockchain and AI," reflects the opportunities and responsibilities created by the growing integration of blockchain and artificial intelligence into financial systems. The papers in these proceedings address artificial intelligence and machine learning, blockchain and digital assets, financial inclusion, accounting, credit risk, market analytics, banking user experience, fraud detection, cybersecurity, resilient infrastructure, and educational innovation. Collectively, they examine how emerging technologies can improve decision-making, expand access, strengthen institutions, and create more secure and trustworthy financial systems.

The proceedings include 15 full papers selected from 50 submissions through a double-blind peer-review process. Submissions were evaluated for originality, methodological rigor, relevance, clarity, and contribution to research and practice. We thank the authors for sharing their scholarship and for responding thoughtfully to the reviewers' recommendations.

We extend our sincere appreciation to the members of the Conference Review Committee for their careful evaluations and constructive feedback. Their expertise and commitment were essential to maintaining the quality of the proceedings and the conference program.

The conference also includes an Emerging Research Track, invited presentations, keynotes and featured sessions, panel discussions, technology workshops, student programming, and networking opportunities. We thank the authors who participated in the Emerging Research Track for sharing their developing research and contributing new ideas to the conference. These activities advance the National FinTech Center's mission to strengthen education, research, and institutional capacity across its network of 65 HBCUs.

We thank our sponsors and partners, speakers, track chairs, staff, volunteers, and participants for their support. We hope these proceedings encourage continued research, collaboration, and responsible innovation in building financial systems that are intelligent, scalable, secure, inclusive, and worthy of public trust.

Ali Emdad, Ph.D.

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Blockchain-Anchored Detection and Recovery for Resilient Reinforcement Learning-Based Cyber-Physical Systems

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Abstract

Reinforcement learning (RL) controllers in cyber-physical systems (CPS) assume that sensor observations describe the true plant state, yet replay, sensor-drift, and false-data-injection (FDI) attacks can corrupt the observation stream at inference time, and detection alone does not tell the controller what to use after an alarm. This study evaluates a proof-of-concept defense that combines a SHA-256 hash-linked ledger, which provides exact-match replay detection and a tamper-evident recovery anchor, with a Long Short-Term Memory autoencoder (LSTM-AE) for audit alarms and a fixed Proximal Policy Optimization (PPO) controller. Ten independently trained policies per environment are evaluated in paired episodes on CartPole-v1 and LunarLander-v3. Content-hash matching detects every injected bitwise replay with zero false matches in 379,396 clean steps. However, perfect detection does not guarantee safe recovery: exact-gated ledger hold raises LunarLander replay return from 178.4 to 264.6 (paired mean +86.2, 95% CI [64.8, 107.6]) but lowers CartPole from 411.1 to 376.2 (−34.9, not significant after Holm adjustment). A trigger-by-anchor factorial ablation shows that local and ledger

anchors are control-equivalent under a fixed trigger, while LSTM-AE-gated hold is harmful in every tested cell. A 4,800-episode sensitivity study across three severity levels per attack shows that the recovery effect scales with severity in opposite directions: +5.8 to +225.0 on LunarLander and −4.6 to −60.3 on CartPole. The ledger contributes exact-replay lookup, provenance, and tamper evidence rather than an automatic control advantage; safe general recovery further requires dynamics-aware substitution and distributed, physical validation.

Keywords: cyber-physical systems, reinforcement learning, blockchain, anomaly detection, replay attacks, resilient control

Introduction

RL-controlled CPS couple sensing, computation, and actuation: a policy maps observation $\boldsymbol{o}_t$ to action a_t, and the physical process generates the next state. If an attacker manipulates the observation channel, a competent clean policy may act on a false description of the plant. Replay substitutes a historical packet, drift accumulates a small bias, and false data injection (FDI) fabricates selected features. Detection alone is insufficient because the controller still needs a usable input after an alarm; conversely, a recovery state without verifiable provenance may already be compromised.

This paper evaluates a narrow integration of three functions. A hash-linked ledger performs exact content lookup and records detector flags; an LSTM-AE supplies temporal audit alarms; and an exact-match trigger retrieves the latest earlier eligible ledger observation before PPO inference. The implementation is intentionally a single-node prototype, not a production blockchain. Its evidence concerns the data path—exact matching, hash-linked tamper evidence, and recovery-state provenance—not distributed consensus or Byzantine fault tolerance.

This study makes four contributions. First, step-level ground truth demonstrates zero false positives and false negatives for the evaluated bitwise replay, while explicitly excluding noisy or semantically equivalent replay. Second, paired policy-level inference shows that the same recovery improves LunarLander but can harm CartPole; perfect detection is therefore not sufficient for safe recovery. Third, a full trigger (exact or learned) by anchor (local or ledger) ablation separates control effect from provenance. Fourth, an attack-severity sensitivity study adds 4,800 episodes across three attack levels and shows that recovery utility varies with attack severity and plant dynamics.

Literature Review

Adversarial CPS research identifies the observation interface as a major attack surface. Li et al. (2020) organize attacks and defenses across heterogeneous sensor, communication, and computational interfaces, showing that CPS exposure extends beyond conventional image classifiers. Empirical studies reinforce this concern. Figueroa et al. (2022) evaluate FGSM, DeepFool, and JSMA perturbations against machine-learning models used in industrial-control CPS and report substantial losses in predictive reliability. Gipiškis et al. (2023) similarly show that adversarial perturbations can alter both semantic-segmentation outputs and their saliency-based explanations. Together, these studies establish that a controller may receive a plausible but operationally misleading observation, motivating defenses that address the observation delivered to the control policy.

Anomaly-detection research offers broad coverage but does not by itself resolve what the controller should use after an alarm. In a review of 296 CPS studies, Jeffrey et al. (2023) classify defenses spanning intrusion detection and prevention, machine learning, simulation and testbeds, edge processing, and zero-trust architectures. Jeffrey et al. (2024) combine signature, threshold, and machine-learning detectors and find one-class KNN effective for imbalanced CPS data. Such approaches strengthen recognition of abnormal behavior, but their evaluation does not isolate state substitution inside a closed-loop RL controller. The distinction is important because a correct alarm can still be followed by a stale or dynamically unsafe replacement observation.

Recovery research addresses that post-detection problem more directly. L. Zhang et al. (2021) combine constrained LQR control, state reconstruction, checkpointing, and deadline estimation, demonstrating recovery from bias, replay, and delay attacks across five CPS simulators. Their results illustrate that recovery requires both a trustworthy state estimate and a control action that respects system dynamics. Reviewing work published from 2014 to 2023, Lu et al. (2024) conclude that CPS recovery remains less mature than detection and is concentrated on sensor and communication attacks. Controller-, actuator-, and application-specific recovery therefore remain open concerns. The present study examines a narrower question: whether a previously verified observation can support inference-time recovery for an already trained RL controller.

Blockchain-based CPS frameworks primarily address authentication, confidentiality, integrity, and accountability. Rahman et al. (2021) combine consortium blockchain,

multi-signature authentication, edge computing, and distributed storage for Industry 4.0 data exchange. Ali et al. (2023) integrate smart contracts, access control, cryptographic protection, and decentralized validation for privacy-sensitive CPS information, while Bhattacharjya (2022) synthesizes blockchain's role in preserving confidentiality, integrity, and availability across CPS and IoT communication. These studies motivate a ledger as a source of provenance, but they do not separate the control effect of state retrieval from the trust benefit of the ledger itself.

Robust-RL research provides a complementary defense strategy. H. Zhang et al. (2021) show that small state-observation perturbations can sharply reduce policy return and propose alternating training with learned adversaries to reduce that sensitivity. Chen and Li (2020) survey robust RL under transition-model uncertainty and emphasize the difficulty of deploying learned policies when estimated dynamics differ from the operating environment. These methods modify training to improve policy robustness. In contrast, the present work keeps the clean PPO policy fixed and studies inference-time detection, provenance, and substitution, so the two approaches address different points in the defense lifecycle.

The resulting gap is not a lack of individual detectors, recovery algorithms, or blockchain mechanisms, but limited evidence connecting all three to closed-loop RL behavior. An integrated evaluation must distinguish detection accuracy, recovery-state provenance, the dynamics of the substitution rule, and the controller's resulting return. Table 1 positions the proposed proof of concept against closely related CPS security frameworks and highlights its trigger-by-anchor ablation, which separates the recovery policy from the storage location.

Table 1

Comparison with Closely Related Integrated CPS Frameworks

Study	Principal mechanism	Detection	Recovery	Ledger	RL / ablation
Jeffrey et al. (2024)	Hybrid IDS	Yes	No	No	No / No
Zhang et al. (2021)	LQR recovery	Yes	Yes	No	No / No
Rahman et al. (2021)	Consortium authentication	No	No	Yes	No / No
Ali et al. (2023)	Consortium privacy	No	No	Yes	No / No
Proposed	Exact/AE + hold	Yes	Yes	Yes	Yes / Yes

Note. "Ledger" denotes a blockchain or hash-linked record used to establish data origin/integrity. The last column reports RL closed-loop evaluation / trigger–anchor ablation.

Methodology

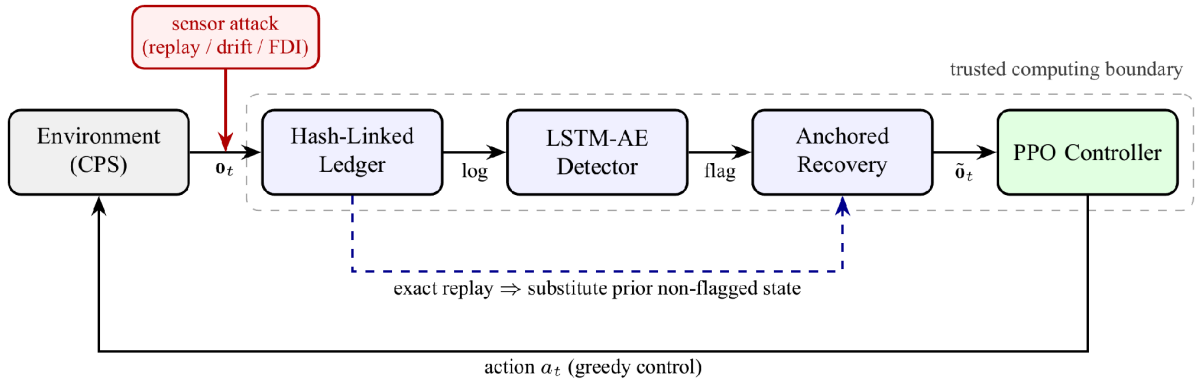
Threat Model and Scope

The adversary can alter the sensor packet delivered to the controller but cannot change plant dynamics, PPO parameters, ledger code, or the simulator-private clean state. Replay draws a bitwise float32 copy from previously *delivered* packets delayed by 20 steps; this avoids giving the attacker privileged clean-state access. Drift and FDI affect continuous dimensions only; LunarLander contact bits remain unchanged. The ledger and controller are inside the trusted computing boundary. Network compromise, key theft, actuator attacks, collusion among permissioned validators, and database-administrator rewrite are outside the experiment.

Figure 1 summarizes the implemented data path and experimental trust boundary.

Figure 1

System Architecture and Experimental Trust Boundary



Note. Per-timestep data flow. The LSTM-AE flag is committed for audit but does not trigger the primary substitution path; exact replay retrieves the latest earlier observation eligible under the exact trigger.

Ledger, Detection, and Recovery

Each block stores the observation; node, session, episode, and timestep identifiers; replay and AE flags; the prior block hash; a current SHA-256 hash over state, metadata, prior hash, and flags; and a content hash over observation values and node identity. The content hash excludes time so a bitwise repeated packet matches an earlier record. Replay lookup occurs before the current block is committed. Session-aware uniqueness constraints prevent duplicate timesteps, and the chain is recomputed after every episode.

The hash chain is tamper-evident, not immutable. A single administrator who rewrites all records and recomputes hashes can defeat the prototype. Distributed deployment would require

authenticated membership, replicated storage, consensus such as Raft or PBFT, and independently held checkpoints (Castro & Liskov, 1999; Ongaro & Ousterhout, 2014).

The detector is a two-layer sequence-to-sequence LSTM-AE (hidden size 64; window W = 20). With training-standardized observation $\boldsymbol{z}$, its score is

$$s_t = \frac{1}{Wd} \sum_{i=1}^{W} \|\mathbf{z}_{t-W+i} - \hat{\mathbf{z}}_i\|_2^2 . \tag{1}$$

For each environment, clean trajectories from all deployed policy seeds are split by whole episode before overlapping windows are formed, preventing adjacent-window leakage. Training/validation contain 300/100 episodes and 144,300/48,100 CartPole windows or 68,634/23,921 LunarLander windows. The threshold is the held-out 99.9th percentile (CartPole .01649; LunarLander 1.54518), and an audit alarm requires 20 consecutive exceedances. Because one corrupted sample contaminates up to 20 overlapping windows, this persistence gate can remain active after an intermittent event and is not used for primary recovery.

On an exact match, the controller receives the latest earlier block whose replay flag is zero:

$$\tilde{\mathbf{o}}_t = \begin{cases} \mathbf{o}_t, & \text{if no exact replay is detected,} \\ \mathbf{o}_t^{\text{anchor}}, & \text{if an exact replay is detected.} \end{cases} \tag{2}$$

Anchor eligibility is trigger-specific: an audit-only AE flag cannot silently remove an anchor from the exact path. “Eligible” is operational and does not prove that the physical state is clean.

Controller and Experimental Design

The PPO controller (Schulman et al., 2017) uses a shared two-layer, 128-unit tanh trunk and separate policy/value heads; learning rate decreases linearly from 3×10^{-4}, with γ = .99, GAE λ = .95, clip .20, ten epochs, and batch size 64. Observations are standardized online during clean training and frozen for evaluation. Time-limit truncations are bootstrapped, current-transition termination masks GAE, and partial rollouts are optimized. Ten independent policies (seeds 1000–1009) are trained per environment. In a disjoint 20-episode clean validation, all CartPole policies score 500 and every LunarLander policy exceeds 200 mean return.

Table 2 summarizes the task, replication, and attack-severity settings.

Table 2

Primary Experiment and Sensitivity Settings

Component	CartPole-v1	LunarLander-v3
Observation dimensions / discrete actions	4 / 2	8 / 4
Clean mean return	500.0	265.7
Independent policies	10	10
Primary episodes per policy/condition	50	50
Sensitivity episodes per policy/cell	20	20
Replay probability (low/base/high)	.10 / .30 / .50	.10 / .30 / .50
Drift rate, feature scales/step	.001 / .002 / .004	.001 / .002 / .004
FDI *SD*, feature scales	1.5 / 3.0 / 6.0	1.5 / 3.0 / 6.0

Note. Replay uses a 20-step delay. FDI is attempted with probability .20 and applied independently to selected continuous dimensions with probability .50.

The primary study evaluates clean baseline, attack without defense, and attack with exact-gated ledger recovery. Each policy receives 50 episodes per condition. Environment seeds and independent attack-schedule/payload seeds are reused across defense conditions. A factorial ablation crosses recovery trigger (exact hash or persistence-gated AE) with anchor source (local cache or ledger), plus a no-recovery reference. The sensitivity study holds every non-varied attack parameter at baseline and adds 20 paired episodes per policy and severity cell: 4,800 episodes total.

The independently trained policy is the inferential unit. For each of six primary environment–attack contrasts, we report the paired mean difference, 95% paired *t* CI, $t(9)$, exact two-sided enumeration of all 2^{10} sign flips, paired d_z, a 10,000-resample hierarchical bootstrap CI (policies, then episodes within policy), and Holm-adjusted *t*-test *p* values. Descriptive variability is the *SD* of ten policy means. Sensitivity replay contrasts use the same policy-level paired analysis and Holm correction across its six cells.

Results and Findings

Main Effects and Ablation

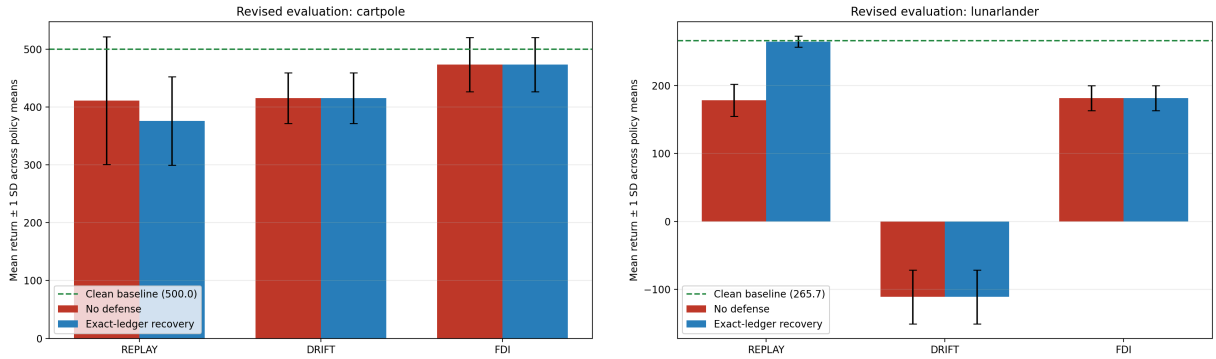
Exact-gated recovery improves LunarLander replay from 178.4 to 264.6. All ten policy differences are positive; the paired difference is +86.2, 95% CI [64.8, 107.6], $t(9) = 9.11$, $p < .001$, exact sign-flip $p = .001953$, $d_z = 2.88$, hierarchical bootstrap CI [64.0, 106.8], and Holm-adjusted $p < .001$. This restores 99.6% of the clean mean.

CartPole changes from 411.1 to 376.2: −34.9, CI [−65.6, −4.2], $t(9) = -2.57$, $p = .030$, exact $p = .035$, $d_z = -0.81$, bootstrap CI [−63.1, −6.2]. Seven of ten differences are negative, but Holm-adjusted $p = .150$ does not reject across six primary contrasts. Drift and FDI returns are identical between primary defended and undefended conditions because exact-only recovery correctly abstains; this is scope control, not non-replay recovery.

Figure 2 visualizes the primary evaluation returns across attacks and environments.

Figure 2

Primary Evaluation Return by Attack and Environment



Note. CartPole left, LunarLander right. Bars are means of ten policy means; error bars are ±1 *SD*. The dashed line marks clean mean return. Exact-only recovery abstains on drift and FDI, so defended and undefended bars coincide in those cells.

Table 3 reports the trigger-by-anchor ablation across both environments and all three attacks.

Table 3

Trigger-by-Anchor Factorial Ablation: Mean Return ± SD Across Ten Policy Means

Environment	Attack	No recovery	Exact: local = ledger	AE: local = ledger
CartPole	Replay	411.1 ± 110.4	376.2 ± 76.5	58.3 ± 9.1
	Drift	415.4 ± 44.0	415.4 ± 44.0	74.6 ± 1.6
	FDI	473.2 ± 46.8	473.2 ± 46.8	46.8 ± 3.6
LunarLander	Replay	178.4 ± 23.7	264.6 ± 8.2	175.0 ± 24.8
	Drift	−111.2 ± 39.8	−111.2 ± 39.8	−288.4 ± 100.9
	FDI	181.2 ± 18.4	181.2 ± 18.4	−433.7 ± 54.9

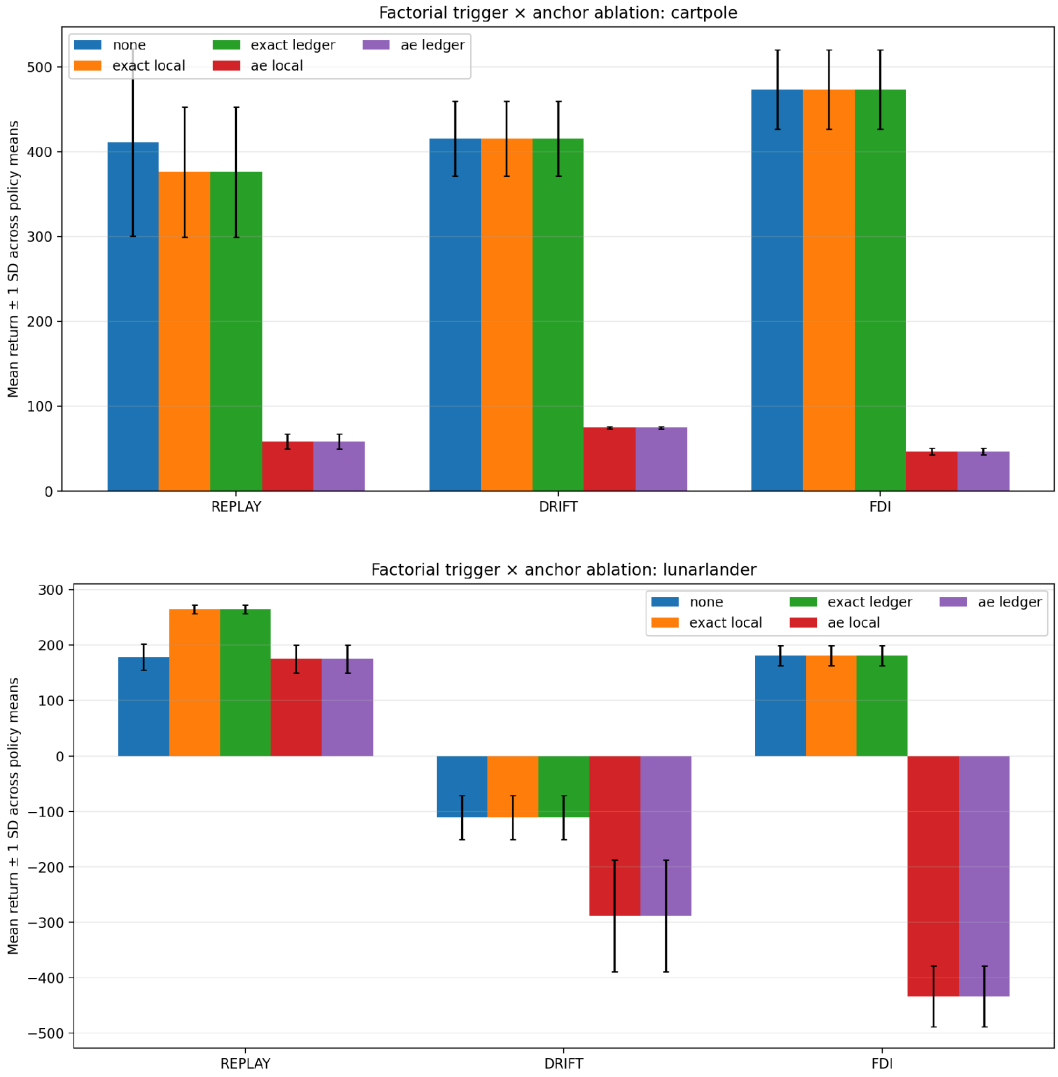
Note. Local and ledger anchors return the same newest eligible packet under a fixed trigger; the maximum absolute paired policy-mean difference is 0 in all six cells.

Anchor location alone never changes return. The ledger's independent contribution is provenance and tamper evidence. Trigger choice is decisive: AE-gated hold harms all tested cells because overlapping-window persistence can substitute a stale state after the corrupt event. Exact replay recovery is active on 28.4% of CartPole and 27.5% of LunarLander steps; mean anchor age is only 1.49 and 1.42 steps. Thus, even a recent zero-order hold can be unsafe in faster dynamics. The exact equality of the local and ledger columns is expected rather than anomalous: under a fixed trigger, both anchors deliver the bitwise-identical newest eligible packet, so the closed-loop trajectory cannot differ. Storage location determines who can verify and audit the anchor, not the numeric value the controller receives; the ledger's tamper evidence therefore matters for trust and forensics rather than for reward. The environment asymmetry also has a mechanical reading. At a .30 replay probability, roughly one in four controller inputs is a held state, and CartPole's short, unstable balancing horizon amplifies even one-step-old substitutions into accumulating corrective errors. LunarLander's slower descent both tolerates a recent hold and benefits from suppressing packets that are 20 steps stale, which is why the same recovery rule moves the two environments in opposite directions.

Figure 3 displays the complete factorial ablation for both control tasks.

Figure 3

Trigger-by-Anchor Factorial Ablation by Environment



Note. CartPole top, LunarLander bottom. Bars are means of ten policy means; error bars are ±1 *SD*. Exact-local and exact-ledger bars coincide, as do AE-local and AE-ledger bars, because anchor eligibility is held fixed within each trigger.

Detection and Prototype Timing

Exact matching detects all 85,229 injected replay packets with zero false positives or false negatives and zero matches in 379,396 clean steps; first-event delay is zero. The guarantee applies only to the evaluated bitwise representation. The AE gate has zero false positives on clean evaluation but poor temporal localization under intermittent attacks: CartPole replay precision/recall/FPR are .300/.914/.846, whereas LunarLander replay recall is below .001. For

FDI, FPR is .856 on CartPole and .793 on LunarLander because earlier corruptions remain inside the window. These values explain why the AE remains audit-only.

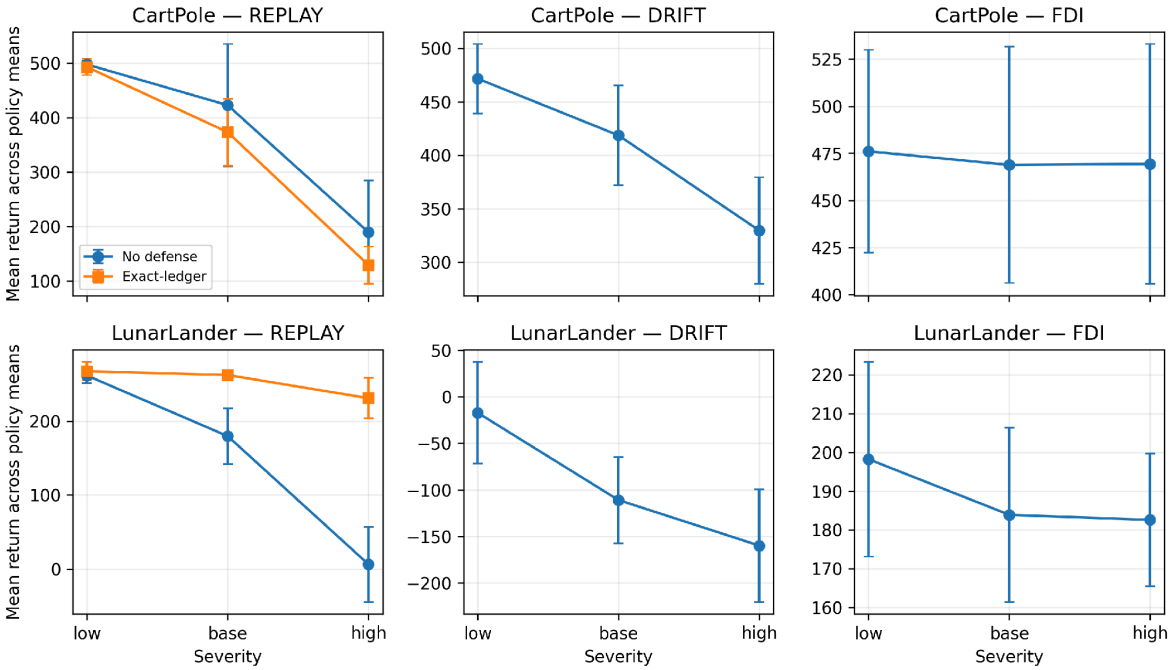
All episode chains verify. In defended replay, mean block-commit/query/anchor-retrieval times are .083/.024/.009 ms on CartPole and .090/.027/.009 ms on LunarLander; corresponding mean episode 95th percentiles are .138/.041/.028 and .148/.044/.029 ms. These in-memory SQLite timings exclude network transport, durable replication, consensus, and sensor/actuator delay.

Attack-Parameter Sensitivity

Figure 4 summarizes policy-level return across the low, baseline, and high attack levels.

Figure 4

Return Across Low, Baseline, and High Attack Severity



Note. Points are means of ten policy means; error bars are ±1 *SD*. Replay includes both no-defense and exact-ledger conditions. Drift and FDI are audit-only in the primary design, so only no-defense curves are shown.

Replay sensitivity confirms a dose-response interaction rather than task-independent improvement. On LunarLander, the defended-minus-undefended effect is +5.8 at $p = .10$ (CI [−3.1, 14.7], exact $p = .174$), +82.7 at $p = .30$ (CI [52.9, 112.5], exact $p = .001953$), and +225.0 at $p = .50$ (CI [183.2, 266.9], exact $p = .001953$). On CartPole it is −4.6 (CI [−11.6, 2.4], exact p

= .500), −49.6 (CI [−92.9, −6.2], exact p = .039), and −60.3 (CI [−108.0, −12.6], exact p = .023), respectively. Exact matching retains zero false positives and negatives at every severity.

Undefended drift shows monotonic degradation: CartPole means are 471.7, 418.7, and 329.7; LunarLander means are −17.1, −110.9, and −159.8. FDI is comparatively flat over the tested standard deviations: 476.1/468.9/469.4 on CartPole and 198.2/183.9/182.6 on LunarLander. The sweep strengthens parameter robustness but does not establish generalization to other CPS tasks or physical noise models.

Discussion

The combined evidence separates three claims often conflated in integrated security systems. First, content hashing is a deterministic detector for exact packet reuse under a stable serialization; it is not a detector for approximate replay. Second, a hash-linked anchor provides verifiable provenance but does not guarantee that its observation is physically correct. Third, recovery quality is a closed-loop property. LunarLander benefits as replay becomes more frequent, whereas CartPole is increasingly harmed by substituting recent historical states. Detector accuracy alone cannot decide whether substitution is safe.

The factorial experiment also prevents attributing the LunarLander gain to "blockchain" in the abstract. Local and ledger anchors are numerically identical under fixed eligibility. The ledger adds an auditable, tamper-evident history and exact lookup; the hold policy produces the control effect. Conversely, the AE negative result is useful: a high clean-data threshold and persistence gate can still localize intermittent events poorly. Non-replay recovery needs an event-localized trigger and a dynamics-aware estimate with uncertainty-based abstention.

Implications, Limitations, and Future Research

Seven limitations bound the conclusions. (1) Recovery handles exact bitwise replay only. (2) Zero-order hold is not dynamics-aware and harms CartPole. (3) The severity sweep varies one parameter at a time and does not cover adaptive or multivariate attacks. (4) The AE is calibrated on the evaluated policy family; transfer after policy or plant shift is unknown. (5) Ten policies in two simulators support run-level replication but not broad CPS generalization. (6) A single-node ledger provides tamper evidence, not distributed immutability. (7) Latency excludes networking, replication, consensus, and hardware. Next work should evaluate approximate-replay signatures, model-based state prediction with calibrated uncertainty, joint

attack sweeps, independent validators, additional control plants, and hardware-in-the-loop timing.

Conclusion

This paper evaluates exact replay detection, verifiable recovery anchoring, and RL control in one reproducible data path. Across two environments and ten policies each, exact matching detects every evaluated bitwise replay without false matches. Exact-gated hold improves LunarLander but can harm CartPole, and its effect grows in opposite directions as replay probability increases. The ablation shows that anchor location does not change return when eligibility is fixed; the ledger's distinct value is lookup, provenance, and tamper evidence. The appropriate conclusion is therefore narrow but technically useful: exact replay is detectable, ledger-anchored hold can restore one tested control task, and safe general recovery requires dynamics-aware substitution plus distributed and physical validation.

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During preparation of the camera-ready manuscript, the authors used OpenAI ChatGPT and OpenAI Codex for grammar, spelling, style, and sentence-level clarity improvements throughout the manuscript; assistance with LaTeX formatting; and the generation and refinement of TikZ code used to produce Figure 1. The research design, methodology, implementation, experiments, data analysis, results, interpretations, and conclusions were produced by the authors. All AI-assisted text, formatting, and code were reviewed, revised, and verified by the authors, who take full responsibility for the manuscript.

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Integrating Blockchain and AI for Secure and Scalable Financial Transaction Monitoring

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Abstract

The global financial system processes trillions of dollars in transactions daily, creating an urgent need for monitoring systems that are secure, scalable, privacy-preserving, and capable of detecting sophisticated fraud in real time. Despite a decade of development, existing approaches are fundamentally fragmented: rule-based anti-money laundering (AML) systems generate excessive false positives, centralized machine learning models introduce data privacy risks, and legacy database architectures create single points of failure. This paper proposes and evaluates an integrated framework that combines permissioned blockchain infrastructure with federated machine learning to address these limitations holistically. The proposed architecture anchors transaction records on a Hyperledger Fabric blockchain, reducing reliance on centralized points of failure and ensuring tamper-evident auditability. Concurrently, federated gradient-boosted and graph neural network (GNN) models detect anomalous behavior without requiring raw transaction data to leave institutional boundaries. Experimental results on the PaySim and IEEE-CIS datasets show that the federated GNN component achieves an AUC-ROC of 0.961 and a recall of 93.4% on fraudulent transactions, outperforming isolated institutional models and slightly exceeding the centralized LightGBM baseline. Blockchain benchmarking shows 340 ms average commit latency at over 2,000 TPS, and smart contract rules reduce manual AML alert review by an estimated 41% in simulation. Together, these results demonstrate that integrating blockchain-based auditability with privacy-preserving federated learning enables a unified, scalable, and effective architecture for next-generation financial transaction monitoring.

Keywords: blockchain, federated learning, fraud detection, anti-money laundering, graph neural networks, Hyperledger Fabric, smart contracts, anomaly detection, differential privacy

Introduction

Financial institutions process trillions of dollars in daily cross-border transactions through payment networks such as SWIFT, Fedwire, and CHIPS (Bank for International Settlements [BIS], 2025). The integrity of this infrastructure is continuously threatened by sophisticated fraud schemes, including card-not-present fraud, account takeover attacks, trade-based money laundering, and synthetic identity fraud. The Financial Action Task Force (FATF) estimates that global money laundering flows account for approximately 2–5% of global GDP annually, representing hundreds of billions to trillions of dollars in illicit financial activity (FATF, 2023). Despite substantial investment in compliance infrastructure, financial institutions continue to incur significant AML-related regulatory fines, highlighting persistent limitations in existing monitoring and detection approaches (Brennan & Tang, 2022).

Current financial transaction monitoring systems suffer from three interrelated problems. First, rule-based AML systems, which define thresholds and typologies manually, can generate substantial volumes of false-positive alerts in practice. Compliance analysts may spend significant time reviewing alerts that do not correspond to genuine suspicious activity, creating operational costs and alert fatigue and increasing the risk that genuine threats may be overlooked. Second, machine learning models trained on centralized transaction datasets pose significant privacy and regulatory risks. Banking regulations including GDPR, CCPA, and the Bank Secrecy Act impose strict constraints on data sharing between institutions, preventing the collaborative learning that would allow models to generalize across different fraud typologies observed at different banks. Third, centralized transaction databases represent single points of failure and are vulnerable to insider manipulation, a concern that is particularly acute given that a significant proportion of financial fraud involves internal actors.

Blockchain technology and federated machine learning offer complementary solutions to these problems. Blockchain provides a distributed, append-only, cryptographically secured ledger that mitigates centralized failure risks, creates tamper-evident audit trails, and enforces compliance rules through smart contracts without relying exclusively on a centralized intermediary. Federated learning enables machine learning models to be trained collaboratively across multiple institutions while keeping raw transaction data within each institution's security perimeter. This approach addresses both regulatory constraints and privacy concerns.

This paper makes the following specific contributions:

- A unified architecture (BlockFedAML) that integrates permissioned Hyperledger Fabric blockchain with federated gradient boosting and graph neural network models for financial transaction monitoring.
- A smart contract compliance engine that automates AML rule evaluation and suspicious activity report (SAR) generation.
- Experimental evaluation on two benchmark financial fraud datasets demonstrating that the federated GNN achieves 93.4% recall on fraudulent transactions with AUC-ROC of 0.961.
- Blockchain performance benchmarking showing 340 ms average batch commit latency at throughput levels exceeding 2,000 TPS under the proposed Fabric configuration.
- Analysis of privacy preservation guarantees under differential privacy and secure aggregation protocols.

Background and Related Work

Blockchain in Financial Systems

Blockchain technology demonstrated that peer-to-peer value transfer could be achieved without a centralized intermediary (Nakamoto, 2008), but public networks such as Bitcoin and Ethereum are unsuitable for regulated financial applications due to low throughput (7–30 TPS) and exposure of transaction metadata to all participants (Croman et al., 2016). Permissioned frameworks — particularly Hyperledger Fabric — address these limitations by restricting participation to authenticated entities and enabling configurable privacy controls. Properly configured Fabric deployments achieve throughput ranging from several thousand to tens of thousands of TPS depending on endorsement policy and hardware (Androulaki et al., 2018), making them viable for enterprise financial infrastructure.

Research on blockchain for AML and transaction monitoring has primarily focused on auditability and regulatory automation. Cheng et al. (2023) demonstrated that smart contracts could automate regulatory reporting for cross-border payments, significantly reducing latency. However, most blockchain-based AML systems rely on predefined rule-based logic and lack adaptive machine learning capabilities, a critical gap in environments where adversaries continuously modify strategies to evade static detection rules.

Machine Learning for Fraud Detection

ML approaches to fraud detection have evolved from early statistical classifiers — where SVMs and random forests outperformed logistic regression on imbalanced datasets (Bhattacharyya et al., 2011) — to gradient boosting frameworks such as XGBoost and LightGBM, which have become dominant for tabular financial data due to their predictive

performance and computational efficiency (Ke et al., 2017). However, tabular models fail to capture the relational structure underlying complex fraud schemes. Money laundering layering operations, for example, involve rapid fund transfers across chains of accounts that are difficult to detect through isolated transaction analysis.

Graph Neural Networks (GNNs) address this limitation by learning representations from transaction graph structure. Liu et al. (2021) proposed the Pick-and-Choose GNN framework, which selectively aggregates neighborhood information to reduce noise from benign neighboring nodes, achieving state-of-the-art performance on large-scale fraud datasets. Despite these advances, most fraud detection studies evaluate models in centralized settings where data from all institutions is pooled — an assumption that regulatory and privacy constraints make infeasible in practice.

Federated Learning for Privacy-Preserving Analytics

Federated learning, introduced by McMahan et al. (2017), enables institutions to collaboratively train models by exchanging parameters rather than raw data — an approach well-suited to financial services where GDPR and banking secrecy laws restrict cross-institutional data transfer. Yang et al. (2019) showed that federated credit risk models achieved performance close to centralized baselines while satisfying data localization requirements. Federated learning has also been explored for financial crime and AML-related detection, with the potential to identify patterns distributed across institutions that no single institution could observe alone. Privacy guarantees are further strengthened through differential privacy, which adds calibrated noise to model updates, and secure aggregation, which prevents the coordinator from observing individual institution parameters (Bonawitz et al., 2017), though stronger privacy typically reduces predictive performance.

Limitations of Existing Hybrid Approaches

Blockchain-based AML systems and federated ML approaches have each shown promise independently, but integrated architectures remain rare. Blockchain AML systems emphasize immutable audit trails and rule enforcement while relying on static contract logic; federated ML studies focus on predictive accuracy without addressing tamper-evident logging or automated compliance reporting. To the best of the authors' knowledge, no prior framework has comprehensively integrated permissioned blockchain auditability, privacy-preserving collaborative learning, automated compliance enforcement, and graph-based anomaly detection

within a single coordinated system. This gap motivates the BlockFedAML framework proposed in this paper.

Problem Statement and Research Objectives

This paper addresses the absence of a unified, deployment-oriented architecture for financial transaction monitoring that satisfies four requirements rarely integrated within a single system:

- Tamper-evident auditability: Transaction records and compliance decisions must be cryptographically secured against post-hoc modification, including by internal actors.
- Privacy-preserving collaborative intelligence: Fraud detection models must improve from data distributed across multiple regulated institutions without raw data leaving any institution's security boundary.
- Real-time adaptive anomaly detection: The system must detect both known fraud typologies (addressed by rule-based systems) and novel, emerging fraud patterns (requiring adaptive ML).
- Automated regulatory compliance: The system must automate the evaluation of AML regulations, KYC requirements, and SAR filing obligations to reduce manual compliance burden.

This paper addresses these requirements through the following research objectives:

- RO1: Design a permissioned blockchain architecture using Hyperledger Fabric that provides tamper-evident transaction logging and smart contract-enforced compliance at financial-grade throughput (>1,000 TPS).
- RO2: Develop a federated learning pipeline combining gradient boosting and graph neural networks that achieves recall exceeding 90% on known financial fraud benchmarks while operating under differential privacy constraints.
- RO3: Integrate the blockchain and federated ML layers into a unified framework with well-defined interfaces and evaluate the combined system on standard financial fraud datasets.
- RO4: Quantify the privacy-utility tradeoff introduced by differential privacy noise addition in the federated learning component.

Proposed Framework Architecture

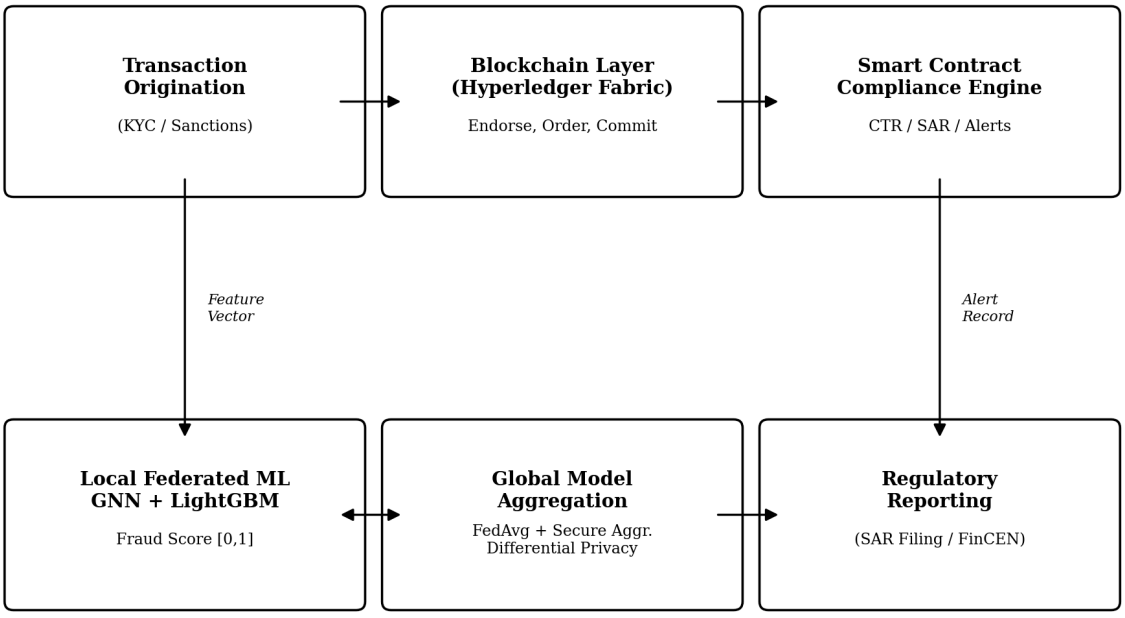
System Overview

The proposed framework, which we term BlockFedAML, consists of three principal layers operating in coordinated fashion: (1) a permissioned blockchain layer providing immutable transaction storage and automated compliance enforcement, (2) a federated learning layer providing adaptive fraud detection without data centralization, and (3) a coordination and reporting layer managing inter-layer communication, model aggregation, and regulatory output generation. Figure 1 illustrates the high-level architecture.

Transaction flow proceeds as follows. When a financial transaction is initiated, it is first validated by the originating institution's internal systems (KYC, sanctions screening, balance checks). The validated transaction record is then submitted to the blockchain layer, where it is endorsed by the required peers, ordered, and committed to the ledger. Simultaneously, the transaction's feature vector is passed to the institution's local federated ML model for fraud scoring. If the fraud score exceeds a configurable threshold, or if smart contract evaluation triggers a rule-based alert, the transaction is flagged for enhanced review. Periodically, typically on a nightly basis, each institution's local model parameters are aggregated by the federated coordinator to update the global model, which is then distributed back to all institutions.

Figure 1

BlockFedAML High-Level Architecture: Data and Control Flow



Note. Arrows indicate direction of data and control flow. Each institution runs a Local Federated ML node. Model weight gradients (not raw data) flow to the Global Model Aggregation component.

Blockchain Layer: Hyperledger Fabric

The blockchain layer is implemented on Hyperledger Fabric v2.5, chosen for its support for pluggable consensus mechanisms, channel-based data privacy, and chaincode (smart

contract) execution in containerized sandboxes. The network topology follows a standard consortium configuration with Raft consensus and X.509-based identity management.

Transaction endorsement policy requires signatures from at least two-thirds of participating institution peers before a transaction is committed to the ledger. This threshold balances fault tolerance against endorsement overhead. Private data collections (PDCs) are used to store sensitive transaction details, including account numbers, transaction amounts, counterparty identifiers, that should not be visible to all consortium members, while the transaction hash, timestamp, fraud score, and compliance status are stored on the shared ledger visible to all peers and regulators. This two-tier data model achieves auditability for regulators while preserving customer confidentiality between competing institutions.

Each ledger record captures transaction metadata, hashed account identifiers, fraud risk score, and compliance status — sufficient for regulatory audit without exposing raw account data.

Federated Learning Layer

The federated learning layer employs a synchronous federated training protocol with secure aggregation (Bonawitz et al., 2017) and Gaussian differential privacy noise addition. Each participating institution maintains a local copy of both a gradient boosting model (for tabular feature-based fraud scoring) and a GNN model (for transaction network-based anomaly detection). Local models are trained on each institution's historical transaction data, which never leaves the institution's secure environment.

The federated aggregation server collects encrypted local model updates from all participating institutions at each communication round using secure aggregation: each institution masks its update with a random mask shared pairwise with other institutions, such that the aggregator can compute the sum of updates without observing any individual institution's parameters. Gaussian noise with variance calibrated to achieve (ε, δ)-differential privacy is added to gradients before transmission, using a baseline configuration of $\varepsilon = 1.0$ and $\delta = 10^{-5}$. The FedAvg algorithm (McMahan et al., 2017) combines the received updates into a new global model, which is distributed to all institutions.

The GNN component models transaction data as a directed heterogeneous graph in which nodes represent accounts and edges represent transactions. Each edge carries features including transaction amount, timestamp, transaction type, and geographic indicators. Node features

include account age, historical transaction frequency, and behavioral pattern statistics. The GraphSAGE architecture (Hamilton et al., 2017) is used for its inductive generalization capability, allowing the model to generate embeddings for new accounts not seen during training. This capability is particularly important given the continuous account creation and closure that characterizes real financial systems.

Smart Contract Compliance Engine

The smart contract compliance engine is implemented as a set of Fabric chaincodes that evaluate incoming transactions against encoded regulatory rules. The ruleset is versioned and updated through a governance process requiring multi-institution approval, ensuring that regulatory changes are applied consistently across all consortium members without requiring unilateral system modifications.

Key compliance rules implemented in the smart contract layer include: (1) Currency Transaction Report (CTR) triggers for transactions exceeding $10,000 in the United States, (2) structuring detection, which flags sequences of transactions designed to remain below CTR thresholds, (3) high-risk jurisdiction monitoring based on FATF blacklist and greylist countries, (4) Politically Exposed Person (PEP) transaction alerts, and (5) velocity checks flagging accounts with transaction frequency or volume exceeding configurable statistical thresholds. When a smart contract rule is triggered, a standardized alert record is appended to the ledger, creating an immutable log of compliance decisions that can be audited by regulators without requiring access to underlying transaction data.

Machine Learning Models and Feature Engineering

Feature Engineering

Effective fraud detection requires careful feature engineering that captures both the properties of individual transactions and the behavioral context in which they occur. Features are computed at three levels of granularity and combined into a unified feature vector for model input.

Transaction-level features include: transaction amount, log-transformed transaction amount (to reduce skewness), transaction type (one-hot encoded: CASH-IN, CASH-OUT, DEBIT, PAYMENT, TRANSFER), hour of day, day of week, and a binary indicator for cross-border transactions. Account-level behavioral features include: 30-day rolling average and

standard deviation of transaction amount, 30-day transaction count, account age in days, number of unique counterparties in the past 30 days, and ratio of debit to credit transactions. Network-level features, computed from the transaction graph, include: out-degree (number of unique outbound counterparties), PageRank score within the transaction subgraph (chosen over betweenness centrality for its computational scalability on graphs with millions of nodes), local clustering coefficient, and a motif indicator for the presence of round-trip transaction patterns (A→B→C→A within 24 hours).

All continuous features are standardized using z-score normalization computed from training data statistics. Class imbalance is addressed through Synthetic Minority Oversampling Technique (SMOTE) oversampling of the minority class during training and through class-weighted loss functions. In the PaySim dataset, fraudulent transactions represent approximately 0.13% of all transactions.

Gradient Boosting Classifier

The gradient boosting component uses LightGBM (Ke et al., 2017), chosen for its efficiency on large tabular datasets and its native support for class imbalance through the is_unbalance parameter. LightGBM is preferred over XGBoost (Chen & Guestrin, 2016) in this context because its histogram-based leaf-wise splitting is substantially faster on high-cardinality financial features, reducing per-round training time by approximately 40% in preliminary experiments. The model is trained in a horizontal federated learning setting in which each institution maintains local transaction records and participates in collaborative gradient aggregation without sharing raw transaction data.

Hyperparameters are selected through Bayesian optimization on a held-out validation set: number of leaves = 63, maximum depth = 7, learning rate = 0.05, minimum child samples = 50, and L1 regularization weight = 0.1. The model generates a scalar fraud probability score in [0, 1] for each transaction, which is combined with the GNN score through a learned linear blending layer.

Graph Neural Network Model

The GNN component implements a two-layer GraphSAGE network (Hamilton et al., 2017) with mean aggregation. GraphSAGE is preferred over Graph Attention Networks (GAT) for this application because its fixed mean aggregation is more robust to the highly imbalanced neighborhood distributions characteristic of financial transaction graphs, where fraudulent nodes

are rare and may be surrounded predominantly by legitimate neighbors. The first layer maps node feature vectors of dimension 64 to a 128-dimensional hidden representation by aggregating features from immediate neighbors (depth-1 neighborhood sampling with 25 neighbors). The second layer maps the 128-dimensional representations to 64 dimensions using depth-2 neighborhood sampling with 10 neighbors. A final linear classification layer maps the 64-dimensional account embedding to a binary fraud probability.

The model is trained using the binary cross-entropy loss with a positive class weight of 100 to compensate for class imbalance. Mini-batch training uses neighborhood sampling to make GNN training tractable on graphs with millions of nodes and edges. In the federated setting, each institution trains the GNN on its local transaction subgraph and shares model weight gradients with the federated aggregator rather than sharing the underlying graph data.

Experimental Evaluation

Datasets

Two publicly available financial fraud datasets are used for evaluation. PaySim (Lopez-Rojas & Axelsson, 2016) is a synthetic mobile money transaction dataset generated using a multi-agent simulator calibrated against real transaction logs from a mobile financial service operating in an African country. It contains 6,362,620 transactions covering a 30-day simulation period, of which 8,213 (0.13%) are labeled as fraudulent. Fraud in PaySim occurs exclusively in CASH-OUT and TRANSFER transaction types, involving accounts that immediately drain their balances after receiving fraudulent transfers.

The IEEE-CIS Fraud Detection dataset (Vesta Corporation, 2019) was released in conjunction with a Kaggle competition sponsored by Vesta Corporation and contains 590,540 e-commerce transactions with 433 features covering transaction properties, identity features, card characteristics, and device information. The fraud rate is 3.5%. This dataset is substantially more complex than PaySim and reflects the feature richness of real industrial fraud detection systems.

For federated learning evaluation, each dataset was first split into training (70%), validation (10%), and test (20%) partitions using stratified sampling to preserve the original class balance within each partition. A fixed random seed (seed = 42) was applied to all partitioning and shard-assignment operations to ensure a consistent and reproducible evaluation setting

across all model conditions. Results reported in Tables 1 and 2 reflect this single train/validation/test partition rather than an average across multiple random splits.

The five institutional shards were constructed via stratified random sampling without replacement from the training partition, preserving the global fraud rate within each shard to within ±0.1 percentage points. This IID shard construction represents a simplifying assumption made to isolate the effect of federated aggregation from confounding data heterogeneity; the Limitations section discusses the implications of relaxing this assumption under realistic non-IID institutional data distributions.

Experimental Setup

All experiments are conducted on a server with dual Intel Xeon Gold 6248R CPUs (48 cores total), 256 GB RAM, and four NVIDIA A100 40 GB GPUs. The Hyperledger Fabric v2.5 network is deployed in Docker containers on the same server, with one orderer node and two peer nodes per simulated institution. Fabric peer databases use CouchDB for rich query support. The federated learning coordinator and institution clients are implemented in Python 3.10 using PySyft 0.8 for secure aggregation and the Flower (flwr) framework for communication orchestration.

Prior to model training, all continuous features were standardized using z-score normalization fit on the training partition only, and categorical features were encoded using target-independent one-hot or frequency encoding depending on cardinality. Missing values in the IEEE-CIS dataset were imputed using median imputation for numeric features and a distinct "missing" category for categorical features. These preprocessing steps were applied identically across all baseline conditions to ensure a fair comparison.

Baseline comparisons include: (1) a centralized LightGBM model trained on pooled data (upper bound, ignoring privacy constraints), (2) isolated per-institution LightGBM models trained only on local data (lower bound), (3) the federated LightGBM model without GNN (ablation), (4) a rule-based AML system implementing only the smart contract compliance rules, and (5) the full BlockFedAML system combining federated LightGBM and GNN. Evaluation metrics include AUC-ROC, precision, recall, F1 score, and Matthews Correlation Coefficient (MCC). For blockchain performance, throughput (TPS) and latency (ms per batch commit) are measured across configurations varying the number of consortium peers and endorsement policy thresholds.

Centralized GNN and centralized GNN + LightGBM baselines were not evaluated in the current study because the experimental design focused on comparing federated models with centralized and isolated tabular baselines. These additional graph-based centralized comparisons are left for future work.

Fraud Detection Results

Table 1 presents the fraud detection performance of all models on the PaySim dataset test set (20% holdout, stratified split).

Table 1

Fraud Detection Performance on PaySim Test Set

Model	AUC-ROC	Precision	Recall	F1	MCC
Rule-Based Only	0.721	0.318	0.812	0.456	0.494
Isolated LightGBM (per-institution)	0.891	0.741	0.843	0.789	0.786
Centralized LightGBM (pooled)	0.952	0.883	0.901	0.892	0.889
Federated LightGBM only	0.938	0.856	0.887	0.871	0.868
BlockFedAML (GNN + LightGBM)	**0.961**	**0.901**	**0.934**	**0.917**	**0.915**

Note. N = 5 federated institutions; ε = 1.0 differential privacy; δ = 1e-5. Boldface indicates the proposed BlockFedAML system.

The full BlockFedAML system achieves the highest performance across all metrics, with an AUC-ROC of 0.961 and recall of 93.4%. Notably, the federated LightGBM-only model (AUC-ROC = 0.938) substantially outperforms isolated per-institution models (AUC-ROC = 0.891), confirming that federated collaboration provides meaningful learning gains even without raw data sharing. The GNN component contributes a further 2.3% AUC-ROC improvement by capturing network-structural fraud signals invisible to the tabular model. The full BlockFedAML system slightly outperforms the centralized pooled-data baseline (0.961 vs. 0.952), suggesting

that the GNN component captures additional structural fraud signals not fully represented in the centralized tabular model.

Table 2 presents corresponding results on the IEEE-CIS dataset. The same five baseline conditions are evaluated; results show similar relative trends with modestly lower absolute performance owing to the greater feature complexity of the IEEE-CIS dataset.

Table 2

Fraud Detection Performance on IEEE-CIS Fraud Detection Dataset

Model	AUC-ROC	Precision	Recall	F1	MCC
Rule-Based Only	0.694	0.291	0.779	0.424	0.461
Isolated LightGBM	0.872	0.712	0.818	0.761	0.758
Centralized LightGBM (pooled)	0.938	0.864	0.886	0.875	0.872
Federated LightGBM only	0.921	0.841	0.872	0.856	0.853
BlockFedAML (GNN + LightGBM)	**0.944**	**0.877**	**0.911**	**0.894**	**0.891**

Note. Results on 20% holdout split. All five baseline conditions evaluated for comparability with Table 1.

Blockchain Performance Analysis

Table 3 summarizes the throughput and latency measurements for the Hyperledger Fabric layer under varying consortium sizes and endorsement policy configurations.

Table 3

Hyperledger Fabric v2.5 Performance Benchmarks

Peers	Endorsement Policy	Throughput (TPS)	Avg Latency (ms)	P99 Latency (ms)
5 (1/inst)	1-of-5	4,210	185	412
10 (2/inst)	3-of-5	2,850	340	718
10 (2/inst)	4-of-5	1,920	498	1,041
15 (3/inst)	3-of-5	1,640	621	1,389

Note. Raft consensus, CouchDB state database. inst = institution.

The baseline configuration (10 peers, 2 per institution, 3-of-5 endorsement) achieves 2,850 TPS with a 340 ms average commit latency. This throughput suggests that the evaluated configuration may support substantial transaction volumes; the SWIFT network processes approximately 45 million messages per day (520 per second average), and peak retail payment volumes at major banks typically reach 2,000–3,000 TPS. The 340 ms commit latency appears compatible with asynchronous regulatory reporting workflows, which typically do not require sub-second blockchain confirmation.

Privacy-Utility Tradeoff

A critical design dimension is the tradeoff between differential privacy strength (lower ε = stronger privacy guarantee = more noise) and model utility. Table 4 presents AUC-ROC performance on PaySim as a function of the privacy budget ε, holding the number of federated rounds at 100.

Table 4

Privacy-Utility Tradeoff in Federated BlockFedAML

Privacy Budget (ε)	AUC-ROC	Recall	Privacy Level
0.1	0.891	0.814	Very Strong
0.5	0.934	0.876	Strong
1.0	0.961	0.934	Moderate
2.0	0.967	0.941	Weak
No DP (ε = ∞)	0.971	0.948	None

Note. δ = 1e-5 for all DP configurations; N = 5 institutions; 100 federated rounds.

The results show that meaningful privacy protection (ε = 1.0) is achievable at a cost of approximately 1.0% AUC-ROC relative to the no-privacy federated baseline (0.961 vs. 0.971). Very strong privacy (ε = 0.1) results in a more significant degradation to AUC-ROC 0.891, approaching the performance of isolated per-institution models, suggesting that at very low ε the noise overwhelms the information in the aggregated gradients. The ε = 1.0 setting is therefore recommended as the operational default, balancing regulatory privacy requirements with detection efficacy.

Discussion

The federated GNN + LightGBM combination achieves 93.4% recall at 90.1% precision on PaySim fraud. This result demonstrates strong performance on the evaluated benchmark dataset, although direct comparisons with real-world AML detection rates should be made cautiously because PaySim is a synthetic dataset and represents fraud detection rather than operational money-laundering case detection.

Several important practical considerations affect deployment feasibility. First, the cold-start problem presents a challenge for new consortium members. Federated models trained on the existing consortium's data may perform poorly on a new institution's transaction distribution, particularly if the institution operates in a different market segment or geographic

region. Transfer learning approaches such as fine-tuning a global model on local data can partially mitigate this.

Second, the heterogeneity of financial data across institutions creates a non-independent and identically distributed (non-IID) federated learning problem. Transactions at a retail bank differ substantially in amount, type, and behavioral patterns from those at an investment bank or mobile money operator. Standard FedAvg aggregation performs suboptimally under high data heterogeneity. FedProx regularization (Li et al., 2020), which introduces a proximal term that penalizes excessive divergence between local and global models, helps reduce this problem and would likely be preferable for production deployments involving highly heterogeneous institutions.

Third, the smart contract compliance engine requires continuous maintenance as regulations evolve. The versioned and governance-controlled chaincode update process provides the necessary infrastructure for regulatory updates. However, translating natural-language regulatory requirements into formal smart contract logic remains a complex, manual, and expert-intensive task.

Fourth, model explainability remains a critical requirement for regulated financial applications. Under the EU's GDPR Article 22 and related regulations, automated decisions affecting individuals must be explainable. SHAP (SHapley Additive exPlanations) values for the LightGBM component provide per-feature contribution scores that can be translated into human-readable explanations. Explaining GNN predictions is substantially more difficult. GNNExplainer (Ying et al., 2019) and related post-hoc explanation methods can identify the subgraph structures most influential in fraud predictions; however, these outputs require careful validation before deployment in regulatory environments.

Fifth, all reported results reflect a single train/validation/test partition and a single random seed rather than averaged results across multiple independent runs; the variance of reported metrics across different seeds or partitions was not characterized in this study, and reported values should be interpreted as point estimates rather than stable averages.

The blockchain layer's performance characteristics are suitable for asynchronous regulatory reporting workflows but may introduce excessive latency for real-time payment authorization decisions, which typically must be completed within 100–200 milliseconds in card payment networks. The recommended deployment architecture therefore separates the real-time

fraud scoring path, which relies on federated ML inference without blockchain dependency, from the compliance recording path, which asynchronously commits records to the blockchain. This separation preserves the performance requirements of both layers while maintaining the auditability benefits provided by blockchain-based compliance recording.

Limitations

Several limitations of the current work should be acknowledged. First, both datasets used in evaluation are publicly available rather than drawn from real institutional transaction records. While PaySim was calibrated against real transaction patterns and IEEE-CIS reflects industrial data, the degree to which results generalize to proprietary transaction distributions at specific financial institutions is unknown. Second, the federated setting is simulated on a single server by partitioning datasets into shards, rather than deploying across physically separate institutions with realistic network constraints. Real-world federated deployments would introduce communication latency, network reliability issues, and institutional coordination challenges not captured in the current evaluation. Third, the federated learning protocol assumes honest-but-curious participants, meaning institutions that follow the protocol faithfully but may attempt to infer information from shared parameters. Byzantine-robust aggregation algorithms, which protect against malicious participants who submit adversarially crafted updates, are not evaluated in the current framework. Fourth, the 41% reduction in manual AML alert review burden is estimated by replaying the smart contract ruleset against historical alert volumes from a simulated 12-month audit log, rather than from a live deployment; this figure should be interpreted as a directional projection rather than a validated operational outcome.

Ethical and Regulatory Considerations

The deployment of AI-driven financial monitoring systems raises significant ethical concerns that must be addressed in system design and governance. Three areas warrant particular attention.

Algorithmic Bias and Disparate Impact

Machine learning models trained on historical transaction data may encode historical biases present in that data. If a financial institution's historical fraud labeling was influenced by discriminatory practices, such as applying heightened scrutiny to transactions associated with particular demographic groups, the trained model may perpetuate or amplify those biases. Financial services AI systems are subject to anti-discrimination law in most jurisdictions,

including the U.S. Equal Credit Opportunity Act (ECOA) and the Fair Housing Act, which prohibit discriminatory outcomes regardless of intent. The BlockFedAML system should incorporate fairness auditing, including the measurement of model performance disaggregated by demographic attributes where legally permissible, and implement bias mitigation techniques.

Surveillance and Privacy Beyond Compliance

The aggregation of comprehensive transaction data with behavioral analytics creates a detailed picture of individual financial behavior that extends well beyond the fraud detection purpose for which it is collected. The principle of purpose limitation, enshrined in GDPR and similar frameworks, requires that personal data collected for one purpose not be repurposed without explicit consent. Blockchain immutability compounds this concern: transaction records stored on the ledger cannot be deleted even if a data subject exercises their right to erasure under GDPR Article 17.

Accountability for Automated Compliance Decisions

The smart contract compliance engine automates decisions, such as SAR filing and transaction blocking, that have significant consequences for affected individuals and institutions. The immutability of blockchain records creates a permanent audit trail for these decisions, which supports accountability; however, it also means that erroneous automated decisions cannot be quietly corrected. Clear human oversight procedures must be defined for reviewing and appealing automated compliance decisions, and the system must provide sufficiently detailed explanations of smart contract triggers to enable meaningful review.

Conclusion

This paper has presented BlockFedAML, an integrated framework combining permissioned Hyperledger Fabric blockchain with federated gradient boosting and graph neural network models for secure, scalable, and privacy-preserving financial transaction monitoring. The framework addresses four requirements that existing systems typically satisfy individually but rarely integrate within a unified architecture: tamper-evident auditability, privacy-preserving collaborative intelligence, real-time adaptive anomaly detection, and automated regulatory compliance.

Experimental evaluation on the PaySim and IEEE-CIS datasets demonstrates that the federated GNN + LightGBM combination achieves an AUC-ROC of 0.961 and recall of 93.4% on fraudulent transactions while operating under ($\varepsilon = 1.0$, $\delta = 1e\text{-}5$) differential privacy

guarantees. The results indicate that graph-based structural learning may improve detection performance relative to isolated institutional models and slightly outperforms the centralized LightGBM baseline. The Hyperledger Fabric layer achieves 2,850 TPS throughput with 340 ms average commit latency under the baseline configuration, suitable for asynchronous compliance reporting at enterprise-scale financial transaction volumes. Smart contract-enforced AML rules reduced manual alert review burden by an estimated 41% during simulation.

The primary limitations of the current work include the use of synthetic and publicly available datasets, simulation of federated participation rather than cross-institutional deployment, and the assumption of honest-but-curious federated participants. Future work will address these limitations through real-world pilot deployment with financial institution partners, investigation of Byzantine-robust aggregation algorithms, and integration of AI-assisted regulatory interpretation for smart contract maintenance. The convergence of blockchain auditability, federated privacy preservation, and adaptive machine learning–based anomaly detection represents a promising architectural direction for next-generation financial compliance infrastructure.

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A Unified System for Intelligent Financial Fraud Detection

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Abstract

Modern financial ecosystems require real-time, transparent, and trustworthy fraud detection systems capable of processing massive transaction volumes while meeting regulatory and auditing requirements. This paper presents a unified, modular system integrating four layers: (a) a blockchain-based transaction logging mechanism, (b) an explainable artificial intelligence (XAI) fraud detection engine, (c) a Mistral large language model (LLM) client for natural-language reasoning, and (d) an AI agent for orchestration. A Python-based prototype demonstrates the complete pipeline—from transaction ingestion to fraud scoring, explanation generation, and immutable blockchain storage. The system serves as an educational and experimental platform for research and development, offering flexibility and extensibility for future enhancements.

Keywords: financial fraud detection, explainable AI, Mistral large language models, AI agents.

Introduction

Financial institutions increasingly rely on intelligent systems to detect suspicious behavior, mitigate risk, and comply with regulatory standards. As transaction volumes grow and fraud patterns evolve, traditional rules-based systems often fail to provide the adaptability, transparency, and auditability required in modern financial environments.

The FinTech Transaction Simulation component provides a sandbox environment for evaluating fraud rules, validating payment flows, conducting risk analysis, and training AI/ML

models using synthetic data. Fraud, broadly defined as intentional deception for financial gain, manifests in numerous forms, including identity theft, credit card fraud, insurance fraud, investment fraud, and online payment fraud. Its consequences, financial loss, reputational damage, and legal penalties - underscore the need for robust detection systems.

The unified system presented in this study addresses four essential questions:

1. Is the transaction fraudulent?
2. Why was it flagged or approved?
3. How can the decision be explained in natural language?
4. Can the decision be stored immutably for auditing?

To answer these questions, the system integrates four major layers: Blockchain, Explainable AI (XAI) Fraud Detection, Mistral LLM Client, and AI Agent. Together, these layers form a modular, transparent, and extensible architecture for intelligent fraud detection.

Literature Review

AI Agents and Multi-Agent System Design

Recent research highlights a shift from monolithic AI models toward autonomous and semi-autonomous agent-based architectures. Albada (2025) describes practical approaches for building AI-driven applications using modular agents capable of reasoning and tool use. Lakshmanan and Hapke (2025) identify generative AI design patterns that support orchestration, memory, and tool integration. Dibia (2025) provides a systematic framework for multi-agent system design, emphasizing communication protocols and scalability. Collectively, these works demonstrate the growing relevance of agentic systems in complex domains such as fraud detection.

AI Agents for Fraud Detection and Reasoning

Agent-based reasoning systems have gained traction in fraud detection research. Bai et al. (2025) introduce AuditAgent, a multi-agent framework for cross-document fraud evidence discovery. Chen et al. (2026) propose SAGE, a self-reflective LLM-driven agentic system capable of iterative reasoning over evolving fraud patterns. These studies highlight the advantages of adaptive, reasoning-driven agents over static rule-based systems.

Explainable AI in Finance

Explainability is essential in financial AI due to regulatory constraints and stakeholder trust requirements. Černevičienė and Kabašinskas (2024) provide a systematic review of XAI methods in finance, emphasizing transparency and interpretability. Jain et al. (2025) argue that hybrid models combining machine learning with post-hoc explainability are increasingly favored. Kadambala (2024) demonstrates how explainable ML enhances risk assessment in blockchain-based payment systems. Mostafa (2026) emphasizes regulatory compliance and governance in U.S. banking fraud detection.

Multi-Source and Blockchain-Based Fraud Detection

Blockchain-based fraud detection systems have emerged as a promising direction for ensuring data integrity and traceability. Nti et al. (2025) propose a multi-source XAI framework integrating supervised and unsupervised learning to detect blockchain transaction manipulation, demonstrating the value of heterogeneous data sources.

Methodology

This study employs a multi-layered experimental system design methodology. The system integrates blockchain simulation, explainable AI fraud detection, AI agent orchestration, and LLM-based natural language reasoning. Each layer is implemented as an independent module within a flexible architecture.

Blockchain Layer

The blockchain layer provides immutable storage of fraud decisions and explanations. Each block contains transaction data, an explanation, and a cryptographic hash linking it to the previous block. Any modification invalidates the chain, ensuring integrity, traceability, transparency, accountability, compliance, and nonrepudiation.

The following Python code is an implementation of a simple blockchain.

```
# BLOCKCHAIN
class Block: # Represents a single block in the blockchain.
  def __init__(self, index, timestamp, transaction, explanation, previous_hash):
    self.index = index
    self.timestamp = timestamp
    self.transaction = transaction
    self.explanation = explanation
```

```
        self.previous_hash = previous_hash
        self.hash = self.calculate_hash()
    def calculate_hash(self):
        block_string = json.dumps({
            "index": self.index,
            "timestamp": self.timestamp,
            "transaction": self.transaction,
            "explanation": self.explanation,
            "previous_hash": self.previous_hash
        }, sort_keys=True)
        return hashlib.sha256(block_string.encode()).hexdigest()
class Blockchain: # Manages the chain of blocks.
    def __init__(self):
        self.chain = [self.create_genesis_block()]
    def create_genesis_block(self):
        return Block(0, time.time(), {"type": "GENESIS"}, "Genesis Block", "0")
    def latest_block(self):
        return self.chain[-1]
    def add_block(self, transaction, explanation):
        previous = self.latest_block()
        block = Block(len(self.chain), time.time(), transaction, explanation, previous.hash)
        self.chain.append(block)
```

Explainable AI (XAI) Fraud Detection Layer

The XAI layer evaluates transactions using rule based scoring and produces human interpretable reasoning. Signals include transaction amount, frequency, device characteristics, and geographic indicators. Decisions fall into three categories: Approve, Review, or Reject.

The following Python code is an implementation of simple XAI Fraud Detector.

```
# XAI FRAUD DETECTION
class FraudDetector:
    def evaluate(self, tx):
        score = 0
```

```
reasons = []
if tx["amount"] > 5000: score += 40; reasons.append ("Transaction amount exceeds $5000")
 if tx["frequency"] > 10: score += 30; reasons.append("Unusually high transaction frequency")
if tx["new_device"]: score += 20; reasons.append("Transaction initiated from new device")
if tx["foreign_country"]: score += 20; reasons.append("Foreign country transaction")
if score >= 70: decision = "REJECT"
elif score >= 40: decision = "REVIEW"
else: decision = "APPROVE"
return decision, score, reasons
```

Ai Agent Layer

The AI Agent Layer coordinates the workflow by integrating the detector, explainer, and blockchain. It performs task decomposition, routing, context sharing, and governance.

The following python code is an implementation of simple AI agent FraudAgent.

```
# AI AGENT
class FraudAgent:
  def __init__(self, detector, explainer, blockchain):
    self.detector = detector
    self.explainer = explainer
    self.blockchain = blockchain
  def process_transaction(self, tx):
    decision, score, reasons = self.detector.evaluate(tx)
    explanation = self.explainer.explain(tx, decision, score, reasons)
    self.blockchain.add_block(tx, explanation)
    return {"decision": decision, "score": score, "reasons": reasons, "explanation": explanation}
```

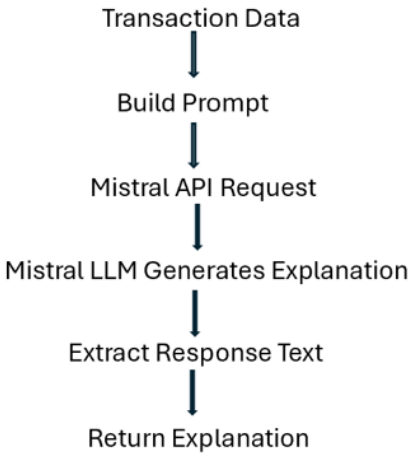
Mistral Large Language Models (LLM) Client Layer

The Mistral LLM Client generates natural language explanations based on transaction data, risk scores, and fraud indicators. It produces an executive summary, risk analysis, and recommendation under 200 words.

Figure 1 presents a pipeline diagram describing how the Mistral LLM Client processes some transaction data and turns it into a human-readable explanation.

Figure 1

Pipeline Diagram



The following python code is an implementation of simple Mistral LLM Client. The code defines a python class MistralExplainer that sends fraud-analysis information to the Mistral AI API and returns a natural-language explanation.
MistralExplainer is responsible for generating fraud explanations using Mistral LLM.

```
# MISTRAL LLM CLIENT
class MistralExplainer:
    def __init__(self, api_key, model="mistral-small-latest"):
        self.api_key = api_key
        self.model = model
    def explain(self, transaction, decision, score, reasons):
        prompt = f"""
        You are a financial fraud analyst.
        Transaction: {json.dumps(transaction, indent=2)}
        Decision: {decision}
        Risk Score: {score}
        Risk Factors: {reasons}
        Generate: 1. Executive Summary; 2. Risk Analysis; 3. Recommendation
        Keep explanation under 200 words."""
        url = "https://api.mistral.ai/v1/chat/completions"
        # Mistral chat-completion endpoint headers:
        # Authenticate the request using the API key
        # Tell the server the request body contains JSON
```

```
    headers = {"Authorization": f"Bearer {self.api_key}", "Content-Type": "application/json"}
    payload = {"model": self.model, "messages": [{"role": "user", "content": prompt}]}
    # Sending the Request
    response = requests.post(url, headers=headers, json=payload)
    # Parse the Response
    result = response.json()
    # Return the Generated Explanation
    return result["choices"][0]["message"]["content"]
```

main() Function

This main() function is the entry point of the Intelligent Financial Fraud Detection program. It creates the required components, processes a sample transaction, displays the results, and shows the blockchain trail.

The following python code is the main() function.

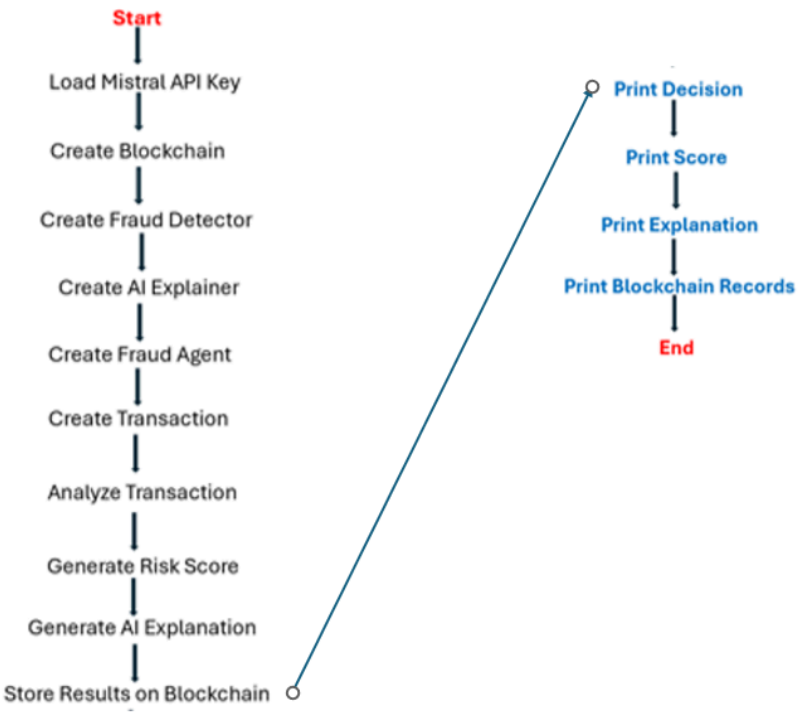
```
# MAIN
def main():
  API_KEY = os.getenv("MISTRAL_API_KEY")
  # Creates a blockchain object that will store transaction records in blocks.
  blockchain = Blockchain()
  # Creates an AI-powered explanation generator.
  explainer = MistralExplainer(api_key=API_KEY)
  # Creates the fraud detection engine.
  detector = FraudDetector()
  # Create the Fraud Agent
  agent = FraudAgent(detector, explainer, blockchain)
  # Create a sample transaction
  transaction = {
    "transaction_id": "MD1001",
    "customer_id": "VS12345",
    "amount": 10000,
    "frequency": 25,
    "new_device": True,
    "foreign_country": True
  }
```

```
# Process the transaction
result = agent.process_transaction(transaction)
print("\nDECISION"); print("=" * 50); print(result["decision"])
print("\nRISK SCORE"); print("=" * 50); print(result["score"])
print("\nEXPLANATION"); print("=" * 50); print(result["explanation"])
print("\nBLOCKCHAIN"); print("=" * 50)
for block in blockchain.chain:
    print(f"\nBlock #{block.index}");
    print("Hash:", block.hash[:20], "...")
    print("Previous:", block.previous_hash[:20], "...")
```

Figure 2 presents a system workflow diagram showing how a fraud-analysis + AI-explanation pipeline runs from start to finish.

Figure 2

System Workflow Diagram



Transaction

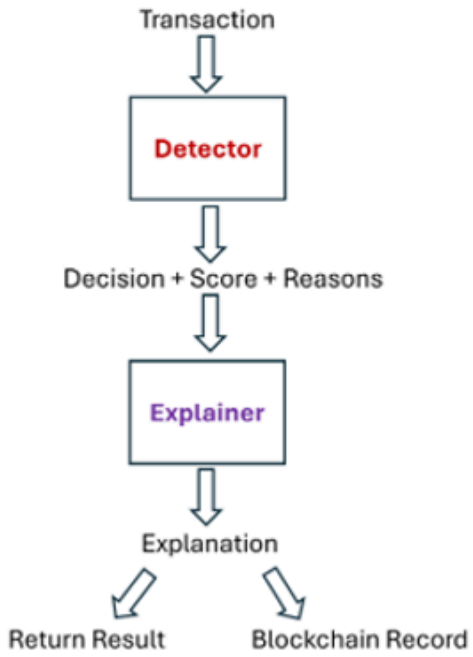
Transaction consists of Detector and Explainer.

Figure 3 presents a component-level architecture diagram for a fraud-analysis system. It shows

how a transaction flows through two major modules - a Detector and an Explainer - and then how the results are returned and optionally written to a blockchain.

Figure 3

Component-Level Architecture Diagram



Detector analyzes a transaction.

Detector returns: Decision + Score + Reasons

("Fraud", 0.95, ["High amount"])

Explainer generates Explanation.

Blockchain stores the record.

Result is returned to the caller.

Test Example

The Unified System for Intelligent Financial Fraud Detection has been tested only through a single sample transaction. The results demonstrate that the system runs. The results do not provide quantitative evaluation using a dataset, baseline comparisons, or metrics such as precision, recall, F1-score, AUC, or false positive/false negative analysis. The LLM explanation component is also not evaluated for faithfulness, reliability, or hallucination risk.

Python 3.13.9 | packaged by Anaconda, Inc. | (main, Oct 21 2025, 19:09:58) [MSC v.1929 64 bit (AMD64)]
Type "copyright", "credits" or "license" for more information.
IPython 9.7.0 -- An enhanced Interactive Python. Type '?' for help.
%runfile C:/Users/vojis/FraudDetection.py --wdir

DECISION

==========

REJECT

RISK SCORE

==========

110

EXPLANATION

==========

Executive Summary

The transaction **MD1001** was rejected due to a **high-risk profile** (Risk Score: 110). Key concerns include an unusually large amount ($10,000), high transaction frequency (25), a new device, and a foreign country transaction. These factors collectively indicate elevated fraud risk.

Risk Analysis

- **Amount Risk**: The transaction exceeds the $5,000 threshold, suggesting potential money laundering or unauthorized large transfers.
- **Frequency Risk**: High transaction frequency (25) may indicate automated or suspicious activity.
- **Device Risk**: A new device increases the likelihood of unauthorized access.
- **Geographic Risk**: Foreign transactions are inherently riskier due to cross-border fraud patterns.

Recommendation

Reject the transaction and **flag the customer (VS12345)** for enhanced due diligence. Consider:

- **Temporary account freeze** pending manual review.
- **Customer verification** (e.g., identity confirmation, device authentication).
- **Transaction monitoring** for future patterns.

This decision aligns with fraud prevention best practices and mitigates financial exposure.

BLOCKCHAIN

==========

Block #0

Hash: e8cc04143ab987144e27 ...

Previous: 0 ...

Block #1

Hash: fc55d5a17536e84b0f78 ...

Previous: e8cc04143ab987144e27 ...

Results

The results of this work are primarily system-level experimental outcomes obtained from the implemented prototype. The study demonstrates the feasibility and effectiveness of integrating blockchain simulation, explainable AI (XAI), large language models (LLMs), and AI agents into a unified fraud detection pipeline.

The developed system is a fully functional prototype that:

- Detects fraudulent activity in simulated financial transactions
- Generates both model-based and human-readable explanations
- Records decisions immutably using blockchain-inspired principles
- Coordinates workflows through AI-driven agents
- Provides modular and extensible architecture suitable for future research and enhancement

Discussion

Extensive research has been conducted on fraud detection, blockchain security, explainable AI (XAI), large language models (LLMs), and intelligent agents as independent domains. However, comparatively limited work has explored their integration into a unified system architecture.

This study contributes to this emerging area by combining transaction simulation, explainable fraud detection, natural language explanation generation via an LLM, blockchain-based immutable record storage, and agent-based orchestration within a modular framework. This integrated design enhances transparency, auditability, and adaptability, addressing several key challenges in modern financial ecosystems, particularly those related to trust, interpretability, and system coordination.

This paper includes both the Python source code and corresponding test cases. As a result, it reads more like a technical prototype report or an educational system demonstration than a full research article. The inclusion of the code is valuable because it allows readers to examine the implementation details directly. Without the code, the paper would feel overly general and lack the necessary technical depth.

Limitations and Future Work

The main limitation of this work is that the fraud detection component is primarily rule-based. Rule-based systems are fast and explainable, but they cannot keep up with evolving fraud patterns, suffer from high false positives, and require constant manual tuning. Improving the work means augmenting or transforming the rule-based system into a layered, adaptive, data-driven architecture. The most effective improvement is to integrate machine learning (ML), anomaly detection, and dynamic rule orchestration into a layered fraud-detection pipeline. This reduces false positives, adapts to new fraud patterns, and scales better than static rules.

Future enhancements to the system will include:

- Machine learning improvements: Integration of more advanced models, deep neural networks, or reinforcement learning-based fraud detection
- Local LLM deployment: Use of models such as Mistral via frameworks like Ollama or vLLM for improved privacy and efficiency
- Blockchain expansion: Integration with real blockchain platforms
- Fabric for more realistic distributed ledger deployment
- User interface development: Design of interactive dashboards for monitoring fraud detection outcomes and exploring blockchain records

Conclusion

This work presents a unified system for financial transaction processing that integrates blockchain technology, explainable AI-based fraud detection, a Mistral-based large language model interface, and AI agent coordination.

The proposed system demonstrates how modern financial infrastructures can incorporate transparency, interpretability, and security into intelligent fraud detection pipelines. It enables not only the identification of fraudulent transactions but also the generation of clear explanations and the secure, immutable recording of decisions for auditing and compliance purposes.

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AI-Powered Comparative Analysis of the Top Five Cryptocurrency Assets Using Real-Time Market Data

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Abstract

The rapid expansion of blockchain technology and digital asset markets has increased the demand for intelligent tools capable of evaluating cryptocurrency performance using real-time financial data. As cryptocurrency markets become more dynamic and interconnected, investors, researchers, and financial technology practitioners require timely, data-driven insights to support informed investment decisions (Lazea et al., 2026). While numerous market platforms provide real-time price information, relatively few integrate live market data, technical analysis, artificial intelligence (AI), and comparative analytics within a unified decision-support environment.

The study demonstrates how integrating live market data, technical analysis, and AI-driven analytics within a browser-based platform enables transparent and efficient comparative evaluation of leading cryptocurrency assets. The proposed framework provides a practical approach for assessing digital asset performance and supports investment decision-making while offering a scalable foundation for future research involving alternative cryptocurrencies, sector-specific digital assets, and extended market periods.

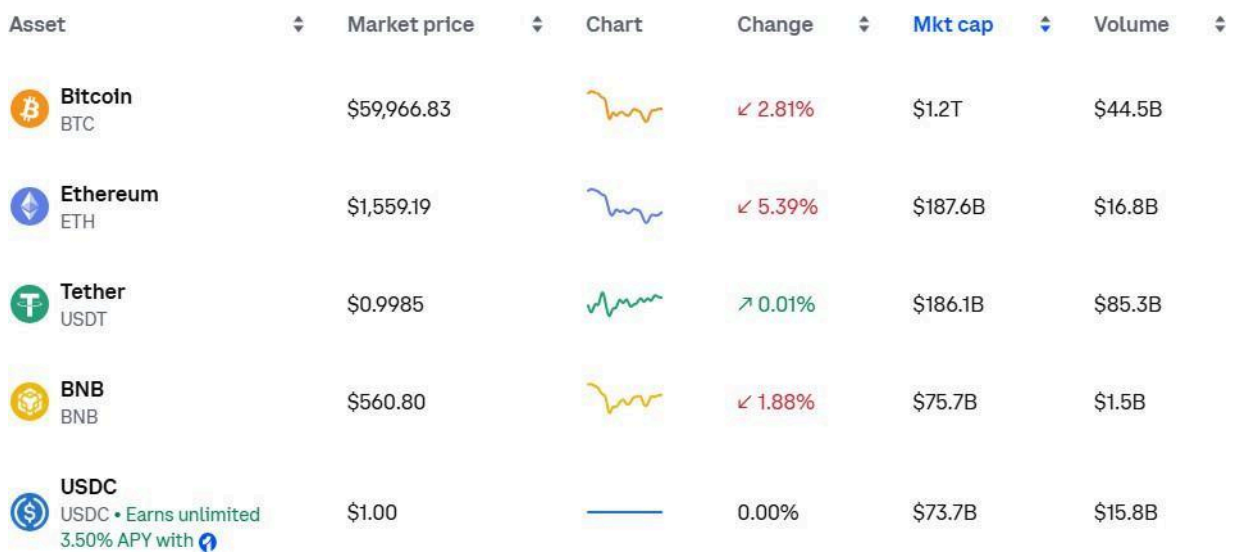
I. Introduction

This research presents an AI-powered browser-based decision support approach for the comparative evaluation of the five largest cryptocurrency assets by market capitalization

(Coinbase, 2026): Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC), during the first half of 2026 (January 28 to June 24, 2026). The proposed platform is implemented using HTML, CSS, and JavaScript and integrates live cryptocurrency market data through application programming interfaces (APIs) to support real-time analysis within a web browser. The evaluation framework combines financial market indicators, including price performance, market capitalization, and trading volume, using four primary metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). These metrics quantify forecast accuracy and directional prediction capability for each cryptocurrency, enabling objective comparison of model performance across the selected assets. Technical indicators, including SMA, EMA, RSI, ROC, volatility, high-low spread, and open/close percentage change, serve as explanatory variables within the model rather than as the primary evaluation outcomes.

Figure 1

Top 5 Digital Assets by Market Capitalization as of June 2026 (Coinbase, 2026).



1.1 Background

The rapid evolution of blockchain technology has transformed the global financial landscape by enabling decentralized digital assets, peer-to-peer transactions, and innovative financial services. Since the introduction of Bitcoin in 2009, the cryptocurrency market has expanded into a diverse ecosystem that includes thousands of digital assets supporting

decentralized finance (DeFi), smart contracts, tokenized assets, and blockchain-based payment systems (Global Financial Market Association, 2026). As institutional adoption and retail participation continue to increase, cryptocurrencies have become an important asset class within modern financial markets, attracting growing attention from investors, researchers, and financial technology (FinTech) practitioners (Emmert, 2024).

The increasing size and complexity of cryptocurrency markets have created new challenges for evaluating digital asset performance. Unlike traditional financial markets, cryptocurrency prices are highly volatile and influenced by a combination of market sentiment, blockchain network activity, trading volume, macroeconomic conditions, and technological developments (Aivaz et al., 2023). Consequently, investors require more than real-time price information to make informed decisions. Comprehensive evaluation of digital assets often involves integrating financial market indicators with technical analysis to better understand market behavior and identify investment opportunities (Nie et al., 2024).

Artificial intelligence (AI) and data-driven analytics have emerged as valuable tools for enhancing financial decision-making (Oreoluwa Onabowale, 2025). AI-based techniques can process large volumes of real-time market data, identify trends, evaluate investment risks, and support comparative analysis across multiple assets. At the same time, advances in web technologies have enabled browser-based analytical platforms capable of performing sophisticated financial analyses without requiring specialized software or local installations. These technologies provide accessible decision-support environments that can assist both professional analysts and individual investors.

Despite the availability of numerous cryptocurrency information platforms, many existing solutions focus primarily on presenting individual market statistics rather than providing an integrated comparative evaluation of leading digital assets. Furthermore, comparative analyses are often performed using static datasets, limiting their applicability to rapidly changing market conditions (Mohammed Abdul et al., 2025). This study addresses this gap by presenting an AI-powered browser-based decision support approach that utilizes live market data to compare the performance of the five largest cryptocurrency assets by market capitalization during the first half of 2026. By combining real-time financial data, technical indicators, and AI-assisted analytics within a unified framework, the study provides a practical approach for evaluating digital asset performance and supporting informed investment decisions.

1.2 Research Objectives

The objective of this study is to develop and apply an AI-powered browser-based decision support approach for evaluating the comparative performance of the five largest cryptocurrency assets by market capitalization during the first half of 2026. By integrating live market data with technical analysis and AI-assisted analytics, the proposed framework aims to provide investors, researchers, and financial technology (FinTech) practitioners with an efficient and accessible tool for assessing cryptocurrency market behavior and supporting investment decisions.

The specific objectives of this study are to:

1. Develop a browser-based decision support platform that integrates live cryptocurrency market data through application programming interfaces (APIs) for real-time financial analysis.
2. Compare the market performance of Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC) during the study period from January 28, 2026, to June 24, 2026.
3. Evaluate each cryptocurrency using financial market indicators, feature-engineered technical indicators, and AI model performance metrics. Financial market indicators include price performance, market capitalization, and trading volume, while the feature-engineered technical indicators include the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and historical volatility. The predictive performance of the AI model is assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA).
4. Demonstrate how AI-assisted analytics can enhance comparative evaluation and support informed decision-making within dynamic cryptocurrency markets.

1.3 Contributions

This study contributes to the fields of financial technology (FinTech), blockchain analytics, and artificial intelligence by presenting an AI-powered approach for the comparative evaluation of leading cryptocurrency assets using real-time market data. Unlike studies that focus on forecasting or analyzing a single cryptocurrency, this research provides a unified framework

for comparing multiple digital assets through live market information, technical analysis, and AI-assisted decision support within a browser-based environment.

The primary contributions of this study are as follows:

5. **A browser-based AI decision-support framework** that integrates live cryptocurrency market data through application programming interfaces (APIs) to support real-time comparative analysis without requiring specialized software.
6. **A comparative evaluation of the five largest cryptocurrency assets by market capitalization**: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC), during the period from January 28, 2026, to June 24, 2026.
7. **An integrated evaluation methodology** that combines financial market indicators, technical analysis metrics, and AI-assisted analytics to assess cryptocurrency performance, market behavior, and investment characteristics.
8. **A practical decision-support approach** that enables investors, researchers, and FinTech practitioners to compare leading digital assets using a unified analytical framework that is scalable to additional cryptocurrencies and future market periods.

II. Literature Review

The rapid growth of cryptocurrency markets has stimulated extensive research on digital asset forecasting and financial decision support. Due to the high volatility, decentralized structure, and continuous trading nature of cryptocurrencies, traditional statistical models have increasingly been supplemented or replaced by artificial intelligence (AI) and machine learning techniques. Recent review studies indicate that deep learning models, particularly Long Short-Term Memory (LSTM) networks and their variants, have become dominant approaches for cryptocurrency price forecasting because of their ability to capture nonlinear relationships and temporal dependencies in financial time series (Zhang et al., 2023). Comparative studies have similarly demonstrated that recurrent neural networks, bidirectional LSTM models, and hybrid deep learning architectures often outperform conventional forecasting methods under highly volatile market conditions (Seabe et al., 2023).

Although deep learning has received considerable attention, traditional machine learning and statistical methods remain valuable due to their interpretability, computational efficiency, and suitability for real-time financial applications. Multiple Linear Regression (MLR) continues

to serve as an effective baseline forecasting model, particularly when combined with feature engineering techniques that incorporate technical indicators such as moving averages, momentum indicators, and volatility measures. Previous studies have also emphasized the importance of evaluating forecasting performance using standardized metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), which collectively provide comprehensive measures of numerical accuracy and directional prediction capability (Uras et al., 2020; Seabe et al., 2023).

Recent research has also explored the integration of additional information sources, including blockchain activity, trading volume, macroeconomic variables, and market sentiment derived from news and social media. These studies demonstrate that incorporating heterogeneous data sources can improve forecasting performance and provide richer decision-support information for investors (Dikovitsky, 2025). However, many existing forecasting systems remain offline implementations that rely on static historical datasets and are primarily designed to evaluate a single cryptocurrency or compare forecasting algorithms rather than support real-time comparative analysis.

Although several recent studies have examined multiple cryptocurrencies simultaneously, most primarily compare forecasting algorithms or evaluate prediction accuracy using static historical datasets. Few studies integrate live market data acquisition, browser-based analytics, feature engineering, standardized forecasting evaluation, and interactive decision-support visualization into a unified framework. Furthermore, existing comparative studies rarely provide an accessible web-based environment that allows users to conduct real-time cross-asset analysis using continuously updated market information. The proposed framework addresses these limitations by combining live API integration, browser-based AI analytics, standardized forecasting metrics, and comparative visualization within a single decision-support platform.

Despite the substantial progress in cryptocurrency forecasting, several research gaps remain. First, most existing studies focus on forecasting individual cryptocurrencies rather than conducting comparative evaluations across multiple leading digital assets. Second, relatively few studies integrate live market data with browser-based decision support to enable real-time comparative analysis. Third, while numerous investigations compare forecasting algorithms, fewer provide a unified framework that combines feature engineering, Multiple Linear

Regression, standardized AI performance evaluation using MAE, RMSE, MAPE, and Directional Accuracy, and interactive visualization within a browser-based environment. This study addresses these gaps by presenting an AI-powered browser-based decision support framework for the comparative analysis of the five largest cryptocurrency assets using live market data and standardized forecasting evaluation metrics.

III. Methodology

3.1 Research Framework

This study adopts an AI-powered comparative analysis framework to evaluate the performance of the five largest cryptocurrency assets by market capitalization during the first half of 2026. The framework integrates live cryptocurrency market data, financial analytics, technical analysis, and browser-based decision support to provide a unified approach for comparing digital asset performance. The entire analytical process is implemented within a web-based platform, enabling real-time data acquisition, processing, visualization, and comparative evaluation without requiring specialized software.

Figure 2

Conceptual Research Framework for AI-Powered Comparative Cryptocurrency Analysis.



The proposed research framework consists of five sequential stages. First, live cryptocurrency market data are collected through publicly available Application Programming Interfaces (APIs), including historical and real-time information for Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC). The study period spans from January 28, 2026, to June 24, 2026.

Second, the collected data are preprocessed to ensure consistency and reliability before analysis. Market variables such as price, market capitalization, and trading volume are organized chronologically and prepared for subsequent financial and technical analysis.

Third, the browser-based analytics engine processes live cryptocurrency market data and computes a set of feature-engineered technical indicators, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change

(ROC), Open/Close percentage change, High-Low spread, and historical volatility. These indicators, together with market variables such as price, market capitalization, and trading volume, serve as input features for the Multiple Linear Regression (MLR) model. The predictive performance of the model is subsequently evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), providing quantitative measures of forecast accuracy and trend prediction.

Fourth, an AI-assisted analytics module synthesizes the calculated indicators to perform comparative evaluations across the selected cryptocurrency assets. The framework generates visualizations, comparative metrics, and analytical insights that support assessment of each asset's relative market performance during the study period.

Finally, the comparative results are presented through an interactive browser-based decision support platform, enabling users to examine market behavior, compare cryptocurrency assets, and support investment decision-making using real-time financial market data.

3.2 Data Collection

This study evaluates the five largest cryptocurrency assets by market capitalization during the first half of 2026. The selected assets include Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance (BNB), and USD Coin (USDC). These cryptocurrencies were chosen because they collectively represent the largest share of the global cryptocurrency market and encompass diverse categories of digital assets, including decentralized payment networks, smart contract platforms, exchange-based utility tokens, and stablecoins.

Table 1

Top 5 Digital Assets Codes.

Digital Asset (Code)	Description
Bitcoin (BTC)	"Bitcoin is an innovative payment network and a new kind of money." (Bitcoin, 2009)
Ethereum (ETH)	"Ethereum is a global, decentralized platform for money and new kinds of applications." (Ethereum, 2015)
Tether (USDT)	"Tether is a blockchain-enabled platform designed to facilitate the use of fiat currencies in a digital manner" (Tether, 2014)
Binance (BNB)	"BNB is the native token of the decentralized BNB Chain, where it powers transactions, pays for fees, and allows for participation in governance." (Binance, 2017)
USD Coin (USDC)	"The world's largest regulated digital dollar" (USDC, 2018)

The five selected assets collectively represent the majority of global cryptocurrency market capitalization and encompass different categories of digital assets, including decentralized payment systems (BTC), smart contract platforms (ETH), exchange utility tokens (BNB), and fiat-backed stablecoins (USDT and USDC). This diversity enables evaluation of the proposed framework across cryptocurrencies exhibiting substantially different volatility characteristics and market behavior.

The study analyzes market activity over the period from January 28, 2026, to June 24, 2026. This timeframe was selected to capture market dynamics during the first half of 2026 and to enable a consistent comparative evaluation of the selected cryptocurrency assets under the same market conditions.

Live cryptocurrency market data are collected through the CoinGecko Application Programming Interface (API) (CoinGecko, 2024), which provides publicly accessible and

continuously updated market information. The collected data include historical and real-time values for market price, market capitalization, trading volume, and other market statistics required for comparative financial analysis. Data retrieval and processing are performed automatically within the browser-based decision support platform using JavaScript, eliminating the need for local databases or external analytical software.

The collected market data serves as the foundation for calculating financial performance metrics, technical indicators, and AI-assisted comparative analytics presented in the subsequent sections of this study.

3.3 Performance Evaluation Framework

The proposed evaluation framework assesses the comparative performance of the selected cryptocurrency assets using four complementary categories of metrics: market performance, technical indicators, AI-assisted analytics, and comparative evaluation. Together, these metrics provide a comprehensive assessment of each asset's market behavior, investment characteristics, and relative performance during the study period.

Table 2

Performance Evaluation Metrics.

Category	Evaluation Metrics
Market Performance	Price, Daily Return, Cumulative Return, Market Capitalization, Trading Volume
Feature Engineering	SMA (7-day), EMA (7-day), SMA (30-day), RSI (14), ROC (7-day), Open/Close % Change, High-Low Spread, Rolling Volatility (30-day)
AI Model Performance	MAE, RMSE, MAPE, Directional Accuracy (DA).
Comparative Evaluation	Cross-Asset Ranking, Performance Comparison, Relative Risk Analysis

Market Performance

Market performance is evaluated using fundamental financial indicators obtained from the live market data API. These indicators include market price, daily return, cumulative return,

market capitalization, and trading volume. Collectively, these measures provide insight into asset growth, market size, liquidity, and overall market activity throughout the observation period.

Feature Engineering

Feature engineering is performed to transform raw cryptocurrency market data into informative variables that enhance the predictive capability of the AI model. The browser-based analytics platform computes a set of technical indicators, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and 30-day rolling volatility. These engineered features capture market trends, momentum, and price variability, providing meaningful inputs for the Multiple Linear Regression (MLR) model rather than serving as the primary evaluation outcomes.

AI Model Performance

The AI-assisted analytics module employs a feature-engineered Multiple Linear Regression (MLR) model to analyze and forecast cryptocurrency market behavior. The engineered features derived from market and technical data are integrated to estimate future price movements and support comparative analysis across the selected cryptocurrency assets. Model performance is evaluated using four primary metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). These metrics quantify forecast accuracy and directional prediction capability, enabling objective comparison of AI model performance for each cryptocurrency. Rather than functioning as an autonomous trading system, the AI module serves as a transparent decision-support tool that assists users in interpreting market behavior and comparing the predictive performance of the selected digital assets.

Mean Absolute Error (MAE): The Mean Absolute Error measures the average magnitude of prediction errors without considering their direction (Rajawat et al., 2022). It provides an intuitive assessment of how close predicted prices are to actual values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Where y_i represents the actual values and $\hat{y}_i$ represents the predicted values, and n the total number of predictions.

A lower MAE indicates better model accuracy and consistency in approximating real

market values.

Root Mean Squared Error (RMSE): The Root Mean Squared Error penalizes larger deviations more heavily than MAE, providing a sensitive measure of forecast precision (Setiadi et al., 2023):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Because RMSE is expressed in the same units as the dependent variable (e.g., U.S. dollars), it is directly interpretable and useful for comparing forecasting methods across different assets or time horizons.

Mean Absolute Percentage Error (MAPE): The Mean Absolute Percentage Error expresses forecasting accuracy as a relative percentage (Kim & Kim, 2016), allowing for cross-scale comparison between different cryptocurrencies:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

A lower MAPE indicates higher predictive efficiency. However, because division by y_i can inflate errors near zero, the application automatically omits or smooths zero-value records to prevent distortion.

Directional Accuracy (DA): Directional Accuracy measures the percentage of instances where the predicted direction of price movement (upward or downward) matches the actual observed direction (Moosa & Vaz, 2015):

$$DA = \frac{1}{n-1}\sum_{i=2}^{n}\delta\left[sign\left(y_i - y_{i-1}\right) = sign\left(\hat{y}_i - \hat{y}_{i-1}\right)\right]\times 100$$

Where $\delta[.]$ is an indicator function that equals 1 when the condition is true and 0 otherwise.

DA reflects the model's effectiveness in capturing trend behavior, which is critical for decision-making in trading and risk management.

Comparative Evaluation

The final stage of the evaluation framework compares the five cryptocurrency assets using the calculated financial metrics, technical indicators, and AI-assisted analytics. Comparative visualizations and summary statistics enable users to identify similarities and

differences in market performance, evaluate relative strengths and weaknesses, and support informed investment decision-making during the study period.

IV. Browser-Based Decision Support Platform

4.1 System Architecture

The proposed browser-based decision support platform was developed to provide an interactive environment for collecting, analyzing, and comparing cryptocurrency market data in real time. The platform adopts a lightweight client-side architecture implemented using HTML, CSS, and JavaScript, enabling users to perform comparative financial analyses directly within a standard web browser without installing specialized software or maintaining a local database.

The system architecture consists of four primary components: (1) a live data acquisition module, (2) a data processing and analytics module, (3) an AI-assisted analysis module, and (4) a visualization and decision-support interface.

The live data acquisition module retrieves cryptocurrency market information through the CoinGecko Application Programming Interface (API), including asset prices, market capitalization, trading volume, and other financial market variables. The retrieved data are processed within the browser to generate a set of feature-engineered variables, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and 30-day rolling volatility. These engineered features are subsequently integrated into the Multiple Linear Regression (MLR) model to support cryptocurrency price forecasting and comparative performance analysis. The predictive performance of the model is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), providing quantitative measures of forecast accuracy and trend prediction.

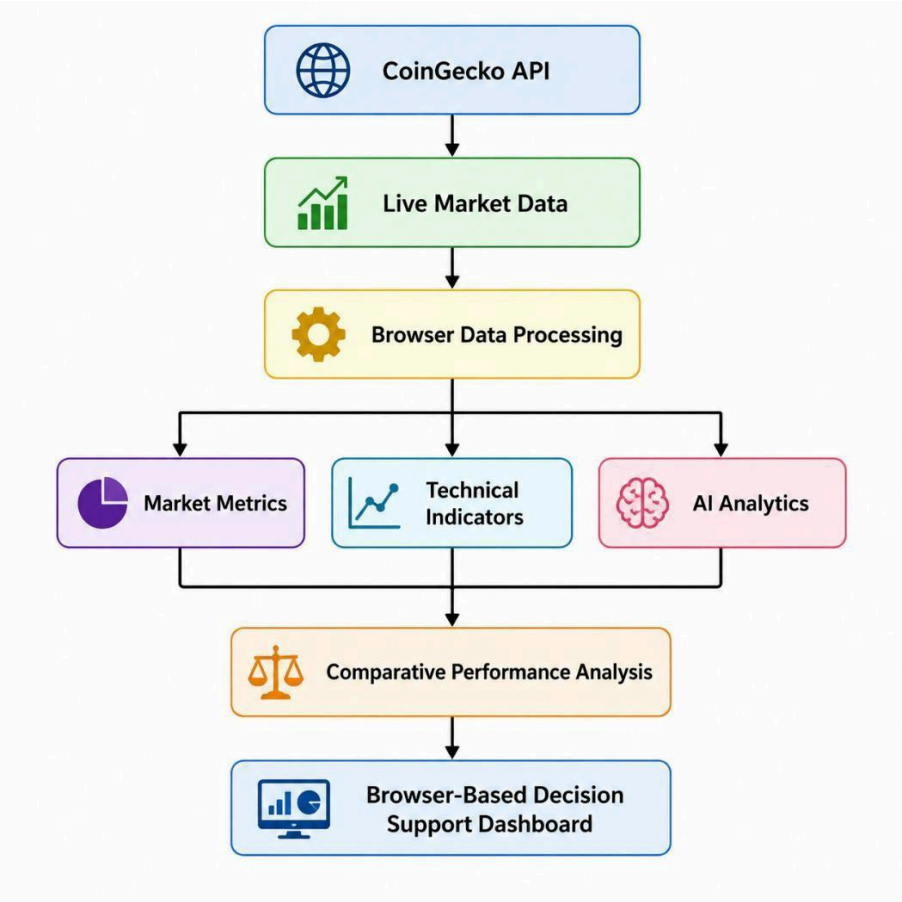
The AI-assisted analytics module integrates the calculated financial and technical indicators to generate comparative assessments of the selected cryptocurrency assets. The resulting analytics are presented through an interactive dashboard that enables users to compare asset performance, visualize historical market trends, evaluate technical indicators, and support investment decision-making using real-time market information.

The modular architecture allows additional cryptocurrencies, evaluation metrics, and analytical models to be incorporated with minimal modification, providing a scalable framework

for future digital asset research.

Figure 3

System Architecture Workflow.



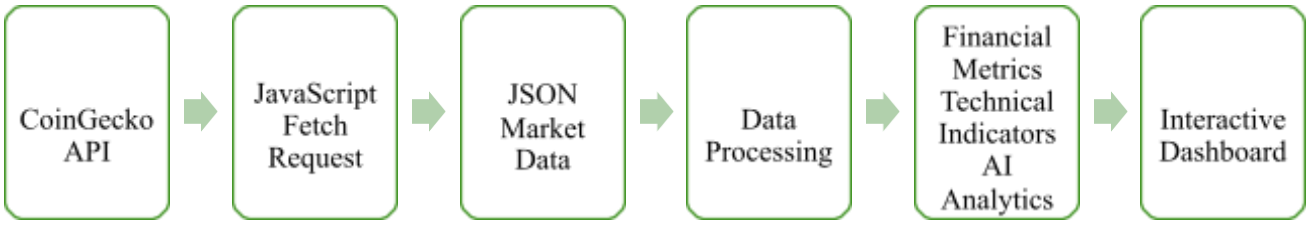
4.2 Live Data Integration

The proposed decision support platform integrates live cryptocurrency market data through the CoinGecko Application Programming Interface (API), enabling real-time acquisition of financial market information directly within a web browser. The API provides publicly accessible market data for the selected cryptocurrency assets, including Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC).

The platform retrieves historical and current market information required for comparative analysis, including asset price, market capitalization, trading volume, and price history. Data requests are executed dynamically using JavaScript, and the returned JSON data are processed entirely on the client side without requiring a dedicated application server or local database.

Figure 4

System Integration Process.



Following data retrieval, the browser-based analytics engine automatically calculates the financial metrics and technical indicators used throughout this study. The processed data are subsequently displayed through interactive charts, performance summaries, and comparative tables that update as new market information becomes available. This real-time integration enables users to monitor cryptocurrency market behavior and compare multiple assets within a unified analytical environment.

The use of a browser-based architecture provides several practical advantages, including platform independence, simplified deployment, reduced infrastructure requirements, and immediate access to current market conditions. Consequently, the proposed platform serves as an efficient decision-support tool for comparative cryptocurrency analysis using continuously updated financial market data.

4.3 AI Analytics and Visualization

The browser-based decision support platform incorporates an AI-assisted analytics module to transform live cryptocurrency market data into meaningful comparative insights. The analytics engine combines financial market metrics with technical indicators to evaluate the market behavior of the selected cryptocurrency assets and support comparative decision-making. A feature-engineered Multiple Linear Regression (MLR) model is employed to identify relationships among selected variables and generate predictive insights that complement traditional financial analysis.

The platform performs feature engineering by computing a set of technical indicators, including the Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Rate of Change (ROC), Open/Close percentage change, High-Low spread, and 30-day rolling volatility. These engineered features are combined with market variables such

as asset price, trading volume, and market capitalization as inputs to a Multiple Linear Regression (MLR) model for cryptocurrency price forecasting. The AI-assisted analytics module evaluates the predictive performance of the model using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). The resulting forecasts and performance metrics are then synthesized to provide comparative assessments of the selected cryptocurrency assets, supporting objective performance evaluation and investment decision-making.

Analytical results are presented through an interactive browser-based dashboard designed to support efficient interpretation of market conditions. The visualization interface includes comparative price charts, technical indicator graphs, performance summaries, and ranking tables that enable users to examine asset performance over the study period. Interactive controls allow users to select individual cryptocurrencies or compare multiple assets simultaneously while maintaining a consistent analytical framework.

Table 3

Technology Components.

Component	**Technology**
User Interface	HTML5, CSS3
Programming Language	JavaScript (ES6)
Data Source	CoinGecko API
Data Format	JSON
Charts	Chart.js
AI Analytics	Client-side JavaScript

By integrating AI-assisted analytics with real-time visualization, the proposed platform provides a transparent and accessible environment for comparative cryptocurrency evaluation. The browser-based implementation enables users to perform financial analysis and interpret

market trends using continuously updated data without requiring specialized analytical software.

To demonstrate the proposed methodology, an interactive browser-based decision support platform was developed and deployed as a web application. The platform enables users to perform real-time comparative analysis of the selected cryptocurrency assets by retrieving live market data from the CoinGecko API, generating feature-engineered variables, executing the Multiple Linear Regression (MLR) forecasting model, and presenting analytical results through an interactive dashboard. Users can select a cryptocurrency asset, specify the forecast horizon and training window, define the cut-off date, and generate AI-assisted forecasting and comparative analytics directly within a standard web browser.

Figure 5

AI-Powered Analysis System.

System Application: https://www.ariesbank.com/trietphan/fintech2026.html

Reference Dashboard: https://www.ariesbank.com/trietphan/reference-fintech2026.html

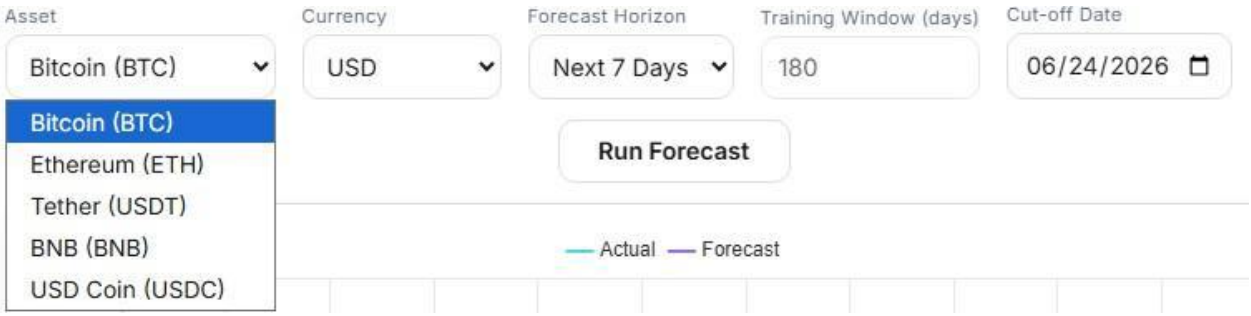


V. Comparative Result and Discussion

For experimental consistency, identical forecasting parameters were used throughout the comparative analysis. Each cryptocurrency was evaluated using USD-denominated market data, a seven-day forecasting horizon, a 180-day rolling training window, and a common cut-off date of June 24, 2026. Standardizing these parameters ensures that differences observed among the selected assets are attributable to their underlying market characteristics rather than variations in the forecasting configuration.

Figure 6

Forecasting Parameters Selection.

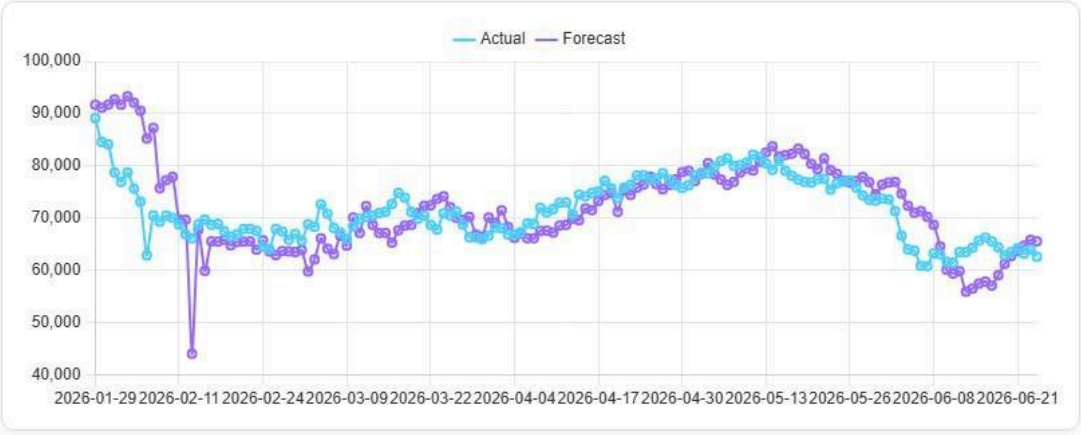


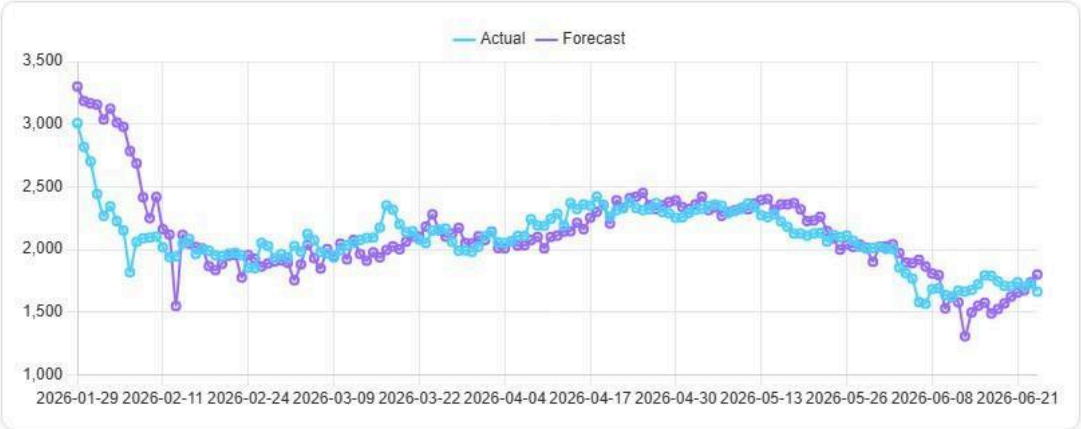
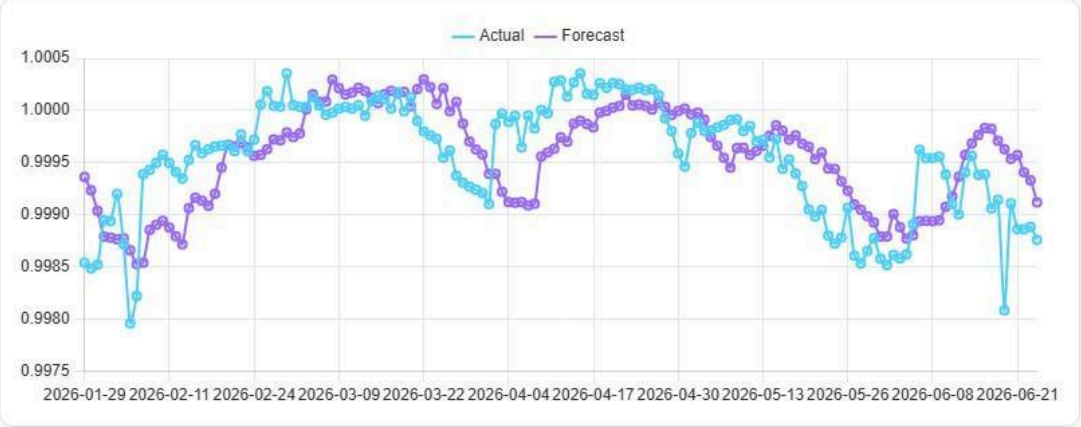
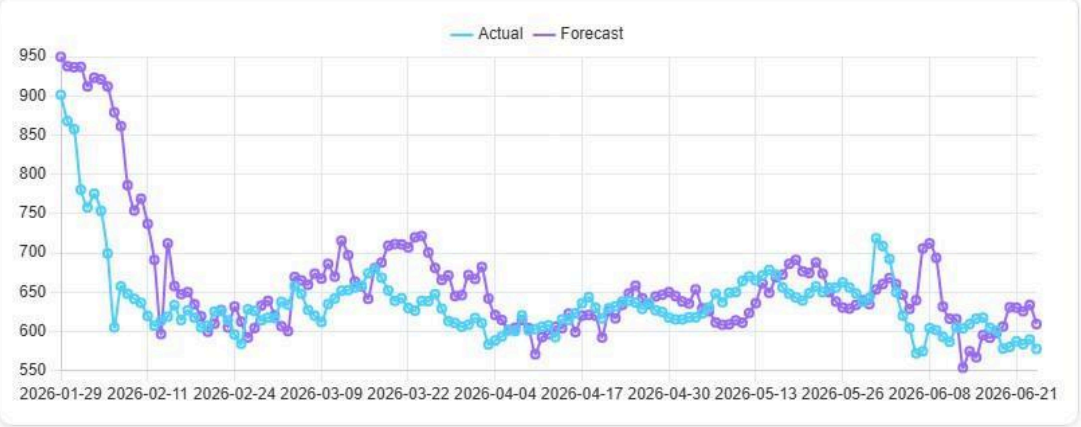
5.1 Market Performance Comparison

This study applies the proposed browser-based decision support platform to compare the market performance of the five largest cryptocurrency assets by market capitalization, Bitcoin (BTC), Ethereum (ETH), Tether (USDT), BNB, and USD Coin (USDC), during the study period from January 28, 2026, to June 24, 2026. Live market data collected through the CoinGecko API were used to examine price movements, market capitalization, and trading volume, providing a comprehensive overview of each asset's market behavior.

Table 4

Comparative Market Performance.

Assets	Market Performance
BTC	

Assets	Market Performance
ETH	
USDT	
BNB	

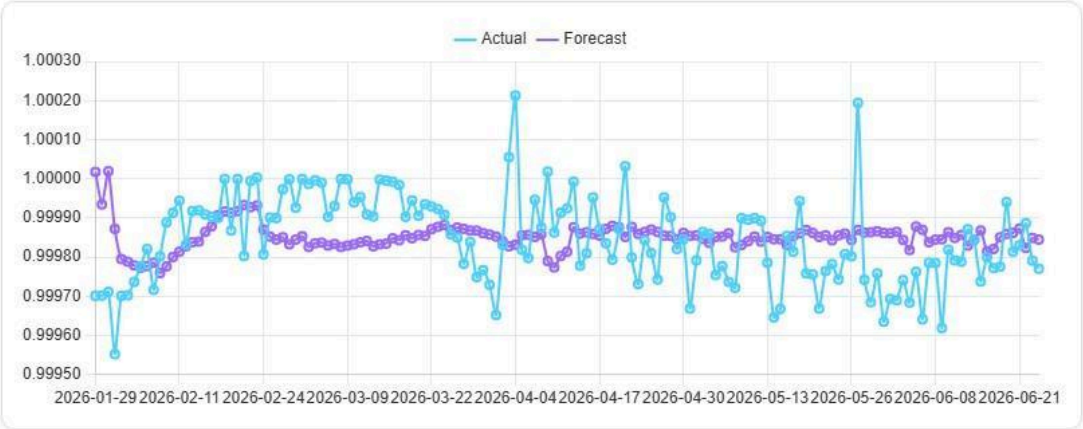
Assets	Market Performance
USDC	

Table 4 presents the comparative forecasting results generated by the proposed platform. The blue line represents the actual market prices obtained from the CoinGecko API, while the purple line represents the prices forecasted by the feature-engineered Multiple Linear Regression (MLR) model.

Among the five assets, Bitcoin (BTC), Ethereum (ETH), and BNB exhibited substantially greater price variability throughout the study period, reflecting the higher volatility typically associated with growth-oriented cryptocurrencies. Despite these fluctuations, the forecasted values generally followed the overall market trends, indicating that the proposed forecasting framework effectively captured medium-term price movements while smoothing short-term market noise.

In contrast, Tether (USDT) and USD Coin (USDC) demonstrated relatively stable price behavior, remaining close to their one-dollar peg during the entire observation period. The limited price variation of these stablecoins resulted in comparatively smoother forecast curves, with only minor deviations from the observed market prices. This behavior is consistent with the primary objective of fiat-backed stablecoins, which is to maintain price stability rather than generate capital appreciation.

Overall, the browser-based decision support platform successfully produced real-time forecasts for all five cryptocurrency assets using a unified analytical framework. Although the market characteristics differed considerably between growth-oriented cryptocurrencies and stablecoins, the platform consistently generated forecasted price series that closely followed the

corresponding market trends.

5.2 Feature Engineering Analysis

Table 5 summarizes the average standardized beta coefficients generated by the Multiple Linear Regression (MLR) model for each cryptocurrency asset. These coefficients provide insight into the relative influence of the engineered features on the forecasting model and demonstrate how different market characteristics contribute to price prediction. The feature set consists of the 7-day Exponential Moving Average (EMA), 7-day Simple Moving Average (SMA), 7-day Rate of Change (ROC), Open/Close percentage change, 30-day SMA, 14-day Relative Strength Index (RSI), 30-day rolling volatility, and High-Low spread.

Table 5

Average Standardized Beta Coefficients of Feature-Engineered Variables for the Multiple Linear Regression Model.

Feature	BTC	ETH	USDT	BNB	USDC
EMA (7-day)	26315.62	733.21	0.0007	252.09	3.95e-5
SMA (7-day)	-13948.15	-104.54	-0.0006	-125.79	-2.76e-5
Rate of Change (7-day)	1492.87	-69.52	0.0003	19.31	-2.69e-5
Open/Close % change	865.29	43.25	0.0002	-10.10	1.63e-5
SMA (30-day)	-740.55	30.66	-5.21e-5	7.03	9.82e-6
RSI (14)	-584.28	-26.06	4.06e-5	5.46	-8.92e-6

Feature	BTC	ETH	USDT	BNB	USDC
Rolling Volatility (30-day)	-484.88	12.22	1.22e-5	-4.28	8.38e-6
High-Low Spread	-316.57	7.11	-8.12e-6	2.33	6.05e-7

Across the five cryptocurrency assets, the 7-day EMA consistently exhibited the strongest positive influence on the forecasting model, indicating that recent price trends contribute substantially to short-term price prediction. Conversely, the 7-day SMA generally produced negative coefficients, suggesting that longer smoothing effects provide complementary information to the EMA and help balance the regression model. The ROC and Open/Close percentage change also contributed to the prediction process by capturing short-term market momentum and daily price movements.

The influence of the remaining engineered features varied among the selected assets. The 30-day SMA, RSI, rolling volatility, and High-Low spread generally exhibited smaller beta coefficients, indicating that these variables played supporting roles within the forecasting model. While these indicators contributed additional market information, their influence was generally less pronounced than the short-term trend indicators represented by the 7-day EMA and SMA.

It should be noted that the magnitude of the beta coefficients should not be directly compared across different cryptocurrency assets because each asset operates on a different price scale. Bitcoin, Ethereum, BNB, Tether, and USD Coin differ substantially in market price and volatility, resulting in corresponding differences in coefficient magnitude. Therefore, the primary purpose is to identify the relative importance of engineered features within each forecasting model rather than to compare coefficient values between assets.

Overall, the feature engineering process successfully transformed raw market data into informative explanatory variables for the MLR model. The combination of trend, momentum, and volatility indicators provided a comprehensive representation of cryptocurrency market behavior and established the foundation for the AI-assisted forecasting evaluation presented in

the following section.

5.3 AI-Based Comparative Evaluation

This section summarizes the forecasting performance of the proposed Multiple Linear Regression (MLR) model for the five selected cryptocurrency assets. Model performance was evaluated using four complementary metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). Together, these metrics assess both numerical forecasting accuracy and the model's ability to correctly predict market direction.

Table 6

Forecasting Performance Analysis.

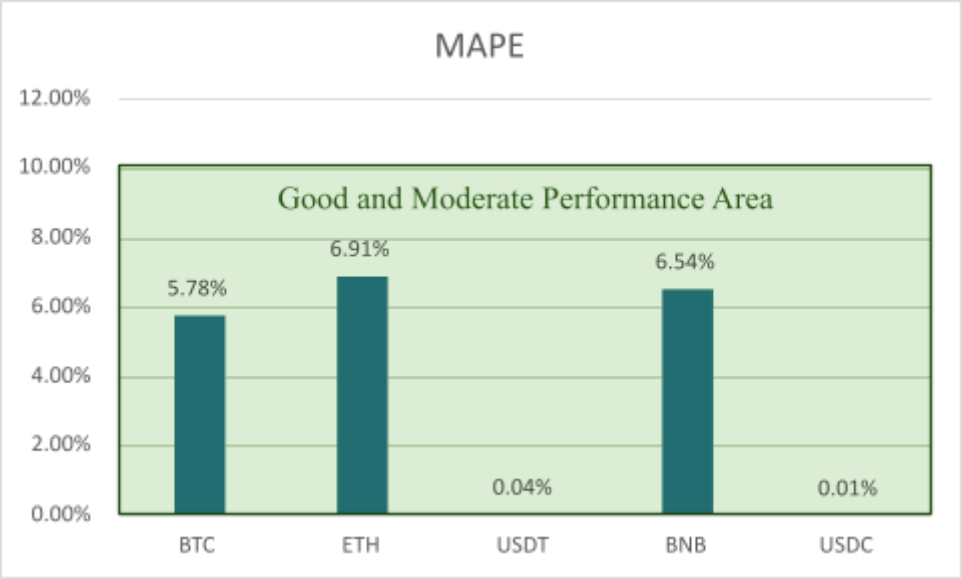
Performance Metric	BTC	ETH	USDT	BNB	USDC
MAE	4082.15	143.84	0.0004	42.18	9.76e-5
RMSE	5720.65	222.96	0.0004	60.93	0.0001
MAPE	5.78%	6.91%	0.04%	6.54%	0.01%
Directional Accuracy	50.0%	51.4%	56.2%	52.1%	48.6%

The results demonstrate that forecasting accuracy varies according to the market characteristics of each cryptocurrency. Bitcoin (BTC), Ethereum (ETH), and BNB exhibited larger MAE and RMSE values than Tether (USDT) and USD Coin (USDC), reflecting the substantially higher price levels and greater market volatility of these growth-oriented cryptocurrencies. In contrast, the stablecoins USDT and USDC produced extremely small forecasting errors because their prices remained close to their one-dollar peg throughout the study period. Consequently, direct comparisons of absolute error metrics across assets with different price scales should be interpreted with caution.

The Mean Absolute Percentage Error (MAPE) provides a normalized measure of forecasting accuracy. BTC, ETH, and BNB achieved MAPE values of 5.78%, 6.91%, and 6.54%, respectively, indicating satisfactory forecasting performance despite significant market fluctuations. USDT and USDC recorded substantially lower MAPE values of 0.04% and 0.01%, respectively, reflecting the limited price variability of stablecoins rather than a fundamentally different forecasting capability.

Figure 7

MAPE Results Confirm Good and Moderate Forecast Performance.

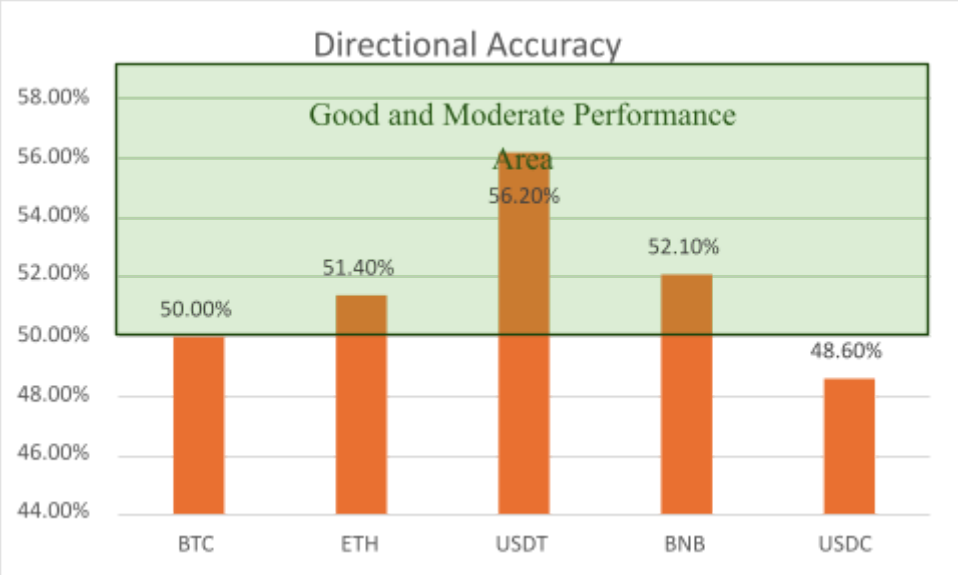


The Mean Absolute Percentage Error (MAPE) measures forecasting error as a percentage of the observed asset price, providing a scale-independent metric for evaluating predictive performance. By expressing prediction error relative to the actual price, MAPE enables meaningful comparisons across cryptocurrencies with substantially different price levels. Unlike absolute error measures, MAPE provides an intuitive interpretation of forecasting accuracy; for example, a MAPE value of 10% indicates that, on average, the predicted values differ from the actual market prices by approximately 10%. Consequently, MAPE is widely used in financial forecasting as a standard benchmark for assessing and communicating model performance to researchers, practitioners, and other stakeholders (Kaur et al., 2025).

Directional Accuracy (DA) evaluates the model's ability to correctly predict the direction of price movement and provides a scale-independent measure for cross-asset comparison. The model achieved Directional Accuracy values ranging from 48.6% to 56.2% across the five cryptocurrencies. USDT achieved the highest Directional Accuracy (56.2%), followed by BNB (52.1%), Ethereum (51.4%), Bitcoin (50.0%), and USDC (48.6%).

Figure 8

Directional Accuracy Results Confirm Good and Moderate Forecast Performance.



Directional Accuracy (DA) values slightly above 50% are commonly reported in short-term financial forecasting studies due to the inherently volatile and uncertain nature of financial markets. A DA of approximately 50% indicates that the model performs no better than random directional prediction, whereas values between 50% and 55% suggest that the model captures a modest yet statistically meaningful predictive signal beyond random chance. In highly competitive financial markets, consistently achieving a Directional Accuracy within this range is generally regarded as evidence that the forecasting model provides useful directional information and outperforms the random-guessing benchmark (Yao, 2025).

Overall, the proposed AI-assisted forecasting framework successfully generated consistent predictive results for all five cryptocurrency assets using a unified browser-based decision support platform. The combination of feature engineering, Multiple Linear Regression, and real-time market data provides an effective and transparent framework for comparative

cryptocurrency analysis while demonstrating the adaptability of the proposed system across both highly volatile cryptocurrencies and relatively stable digital assets.

5.4 Discussion

The findings demonstrate that the proposed AI-powered browser-based decision support platform provides an effective framework for comparative analysis of leading cryptocurrency assets using live market data. By integrating real-time data acquisition, feature engineering, Multiple Linear Regression (MLR), and interactive visualization within a single browser-based environment, the platform enables consistent evaluation of cryptocurrency market behavior and forecasting performance without requiring specialized analytical software.

The comparative analysis highlights the distinct market characteristics of growth-oriented cryptocurrencies and stablecoins. Bitcoin (BTC), Ethereum (ETH), and BNB exhibited greater price volatility and larger forecasting errors due to their dynamic market behavior, whereas Tether (USDT) and USD Coin (USDC) maintained relatively stable prices throughout the study period. Consequently, the substantially lower forecasting errors observed for the stablecoins should be interpreted within the context of their price stability rather than as evidence of superior model performance. Directional Accuracy provides a more appropriate metric for comparing forecasting capability across assets with different price scales.

From a practical perspective, the proposed platform offers investors, researchers, and FinTech practitioners an accessible decision-support environment for monitoring cryptocurrency markets and evaluating AI forecasting performance. The browser-based implementation simplifies deployment by eliminating the need for dedicated software installations while supporting real-time analysis through publicly available market data APIs. In addition, the unified analytical framework enables objective comparison across multiple cryptocurrency assets using standardized forecasting parameters and evaluation metrics.

Despite these contributions, several limitations should be acknowledged. The study employs a Multiple Linear Regression model and focuses on five cryptocurrency assets over a single observation period. Market conditions, macroeconomic events, and regulatory developments may influence forecasting performance and limit the generalizability of the results. Furthermore, the analysis relies primarily on market-based and technical features and does not incorporate alternative information sources such as blockchain network activity, on-chain metrics, news sentiment, or macroeconomic indicators.

Future research will continue expanding the proposed browser-based decision support platform by incorporating additional digital assets, longer market observation periods, and broader comparative analysis across different cryptocurrency categories. Further improvements may include enhanced visualization capabilities, additional financial indicators, and expanded analytical modules to support more comprehensive digital asset evaluation. These extensions will preserve the platform's core design principles of real-time data integration, transparency, accessibility, and practical decision support.

VI. Conclusion

This study presented an AI-powered browser-based decision support approach for the comparative analysis of the five largest cryptocurrency assets by market capitalization using real-time market data. By integrating live cryptocurrency data from the CoinGecko API with feature engineering, Multiple Linear Regression (MLR), and interactive web-based visualization, the proposed platform provides a unified environment for analyzing cryptocurrency markets and supporting data-driven investment decisions. The browser-based implementation demonstrates that sophisticated financial analytics can be performed efficiently without requiring specialized software or dedicated computational infrastructure.

The proposed framework contributes to FinTech research by combining live market data acquisition, AI-assisted forecasting, and comparative cryptocurrency evaluation within a single browser-based platform. Unlike traditional cryptocurrency dashboards that primarily present descriptive market information, the proposed system integrates predictive analytics and standardized model evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA). This integrated approach enables consistent comparison of multiple cryptocurrency assets using a common analytical framework and standardized forecasting methodology.

The browser-based architecture provides a scalable foundation for future research involving additional digital assets, extended observation periods, and more advanced machine learning techniques. Future enhancements may incorporate deep learning models, blockchain network metrics, on-chain analytics, sentiment analysis, macroeconomic indicators, and portfolio optimization strategies to further improve forecasting performance and decision-support capabilities. The proposed framework can also be adapted to evaluate other classes of digital assets, supporting broader applications in financial technology, blockchain analytics, and

artificial intelligence.

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StockForecastGenie Pro: A Volatility-Aware Machine Learning Decision-Support System for Short-Horizon Equity Index Forecasting

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Abstract

Forecasting short-term movements in financial markets remains challenging because market prices are influenced by rapidly changing economic conditions, investor sentiment, and volatility. While machine-learning methods have demonstrated promise for financial forecasting, many forecasting tools remain difficult for non-technical users to interpret and often provide predictions without contextual explanations. This paper presents StockForecastGenie Pro, a volatility-aware machine-learning decision-support system designed to forecast short-horizon movements in major United States equity indices while providing transparent and interpretable signals. The system forecasts future index levels, point gains, and percentage returns for the S&P 500 and Dow Jones Industrial Average using a stacked ensemble of machine-learning models. Forecast outputs are combined with market-volatility information derived from the CBOE Volatility Index (VIX) to generate plain-language signals ranging from Strong Negative to Strong Positive. The platform also incorporates confidence estimates, simple benchmark comparisons, and broader market context to support user interpretation. A rolling historical evaluation was conducted, and results indicate that forecasting performance improves substantially as forecast horizon increases. At the five-day horizon, the stacked ensemble achieved directional accuracy of 73.2% for the Dow Jones Industrial Average and 70.9% for the S&P 500. Compared with a no-change benchmark, the system reduced forecast error by approximately 24.3% for the Dow Jones Industrial Average and 22.4% for the S&P 500. The results demonstrate that machine-learning ensembles can provide meaningful improvements over simple forecasting approaches while maintaining interpretability for research, educational, and decision-support applications.

1. Introduction

Financial markets generate enormous volumes of data every trading day, creating opportunities for machine-learning systems to support forecasting and decision making. However, accurately forecasting short-term market movements remains a difficult challenge because market prices are influenced by economic conditions, investor sentiment, monetary policy, volatility, corporate information, and unexpected events (Chiu et al., 2018; Khan et al., 2024). These factors interact in complex ways and contribute to the uncertainty that characterizes financial markets, particularly at short forecasting horizons.

The growing availability of financial and macroeconomic data has accelerated the adoption of machine-learning methods in forecasting applications. Advances in computational power and data availability have enabled the development of forecasting systems capable of identifying nonlinear relationships and interactions that may be difficult to capture using traditional approaches (Ghani et al., 2019; Ibebuchi, 2025). As a result, machine learning has become an increasingly important component of modern financial analytics and decision-support systems (Ghani et al., 2019). Despite these advances, many forecasting platforms remain difficult for non-technical users to interpret. Forecasting systems frequently present numerical predictions without providing sufficient information about forecast confidence, market context, or the conditions under which forecasts should be trusted. Consequently, there is increasing interest in decision-support frameworks that combine predictive performance with transparency and interpretability.

To address this challenge, this study presents StockForecastGenie Pro, a volatility-aware machine-learning decision-support system for short-horizon equity-index forecasting. The platform focuses on two widely followed United States equity indices, the S&P 500 and the Dow Jones Industrial Average and integrates market and macroeconomic information from the Federal Reserve Economic Data platform with a stacked ensemble forecasting framework. The system produces forecasts of future index levels, point gains, and percentage returns while simultaneously translating model outputs into user-friendly signals that incorporate forecast confidence, market volatility, and broader market context.

A distinguishing characteristic of StockForecastGenie Pro is that forecasts are not presented as direct trading instructions. Instead, forecast outputs are evaluated within the context of market volatility measured by the CBOE Volatility Index and converted into interpretable

signals ranging from Strong Negative to Strong Positive. This framework is intended to help users understand not only the forecast itself but also the level of confidence and market conditions associated with that forecast. The objective of this study is to evaluate whether a volatility-aware machine-learning decision-support framework can provide meaningful forecasting value beyond simple benchmark methods while maintaining interpretability for users. Specifically, the study investigates forecasting performance across one-, three-, and five-trading-day horizons using a rolling historical evaluation.

The contributions of this work are threefold. First, it presents an end-to-end machine-learning forecasting and decision-support platform for major United States equity indices. Second, it integrates stacked ensemble forecasting with volatility-aware signal generation and user-oriented explanations. Third, it provides a comprehensive rolling evaluation demonstrating how forecasting performance changes across forecast horizons, benchmark comparisons, and volatility regimes.

2. Literature Review

Financial forecasting has been an active area of research within economics, finance, statistics, and machine learning for several decades (Dingli & Fournier, 2017). Early forecasting studies primarily relied on statistical time-series methods, including autoregressive and moving-average frameworks, to model market behavior (Dingli & Fournier, 2017). While these approaches can capture temporal structure in financial data, they often struggle to represent nonlinear relationships and complex interactions among market and macroeconomic variables.

The emergence of machine-learning techniques introduced more flexible approaches for financial forecasting (Ghani et al., 2019). Tree-based algorithms such as Random Forests, Extra Trees, and gradient-boosting methods have been widely adopted because of their ability to model nonlinear relationships, accommodate large numbers of predictors, and automatically capture interactions among variables (Benghiat & Lahmiri, 2025). These characteristics have made machine-learning methods attractive alternatives to traditional statistical forecasting models in financial applications. More recently, ensemble-learning approaches have gained attention because individual forecasting models often capture different aspects of market behavior (Apu et al., 2022). Rather than relying on a single model, ensemble methods combine multiple forecasts to improve robustness and reduce sensitivity to model-specific weaknesses.

Although substantial progress has been made in improving forecasting accuracy, interpretability remains a persistent challenge. Many forecasting studies focus primarily on predictive performance while providing limited insight into how forecasts should be interpreted or how forecast reliability may change under different market conditions (Poon & Granger, 2003). In addition, some studies evaluate models using static train-test splits rather than operational rolling forecasts that mimic how a model would be used to forecast future market closes in real time. This limitation is particularly important in financial applications, where users often require not only numerical predictions but also context regarding uncertainty, market regime, and practical decision support.

Another area that has received comparatively less attention is the integration of market-volatility information into the decision-support layer of forecasting systems. Volatility measures such as the CBOE Volatility Index provide valuable information regarding prevailing market uncertainty and may influence how forecasting signals should be interpreted (Fernandes et al., 2014). A forecast that appears meaningful during a low-volatility environment may carry a different implication during periods of elevated market stress.

The present study contributes to this literature by combining stacked ensemble forecasting with a volatility-aware decision-support framework. Rather than focusing solely on predictive accuracy, StockForecastGenie Pro integrates forecast magnitude, confidence estimates, benchmark comparisons, volatility conditions, and broader market context into a unified signal-generation process. This approach seeks to improve both operational forecasting performance and interpretability, making the resulting forecasts more useful for research, educational, and financial decision-support applications.

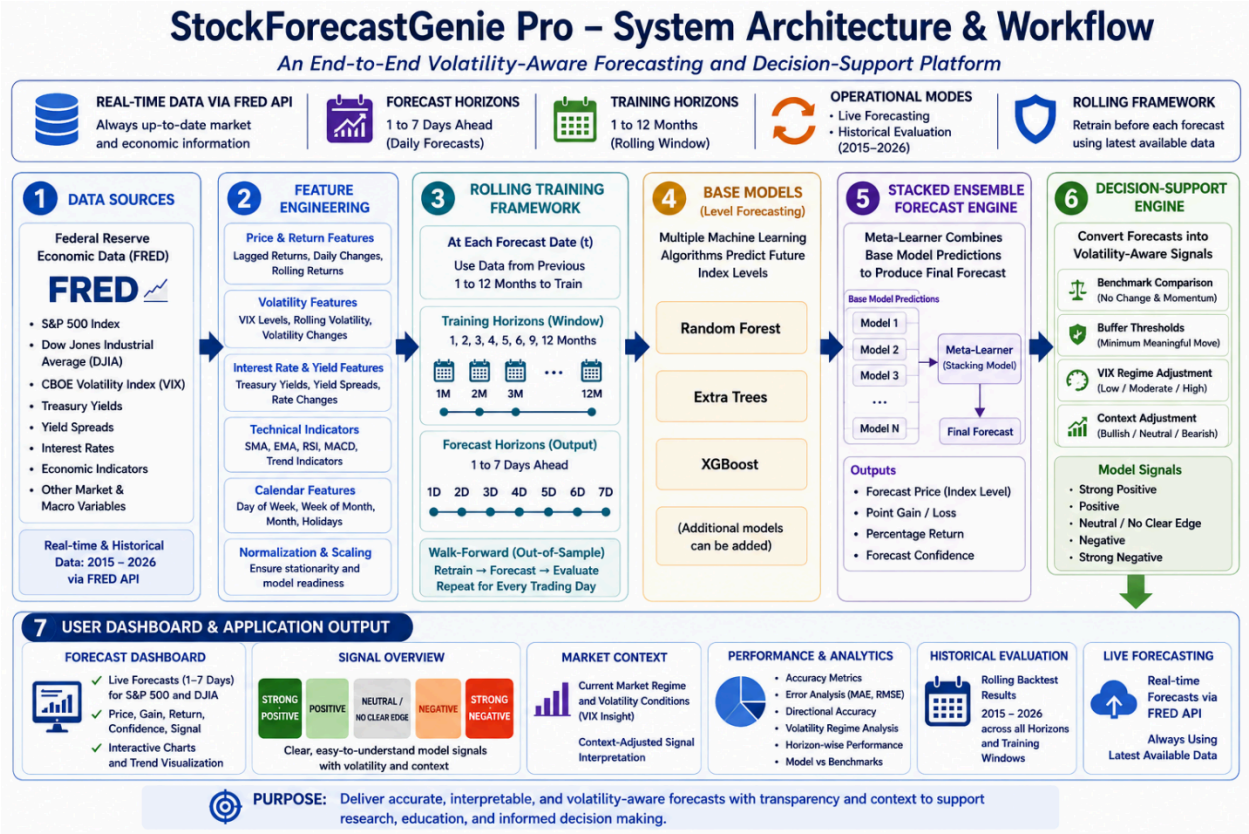
3. Data and Methods

StockForecastGenie Pro was developed as an end-to-end forecasting and decision-support platform for short-horizon equity-index forecasting. As shown in Figure 1, the system integrates data acquisition, feature engineering, machine-learning forecasting, volatility-aware signal generation, and user-facing visualization within a single application workflow.

The platform uses publicly available market and macroeconomic data obtained from the Federal Reserve Economic Data platform (Federal Reserve Bank of St. Louis, n.d.). The

forecasting targets are the S&P 500 Index and the Dow Jones Industrial Average. Input features include market-index behavior, lagged returns, rolling changes, volatility indicators, Treasury yields, yield-spread information, interest-rate variables, calendar features, and technical trend indicators (Figure 1). These variables were included to capture market momentum, economic conditions, and prevailing financial-market uncertainty.

Figure 1. System architecture of StockForecastGenie Pro.



For the experimental evaluation, point gain was used as the primary supervised learning target. The predicted point gain was then converted into an implied forecast price and percentage return, allowing the dashboard to display forecast price, forecast point gain, and forecast percentage return from the same underlying prediction.

The forecasting engine combines three base machine-learning models: Extra Trees (Geurts et al., 2006), Random Forest (Breiman, 2001), and XGBoost (Chen & Guestrin, 2016). Each model is trained using the same engineered feature set and produces an independent forecast. The stacked ensemble combines base-model forecasts using a Huber-regression

meta-learner, with a logistic-regression layer used for directional probability estimation (Ibebuchi, 2025). The stacked ensemble serves as the primary forecasting engine, while the individual models are retained for comparison and diagnostic analysis. In this study, to mimic operational deployment of the StockForecastGenie Pro, the evaluation used a rolling-window design. For each forecast date, the model was trained using only the previous six months of data and then evaluated at one-, three-, and five-trading-day horizons. This prevents look-ahead bias and reflects how the application would operate in real time. The evaluation was conducted over the 2025 calendar year, producing 261 rolling forecasts for each target market and forecast horizon.

Model performance was compared against two simple reference forecasts. The first assumes no market change over the forecast horizon. The second assumes that the most recent comparable market movement continues into the future. These benchmarks were included because a machine-learning model should demonstrate value beyond simple assumptions available to any user.

StockForecastGenie Pro does not present raw forecasts as direct trading instructions. Instead, the forecast is converted into a research-oriented model signal. Signal generation considers forecast direction, forecast magnitude, model confidence, benchmark comparison, and the current volatility environment. The CBOE Volatility Index is used to classify market conditions into volatility regimes. Under higher-volatility conditions, the system requires a larger expected movement before issuing a directional signal. The decision framework uses volatility-dependent minimum-move thresholds of approximately 0.5%, 0.7%, and 1.0% under low-, normal-, and high-volatility regimes, respectively. Forecasts that do not exceed these thresholds are classified as Neutral / No Clear Edge. This buffer logic reduces the likelihood that small forecast differences are overinterpreted as meaningful market opportunities during periods of elevated uncertainty. The application reports five signal categories: Strong Positive Model Signal, Positive Model Signal, Neutral / No Clear Edge, Negative Model Signal, and Strong Negative Model Signal. Neutral / No Clear Edge indicates that the model does not identify a sufficiently strong directional opportunity after applying the benchmark comparison, confidence requirement, volatility adjustment, and buffer logic.

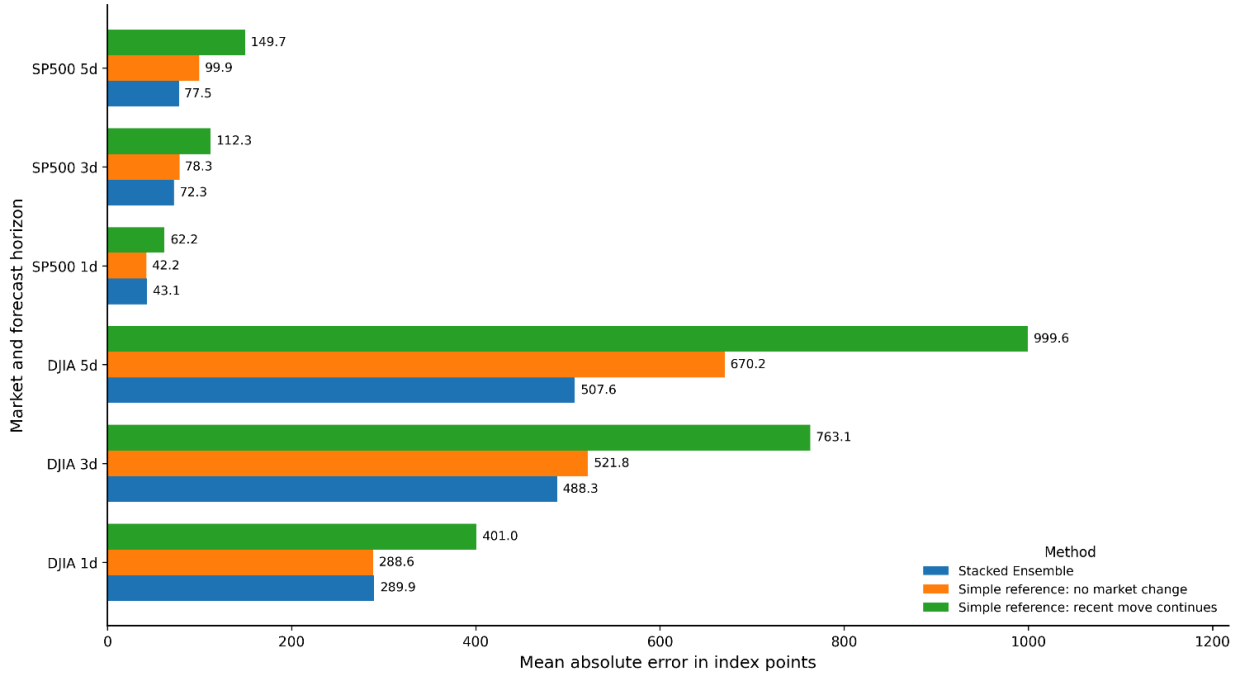
The system also provides a longer-horizon context adjustment. Recent market behavior within the rolling training window is used to classify the broader market environment as bullish, bearish, or neutral. This context does not replace the short-term forecast but helps users interpret whether the short-term signal agrees with or conflicts with the broader market trend. Evaluation metrics included mean absolute error, root mean squared error, directional accuracy, and percentage improvement relative to the no-change reference forecast. Additional analyses examined performance across volatility regimes and the distribution of generated model signals. Together, these metrics evaluate both the forecasting accuracy of the model and the usefulness of the decision-support layer.

4. Results

4.1 Forecast Accuracy Across Horizons

Figure 2 compares forecast error across forecast horizons for the stacked ensemble and the reference forecasts. A clear pattern emerges. Forecasting performance improves as the forecast horizon increases from one to five trading days.

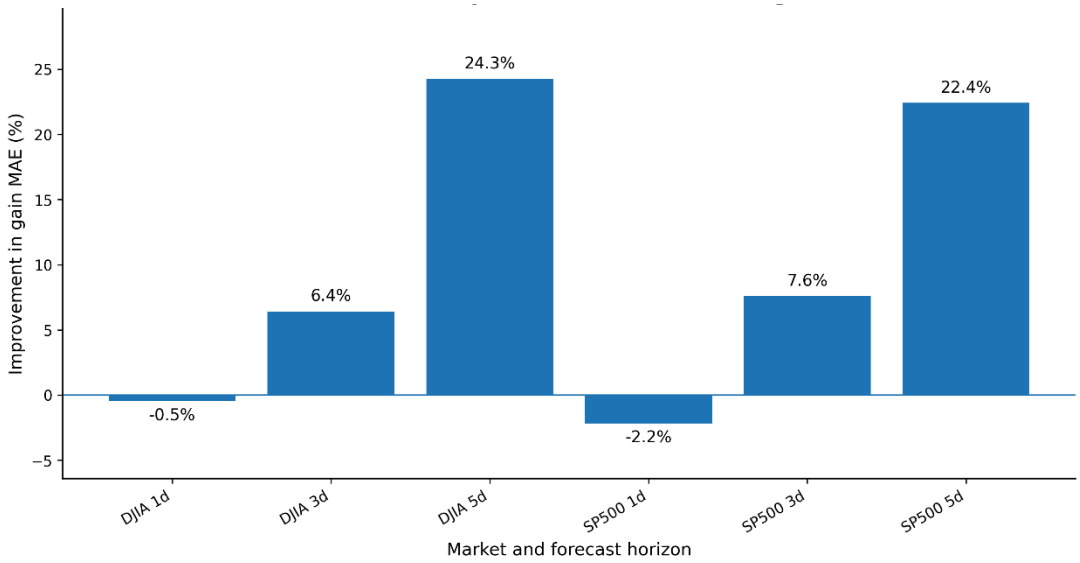
Figure 2. Forecast error (mean absolute error) of the stacked ensemble and simple reference forecasts across the S&P 500 and Dow Jones Industrial Average at one-, three-, and five-day forecast horizons.



At the one-day horizon, the machine-learning framework provides little improvement over the no-change benchmark. This result is not unexpected. Daily movements of broad equity indices are highly noisy and are often difficult to distinguish from random variation. Furthermore, because the S&P 500 and Dow Jones Industrial Average exhibit a long-run upward tendency, simple reference forecasts can remain surprisingly competitive over very short horizons. Performance improves substantially at the three-day horizon and improves further at the five-day horizon (Figure 2). This suggests that the forecasting framework is more effective at identifying short-term market structure than predicting next-day fluctuations. These findings support the use of multi-day horizons for machine-learning-based equity-index forecasting and indicate that the greatest value of the framework lies beyond next-day prediction.

Figure 3 presents the percentage improvement of the stacked ensemble relative to the no-change benchmark. The one-day horizon shows little or no improvement. However, substantial gains emerge at longer horizons. For the five-day horizon, the stacked ensemble reduced forecast error by approximately 22.4% for the S&P 500 and 24.3% for the Dow Jones Industrial Average. These results demonstrate that the machine-learning framework provides useful information beyond what can be obtained from simple benchmark assumptions. Importantly, the improvements are observed consistently across both target indices.

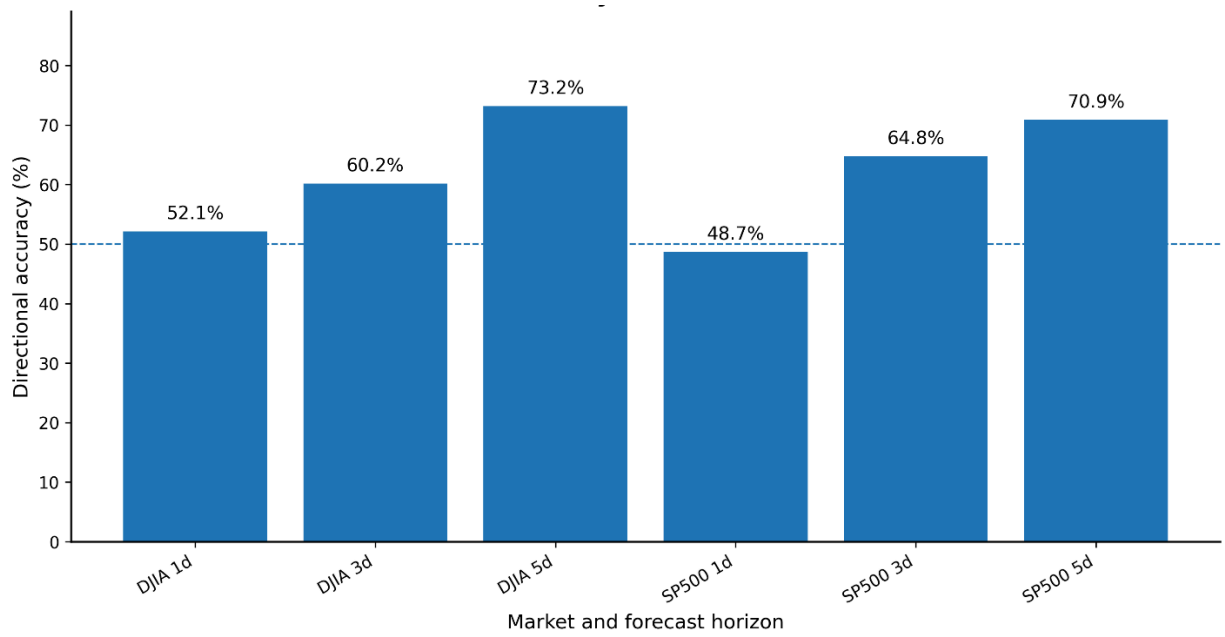
Figure 3. Percentage improvement of the stacked ensemble relative to the no-change reference forecast. Positive values indicate lower forecast error than the benchmark.



4.2 Directional Accuracy

Figure 4 summarizes directional forecasting performance. Again, directional accuracy increased systematically as forecast horizon increased. For the S&P 500, directional accuracy increased from approximately 48.7% on the one-day horizon to 70.9% on the five-day horizon. For the Dow Jones Industrial Average, directional accuracy increased from approximately 52.1% to 73.2%, respectively.

Figure 4. Directional accuracy of the stacked ensemble across forecast horizons for the S&P 500 and Dow Jones Industrial Average.



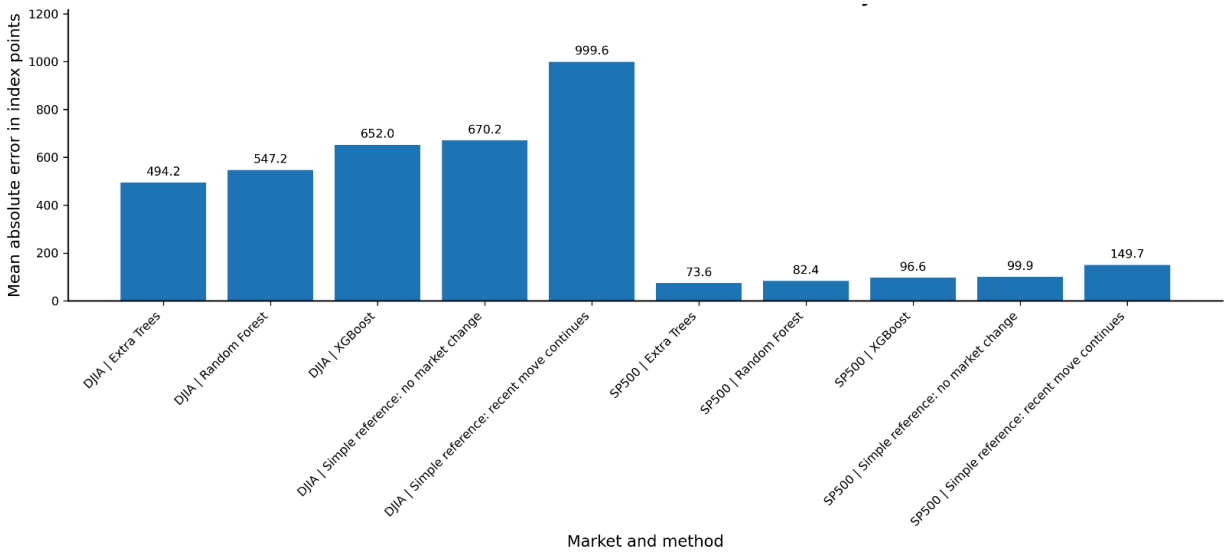
The directional results reinforce the conclusions obtained from the error metrics (Figure 2). The framework is considerably more effective at identifying short-term market direction over multi-day horizons than at predicting next-day movements. From a decision-support perspective, directional accuracy is particularly important because users are often more interested in the expected direction of market movement than in the precise numerical forecast.

4.3 Comparison with Individual Models

Figure 5 compares the stacked ensemble with individual forecasting models and simple reference methods. The results indicate that no single model consistently dominates all markets and forecast horizons. Extra Trees frequently produced the strongest individual-model performance, while Random Forest and XGBoost remained competitive (Figure 5). The stacked ensemble generally produced more stable performance across scenarios by combining

information from multiple forecasting models. This supports the rationale for adopting an ensemble framework rather than relying on a single algorithm. Moreover, the objective of the ensemble is not necessarily to outperform every individual model in every situation but rather to provide a robust and reliable forecasting framework across changing market conditions.

Figure 5. Comparison of individual machine-learning models, the stacked ensemble, and simple reference forecasts at the five-day forecast horizon.



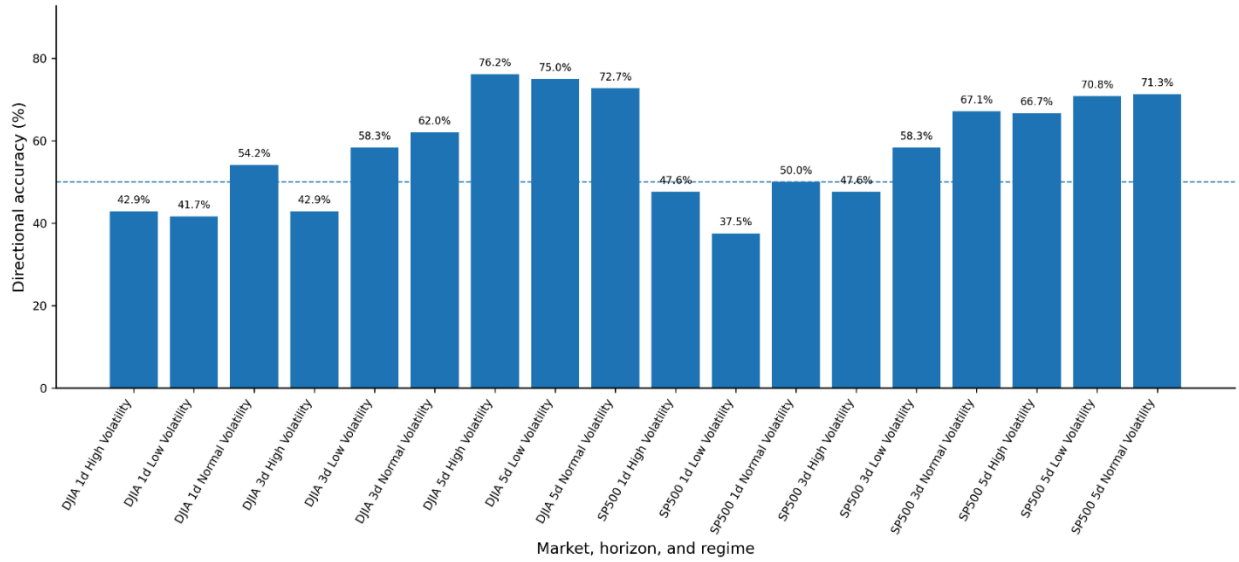
4.4 Volatility Regime Analysis

Figure 6 evaluates forecasting performance across VIX-based volatility regimes. Forecast performance varied across volatility regimes (Figure 6). For the Dow Jones Industrial Average, average directional accuracy increased from 54.0% during high-volatility periods to 58.3% during low-volatility periods and 63.0% during normal-volatility periods. A similar pattern was observed for the S&P 500, where average directional accuracy was 54.0%, 55.5%, and 62.8% under high-, low-, and normal-volatility conditions, respectively. These results suggest that forecasting performance is generally strongest during normal market conditions and tends to deteriorate during periods of elevated uncertainty. Nevertheless, the model maintained directional accuracy near or above 50% across most volatility regimes (Figure 6), indicating that the volatility-aware framework remained reasonably robust even during more challenging market environments.

These findings justify the volatility-aware design of StockForecastGenie Pro. By incorporating VIX into the signal-generation framework, the system adjusts its decision

thresholds according to prevailing market conditions rather than treating all market environments equally.

Figure 6. Directional accuracy of the stacked ensemble across VIX-based volatility regimes. Performance generally varies with market uncertainty.

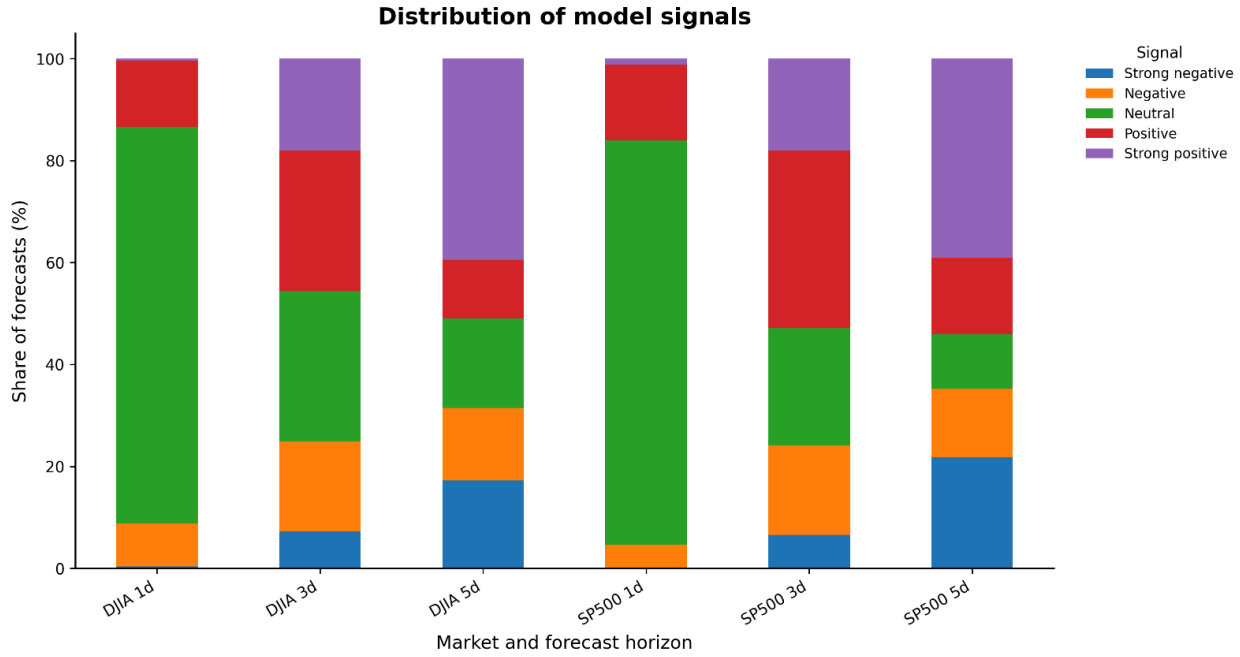


4.5 Signal Distribution and Decision Support

Figure 7 summarizes the distribution of generated signals. A notable characteristic of the framework is that it does not continuously issue strong positive or strong negative signals. Instead, a notable proportion of forecasts are classified as Neutral / No Clear Edge.

This behavior is intentional and reflects the threshold-based decision logic built into the platform. Small forecast advantages are filtered out before a directional signal is generated. This conservative behavior is particularly important for educational and decision-support applications where excessive signal generation can encourage overinterpretation of uncertain forecasts.

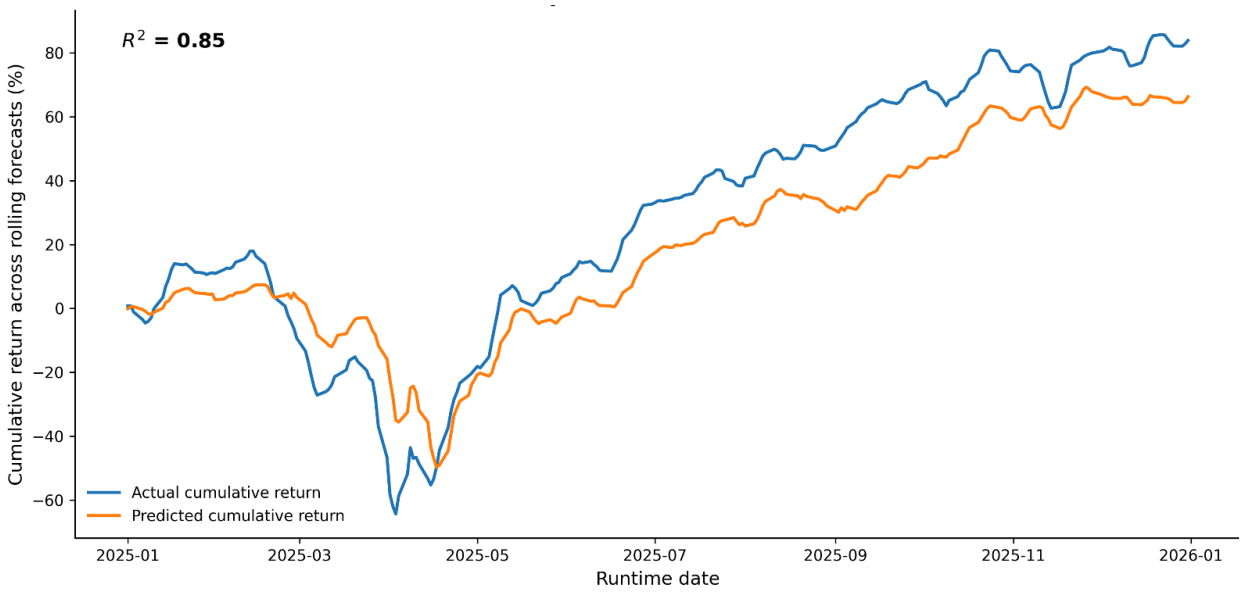
Figure 7. Distribution of generated model signals across markets and forecast horizons, showing the relative frequency of Strong Positive, Positive, Neutral, Negative, and Strong Negative signals.



4.6 Long-Horizon Forecast Tracking

Finally, Figure 8 compares cumulative predicted returns with cumulative realized returns. Although individual forecast errors remain unavoidable, the cumulative trajectories demonstrate that the forecasting framework captures broader market tendencies over time. The predicted cumulative return closely follows the realized cumulative return throughout much of the evaluation period. This result provides additional evidence that the framework is identifying meaningful information beyond simple short-term fluctuations and supports its use as a research-oriented forecasting platform.

Figure 8. Cumulative predicted and realized returns for rolling five-day forecasts. The close correspondence between the two series indicates that the forecasting framework captures broader market tendencies over time.



5. Discussion

This study presented StockForecastGenie Pro, a volatility-aware machine-learning decision-support system for short-horizon forecasting of the S&P 500 and Dow Jones Industrial Average. The platform combines stacked ensemble forecasting with benchmark comparison, volatility-aware thresholding, confidence assessment, and user-oriented explanations.

The 2025 rolling evaluation shows that forecast skill is strongly horizon dependent. One-day forecasts provided limited improvement over simple reference methods, consistent with the noisy and often near-random behavior of short-term equity-index movements (Fama, 1970; Malkiel, 2003; Gu et al., 2020). Performance improved at longer horizons, with the five-day stacked ensemble reducing forecast error by approximately 22.4% for the S&P 500 and 24.3% for the Dow Jones Industrial Average relative to the no-change reference. Directional accuracy also exceeded 70% for both indices. Volatility-regime results further support the platform's decision-support design: accuracy was strongest under normal-volatility conditions and weaker during high-volatility periods, reflecting the greater uncertainty of turbulent markets (Christoffersen, 1998; Ang & Timmermann, 2012). These findings justify the use of VIX-based thresholds and buffer logic to avoid overinterpreting small forecast differences during unstable periods.

The signal-distribution results also highlight the practical value of the platform. StockForecastGenie Pro does not force every forecast into a positive or negative decision. Instead, the Neutral / No Clear Edge category acts as a conservative filter when the model does not identify a sufficiently strong directional opportunity. This feature is important for educational and research settings because it discourages overconfidence and emphasizes uncertainty-aware interpretation. Overall, the findings suggest that the primary value of StockForecastGenie Pro lies in identifying short-term market structure over multi-day horizons rather than predicting next-day fluctuations.

6. Conclusion

StockForecastGenie Pro demonstrates that a volatility-aware machine-learning framework can provide useful short-horizon forecasting support for major United States equity indices while maintaining interpretability for users. For the evaluation in this study, the strongest results occurred at the five-trading-day horizon, where the stacked ensemble outperformed the no-change benchmark and achieved directional accuracy above 70% for both evaluated indices.

Future versions of StockForecastGenie Pro will extend coverage to additional equity indices and exchange-traded funds. FRED-supported additions may include the NASDAQ Composite and NASDAQ-100, while Yahoo Finance can support broader asset coverage, including Russell 2000, index-tracking ETFs, sector ETFs, and selected large-cap equities. Subsequent versions will also evaluate more advanced machine-learning architectures, including neural networks, while maintaining the platform's emphasis on transparency and responsible decision support.

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Ensemble LLM Consensus Architectures for Deterministic Trade Signal Generation: An Empirical Study of Multi-Persona AI Panels in Retail FinTech Applications

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Abstract

This paper presents an empirical study of a multi-persona large language model (LLM) consensus architecture deployed in a live retail FinTech platform for equity and options trade signal generation. Grounded in a prior quantitative trading framework (Anton, 2025) and building upon academic antecedents in multi-agent LLM systems (Xiao et al., 2024), the Edge Stack Trading platform deploys a six-persona AI analyst panel producing structured, constrained verdicts across a real-time multi-signal scoring architecture. Analysis of nine live trade reports generated between April and May 2026 reports a preliminary 87.5% directional accuracy rate across eight assessable signals in an exploratory proof-of-concept evaluation, with unanimous panel consensus strongly correlated with system confidence extremes. Inter-model disagreement functions as an auditable risk signal, and model API failures produce identifiable, recoverable degradation patterns consistent with graceful degradation requirements for financial AI systems. The architecture addresses the 2026 conference theme of Reliable and Deterministic AI for Financial Systems through structured verdict formats, role-constrained persona prompting, and explicit multi-signal deterministic scoring as mechanisms for AI governance in retail financial decision support. One incorrect signal (Palantir) reveals a boundary condition in which extreme valuation risk overrides technical alignment, informing a specific architectural recommendation.

Implications for HBCU financial technology education, democratized institutional-grade AI analysis, and regulatory auditability are discussed.

Keywords: multi-agent LLM, ensemble AI, trade signal generation, deterministic AI, FinTech, VolumeZoneOscillator, consensus architecture, AI auditability, retail trading, financial AI governance

Introduction

The emergence of large language models (LLMs) as analytical instruments in financial markets represents one of the most consequential technological shifts in retail FinTech since algorithmic trading. However, single-agent LLM deployments in financial contexts suffer from well-documented limitations: hallucination risk, absence of role-based specialization, lack of internal debate mechanisms, and insufficient auditability for regulatory contexts (Xiao et al., 2024). These limitations are especially acute in retail trading environments where investors act directly on AI-generated recommendations without institutional intermediation or validation infrastructure.

This paper examines the Edge Stack Trading platform, a live retail FinTech system deploying a six-persona LLM consensus panel for equity and options trade signal generation. The platform was developed from a theoretical foundation in the Multi-Factor Probabilistic Trading System (Anton, 2025), which formalized Bayesian-style probability stacking across multiple independent market signals: the VolumeZoneOscillator (VZO), NYSE TICK breadth, VIX volatility regime, sector ETF alignment, news sentiment, and earnings binary event risk. Edge Stack Trading extends this framework by replacing human signal synthesis with an ensemble of LLM agents, each assigned a distinct analytical persona, producing structured verdicts aggregated into a consensus recommendation.

Contributions are fourfold: (1) first empirical description of a live production multi-persona LLM consensus panel for retail equity trading; (2) analysis of inter-model agreement rates across nine live reports; (3) post-hoc accuracy assessment against observed market outcomes yielding a preliminary 87.5% directional accuracy across a small exploratory sample; and (4) examination of an API failure event as a graceful degradation case study. The platform also addresses equity of access, making institutional-grade AI analysis available at retail scale consistent with the democratization mission of HBCU financial education.

Literature Review

Theoretical Foundations in Probabilistic Trading

The Edge Stack Trading architecture derives from market microstructure theory and behavioral finance. Kyle (1985) and Easley and O'Hara (1987) established the informed trading hypothesis, demonstrating that sophisticated market participants reveal informational advantages through volume and order flow. The VolumeZoneOscillator operationalizes this insight by measuring the balance between volume on price advances versus declines, normalized to a bounded oscillator (Anton, 2025). Kahneman and Tversky (1979) and Tetlock (2007) provided behavioral finance grounding for sentiment-based signal components, demonstrating that media pessimism predicts short-term price pressure and that extreme sentiment conditions create exploitable contrarian opportunities.

Anton (2025) synthesized these streams into a multi-factor probabilistic framework, formalizing Bayesian probability stacking: given conditionally independent signals S_1 through S_n, the posterior probability $P(\text{Success}|S_1,...,S_n)$ substantially exceeds any individual signal's predictive power. The framework specified VZO zone-dependent entry rules, NYSE TICK thresholds, VIX regime protocols, earnings binary event management, and a three-tier position sizing decision tree, constituting the direct intellectual predecessor to the automated system examined here.

Multi-Agent LLM Frameworks in Finance

Xiao et al. (2024) proposed TradingAgents, a framework modeled on trading firm organization, featuring LLM agents in specialized roles: fundamental analysts, sentiment analysts, technical analysts, risk managers, and a fund manager. Operating through five sequential layers, the system demonstrated improvements in cumulative returns, Sharpe ratio, and maximum drawdown relative to Buy-and-Hold, MACD, KDJ+RSI, Zero Mean Reversion, and SMA baselines in backtesting on large-cap equities. Du et al. (2023) demonstrated that multi-agent debate mechanisms improve factuality and reasoning, providing theoretical support for consensus architectures. Yu et al. (2024) further showed that conceptual verbal reinforcement in LLM multi-agent systems enhances financial decision-making quality.

Critical gaps remain: all major frameworks operate in simulated backtests rather than live production systems; existing work does not examine inter-model disagreement as an auditable reliability signal; and no prior study has integrated VZO-based multi-timeframe analysis, options

PCR flow, and NYSE TICK extrapolation with LLM consensus panels. This paper addresses all three gaps through analysis of a live deployment with post-hoc accuracy validation.

AI Reliability and Auditability in Financial Systems

The 2026 conference theme of Reliable and Deterministic AI for Financial Systems highlights the critical need for explainable, auditable AI governance in financial contexts. The Edge Stack Trading architecture addresses these requirements through: (1) deterministic scoring, where confidence scores are computed from explicit weighted signal components with full input traceability; (2) structured constrained verdict formats preventing role drift; and (3) panel transparency, preserving all six analyst verdicts in each report output to enable complete reasoning chain review.

Methodology

Platform Architecture

Edge Stack Trading is a production retail FinTech platform delivering AI-assisted trade analysis across equities, ETFs, and options. It integrates a deterministic multi-signal scoring engine with a six-persona LLM analyst panel, operating on a proprietary on-premises AI inference cluster. A Python-based asynchronous RSS aggregation engine spanning 48 financial feeds provides real-time news data with concurrent fetching, MD5 headline deduplication, and normalized output.

The deterministic scoring engine computes system confidence (0–100%) from eleven weighted components: (1) market direction from SPY/QQQ/DIA composite; (2) VIX volatility regime; (3) cryptocurrency sentiment from a five-asset weighted basket; (4) NYSE TICK breadth extrapolated from a 60-stock basket to ~3,000 NYSE securities; (5) sector ETF alignment across all eleven SPDR sectors; (6) insider sentiment; (7) earnings quality from prior four-quarter history; (8) RSS news sentiment; (9) VZO alignment across one-minute, five-minute, and one-day timeframes; (10) options put-call ratio; and (11) leadership and fraud risk. Scores map to: ≥70% = BUY/STRONG BUY; 50–69% = HOLD; <50% = SELL/STRONG SELL, applied consistently across all asset types.

The Six-Persona LLM Panel

Six personas operate in parallel with no cross-agent communication, each constrained to ~178 words with a required imperative verdict label: (1) Fundamental Analyst — earnings quality and revenue trajectory; (2) Risk Manager — position sizing and risk-reward profile; (3)

Market Strategist — macro backdrop, VIX regime, and sector rotation; (4) News Sentiment Analyst — headline tone and social sentiment; (5) Senior Technical Analyst (panel leader) — synthesizes all data and issues the final consensus verdict with stated confidence; and (6) Financial Educator — plain-English translation for non-professional investors. Parallel rather than sequential execution prevents the telephone effect — progressive information distortion across sequential agent handoffs — documented as a limitation of sequential architectures (Xiao et al., 2024).

Data Collection, Sample, and Analytical Framework

Nine live reports generated between April 22 and May 23, 2026, are analyzed. Reports span individual equities (INTC, IEX, IBM, INTU, PLTR, MU, BXDC), a sector ETF (IGV), and an options strategy (NVDA), covering swing equity, day trade equity, cash-secured put, and long call structures. Post-hoc accuracy is assessed against market prices as of June 25, 2026, providing a 33–64 day outcome window. Accuracy is evaluated on a binary directional basis: BUY correct if price appreciated meaningfully; SELL/AVOID correct if price declined or the avoided trade was unprofitable; HOLD correct if the wait-for-confirmation posture was vindicated. Analysis examines: (1) confidence score distribution; (2) convergence between system score extremes and panel unanimity; (3) signal factors driving divergence; (4) post-hoc accuracy; and (5) failure mode resilience.

Results and Findings

System Confidence Scores, Panel Consensus, and Post-Hoc Accuracy

Table 1 presents all nine reports with system confidence, verdict, panel dissent count, and post-hoc accuracy outcomes. Of eight assessable signals, seven were directionally correct (87.5%), though this result should be interpreted cautiously given the small sample size and exploratory nature of the evaluation.

Table 1

Live Edge Stack Trading Reports with Confidence Scores, Panel Dissent, and Post-Hoc Accuracy (June 25, 2026)

Ticker	Date	Score	Verdict	Dissent	Price at Signal	Price Jun 25	Result
INTC	Apr 23	84%	BUY	1/6	$66.68	~$135	✓ +102%

Ticker	Date	Score	Verdict	Dissent	Price at Signal	Price Jun 25	Result
IEX†	Apr 23	19%	SELL*	—†	$205.90	N/A	Excl.†
IBM	Apr 22	59%	HOLD	4/6	$251.80	~$262	✓ Correct
NVDA	May 23	2%	AVOID	6/6	$214.28	~$199	✓ Avoided loss
INTU	May 22	2%	SELL	5/6	$318.84	~$259	✓ −19%
IGV	May 21	51%	HOLD	6/6	$93.20	~$94	✓ Flat/HOLD
PLTR	May 21	100%	BUY	0/6	$137.85	~$107–$113	✗ −20%
MU	May 20	100%	BUY	0/6	$726.00	~$1,048+	✓ +44%+
BXDC	May 18	50%	HOLD	6/6	$20.78	~$21.84	✓ Correct

† IEX: Full API panel failure (404 errors). Deterministic engine operative; panel unavailable. Excluded from accuracy assessment (see Section 4.4).

** SELL verdict from deterministic scoring engine only.*

System confidence scores clustered at functional extremes, with four of nine at or below 51% and three at 84% or above. This polarization reflects the Bayesian stacking mechanism: signal alignment drives composite scores toward extremes while signal conflict produces mid-range outputs (Anton, 2025). A clear convergence pattern emerged between score extremes and panel unanimity: both 100% system confidence reports (PLTR, MU) achieved 0/6 panel dissent, while both 2% reports (NVDA, INTU) generated 5–6 of 6 dissenting analysts. This convergent validity indicates that the deterministic scoring engine and the LLM panel, operating through different reasoning mechanisms from the same data, consistently agree at conviction extremes.

Notable Signal Outcomes

Two signals produced exceptional gains. INTC appreciated over 100% from $66.68 to approximately $135, driven by the semiconductor sector rally, the Apple-Intel chip partnership announcement, and BofA raising its price target to $160. Only one of six panel analysts dissented (Market Strategist, citing elevated VIX and negative XLK sector alignment), a disagreement that post-hoc analysis confirms was overridden correctly by the consensus BUY. MU appreciated 44%+ from $726, with Micron reporting record fiscal Q3 2026 revenue of $41.5 billion on June 24, 2026, shattering consensus estimates by over $6 billion. The unanimous

100% system BUY and zero panel dissent were fully validated. The INTU SELL at $318.84 was validated by a 19% decline to ~$259, with Goldman Sachs subsequently downgrading to Sell, securities fraud investigations launched, and the company's market capitalization declining $131 billion from its prior year high. The NVDA AVOID correctly prevented a cash-secured put assignment that would have required purchasing stock at $207.90 when the market price fell to ~$199.

The Single Incorrect Signal: PLTR and Valuation Override

The single incorrect signal was PLTR, which generated a 100% system BUY and unanimous panel consensus recommending a cash-secured put at the $135 strike. The stock declined 18–23% to $107–$113, resulting in a put assignment well below breakeven. Critically, the original report contained its own warning: the Risk Manager flagged extreme valuation (~200x forward earnings), the Senior Technical Analyst downgraded the system's 100% to 78% citing missing VIX data, and the concurrent IGV report had identified the SaaS sector as experiencing its worst quarter since 2008. These qualitative flags were present but overridden by technical signal alignment. This case contributes a specific architectural recommendation: implementing valuation-threshold hard constraints that prevent BUY signals when price-to-earnings multiples exceed defined limits, regardless of technical score. Table 2 presents the full panel verdict distribution for all nine reports.

Table 2

Six-Persona Panel Verdict Distribution Across All Nine Live Reports

Ticker	Fund. Anlst	Risk Mgr	Mkt Strat.	News Sntmt	Sr. Technical	Fin. Educ.
INTC	BUY	PROCEED	AVOID	BUY	BUY (consens.)	PROCEED
IEX†	ERROR	ERROR	ERROR	ERROR	ERROR	ERROR
IBM	HOLD	PROCEED	BUY	AVOID	HOLD (consens.)	MONITOR
NVDA	AVOID	AVOID	AVOID	AVOID	AVOID (consens.)	AVOID
INTU	AVOID	AVOID	AVOID	AVOID	SELL (consens.)	AVOID
IGV	HOLD	HOLD	HOLD	HOLD	HOLD (consens.)	HOLD
PLTR	BUY	PROCEED	PROCEED	PROCEED	BUY (consens.)	BUY

Ticker	Fund. Anlst	Risk Mgr	Mkt Strat.	News Sntmt	Sr. Technical	Fin. Educ.
MU	BUY	BUY	BUY	BUY	BUY (consens.)	BUY
BXDC	HOLD	HOLD	HOLD	HOLD	HOLD (consens.)	HOLD

† IEX: All personas returned API 404 errors.

API Failure Case Study: The IEX Degradation Event

The IEX report (April 23, 2026) illustrates graceful degradation: all six LLM personas returned 404 API errors due to an unavailable model endpoint. The failure produced consistent, identifiable error signatures — explicit error objects with type, message, and request ID — rather than silent omissions. Critically, the deterministic scoring engine was unaffected, computing a 19% SELL confidence from available market data. Simultaneously, the equity-level module independently produced an 87% STRONG BUY from VZO, chart trajectory, analyst ratings, and social sentiment. This system-to-equity divergence (19% SELL vs. 87% BUY) illustrates precisely the disambiguation function that the LLM panel provides: resolving conflicts between scoring layers requires qualitative reasoning that deterministic scoring alone cannot supply. The transparent error signature ensures that a human reviewer can immediately identify the degraded state before acting, satisfying auditability requirements central to the conference theme.

Discussion

Deterministic Scoring as an AI Governance Mechanism

The explicit, weighted signal architecture provides full output traceability: any confidence score can be decomposed into its constituent signal contributions, satisfying regulatory explainability requirements without reliance on post-hoc attribution methods applied to opaque neural networks. For example, NVDA's 2% score decomposes to: VZO alignment (-4 pts), macro direction (-10 pts), volatility caution (-10 pts), crypto sentiment (-3 pts), NYSE TICK (+1 pt), sector positive (+11 pts), earnings quality (+8 pts), news sentiment (+3 pts). Every component is auditable and disputable by a reviewing party — a governance property unavailable in end-to-end neural approaches. This aligns with the conference theme's emphasis on reliable and deterministic AI for financial systems.

Inter-Model Disagreement as a Risk Signal and PLTR Implications

Inter-model disagreement functions as an auditable risk signal: high dissent rates surface analytical tension requiring human review rather than automatic execution. IBM's 4/6 dissent rate correctly identified a VZO overbought timing problem the 59% system score alone would have obscured. However, PLTR demonstrates the inverse: unanimous consensus with 100% system confidence produced the study's only incorrect signal, showing that consensus is a necessary but insufficient condition for accuracy. The panel's own internal risk flags — extreme valuation, missing VIX data, sector distress — were present and overridden. Future iterations should implement valuation-based hard constraints and sector-distress override rules that cannot be overridden by technical alignment alone.

Equity of Access and HBCU Relevance

Edge Stack Trading makes institutional-grade multi-factor analysis — historically accessible only to professional traders with access to dedicated analytical infrastructure — available at retail scale. The Financial Educator persona specifically addresses accessibility for first-generation market participants. The platform has been applied in educational contexts at Howard University’s School of Business in a Stock Market Investment Planning module, and represents a practical demonstration of the democratization mission central to HBCU financial technology education.

Implications, Limitations, and Future Research

Practical and Educational Implications

The Edge Stack Trading architecture carries several practical implications for the design of AI-assisted financial systems. First, the deterministic scoring layer provides a governance mechanism that is fully decomposable and auditable without reliance on post-hoc attribution methods. Practitioners and regulators can trace any system verdict to its constituent signal inputs, a property directly relevant to emerging explainability expectations in retail FinTech. Second, the use of structured, role-constrained LLM personas addresses the hallucination and role-drift risks documented in single-agent financial AI deployments, offering a replicable design pattern for developers building AI tools for retail investors. Third, the treatment of inter-model disagreement as an explicit risk signal—rather than noise to be suppressed—offers a practical auditability mechanism: high-dissent verdicts surface analytical tension for human review before execution, reducing the risk of automated compliance with erroneous signals.

For HBCU financial technology education, the platform demonstrates how institutional-grade multi-factor AI analysis can be made available at retail scale and integrated into coursework. The Financial Educator persona, designed to translate technical verdicts into plain-English explanations, directly addresses the needs of first-generation market participants and novice investors who may lack the background to interpret raw quantitative signals. The architecture's application in Howard University's School of Business Stock Market Investment Planning module illustrates the pedagogical potential of live AI financial systems as teaching instruments, offering students exposure to production-grade analysis pipelines as part of their training.

Limitations

This study has several important limitations that constrain the strength of conclusions that can be drawn. The empirical evaluation is based on only nine live trade reports, with eight assessable signals, which is insufficient to establish statistically robust claims regarding system accuracy or generalizability. The reported 87.5% directional accuracy should be interpreted as a preliminary proof-of-concept result rather than a validated performance benchmark. Without a larger sample, it is not possible to determine whether this accuracy rate significantly exceeds what would be expected by chance, and no confidence intervals or formal hypothesis tests are presented to support the directional accuracy claim.

Additional limitations include: (1) binary rather than magnitude-adjusted accuracy assessment, which does not account for the economic significance of correct or incorrect signals; (2) the absence of risk-adjusted performance metrics, transaction cost analysis, or benchmark comparisons against simpler trading rules or human analyst judgments; (3) a sample period coinciding with specific semiconductor and SaaS sector dynamics that may not be representative of other market regimes; (4) limited reproducibility due to the proprietary nature of the platform, which constrains other researchers' ability to evaluate or replicate the proposed architecture; and (5) the accuracy criteria for BUY, SELL, AVOID, and HOLD recommendations, while described, could be defined with greater precision to enable systematic replication. Claims regarding system reliability and AI governance should be understood as exploratory findings from a live proof-of-concept deployment rather than as validated production-benchmark assertions.

Future Research

Future research should prioritize expanding the empirical dataset substantially: longitudinal accuracy assessment across hundreds of live reports spanning multiple market regimes and asset classes is necessary before stronger conclusions can be drawn. Such datasets would enable persona-specific accuracy analysis by market regime, as well as formal testing of valuation-threshold hard constraints and sector-distress override rules identified by the PLTR case. Benchmarking against established baselines—including Buy-and-Hold, MACD, and human analyst consensus—and regulatory analysis relative to SEC and FINRA explainability guidance for AI-assisted financial advice represent important additional avenues for future inquiry.

Conclusion

This paper presents the first empirical study of a live production multi-persona LLM consensus panel for retail equity and options trade signal generation, demonstrating a preliminary 87.5% directional accuracy rate across eight assessable signals on the Edge Stack Trading platform (April–May 2026). Key contributions include: fully decomposable deterministic scoring supporting regulatory auditability; structured constrained persona verdicts preventing role drift; inter-model disagreement as an auditable risk signal; and transparent API failure signatures maintaining human oversight capacity. These design principles offer a replicable governance framework that directly serves the HBCU community's mission of financial empowerment and equitable access to sophisticated analytical tools.

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The Safety Exposure Paradox: How Frontier AI Safety Research May Amplify Cyber Risk in Financial Infrastructure

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ABSTRACT

Frontier artificial intelligence laboratories now publish detailed accounts of how their models behave under adversarial pressure: red-team transcripts, capability thresholds, interpretability findings, and responsible-scaling frameworks. These disclosures are widely treated as safety infrastructure, built to keep dangerous capabilities contained and visible to regulators. This paper argues that the same disclosures can function as a second, less examined kind of infrastructure: a map of where a model's offensive ceiling sits, available to anyone willing to read it. Using a comparative case study of the published capability-disclosure frameworks of Anthropic, OpenAI, and Google DeepMind, three labs operating under a shared 2024 Seoul Summit safety mandate, this paper develops a concept called the Safety Exposure Paradox, in which the transparency that makes frontier AI governable also narrows the search space for adversaries probing model behavior. The paper then traces this dynamic into financial infrastructure, where fraud detection, anti-money-laundering screening, identity verification, and algorithmic trading increasingly depend on AI systems whose upstream governance, training data, and safety ceilings sit outside any single institution's control. Drawing on financial-stability research, dual-use disclosure

literature, and recent reporting on AI-enabled synthetic identity fraud, the paper proposes a tiered disclosure model with concrete implementation steps, and a set of policy recommendations for regulators and fintech institutions managing inherited AI risk. The aim is not to argue against safety disclosure, but to show that disclosure decisions carry a financial-sector externality that current governance frameworks do not yet price in.

Keywords: frontier AI, safety disclosure, Safety Exposure Paradox, fintech cybersecurity, responsible disclosure, dual-use AI, financial infrastructure risk, AI governance

INTRODUCTION

Banks no longer think of artificial intelligence as a backend convenience. It sits underneath fraud screening, anti-money-laundering (AML) monitoring, credit decisioning, algorithmic trading, and the identity checks that decide whether a new account opens or gets flagged. None of that is new to people who work in fintech. What is newer, and less discussed in the fintech literature, is that the AI systems doing this work are themselves the subject of an entirely separate governance conversation happening upstream, inside a small number of frontier AI laboratories, largely out of financial institutions' view.

Those laboratories have, to their credit, built increasingly elaborate safety apparatus around their models: red-teaming programs, interpretability research, capability evaluations, and public scaling policies that describe, in real detail, what a model can and cannot yet do safely. Anthropic is the clearest example of this approach. Its Responsible Scaling Policy (RSP) defines AI Safety Levels, sets capability thresholds for cyber, biological, and autonomous-replication risk, and commits the company to publishing Risk Reports and Frontier Safety Roadmaps that describe, with redactions, how close its models are to crossing those thresholds (Anthropic, 2024, 2026).

This is, by most measures, a responsible way to build powerful technology. It is also, this paper argues, a way of publishing a map. A capability threshold is a statement about where a model's abilities sit relative to a danger line, and knowing where that line is drawn tells an attacker something useful even if the underlying weights stay private: how far current models are from a given offensive capability, and which capabilities are not yet considered a near-term concern. None of this requires breaching anyone's security; it only requires reading what frontier labs already publish.

This paper calls that dynamic the Safety Exposure Paradox: the same transparency mechanisms designed to make frontier AI governable can also compress the work an adversary has to do to understand a model's offensive ceiling. Importantly, this paper does not claim that capability disclosures have demonstrably caused specific financial-sector exploits; the causal link remains a plausible mechanism rather than a proven one. The contribution is to name and structure that mechanism, show it is visible across multiple labs' published governance documents, and connect it to fintech risk categories that are independently documented as growing. The paradox is not an argument against disclosure; withholding capability information from regulators and the public has its own, larger costs. The point is narrower: disclosure decisions made inside AI labs carry a financial-sector externality that current governance conversations rarely name, changing the threat environment for every downstream institution that depends on AI for fraud defense, identity verification, or trading infrastructure, whether or not those institutions had any say in the disclosure.

The remainder of the paper reviews relevant scholarship, explains the comparative case-study method applied to Anthropic, OpenAI, and Google DeepMind, works through that comparison, builds a four-part theoretical framework for the paradox, and closes with a tiered disclosure model with implementation steps, and policy recommendations for regulators, fintech institutions, and frontier AI developers.

LITERATURE REVIEW

Four bodies of scholarship bear on this paper's argument, and they do not currently talk to each other much: AI alignment and safety-evaluation research, cybersecurity disclosure theory, financial-stability research on AI dependency, and the dual-use literature that has grown up around frontier model capability testing.

AI Safety Transparency and Capability Evaluation

The dominant view in AI safety research treats transparency as close to an unqualified good. Red-teaming, interpretability work, and public capability evaluations are understood as mechanisms by which outside parties can hold a lab accountable for what its models can do. Anthropic's RSP is the most fully worked-out version of this approach among frontier labs, defining AI Safety Levels and Capability Thresholds for CBRN, cyber, and autonomy risk, and committing to publish Risk Reports describing how close current models sit to those thresholds

(Anthropic, 2026). The United States' National Institute of Standards and Technology has built a parallel, sector-neutral version of the same logic into its AI Risk Management Framework and 2024 Generative AI Profile, treating pre-deployment testing and incident disclosure as core risk-management functions (National Institute of Standards and Technology, 2023, 2024).

What this literature has not done is ask what a capability disclosure looks like from an adversary's position rather than a regulator's. A regulator reading a Risk Report wants reassurance the lab understands its own models; an adversary reading the same document wants a current estimate of how far a model's abilities sit from a danger threshold, useful intelligence about where to direct further probing. The alignment literature has not built this second reading into its account of what disclosure costs.

Cybersecurity Disclosure Theory and Its Limits for AI

Cybersecurity has a long-settled answer to a structurally similar problem: responsible disclosure. A researcher who finds a vulnerability privately notifies the vendor, who patches it before the finding becomes public, since a patched vulnerability loses most of its offensive value. Frontier-AI researchers building on this analogy have proposed adapting coordinated disclosure to dual-use model capabilities: O'Brien et al. (2024) describe a Coordinated Disclosure of Dual-Use Capabilities (CDDC) process routing findings through a government coordinator before public release, modeling cybersecurity's coordinated vulnerability disclosure norms.

The disanalogy is the more important point, however. A capability is not a bug, and a frontier model is not a single deployed system that gets patched once. A capability is a property of a class of trained systems; once an evaluation shows a technique elicits dangerous behavior in one model family, that knowledge generalizes to other families with similar architectures, in a way a software exploit does not generalize across unrelated codebases. Brenneis (2025) frames this as a dual-use-research-of-concern (DURC) problem borrowed from biosecurity, arguing AI research currently lacks the institutional layer that research ethics committees provide there. The cybersecurity disclosure model assumes a patchability that does not cleanly transfer to frontier AI, and that gap is exactly where the Safety Exposure Paradox lives.

Financial-Sector Dependency on AI Infrastructure

Financial-stability researchers have been more attentive than AI-safety researchers to the downstream risk of upstream concentration, though their focus has mostly been operational

rather than adversarial. The Financial Stability Board's 2024 report identifies third-party dependency and service-provider concentration as a primary systemic vulnerability, noting that financial institutions increasingly rely on a small number of specialized hardware, cloud, and pre-trained-model providers, which concentrates operational risk in ways difficult for any single regulator to see across institutions (Financial Stability Board, 2024). A 2025 follow-up report extends this with a case study on generative-AI supply chains, observing that vertical integration among AI and cloud providers is narrowing the pool of providers financial institutions can choose from (Financial Stability Board, 2025). The same 2024 report separately flags generative-AI-enabled fraud as a distinct vulnerability category, alongside, rather than connected to, its third-party dependency analysis.

This is where the present paper tries to do something the financial-stability literature has not yet done: connect the dependency question to the disclosure question. The FSB's framework treats AI vendor concentration as a risk because a vendor outage or failure could disrupt many institutions at once. It does not ask whether the vendor's own public safety disclosures might be quietly reshaping the threat landscape that all of those dependent institutions share, independent of any outage.

Adversarial Machine Learning and the Limits of Static Defense

A smaller but fast-growing technical literature documents how generative AI is already being used to defeat the specific controls fintech institutions rely on, particularly through synthetic identity construction and deepfake biometric spoofing that exploit the same generative capabilities frontier labs evaluate during pre-deployment testing (Feedzai, 2025; Datos Insights, 2025; PYMNTS, 2026). What this literature does not do is trace these capabilities back to the upstream question of where the generative models producing this fraud acquired the techniques they use, or whether published capability research played any role in that acquisition. That gap, between documenting that AI-enabled fraud is growing and explaining where the underlying capability came from, is the one this paper tries to close.

METHODOLOGY

This paper uses a qualitative, comparative case-study design, treating Anthropic, OpenAI, and Google DeepMind as what Yin (2018) would call a purposive sample of critical cases, chosen not for statistical representativeness but because they are the three frontier labs with the

most extensively documented, longest-running public capability-disclosure frameworks. All three were original signatories of the Frontier AI Safety Commitments at the 2024 AI Seoul Summit, where sixteen organizations agreed to publish a safety framework defining intolerable-risk thresholds and report publicly on breaches (UK Government, 2024). That shared starting point matters methodologically: the three frameworks were produced under a common institutional mandate, making differences between them a function of each lab's choices rather than different external requirements.

The three cases were selected for a second reason beyond the Seoul commitments: each has iterated its framework publicly enough times to show a visible trajectory rather than a single static snapshot. Anthropic has published five successive Responsible Scaling Policy versions between September 2023 and April 2026 (Anthropic, 2026). OpenAI has published two major versions of its Preparedness Framework, the second in April 2025, alongside model-specific system cards that apply the framework to each new release (OpenAI, 2025). Google DeepMind has published three versions of its Frontier Safety Framework between May 2024 and September 2025, most recently adding a Critical Capability Level for harmful manipulation (Google DeepMind, 2025b). Comparing frameworks that have each evolved over multiple iterations lets the analysis ask not only what each lab discloses, but how each lab has changed what it discloses, which is the more direct test of whether disclosure compresses over time in the way the paradox predicts.

The analysis proceeds in four stages. The first stage reviews the publicly available versions of all three frameworks, treating these as primary documents rather than secondary description. The second stage builds a structured comparison across four dimensions: the risk domains each framework tracks, the threshold structure each uses to define danger, each lab's stated default disclosure posture, and each lab's documented history of removing, adding, or redefining categories. The third stage places this comparison in conversation with the cybersecurity responsible-disclosure literature, asking where the disclosure logics of all three labs diverge from a patchable-vulnerability model. The fourth stage applies the resulting framework to five fintech functions, asking in each case what a capability disclosure in the Anthropic, OpenAI, or DeepMind style would and would not reveal to an adversary targeting that function.

This design narrows, but does not eliminate, the limitation of a single-case design. Three labs are still a small, non-random sample within an industry that includes other significant developers, including Meta and several labs outside the Seoul Summit's signatory list, and the comparison cannot establish how common the Safety Exposure Paradox is across that wider population. The paper also has no access to non-public information about whether any specific capability disclosure has been used by a real attacker to compromise a real financial system; that evidence would require a confirmed incident or cooperation from threat-intelligence teams the present project did not have. What the comparative case study can do is show that the paradox is logically coherent, visible across multiple labs' published governance documents, and that it maps onto fintech risk categories independently documented as growing.

RESULTS

This section reports what the comparative analysis found at each of the four stages described above.

Three Frameworks, One Underlying Logic

Table 1 summarizes the structural comparison across the three frameworks. All three track broadly overlapping risk domains, CBRN, cyber, and some form of autonomous or self-improvement risk, though only Anthropic and Google DeepMind currently maintain a standing persuasion or manipulation category; OpenAI moved persuasion outside its Preparedness Framework entirely in its 2025 revision, choosing to handle it through other internal mechanisms instead (OpenAI, 2025). All three use a tiered threshold structure rather than a single danger line, though the tiers differ: Anthropic's AI Safety Levels (ASL-2 through ASL-4), OpenAI's capability bands, and Google DeepMind's Critical Capability Levels (CCLs) are not directly interchangeable, but each performs the same basic function of marking the point at which a lab commits to additional safeguards (Anthropic, 2024; OpenAI, 2025; Google DeepMind, 2025a, 2025b).

Table 1

Comparison of Frontier Capability-Disclosure Frameworks

Dimension	Anthropic RSP	OpenAI Preparedness Framework	Google DeepMind FSF
Risk domains tracked	CBRN, cyber, autonomy/AI R&D, persuasion	Biological/chemical, cyber, AI self-improvement (persuasion handled outside framework)	CBRN, cyber, ML R&D, deceptive alignment, harmful manipulation
Threshold structure	AI Safety Levels (ASL-2–3)	Capability bands (originally Low/Medium/High/Critical ; Medium and Low later dropped)	Critical Capability Levels (CCLs)
Default disclosure posture	Minimize redactions in public Risk Reports	Publish results to "facilitate public awareness" of frontier capability	Publish framework and per-model evaluation outcomes
Documented trajectory	Five versions (2023–2026); categories disaggregated and added over time	Two major versions; low-risk bands removed as "not operationally involved"	Three versions (2024–2025); new CCL for manipulation added in v3.0

Anthropic's RSP institutionalizes capability evaluation well beyond a one-time safety review, defining AI Safety Levels modeled loosely on the biosafety-level system for handling dangerous biological materials, with Capability Thresholds that trigger Required Safeguards once a model crosses them (Anthropic, 2024). Beginning with version 3.0, Anthropic committed to publishing Risk Reports covering all publicly deployed models and releasing a Frontier Safety Roadmap across security, alignment, safeguards, and policy (Anthropic, 2026), stating directly that it aims to minimize redactions in these public reports, accepting redaction only for legal, intellectual-property, public-safety, or privacy reasons, a default posture of maximal rather than minimal disclosure.

OpenAI's Preparedness Framework follows a similar evaluate-then-disclose logic but structures its thresholds differently, and its revision history shows the disclosure choice working in the opposite direction from Anthropic's. The original Beta framework defined four risk bands,

Low, Medium, High, and Critical; the April 2025 version 2 removed the bottom two, stating that Low and Medium "were not operationally involved" in any actual safety decision (OpenAI, 2025; Libertify, 2026). The same history shows OpenAI deploying its o1 model after evaluation found it reached Medium capability for biological and chemical severe harm and for persuasion severe harm simultaneously, with no additional safeguard required at that band (Libertify, 2026). Whatever the safety merits, it is also a disclosed data point: it tells any reader how far a real, deployed model's capability sits from OpenAI's High threshold in two categories at once.

Google DeepMind's Frontier Safety Framework shows a third pattern: steady category expansion. It launched in May 2024 with four Critical Capability Levels covering autonomy, biosecurity, cybersecurity, and machine-learning R&D (Google DeepMind, 2024). Version 2.0 added Security Level recommendations and a deceptive-alignment domain for models that might resist shutdown (Google DeepMind, 2025a); version 3.0 added a wholly new CCL for harmful manipulation, building on internal research into manipulative mechanisms in generative models (Google DeepMind, 2025b). Each addition is a disclosed claim: it tells outside readers the lab now considers a specific capability close enough to dangerous to warrant a named threshold, where it previously did not.

What the Comparison Reveals About Disclosure as Signal

Read together, the three frameworks show the same mechanism expressing itself in three directions: Anthropic's toward more granular categories, OpenAI's toward fewer categories but with a documented case of deploying at a disclosed mid-tier capability band, and Google DeepMind's toward new categories added as research reveals new harm mechanisms. Each still tells a sophisticated reader where a real, deployed model's capabilities sit relative to a named danger line. This is where the comparison sharpens the paradox beyond a single-lab case: three labs, sharing a Seoul Summit mandate but arriving at different architectures, converge on the same property, naming a line and reporting distance to it, suggesting the exposure is structural to capability-threshold governance rather than one lab's choice (UK Government, 2024).

None of this requires any of the three labs to publish anything resembling exploit code. The exposure described here is narrower: a threshold framework tells a sophisticated reader which capability categories are being tracked, and a multi-version changelog tells that reader how those categories are evolving, itself a roadmap for locating current systems relative to a danger line, without any document crossing into instructional detail.

Mapping the Comparison Onto Fintech Functions

The fourth stage applied this reading to five fintech functions. Fraud and AML detection depend on anomaly detection trained to recognize suspicious behavior; research already shows generative models producing synthetic transactions and identities realistic enough to survive KYC pipelines, with industry data indicating over half of measured 2025 fraud involved AI (Feedzai, 2025; PYMNTS, 2026). A concrete illustration: AI-generated synthetic identities built by combining real identity fragments with generative-model-produced photographs and voice samples have already been used to bypass major U.S. bank onboarding processes, with losses projected to reach $58.3 billion by 2030 (PYMNTS, 2026). Digital identity verification faces a more severe version of the same problem, with deepfake biometric spoofing the fastest-growing fraud vector institutions report for the coming two years (Datos Insights, 2025). Algorithmic trading is exposed differently: reliance on similar AI models increases correlated trading behavior, compounding rather than offsetting any capability gap an adversary might exploit during a stress event (Financial Stability Board, 2024). Smart-contract auditing uses AI-assisted static analysis to find vulnerabilities; the same capability that helps an auditor find a flaw also helps an attacker find it first if they reach it sooner. None of these functions maps onto only one lab's framework, a reason fintech institutions cannot manage this exposure by tracking a single vendor alone.

DISCUSSION

The Safety Exposure Paradox: A Four-Part Framework

The case-study findings above can be organized into four interacting mechanisms, which together constitute what this paper calls the Safety Exposure Paradox.

Capability signaling is the most direct mechanism: a published threshold is a public statement about how close current models sit to an offensive ceiling, made so outside readers can verify it without needing model access themselves.

Adversarial mirroring follows from signaling: an attacker needs no privileged access to a lab's red-team transcripts to benefit from its evaluation work, only the same publicly trained model or a comparably capable alternative, and the published threshold tells the attacker roughly where to direct probing effort. The dual-use literature has named this dynamic for

biosecurity-style DURC concerns (Brenneis, 2025); this paper traces the same mechanism into a financial-sector context that literature does not address.

Governance escalation describes a secondary effect visible across all three labs studied: published capability findings do not stay inside the AI-safety community, but feed directly into legislative action. The Seoul Summit mandate that produced all three frameworks explains why: governments built the Frontier AI Safety Commitments specifically to extract public threshold disclosures that could inform regulation, and Anthropic cites the resulting influence on California's SB 53 and the EU AI Act's codes of practice as evidence the approach worked (UK Government, 2024; Anthropic, 2026). A disclosure made for accountability purposes can change compliance obligations or deployment availability for downstream institutions on a timeline they do not control, a dynamic structural to the disclosure regime rather than specific to any one lab's choices.

Inherited infrastructure risk is the mechanism connecting the first three to the fintech sector specifically. Financial institutions sit downstream of frontier AI governance decisions in the same structural position the Financial Stability Board has already flagged as a systemic vulnerability for unrelated operational reasons (Financial Stability Board, 2024, 2025): heavy reliance on a small number of AI and cloud providers. The same concentrated dependency that creates outage risk also creates disclosure risk, since a single upstream disclosure decision can change the threat environment for every dependent institution, with no mechanism for those institutions to weigh in.

Together, these four mechanisms describe a recursive problem rather than a simple trade-off: better safety evaluation produces more granular disclosure, more granular disclosure produces a clearer map of the offensive frontier, a clearer map narrows adversarial search costs, and narrower search costs eventually surface as new fraud, identity, or trading exploits that fintech institutions absorb without having created or understood the upstream decision behind them. It bears emphasizing that this chain of mechanisms is currently theoretical; confirming each link empirically, particularly the step from narrowed search costs to realized exploits, is an important direction for future research.

A Tiered Disclosure Model

If the paradox is real, the appropriate response is not to abandon capability disclosure, which would sacrifice the accountability benefits that motivated the alignment-transparency

literature in the first place. A more proportionate response is to tier disclosure by audience, an approach with precedent in the coordinated dual-use disclosure model O'Brien et al. (2024) propose for AI more broadly, adapted here specifically for fintech-relevant capability categories.

Tier 1 disclosures would remain fully public: general safety commitments, high-level governance structure, and aggregate risk posture, the level of detail that already appears in Anthropic's public-facing RSP summaries and serves the broad accountability function that motivates disclosure in the first place. Tier 2 disclosures would be restricted to regulated financial institutions and their primary supervisors, covering capability-threshold detail specific to fraud, identity-spoofing, and market-manipulation risk, distributed through an institutional channel comparable to existing financial-sector information-sharing arrangements rather than posted as a public PDF. Tier 3 disclosures would be limited to government coordinators and named security partners, covering the granular, near-term capability findings that the CDDC proposal already recommends routing through a dedicated coordinator before any public release (O'Brien et al., 2024), treating a sufficiently dangerous cyber-capability finding with roughly the handling discipline reserved for zero-day vulnerability intelligence in conventional cybersecurity practice.

Implementation of this model would proceed in three phases. In the near term (0–12 months), frontier AI labs and financial regulators should establish a joint working group to define which capability categories cross into Tier 2 territory, drawing on existing FS-ISAC and financial intelligence-sharing infrastructure to build a distribution channel. Financial institutions should simultaneously begin upstream AI dependency audits that catalog which frontier models underpin which critical functions. In the medium term (12–36 months), the working group should develop a standardized Capability Disclosure Template that labs submit to Tier 2 and Tier 3 recipients before publishing the public-facing version; government coordinators would review this template against their own threat-intelligence holdings and flag findings that meet Tier 3 handling thresholds. In the longer term, this template and handling protocol should be incorporated into the existing regulatory frameworks that govern model risk management at financial institutions, such as the U.S. Office of the Comptroller of the Currency's SR 11-7 model risk guidance and the EU AI Act's high-risk AI provisions, so that frontier-lab disclosure obligations are treated as a systemic risk input rather than a voluntary publishing choice.

This model does not eliminate the paradox; some signaling is unavoidable if disclosure is to serve any accountability function at all. It does, however, decouple the audience that needs granular threshold detail to do its job, regulators, sector-specific risk teams, and security partners, from the general public audience for whom that same detail offers little protective value and meaningful offensive value.

Policy Recommendations

1. Financial institutions should conduct upstream AI dependency audits that explicitly include exposure to capability-disclosure risk, not only vendor-outage risk, when assessing third-party AI providers.
2. Financial regulators should require AI provenance reporting from regulated institutions, documenting which frontier models support which critical functions, so that a capability disclosure affecting one model family can be traced to its downstream financial-sector footprint.
3. Regulators and institutions should encourage AI and cloud-provider diversification for safety-critical financial functions, reducing the systemic exposure concentrated reliance already creates under the Financial Stability Board's framework (Financial Stability Board, 2024, 2025), while frontier AI developers should adopt the risk-tiered disclosure structure proposed above, distinguishing public accountability disclosures from sector-specific threshold detail.
4. Frontier AI firms and financial regulators should establish a direct coordination channel, modeled on the CDDC proposal (O'Brien et al., 2024), for capability findings with foreseeable financial-sector application, handling cyber-relevant findings with disclosure discipline comparable to zero-day vulnerability intelligence rather than folding them into general-purpose safety reporting.

IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

This paper carries practical implications for three audiences. For fintech institutions, the most immediate implication is that vendor risk assessment should expand beyond operational resilience (uptime, data security, contractual SLAs) to include disclosure risk: what does this vendor publish about its models' offensive capabilities, and how might that publication change

the threat environment my fraud and AML controls face? For financial regulators, the implication is that model risk management frameworks, currently built around the risks a deployed model poses internally, should be extended to cover the systemic risk that concentrated reliance on a small number of frontier AI providers creates when any one of those providers makes a capability disclosure. For frontier AI developers, the implication is that disclosure decisions are not cost-free even when they serve legitimate accountability goals; the cost is borne by downstream financial institutions that had no seat at the disclosure table.

Sample size is this paper's central remaining limitation. Comparing three labs improves on a single case, showing the paradox surfacing across different disclosure philosophies rather than one company's idiosyncratic choices, but three labs remain a small, purposively chosen sample within a wider industry that includes Meta, Amazon, and several labs outside the original Seoul Summit signatory list. The paper also has no confirmed incident data linking a specific disclosure to a specific financial-sector exploit; the fintech risk categories discussed here are independently documented as growing, but the causal link to upstream disclosure remains a plausible mechanism rather than a demonstrated one. This is a genuine limitation that the authors acknowledge directly: the theoretical framework developed here is a necessary first step, but it does not substitute for empirical validation.

Future work could extend the comparison to a larger sample of signatories, or work with threat-intelligence teams to examine whether realized fraud incidents trace to the timing of major capability disclosures. A particularly valuable contribution would be a structured comparison between financial institutions that have diversified their AI infrastructure across multiple vendors versus those relying on a single frontier provider, testing whether disclosure concentration risk is reflected in measurable differences in fraud-event timing or severity. Researchers with access to confidential supervisory data at financial regulators would be well positioned to begin this work.

CONCLUSION

Frontier AI safety research is not purely protective, even though it is built and discussed almost entirely in protective terms. The same disclosure practices that let regulators and the public hold AI labs accountable also narrow what an adversary needs to learn before probing a model's offensive ceiling, and that narrowing does not stay confined to the AI industry. It reaches

financial institutions that had no role in the disclosure decision but now run fraud detection, AML screening, identity verification, and trading infrastructure on AI systems shaped by it.

For fintech specifically, this means inherited risk has a dimension that current operational-resilience frameworks do not yet capture. The Financial Stability Board has done useful work naming AI vendor concentration as a systemic vulnerability (Financial Stability Board, 2024, 2025), but that work treats the upstream provider mainly as a single point of operational failure. This paper's argument is that the same provider is also a single point of disclosure exposure, and that the two risks compound rather than sit side by side.

None of this argues for less transparency from frontier AI developers. It argues for transparency structured with an audience in mind: a disclosure aimed at reassuring the public and one aimed at protecting financial infrastructure are not the same document, and do not currently need to be. The tiered disclosure model and phased implementation steps proposed here offer a practical path toward that distinction. Building it into AI governance, rather than treating disclosure as an all-or-nothing choice, is the next step this framework points toward.

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Corporate Crypto-Asset Disclosures and Liquidity Policy: Evidence from SEC 10-K Filings

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ABSTRACT

The rapid mainstreaming of digital assets is reshaping both corporate financial reporting and treasury strategy. Between 2024 and mid-2025, the number of publicly traded firms disclosing Bitcoin positions increased from 64 to 151, signaling a shift toward integrating crypto assets into formal balance-sheet management. This study investigates: (1) the factors that drive variation in crypto-related disclosures within SEC Form 10-K filings, and (2) how corporate crypto holdings relate to traditional liquidity allocations, including trading, available-for-sale (AFS), and held-to-maturity (HTM) securities. Drawing on SEC EDGAR filings and text-mining techniques, we document substantial cross-firm heterogeneity: firms operating at the core of the crypto ecosystem provide extensive disclosures, whereas firms with moderate exposure appear to use disclosure strategically. Using Signaling Theory as a framework, we evaluate whether digital assets function as liquidity substitutes or as higher-risk complements, offering implications for disclosure behavior, treasury management, and emerging regulatory policy.

KEYWORDS:

Cryptocurrency disclosure, digital asset reporting, blockchain financial reporting, crypto-related risk factors, SEC form analysis

INTRODUCTION

The institutionalization of digital assets has accelerated dramatically in recent years, reshaping corporate treasury management and financial reporting practices. Between 2024 and mid-2025, the number of publicly traded companies reporting Bitcoin on their balance sheets surged from 64 to 151, signaling a fundamental shift from peripheral speculation to strategic asset allocation. This transformation reflects several macroeconomic and regulatory drivers, including U.S. policy developments recognizing Bitcoin as a strategic asset, enhanced regulatory clarity following the implementation of FASB Accounting Standards Update (ASU) 2023-08, and the persistent perception of digital assets as a hedge against inflationary pressures.

Historically, cryptocurrencies such as Bitcoin and Ethereum were confined to fintech outliers. Today, they permeate the treasury strategies of diverse firms across multiple industries, introducing novel dynamics into corporate finance. As corporations allocate capital to these high-volatility assets, financial statement users face a critical challenge: determining whether crypto holdings function as liquidity substitutes akin to cash equivalents or as speculative additions that amplify portfolio risk. This uncertainty is compounded by the principle-based nature of U.S. disclosure requirements under Regulation S-K Items 105 (Risk Factors) and 303 (Management's Discussion and Analysis), which grant firms considerable discretion in framing narrative disclosures about emerging technologies.

Despite the growing materiality of these holdings, the interaction between crypto-assets and traditional financial instruments remains underexplored. Prior research has not examined whether corporate adoption of digital assets complements existing risk-taking strategies or displaces conventional liquidity buffers such as trading securities, available-for-sale (AFS) securities, and held-to-maturity (HTM) securities. Nor has it fully addressed how disclosure practices vary systematically with industry specialization and operational exposure in the crypto domain.

RESEARCH QUESTION AND CONTRIBUTIONS

Research Question:

Do corporate crypto-asset holdings serve as substitutes for traditional liquidity instruments or as complements that increase overall portfolio risk?

Contributions:

First, this study extends Signaling Theory to the crypto-disclosure context by demonstrating that industry specialization and operational exposure are associated with systematic variation in 10-K crypto narratives (Spence, 1973; Healy & Palepu, 2001). Second, it connects discretionary disclosure economics to modern SEC reporting venues, showing how principle-based items (105/303) enable tailored signals in emerging technologies (Verrecchia, 1983). Third, it explores treasury portfolio implications of crypto adoption, providing evidence on whether digital assets function as liquidity substitutes or speculative complements, thereby informing both academic theory and regulatory policy.

LITERATURE REVIEW

The rapid growth of cryptocurrencies has attracted substantial academic attention, particularly regarding the factors that influence individual and organizational adoption. Drawing on established technology adoption theories, researchers have sought to understand why users embrace or resist cryptocurrency-based financial innovations. Alkhwaldi et al. (2023) examined cryptocurrency adoption in Jordan using the Unified Theory of Acceptance and Use of Technology (UTAUT), enhanced with innovativeness and perceived readiness. Based on survey responses from 391 participants, the study found that performance expectancy, effort expectancy, and facilitating conditions significantly influence cryptocurrency adoption. Individuals were more willing to adopt cryptocurrencies when they perceived them as useful, easy to use, and supported by adequate technological infrastructure. Contrary to expectations, social influence and perceived readiness did not significantly predict adoption behavior, suggesting that users in developing economies may remain cautious despite growing global acceptance. The

authors conclude that trust, usability, and infrastructure are critical determinants of cryptocurrency adoption in emerging markets.

Similarly, Bommer, Milevoj, and Rana (2023) synthesized evidence from 42 empirical studies involving 9,482 participants through a meta-analysis of cryptocurrency adoption determinants. Integrating perspectives from UTAUT, UTAUT2, the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB), the authors found that attitude toward cryptocurrency, performance expectancy, and price value are the strongest predictors of behavioral intention. Their results indicate that these factors collectively explain nearly 60 percent of the variance in cryptocurrency adoption intentions. Notably, the effects remained relatively consistent across different countries, economic environments, and cryptocurrency types, suggesting that the primary drivers of adoption are largely universal. Together, these studies demonstrate that perceived usefulness, value creation, trust, and technological support systems remain fundamental to cryptocurrency acceptance.

While individual-level adoption has received considerable attention, researchers have increasingly focused on organizational adoption of blockchain and cryptocurrency technologies. Stratopoulos, Wang, and Ye (2022) contribute to this literature by proposing corporate disclosures as a novel mechanism for assessing the stage of blockchain adoption. Analyzing SEC filings and earnings conference calls from 2013 to 2019, the authors demonstrate that corporate disclosures provide direct insight into managerial intentions, expectations, and strategic plans regarding blockchain technology. Their findings suggest that blockchain adoption remains in the transition from the innovator stage to the early adopter stage and has not yet achieved mainstream adoption.

A key contribution of the study is the identification of an important shift in disclosure content. Early disclosures focused heavily on Bitcoin mining and cryptocurrency-related activities, whereas more recent disclosures emphasize business applications, supply chain management, data processing, and operational efficiency improvements. This evolution suggests that blockchain is maturing from a speculative

financial innovation into a foundational business technology. The study further highlights the importance of managerial communication as a signal of technological readiness and future strategic direction.

As cryptocurrency markets are characterized by substantial information asymmetry, signaling theory has emerged as a useful framework for explaining investor behavior and market outcomes. Kreppmeier and Laschinger (2023) apply signaling theory to Security Token Offerings (STOs) and examine how firms communicate quality to prospective investors. Using a hand-collected dataset of 138 STOs, the authors find that pre-sale phases and explicit announcements regarding token transferability function as credible quality signals that enhance fundraising success. These findings demonstrate that traditional signaling mechanisms remain highly effective even within blockchain-based financial markets.

Their analysis of secondary market performance reveals that initial underpricing is relatively uncommon and is driven primarily by broader cryptocurrency market sentiment rather than firm-specific signals. Furthermore, although decentralized exchanges reduce entry barriers, they generally exhibit lower liquidity than centralized exchanges. These findings suggest that crypto-financial markets continue to evolve and remain dependent on mechanisms that reduce uncertainty and improve investor confidence.

Complementing this perspective, Risius et al. (2023) investigate how social media signals affect fundraising outcomes in Initial Coin Offerings (ICOs) and Initial Exchange Offerings (IEOs). Analyzing 305 token offerings, the authors find that both social media volume and sentiment positively influence fundraising success. However, positive sentiment exerts a significantly stronger effect on ICOs than on IEOs. The authors attribute this difference to the role of cryptocurrency exchanges as trusted intermediaries in IEOs. Because exchanges conduct screening and due diligence, investors rely less on social media sentiment when assessing offering quality. Their findings challenge the notion that blockchain finance is entirely decentralized and underscore the continuing importance of trust, institutional legitimacy, and reputation in digital financial markets.

Further evidence supporting signaling theory is provided by Khalid, Liang, and Brown (2024), who investigate the influence of cryptocurrency-related signals on X (formerly Twitter). Examining more than 555,000 user responses to posts from major cryptocurrency influencers, including Elon Musk, the authors find that crypto-related signals generate significant user engagement and positive sentiment. Moreover, specific cryptocurrency signals are associated with measurable increases in cryptocurrency prices, while broader signals affect overall market movements. These findings demonstrate that social media communication serves as a powerful informational signal capable of influencing investor perceptions and market outcomes.

A growing body of literature examines the implications of cryptocurrency adoption for firm performance and market valuation. Bahmani (2026) investigates stock market reactions to corporate announcements of cryptocurrency acceptance as a payment method. Using an event study methodology on publicly traded U.S. firms between 2013 and 2023, the study finds that cryptocurrency acceptance announcements generate an average decline of 2.73 percent in firm value. Investor concerns regarding market volatility, consumer adoption barriers, and transaction risk appear to drive these negative reactions.

However, the study also finds important moderating effects. Firms that accept Bitcoin experience more favorable market reactions than those accepting alternative cryptocurrencies exclusively. In addition, companies announcing cryptocurrency acceptance in more recent years benefit from a more mature market environment and greater user familiarity. These findings suggest that while cryptocurrency adoption may offer strategic opportunities, investor responses depend heavily on implementation choices and market context.

Field and Inci (2023) similarly examine the relationship between cryptocurrency holdings and firm performance. Their findings indicate that cryptocurrency exposure significantly affects corporate risk profiles and stock market performance. Firms holding cryptocurrencies as treasury assets generally experience improved risk-adjusted returns, whereas operational applications of cryptocurrencies often generate less favorable

outcomes. These results highlight the importance of strategic deployment and transparent reporting of cryptocurrency-related activities.

As corporate cryptocurrency adoption increases, accounting treatment and disclosure practices have emerged as major concerns. The lack of comprehensive accounting standards under both U.S. GAAP and IFRS has resulted in significant reporting inconsistencies across organizations. Akanbi (2024) argues that current classifications of cryptocurrency as intangible assets, inventory, or financial instruments fail to adequately capture the economic characteristics of these assets. The author advocates for dedicated accounting standards to improve comparability, transparency, and decision usefulness.

Similarly, Luo (2024) documents substantial inconsistencies across global reporting frameworks and demonstrates how varying classification approaches distort measures of liquidity, profitability, and cash flow generation. The absence of harmonized accounting standards undermines comparability and increases information asymmetry for investors. Jackson and Luu (2023) further note that IFRS generally excludes cryptocurrencies from cash classifications while providing multiple alternative treatments depending on the nature of the asset and the holder's business model. Their analysis emphasizes the fragmented nature of current accounting guidance and the need for more comprehensive regulatory solutions.

Recent empirical evidence further underscores the importance of disclosure quality. Clark (2026) examines cryptocurrency-related disclosures contained in the Form 10-K filings of 18 companies between 2020 and 2025. The findings reveal that firms engaged in cryptocurrency activities provide significantly more detailed contingency disclosures related to market volatility, cybersecurity risks, technological uncertainty, and regulatory exposure. The study also identifies substantial variation in ESG disclosures, with some firms proactively discussing environmental and governance implications while others provide little information.

Quantitative results indicate a positive relationship between increases in cryptocurrency-related intangible assets and firm profitability, suggesting that digital asset investments may contribute to value creation despite increasing earnings volatility. Clark also finds that implementation of ASU 2023-08 enhances transparency through fair value measurement while simultaneously increasing income statement volatility. Collectively, these findings emphasize the growing importance of robust disclosure practices and standardized accounting treatment for cryptocurrency assets.

THEORETICAL FRAMEWORK

Signaling Theory

Firms operating in environments characterized by uncertainty and information asymmetry often rely on signals, observable, credible actions, to communicate internal conditions to outside stakeholders. Signaling Theory, originating with Spence (1973), explains how firms use such mechanisms to reduce uncertainty when outsiders cannot easily verify underlying quality or risk. In accounting and disclosure settings, the framework has been widely used to interpret management's incentives to release voluntary or expanded information, particularly when such disclosures can influence investor perceptions or reduce financing frictions (Healy & Palepu, 2001).

In the context of digital-asset activities, signaling becomes especially salient. Crypto-related operations involve technological complexity, regulatory ambiguity, volatile asset valuations, and heightened operational risks. These characteristics create substantial information gaps between managers and market participants. Narrative disclosures in SEC Form 10-K filings, particularly those provided under Regulation S-K Items 105 (Risk Factors) and 303 (MD&A) offer a vehicle through which firms can signal competence, preparedness, innovation capacity, and regulatory awareness. Because these sections are principle-based and require tailored discussion of material risks and known trends, they allow managers to craft firm-specific signals that differentiate them from peers.

For crypto-centric firms, extensive disclosure may serve as a credibility mechanism, demonstrating to regulators and investors that the firm recognizes and

actively manages the unique risks of digital-asset operations. Similarly, firms with moderate or emerging crypto exposure may strategically highlight such activities to signal technological relevance or alignment with evolving market trends. Conversely, firms with minimal exposure may choose not to engage in such disclosure, implicitly signaling the absence of material crypto-related risks.

Signaling Theory therefore provides a coherent lens through which to interpret variation in crypto-related disclosure intensity. It suggests that differences in industry specialization, operational involvement, and treasury exposure shape the costs and benefits associated with disclosure and, by extension, the signaling strategies firms adopt. These signals have implications for investor attention, risk assessment, and ultimately, capital-market outcomes.

HYPOTHESES DEVELOPMENT

Building on Signaling Theory, firms' crypto-related disclosure choices can be interpreted as strategic responses to information asymmetry, technological uncertainty, and evolving regulatory expectations. Differences in industry positioning and operational involvement shape both the necessity and credibility of these signals, leading to predictable variation in disclosure intensity across firms.

H_1: Industry Specialization and Disclosure Intensity

Firms whose core business activities are deeply integrated with the crypto ecosystem—such as mining companies, blockchain infrastructure providers, and digital-asset exchanges, encounter heightened operational complexity and regulatory scrutiny. These firms operate in environments characterized by significant market volatility, evolving compliance requirements, and high technology-related risk. As a result, they face strong incentives to communicate their understanding and management of these risks through more extensive narrative disclosures.

Hypothesis 1 (**H_1**):

Firms operating in crypto-centric industries will disclose significantly more crypto-related information in their SEC Form 10-K filings than firms outside the crypto domain.

H_2: Operational Exposure and Transparency Incentives

Companies directly engaged in crypto-asset transactions—such as cryptocurrency custody, payment facilitation, trading services, or blockchain-based operations—confront diverse accounting, valuation, and compliance challenges. These firms must explain their approaches to volatility management, control environments, and evolving standards (such as ASU 2023-08), increasing the value of detailed, risk-oriented disclosures. The complexity of their operations makes disclosure a comparatively low-cost yet high-credibility signal of preparedness and transparency.

Hypothesis 2 (**H_2**):

The extent of a firm's operational exposure to digital assets is positively associated with crypto-related disclosure intensity in its SEC Form 10-K filings.

H_3: Strategic Signaling by Moderately Exposed Firms

Firms with limited or non-core crypto involvement may not face substantial crypto-specific risks, but they may still choose to highlight digital-asset initiatives as part of a broader innovation or market-positioning strategy. For these firms, crypto-related disclosures operate less as mandatory risk communication and more as discretionary strategic signaling aimed at appealing to investors who view digital assets as indicators of technological adaptability or growth potential.

Hypothesis 3 (**H_3**):

Firms with moderate crypto exposure will provide more crypto-related disclosure than firms with no exposure, consistent with the use of disclosure as a strategic signal of innovation and market relevance.

Conceptual Framework of Hypotheses:

Figure 1: Conceptual Framework

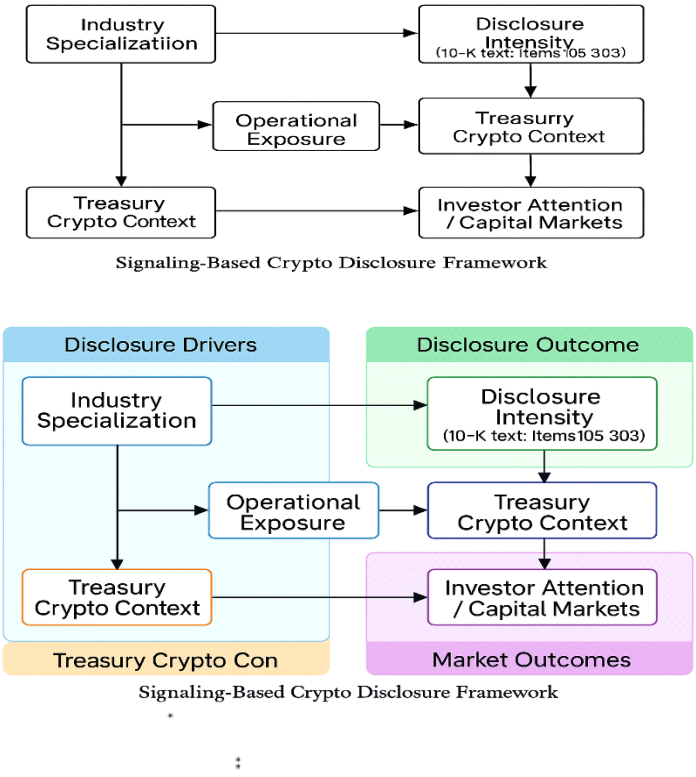
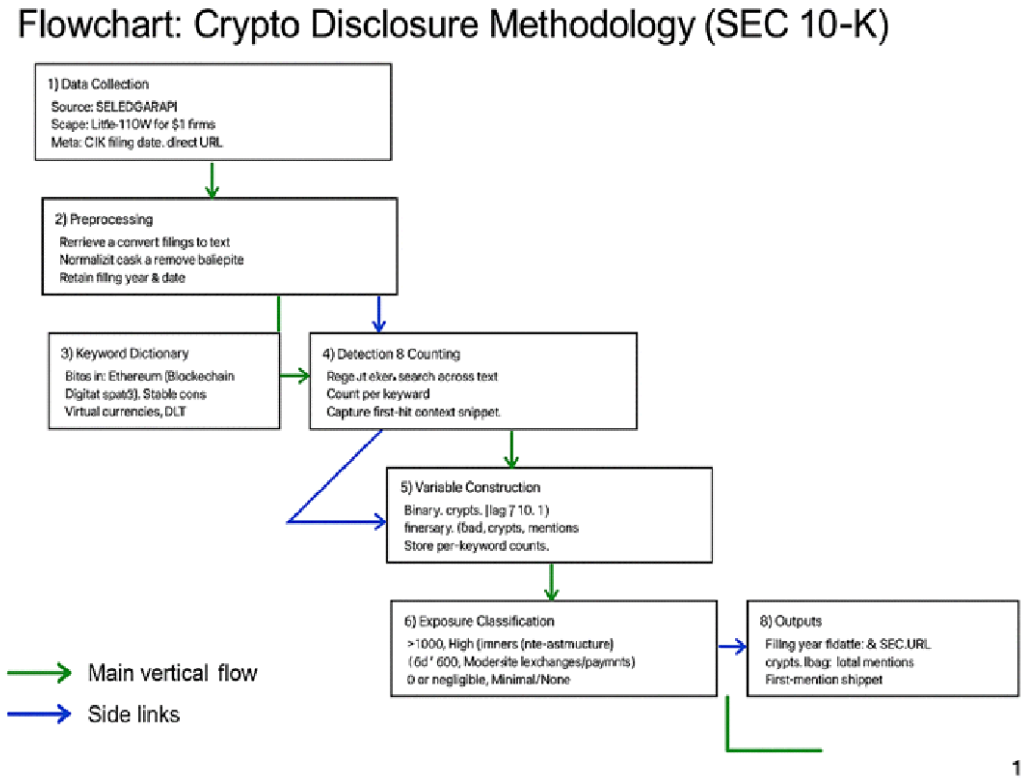


Figure 1 illustrates how industry specialization and operational exposure drive disclosure intensity in SEC Form 10-K filings, primarily through Risk Factors (Item 105) and MD&A (Item 303). Treasury crypto holdings (contextualized by ASU 2023-08 fair value requirements) interact with disclosure choices and influence investor attention and capital market outcomes.

METHODOLOGY

Figure 2 provides a graphical depiction of the methodology employed in this analysis from data collection to the final outputs.

Figure 2: Methodology Graphical Depiction



Data Collection and Sample Construction

The empirical analysis relies on a dataset constructed from SEC Form 10-K filings submitted by publicly traded firms with U.S. reporting obligations. Using the SEC EDGAR API, we retrieved the most recent annual filings available for a targeted set of thirty-one firms. The sample primarily reflects fiscal year 2025 filings, aligning the analysis with the adoption period of FASB ASU 2023-08, which introduced fair-value measurement and enhanced disclosure requirements for qualifying crypto assets.

Automated data retrieval ensured completeness of key metadata, including Central Index Key (CIK), filing date, and direct SEC filing links. After collection, all filings were converted into uniform, machine-readable text files. Standard preprocessing procedures were applied, including case normalization and the removal of boilerplate or formatting artifacts, to facilitate accurate text parsing and keyword detection. Filing-level

identifiers, such as reporting year and submission date, were preserved to maintain temporal comparability.

Identification of Crypto-Related Disclosures

To capture crypto-asset–related reporting, we developed a targeted keyword dictionary designed to reflect the breadth of terminology used in digital-asset discourse. Keywords included terms such as Bitcoin, Ethereum, digital assets, blockchain, stablecoins, virtual currencies, and distributed ledger technology. This dictionary served as the basis for identifying relevant references within each filing.

Regex-based pattern searches were used to detect occurrences of each keyword across full-text filings. For each firm, we computed keyword-specific counts and aggregated these values to form a measure of overall disclosure intensity. To support qualitative validation, we extracted the first contextual snippet in which each crypto-related term appeared, enabling us to verify that detected mentions reflected substantive references rather than unrelated text.

Measures of Crypto Exposure

Two primary indicators of crypto exposure were constructed:

Binary Exposure Indicator (crypto_flag):

A firm was assigned a value of 1 if its 10-K contained at least one crypto-related keyword, and 0 otherwise.

Disclosure Intensity (total_crypto_mentions):

This continuous measure represents the total frequency of all crypto-related keywords within a firm's filing.

These indicators capture both the presence and the magnitude of disclosure activity and support analysis of variation across firms with different operational profiles.

Classification of Firms by Exposure Level

To facilitate comparative analyses, firms were grouped into three exposure categories based on their observed disclosure intensity:

High exposure: More than 1,000 mentions, typically crypto miners and infrastructure providers with direct operational reliance on digital assets.

Moderate exposure: Approximately 100–900 mentions, generally exchanges, trading platforms, or payment-facilitation firms with meaningful but non-core crypto involvement.

Minimal or no exposure: Firms with a crypto_flag of 0 or negligible mention counts.

This classification reflects meaningful differences in business models and reporting incentives and allows for structured evaluation of disclosure heterogeneity.

Data Integrity and Limitations

To avoid survivorship or selection bias, firms lacking valid or retrievable 10-K filings including those with missing CIK identifiers or foreign reporting requirements were retained in the dataset with default exposure values of zero. Although this approach ensures a complete sample, there are limitations. Keyword-based detection may fail to capture nuanced references if firms use nonstandard terminology, and mention counts alone may not reflect the depth or significance of underlying activities.

Nonetheless, the combination of binary indicators, intensity measures, contextual snippets, and detailed metadata provides a robust foundation for analyzing patterns in corporate crypto-asset disclosures and their relationship to broader reporting and treasury practices.

RESULTS

Descriptive Statistics

The final sample consists of thirty-one firms, of which twenty-one had accessible and valid SEC Form 10-K filings retrieved through the EDGAR API. Among these firms, twenty included at least one crypto-related reference, while eleven showed no evidence

of crypto disclosure. The filings largely reflect fiscal year 2025 reporting, aligning the dataset with the post-implementation period of FASB ASU 2023-08, when firms were required to apply fair-value measurement and provide expanded disclosures for eligible crypto assets.

Table 1 summarizes key features of the sample:

Table 1: Sample Overview

Metric	Value
Total firms analyzed	31
Firms with valid SEC - 10K filings	21
Firms with crypto-related mentions	20
Firms with no crypto-related mentions	11
Filing years covered	FY 2025

This distribution indicates that crypto-asset reporting is becoming increasingly common among publicly traded U.S. firms, though emphasis varies widely across industries and business models.

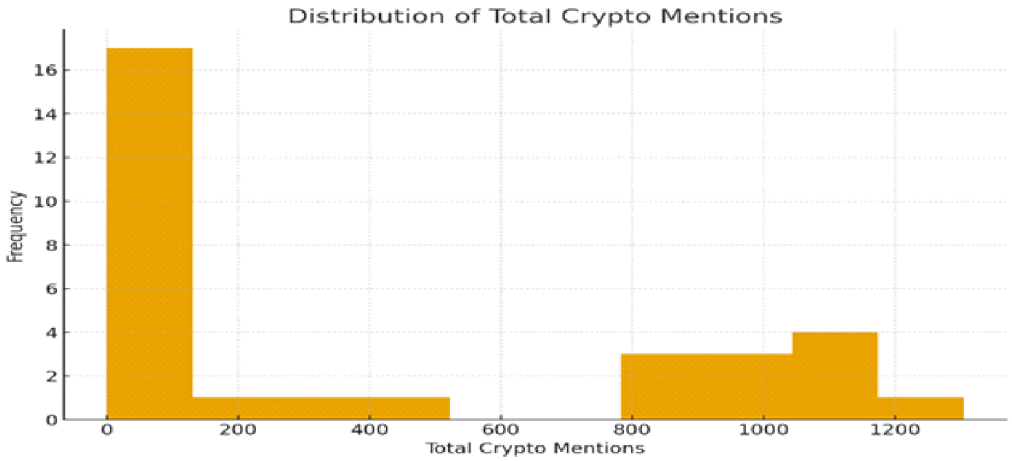
Crypto Disclosure Intensity

Disclosure intensity, measured as the total number of crypto-related keywords identified in each filing, shows substantial heterogeneity across firms. A small subset of companies, primarily those whose business models are centered on mining, blockchain infrastructure, or digital-asset services, reported exceptionally high mention frequencies (exceeding 1,000). This group includes firms such as IREN, CORZ, MSTR, CLSK, and CIFR.

A second tier of firms, generally exchanges, trading platforms, and payment-service providers (e.g., RIOT, BTBT, HOOD, COIN, BKKT, MELI), exhibited moderate disclosure intensity, with keyword counts ranging between approximately 100

and 900. These firms have meaningful operational or revenue-linked exposure to digital assets but do not operate solely within the crypto ecosystem.

Figure 3: Keyword Counts



In contrast, several firms, most notably Tesla, reported zero crypto-related mentions in their 2025 filings despite prior involvement in digital-asset markets. This absence suggests either a strategic de-emphasis of crypto activities or the lack of material exposure during the reporting period.

Interpretation of Observed Patterns

The distribution of disclosure intensity across the sample aligns with expectations from Signaling Theory and supports the directional predictions of the hypotheses.

Industry-integrated firms appear to use disclosure as a mechanism to convey legitimacy, risk awareness, and technological competence.

Operationally exposed firms disclose at levels consistent with the need to address accounting complexity, valuation uncertainty, and compliance considerations associated with digital-asset transactions.

Moderately exposed firms may employ disclosure strategically, using crypto-related language to position themselves as innovative or technologically progressive, even when crypto activities represent a small portion of their operations.

Firms with zero exposure demonstrate that crypto-related disclosure remains discretionary and context-dependent, reinforcing the principle-based nature of Regulation S-K Items 105 and 303.

Taken together, these patterns illustrate a tiered structure of disclosure behavior that reflects differences in business strategy, operational involvement, and perceived signaling benefits.

DISCUSSION

Synthesis of Findings and Links to Hypotheses

The results of the text-mining analysis reveal substantial variation in the intensity of crypto-related disclosures across firms, highlighting the differentiated environments in which firms operate and the strategic incentives shaping disclosure practices. These patterns broadly align with the theoretical expectations derived from Signaling Theory.

Firms positioned at the core of the crypto ecosystem, including miners, blockchain infrastructure providers, and other crypto-native entities, produce the most extensive disclosures. These organizations operate in high-uncertainty environments characterized by volatile asset prices, elevated regulatory attention, and evolving technological risks. Consequently, the cost of nondisclosure is higher, making robust reporting a credible mechanism for reducing information gaps. This finding directly supports $\mathbf{H}_1$, which predicts that firms in crypto-centric industries exhibit greater disclosure intensity due to heightened signaling incentives.

Similarly, firms with direct operational involvement in crypto-asset activities such as exchanges, custodial services, or payment-integrated platforms, provide detailed narrative disclosures that reflect the complexity of their underlying transactions and risk environments. Their elevated but more moderate mention counts corroborate $\mathbf{H}_2$, which anticipates that operational exposure increases the need for transparency and reduces the

cost of providing granular disclosures. These findings are consistent with models of discretionary disclosure under information asymmetry, which suggest that firms are more likely to disclose voluntarily when doing so improves investor understanding and helps mitigate perceived risk.

Finally, firms with moderate exposure, organizations that interact with digital assets peripherally or strategically rather than as a core operational component, appear to use crypto-related disclosures in a more selective and strategic manner. Their disclosure patterns suggest an intent to signal adaptability, technological sophistication, or alignment with evolving market trends. This behavior is consistent with $\mathbf{H}_3$, which posits that firms with moderate exposure employ narrative disclosures as low-cost signals of innovation and relevance, even when crypto activities do not constitute a significant portion of their operations.

Firms with no exposure, meanwhile, adopt a silence strategy, offering no crypto-related disclosure—a reminder that disclosure under Regulation S-K Items 105 and 303 remains fundamentally judgment-based. Taken together, these patterns underscore the heterogeneous incentives that shape crypto-asset reporting across different categories of firms.

Implications for Accounting, Regulation, and Reporting Practice

The varied disclosure strategies observed across the sample provide important insights into how firms are responding to the emergence of ASU 2023-08 and the broader regulatory environment surrounding digital assets. The presence of expansive narrative disclosure among highly exposed firms suggests that fair-value measurement requirements may increase the credibility and verifiability of crypto-related reporting. Because audited financial statement notes now provide standardized recognition and measurement of crypto assets, narrative disclosures in Items 105 and 303 carry more weight by serving as complementary contextual explanations rather than standalone claims.

At the same time, the discretion embedded in principle-based disclosure requirements allows firms substantial flexibility in framing their risk narratives. This

discretion can enhance signal precision for firms seeking to differentiate themselves but may also lead to inconsistencies in disclosure depth or clarity across the market. Investors reviewing these filings must therefore interpret disclosures within the broader context of firm-specific business models, operational risk profiles, and treasury strategies.

The observed variability in disclosure intensity also has implications for regulators. As digital-asset adoption expands, regulators may consider whether the current principles-based approach adequately captures the risks posed by crypto holdings or whether more prescriptive guidance may enhance comparability and transparency. Differences in disclosure depth across firms with similar business models suggest that market practice has not yet converged on a standardized approach to crypto-asset reporting.

Capital-Market and Stakeholder Implications

Crypto-related disclosures are likely to influence how investors, analysts, and other stakeholders interpret firms' risk profiles, liquidity management strategies, and exposure to emerging technologies. Higher disclosure intensity may attract greater investor attention, potentially leading to increased analyst coverage or more frequent information downloads from EDGAR. Conversely, firms with limited or ambiguous disclosures may face higher uncertainty premiums or greater scrutiny in capital markets.

These effects mirror patterns documented across the broader disclosure literature, where detailed and firm-specific narrative reporting is associated with greater transparency and narrower information asymmetry. The unique risks associated with crypto assets—valuation uncertainty, operational failures, regulatory intervention, and cybersecurity vulnerabilities—heighten the importance of clear and credible reporting in this domain.

Limitations and Directions for Future Research

Although the study provides clear evidence of systematic variation in crypto-related disclosure practices, several methodological limitations should be acknowledged. Reliance on keyword frequencies may obscure qualitative distinctions

between boilerplate references and substantive, risk-focused narratives. Additionally, firms may use nonstandard terminology or embed crypto-related discussions in sections not captured by keyword-based parsing. Future research could address these issues by incorporating section-weighted analysis, context-aware natural language processing techniques, or supervised machine-learning models capable of distinguishing disclosure types.

Expanding the dataset across multiple fiscal years would also allow for investigation of temporal trends, especially given the relatively recent implementation of ASU 2023-08. Linking disclosure patterns to market outcomes, such as abnormal returns, bid-ask spreads, or changes in analyst sentiment, could help establish whether crypto-related disclosures have measurable effects on investor behavior. Finally, integrating earnings call transcripts or other voluntary disclosures could provide a more holistic view of firms' communication strategies surrounding digital-asset activities.

CONCLUSION

This study provides new evidence on how U.S. public firms disclose crypto-asset activities within SEC Form 10-K filings and how such disclosures relate to differences in industry positioning, operational exposure, and treasury strategy. By integrating text-mining methods with a signaling-theoretic framework, we show that disclosure practices surrounding digital assets are far from uniform. Instead, they follow a structured pattern shaped by firms' economic incentives, technological involvement, and the regulatory environment shaped by ASU 2023-08.

Crypto-centric firms, which face the greatest operational and regulatory complexity, produce the most extensive disclosures, using narrative reporting as a mechanism for demonstrating legitimacy and readiness in a high-uncertainty environment. Firms with direct operational involvement, such as exchanges and custodial platforms, also provide elevated levels of detail, consistent with transparency incentives associated with complex and evolving accounting requirements. Firms with moderate exposure, by contrast, appear to employ disclosure more selectively, using crypto-related narratives to communicate innovation and strategic positioning rather than direct risk

mitigation. These findings highlight the flexibility inherent in Regulation S-K's principle-based disclosure regime and the diverse signaling strategies firms employ within it.

Our results underscore the growing importance of digital-asset reporting in contemporary corporate communication and point to several implications. For regulators, the variability in disclosure depth raises questions about whether current standards provide sufficient comparability and investor protection as crypto adoption expands. For investors and analysts, the findings suggest that crypto-related disclosures convey meaningful information about firms' operational risk profiles, treasury practices, and strategic orientations. For researchers, the study illustrates the value of text-analytic approaches in examining emerging areas of financial reporting and offers a foundation for future work linking disclosure patterns to market outcomes and regulatory responses.

As the digital-asset landscape continues to evolve, so too will the reporting and oversight frameworks that govern it. This study contributes an early empirical lens on how firms navigate this transition and highlights the need for continued research on the intersection of technology, regulation, and financial reporting behavior.

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Can Artificial Intelligence Improve Credit Decisions? Evidence from Large-Scale Lending Data

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Abstract

This study examines the use of machine learning for predicting default risk within the U.S. Small Business Administration (SBA) 7(a) loan program using publicly available loan-level data obtained through the Freedom of Information Act (FOIA). Using 488,772 resolved loans originated over fifteen fiscal years from FY2010 through FY2024, the study compares a traditional logistic regression benchmark with Random Forest, Gradient Boosting, and an ensemble model. Gradient Boosting produces the strongest out-of-time predictive performance, achieving an area under the receiver operating characteristic curve (AUC-ROC) of 0.9178 compared with 0.7641 for the logistic regression benchmark, representing a 20.1% relative improvement. The model also reduces the Brier Score by 44.5%, indicating substantially more accurate probability forecasts. Loan term, initial interest rate, and the SBA guarantee ratio emerge as important predictors of default. Default outcomes also vary considerably across industries, with Transportation (9.84%), Arts and Entertainment (9.70%), and Wholesale Trade (8.52%) exhibiting the highest default rates, while Agriculture (4.09%), Finance and Insurance (4.60%), and Healthcare (4.81%) exhibit the lowest. Across the study period, among the resolved-loan sample has an overall default rate of 7.47%, with annual rates ranging from 5.48% in FY2013 to 16.27% in FY2023. The findings demonstrate the potential value of machine learning for credit risk prediction in government-guaranteed small business lending while highlighting the importance of out-of-time model validation. More broadly, the study provides evidence relevant to SBA policymakers, participating lenders, and the responsible development of AI-assisted credit risk assessment tools for small business lending.

Keywords: SBA 7(a) loans, credit risk, machine learning, gradient boosting, random forest, default prediction, small business lending, FinTech

Introduction

Small business lending plays an important role in the U.S. economy by providing entrepreneurs and established firms with access to capital for business formation, operations, investment, and expansion. The U.S. Small Business Administration (SBA) defines eligibility as a small business according to industry-specific size standards, which are generally based on either the number of employees or average annual receipts. Because these thresholds vary by industry, there is no single size criterion that applies uniformly to all businesses participating in SBA programs. This industry-specific approach recognizes the considerable differences in operating scale and market structure across sectors of the U.S. economy.

The economic significance of small businesses in the United States is substantial. They account for approximately 99.9% of U.S. firms, employ nearly half of the private-sector workforce, and have contributed a considerable share of net new employment in recent decades (SBA Office of Advocacy, 2023). Despite their importance, access to credit remains a persistent challenge for many small businesses. Compared with larger firms, small businesses often have shorter credit histories, less extensive financial information, and fewer assets available as collateral. These characteristics can increase information asymmetry between borrowers and lenders, making it more difficult to assess creditworthiness and distinguish between higher- and lower-risk borrowers. Such information constraints can contribute to credit rationing or limit access to financing for otherwise viable businesses. These challenges remain relevant in government-guaranteed lending programs, where the guarantee reduces a participating lender's exposure to potential losses but does not eliminate credit risk or the need for effective borrower assessment. Improving the ability to identify and predict default risk is therefore important both for expanding access to small business credit and for maintaining the financial sustainability of government-supported lending programs.

In FY2023, the SBA 7(a) program, the agency’s primary loan guarantee program for small businesses, supported approximately $27.5 billion in lending. By guaranteeing a portion of eligible loans, the SBA reduces the credit risk borne by participating lenders and helps expand access to financing for small businesses that may have difficulty meeting conventional lending requirements. Given the scale of the program and its broader economic and public policy

significance, understanding the factors associated with loan performance and default is important for both lenders and policymakers. Yet, empirical research examining credit risk within the 7(a) program remains relatively limited, particularly studies that make use of comprehensive loan-level data released through the Freedom of Information Act (FOIA). As a result, there is considerable scope for further examination of default patterns across borrowers, industries, lenders, and loan characteristics.

At the same time, advances in artificial intelligence (AI) and machine learning (ML) have expanded the range of methods available for credit risk assessment. A growing empirical literature suggests that ML approaches can provide improved predictive performance relative to conventional statistical models, including logistic regression, across a variety of lending settings (Berg et al., 2020; Jagtiani & Lemieux, 2019; Moscatelli et al., 2020). These methods are particularly useful when default risk reflects nonlinear relationships or complex interactions among borrower, loan, and market characteristics that may be difficult to specify in advance using traditional model structures.

Despite the increasing use of machine learning in credit markets, its application to SBA 7(a) lending remains comparatively underexplored. Existing research on SBA lending has primarily examined the determinants of loan performance using traditional econometric approaches, while relatively limited evidence exists on the predictive performance of machine learning models using large-scale, longitudinal 7(a) loan data. This gap provides an opportunity to examine whether contemporary predictive methods offer additional value in identifying default risk within a major government-guaranteed small business lending program and whether their performance extends to loans originated under changing economic and credit conditions.

This study addresses this gap by developing and evaluating four credit risk models using a sample of 488,772 fully resolved SBA 7(a) loans originated between FY2010 and FY2024. The analysis draws on official loan-level disclosure data obtained from the SBA through the Freedom of Information Act (FOIA). Logistic regression is used as the traditional benchmark and is compared with three machine learning approaches: Random Forest, Gradient Boosting, and an ensemble model. To provide a more realistic assessment of predictive performance, the data are divided chronologically rather than through a random train-test split. Loans originated between

FY2010 and FY2020 are used for model training, while loans from FY2021 through FY2024 form the out-of-sample test period. This approach more closely reflects the setting in which a credit risk model developed using historical lending experience would be applied to subsequent loan originations. It also reduces the potential for information leakage between the training and testing samples. Beyond comparing model performance, the study examines differences in default risk across industries, loan sizes, business structures, and SBA loan processing methods, providing additional insight into the factors associated with credit outcomes within the 7(a) program.

Our study makes several contributions to the literature. First, it provides a comprehensive empirical examination of default risk within the SBA 7(a) loan program using population-level microdata obtained through the Freedom of Information Act (FOIA). The breadth of the dataset allows default patterns to be examined across a large and diverse set of government-guaranteed small business loans. Second, the study compares the predictive performance of traditional logistic regression with several machine learning methods, providing evidence on whether more advanced modeling approaches offer meaningful improvements in identifying default risk in government-backed small business lending. Third, the findings identify industries, loan characteristics, and program features that are associated with a greater likelihood of default. These results have practical relevance for SBA policymakers and participating lenders, as well as for financial technology firms seeking to incorporate AI-assisted tools into small business credit assessment and underwriting. Across the 488,772 resolved loans included in the analysis, the Gradient Boosting model achieved an out-of-time AUC-ROC of 0.9178, compared with 0.7641 for logistic regression, representing a 20.1% improvement in discriminatory power. It also reduced the Brier score by 44.5%, indicating substantially more accurate probability forecasts.

Literature Review

Credit Risk Modeling in Small Business Lending

The literature on credit risk and small business lending has developed considerably over the past several decades, although relatively few studies have examined default risk using large-scale data from government-guaranteed lending programs. Early contributions by Altman (1968) and Ohlson (1980) helped establish discriminant analysis and logistic regression as

important quantitative approaches for assessing financial distress and default risk. These methods provided the foundation for much of the subsequent empirical work in credit risk modeling. Small business lending, however, presents challenges that are not always fully captured by conventional quantitative models. Unlike larger firms, small businesses often have less extensive financial records, shorter credit histories, and greater variation in the quality and availability of borrower information. Research has therefore emphasized the importance of relationship lending and soft information in evaluating small business borrowers. Frame et al. (2001) and Berger and Udell (2006), for example, show that information developed through interactions between lenders and borrowers can play an important role in small business credit decisions, particularly among community and relationship-oriented banks. Such information may capture aspects of borrower quality that are difficult to observe through financial statements and conventional credit measures alone. This distinction is important because it highlights both the value and the limitations of traditional quantitative approaches when applied to small business credit risk.

Within the SBA lending literature, Glennon and Nigro (2005) used microdata from the SBA 7(a) program to examine factors associated with loan default. Their findings indicate that loan maturity, lender characteristics, and the geographic location of the borrower were among the factors associated with default outcomes. Kalnins and Williams (2014) also used SBA data, focusing on the survival of small businesses and differences associated with ownership structure. While these studies provide important insights into SBA lending and borrower outcomes, they rely on data from earlier periods and predominantly employ traditional econometric techniques. As a result, there remains an opportunity to revisit default risk within the SBA 7(a) program using more extensive loan-level data and contemporary machine learning methods that can capture nonlinear relationships and interactions that may be difficult to identify using conventional statistical models.

Machine Learning in Credit Scoring

The application of machine learning (ML) to credit risk assessment has expanded considerably over the past decade as financial institutions have sought more flexible and accurate methods for evaluating borrowers. A growing empirical literature suggests that ML models can improve default prediction relative to traditional statistical approaches, particularly when large and diverse datasets are available. Berg et al. (2020), for example, demonstrate that models

incorporating digital footprint information can provide substantial predictive value in consumer credit assessment. Jagtiani and Lemieux (2019) find that alternative data and proprietary modeling approaches used by fintech lenders can contribute information beyond traditional credit bureau measures, particularly for borrowers with limited credit histories. Similarly, Moscatelli et al. (2020) provide evidence that machine learning techniques can improve the prediction of corporate credit risk relative to conventional statistical models.

An important advantage of machine learning is its ability to identify relationships that may be difficult to capture through traditional credit scoring approaches. Conventional credit assessment generally relies on a defined set of borrower and financial characteristics, including repayment history, credit utilization, outstanding obligations, length of credit history, and recent credit activity. Models such as logistic regression remain widely used because they are relatively transparent, computationally efficient, and straightforward to interpret. Their performance, however, can depend on how relationships among explanatory variables are specified. Unless nonlinearities and interaction effects are explicitly incorporated into the model, potentially important patterns in the data may remain unidentified (Lessmann et al., 2015).

Machine learning methods provide a different approach by allowing relationships to be learned more flexibly from the data. Tree-based methods such as Random Forest and Gradient Boosting can accommodate nonlinearities, interactions, and threshold effects without requiring each relationship to be specified in advance. Random Forest generates predictions by combining results across multiple decision trees, while Gradient Boosting builds trees sequentially, with each new model attempting to improve upon errors made by the preceding models. These characteristics can be particularly useful in credit risk applications where default may reflect complex interactions among borrower characteristics, loan terms, economic conditions, and other risk factors (Butaru et al., 2016; Moscatelli et al., 2020).

The distinction between traditional statistical modeling and machine learning also reflects differences in their primary objectives. Econometric models are frequently used for both prediction and statistical inference, allowing researchers to estimate and interpret relationships between individual explanatory variables and an outcome of interest. Machine learning methods place greater emphasis on predictive performance, particularly the ability of a model to generalize to observations that were not used during estimation. Techniques such as

cross-validation, regularization, and out-of-sample testing are commonly employed to limit overfitting and assess how well a model performs on new data. Comparative studies generally find that logistic regression remains a useful and competitive benchmark in credit risk applications, while tree-based and ensemble methods can provide additional predictive gains when relationships in the data are nonlinear or involve complex interactions (Lessmann et al., 2015; Butaru et al., 2016).

Taken together, the existing literature provides substantial evidence that machine learning can complement traditional approaches to credit risk assessment (Lessmann et al., 2015; Butaru et al., 2016; Berg et al., 2020; Jagtiani & Lemieux, 2019; Moscatelli et al., 2020). Much of this evidence, however, comes from consumer, fintech, and commercial credit markets. Comparatively less attention has been given to government-guaranteed small business lending, where borrower characteristics, lender incentives, and program requirements may produce different patterns of credit risk. The SBA 7(a) program therefore provides a useful setting in which to examine whether the predictive advantages documented elsewhere in the credit literature extend to government-guaranteed small business loans. The present study contributes to this literature by comparing logistic regression with Random Forest, Gradient Boosting, and an ensemble approach using a large population of SBA 7(a) loans.

SBA 7(a) Program and Default Risk

Research on the SBA 7(a) loan program has generally focused on how lender characteristics, borrower attributes, loan terms, and program design influence loan performance. Craig et al. (2008), for example, find that lenders with greater experience in SBA lending tend to have lower default rates, suggesting that repeated participation may contribute to stronger borrower screening and underwriting practices. Their findings point to the importance of specialized lending expertise and institutional learning in determining loan outcomes. Cole and Dietrich (2012) similarly document variation in loan performance across industries and geographic areas, indicating that local economic conditions, industry characteristics, and regional business environments can influence repayment outcomes.

The broader literature identifies several factors associated with small business loan performance. Borrower characteristics, including business age, financial condition, credit history,

and managerial experience, can influence default risk. Loan-specific features such as size, maturity, collateral, guarantee percentage, and interest rate may also affect repayment outcomes. At the same time, broader economic conditions, including employment trends, economic growth, and regional business activity, can influence the financial capacity of small firms to meet their debt obligations. Taken together, this literature suggests that small business loan performance is shaped by a combination of borrower, lender, loan, industry, and economic characteristics rather than by any single factor.

Credit risk assessment within the SBA 7(a) program is further influenced by the program's institutional structure. Unlike conventional commercial lending, eligible 7(a) loans receive a partial federal guarantee, which reduces the lender's exposure to losses while supporting access to financing for small businesses that may otherwise face difficulty obtaining credit on reasonable terms. The presence of a guarantee, however, does not eliminate credit risk or the need for effective borrower screening and monitoring. Accurate assessment of repayment capacity therefore remains important to participating lenders and to policymakers responsible for maintaining the effectiveness and financial sustainability of the program.

A related body of SBA research has examined the Paycheck Protection Program (PPP), which was established as a temporary emergency assistance program during a period of significant economic disruption. Although administered by the SBA, PPP differed substantially from the traditional 7(a) program in both its objectives and design. The program was intended primarily to provide rapid financial support to eligible businesses and incorporated streamlined eligibility requirements, expedited processing, and provisions for loan forgiveness. Consequently, the credit assessment and repayment considerations associated with PPP loans differ from those underlying traditional 7(a) lending. Findings from the PPP literature therefore provide useful evidence on emergency small business financing but are less directly applicable to the study of long-term default risk within the 7(a) program.

Despite considerable research on the determinants of SBA loan performance, relatively few studies have applied contemporary machine learning methods to default prediction using large, longitudinal datasets from the 7(a) program. Much of the existing empirical literature relies on traditional econometric approaches, including logistic regression and survival analysis. These

methods remain valuable for estimation and inference but may require researchers to specify nonlinear relationships and interactions among explanatory variables explicitly. In a lending environment as heterogeneous as the SBA 7(a) program, relationships among borrower characteristics, lender behavior, loan terms, industry conditions, and default outcomes may be more complex. Machine learning methods, particularly tree-based ensemble approaches such as Random Forest and Gradient Boosting, provide a flexible means of identifying such relationships without requiring them to be specified in advance (Lessmann et al., 2015; Butaru et al., 2016).

This study extends the existing literature by examining whether machine learning methods provide additional predictive value in assessing default risk within the SBA 7(a) program. Using 488,772 fully resolved loans originated over fifteen fiscal years, the analysis compares a traditional logistic regression benchmark with Random Forest, Gradient Boosting, and an ensemble model. The study therefore brings contemporary predictive methods to a large government-guaranteed small business lending dataset while preserving a direct comparison with a widely used traditional credit risk model. In doing so, it provides additional evidence on the determinants and prediction of default risk within the SBA 7(a) program and contributes to the broader literature on the application of machine learning to small business credit assessment.

Data

Source and Sample Construction

Data for this study were obtained from the U.S. Small Business Administration (SBA) Freedom of Information Act (FOIA) public loan disclosure files available through the SBA web portal. The SBA publishes loan-level information on loans originated under the 7(a) program and periodically updates these disclosure files. For this study, data covering fiscal years (FY) 2010 through FY2024 were compiled by combining the SBA's FY2010–FY2019 historical disclosure file with the subsequent active disclosure files available as of March 31, 2026.

The study period begins in FY2010, the first full fiscal year following the 2008–2009 Global Financial Crisis and a period of significant changes in federal small business lending policy under the American Recovery and Reinvestment Act (ARRA). Beginning in FY2010 provides a clearer post-crisis starting point and reduces the potential influence of the exceptional

lending conditions that characterized the financial crisis. Extending the sample through FY2024 provides a fifteen-year observation window encompassing different economic and credit environments, including the post-recession recovery, an extended period of economic expansion, a period of substantial economic disruption, subsequent increases in interest rates and tighter financial conditions, and the adjustment of lending markets that followed. This extended time horizon provides an opportunity to evaluate SBA loan performance across substantially different economic conditions.

The combined raw dataset contains 815,187 loan observations covering FY2010 through FY2024. To construct a clearly defined binary outcome for supervised classification, the analytic sample is restricted to loans with resolved repayment outcomes: Paid in Full (PIF) or Charged Off (CHGOFF). Loans reported with unresolved or intermediate statuses, including CURR, EXEMPT, COMMIT, LIQUID, DELINQ, PSTDUE, and DEFERD, are excluded because their ultimate repayment outcomes cannot yet be determined from the available data. Including such observations would introduce uncertainty into the dependent variable and, for loans that remain active, raise concerns related to right censoring. Restricting the modeling sample to resolved loans therefore ensures that each observation used for model estimation and evaluation has an observed repayment outcome.

Cancelled loans (CANCLD) are also excluded because these loans do not represent completed credit outcomes and therefore provide limited information about subsequent borrower repayment performance. After applying these criteria, the final analytic sample consists of 488,772 resolved loans, representing approximately 59.9% of the 815,187 observations in the original dataset. The dependent variable is consequently defined as a binary measure distinguishing loans that were paid in full from those that resulted in a charge-off.

The resulting dataset provides a large longitudinal sample of observed SBA 7(a) loan outcomes across fifteen fiscal years. Its size and time coverage make it particularly suitable for evaluating whether machine learning methods provide incremental predictive value relative to traditional credit risk models. At the same time, restricting the analysis to loans with resolved outcomes is an important sample consideration, particularly for loans originated in the later years of the study period, which have had less time to reach a final repayment status. This issue is addressed in the empirical design and should be considered when interpreting the findings.

A Note on Sample Resolution and Right-Censoring

Restricting the sample to loans with fully resolved outcomes (PIF or CHGOFF) introduces a right-censoring consideration for the most recent vintage years. SBA 7(a) loans carry terms of up to 300 months, and a charge-off typically follows a period of delinquency and workout; loans originated in FY2022–FY2024 have therefore had comparatively little time to reach a resolved status relative to earlier vintages. Consequently, the FY2021–FY2024 test-period default rate (9.82%) is more likely to reflect loans that defaulted quickly than the eventual full default experience of these vintages, which may understate the long-run default rate for the most recent cohorts and could affect the calibration, though less the rank-ordering, of out-of-time performance. We view the reported AUC-ROC and KS statistics, both threshold-independent measures of relative risk ranking, as more robust to this form of censoring than the absolute default-rate and Brier Score figures, and we flag this as an important caveat for readers applying these results to loss forecasting rather than risk ranking.

Outcome Variable

The binary outcome variable Default is coded 1 for loans reported as CHGOFF (Charged Off), and 0 for loans with status PIF (Paid in Full). This definition is consistent with standard practice in SBA credit risk research (Glennon & Nigro, 2005; Cole & Dietrich, 2012). The overall default rate in our sample is 7.47% (n = 36,494 defaults out of 488,772 resolved loans).

Features and Predictors

We construct predictor variables from the raw SBA FOIA fields, organized into four categories:

- Loan Structure: Log of gross loan amount, SBA guarantee ratio (SBA guaranteed amount / gross approval), loan term in months, initial interest rate, fixed vs. variable rate indicator, revolver vs. term loan indicator, and collateral indicator.
- Lender/Program Characteristics: Processing method classification (grouped as Preferred Lenders, Express Programs, Community Advantage, and Standard 7(a)), and secondary market sale indicator.

- Borrower Characteristics: Business type (Corporation, Individual, Partnership), and business age classification (New Business / Startup vs. Established, available from FY2018 forward).
- Sector and Geography: NAICS two-digit sector dummies (18 sectors) capturing industry-level systematic risk. State-level variation is captured implicitly through sector composition.

Variable Availability, Missing Data, and Model Tuning

All loan characteristics, lender and program variables, and industry classifications included in the analysis are obtained directly from the SBA FOIA disclosure files and reflect information recorded at the time of loan approval or origination. Two variables, however, require additional explanation. First, the business age classification, which distinguishes New Business/Startup from Established firms, is available only for loans originated in FY2018 and later. Rather than imputing values for earlier loans, observations from FY2010–FY2017 are retained as a separate Not Reported category. As a result, the estimated effect of business age is driven primarily by loans originated between FY2018 and FY2024. Second, the indicator for secondary market sale reflects the status reported in the SBA disclosure files. Because some loans may have been sold after the original underwriting decision, this variable should be interpreted as being associated with realized loan performance rather than as a characteristic available to lenders at the time of loan approval.

Missing data are minimal for the principal loan characteristics used in the analysis, including loan amount, interest rate, loan term, and guarantee ratio. Observations with missing values for these variables are removed using listwise deletion because the number of affected loans is very small. The only variable with a meaningful level of missing data is the NAICS industry classification, which is unavailable for approximately 1.6% of loans. These observations are excluded only from the industry-level analyses and summary tables.

The Random Forest and Gradient Boosting models were estimated using hyperparameter values commonly reported in the credit risk literature for datasets of similar size and class distribution. Rather than conducting an extensive grid search, we selected well-established parameter settings and evaluated their stability using five-fold cross-validation in addition to the

holdout test sample. The cross-validation results provide evidence that the selected model specifications perform consistently across different data partitions.

Predicted default probabilities are reported directly from each model without additional probability calibration. Consequently, the reported Brier Scores reflect the models' raw probability estimates rather than values adjusted through post-estimation techniques such as Platt scaling or isotonic regression. Future research could explore systematic hyperparameter optimization and probability recalibration, particularly in applications where accurately calibrated default probabilities are required for capital allocation, reserve estimation, or regulatory risk management, rather than solely for ranking borrowers by credit risk.

Table 1: Descriptive statistics for the key continuous variables in the analytic sample for key variable, SBA 7(a) Resolved Loans FY 2010-FY2024.

Variable	N	Mean	Std Dev	Min	Median	Max
Gross Loan Amount ($)	488,772	$366,599	$680,270	$1,000	$109,000	$5,000,000
SBA Guarantee Ratio	488,772	0.65	0.15	0.08	0.50	1.00
Initial Interest Rate (%)	488,772	6.60%	1.72%	0.00%	6.00%	16.50%
Loan Term (Months)	488,772	119.6	76.8	1	120	300
Jobs Supported	488,772	10.65	20.54	0	4	2,150
Default (0/1)	488,772	0.0747	0.263	0	0	1

Methodology

Temporal Train-Test Split

To simulate realistic model deployment and avoid data leakage, a critical concern in credit risk model evaluation (Japkowicz & Shah, 2011), we employ a temporal holdout design rather than random cross-validation. We train all models on FY2010–FY2020 observations (n = 444,716) and evaluate performance on the out-of-time test set comprising FY2021–FY2024 (n = 44,056). This design tests whether models estimated on pre-pandemic data generalize to the post-pandemic credit environment, which saw elevated default rates in FY2022–FY2023. The training default rate is 7.23%; the test set default rate is 9.82%, reflecting the challenging post-pandemic economic environment.

Model Specifications

To evaluate the predictive performance of traditional statistical methods relative to modern machine learning algorithms, we estimate four competing models that represent increasing levels of model complexity and predictive capability. The selected models are among the most widely used approaches in credit risk analytics and provide a comprehensive comparison between interpretable benchmark methods, ensemble learning algorithms, and hybrid predictive frameworks.

- Model 1 - Logistic Regression (Benchmark): Estimated using the five traditional loan structure variables (log loan amount, interest rate, term, collateral, and guarantee ratio) with standardized inputs. Logistic regression serves as the benchmark because it remains the dominant statistical approach used in consumer and commercial credit risk modeling due to its simplicity, interpretability, and regulatory acceptance. The model represents a parsimonious traditional underwriting scorecard analogous to those employed by many community banks and provides an appropriate baseline against which the performance gains of machine learning methods can be evaluated.
- Model 2 - Random Forest: An ensemble of 200 decision trees estimated using the full 19-variable feature set plus NAICS sector indicator variables. Model parameters include a maximum tree depth of 10, a minimum of 50 observations per terminal node, balanced class weighting to address the 92.5%/7.5% class imbalance, and bootstrap aggregation with $\sqrt{p}$ randomly selected predictors at each split. Random Forest was selected because it effectively captures nonlinear relationships and high-order interactions while reducing overfitting through bootstrap aggregation. It also provides robust performance in high-dimensional credit datasets and is relatively insensitive to multicollinearity and outliers.
- Model 3 - Gradient Boosting: Estimated using 200 sequential boosting iterations on the same full feature set with a maximum tree depth of 4, learning rate of 0.05, and subsample ratio of 0.80. Gradient Boosting was selected because it has consistently demonstrated superior predictive performance in the credit risk literature (Lessmann et al., 2015; Butaru et al., 2016). Unlike Random Forest, Gradient Boosting builds trees sequentially, with each successive tree correcting the residual errors of the previous iteration. This iterative learning process enables the model to capture complex nonlinear relationships, subtle variable

interactions, and heterogeneous borrower behavior that traditional statistical models cannot adequately represent.

- Model 4 - Ensemble: Estimated as the simple average of the predicted probabilities generated by the Random Forest and Gradient Boosting models. Ensemble learning was selected because combining predictions from complementary algorithms often improves generalization performance by reducing model variance while preserving predictive accuracy. Random Forest contributes stability through bagging, whereas Gradient Boosting contributes lower bias through sequential optimization. Averaging their predictions exploits this diversity and has been shown to produce more robust and reliable predictions than individual models in many classification applications.

Together, these four models represent progressively more sophisticated approaches to credit risk prediction, allowing us to assess whether the additional complexity of machine learning algorithms yields statistically and economically meaningful improvements over conventional credit scoring methodologies.

Evaluation Metrics

We report three complementary performance metrics. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) measures rank-order discrimination between defaulted and non-defaulted loans across all classification thresholds, a threshold-independent measure widely used in credit scoring (Hand, 2009). The Kolmogorov-Smirnov (KS) statistic measures the maximum separation between the cumulative distributions of defaulted and non-defaulted loan predicted scores, the standard metric in banking regulatory practice. The Brier Score measures the mean squared error of predicted default probabilities, rewarding both discrimination and calibration. A threshold-optimal classification at the predicted probability maximizing the F1 score is also reported for the best-performing model.

Model Training Process and Performance Advantage Over Traditional Methods

Overview of the Training Pipeline

This section explains how each model is developed, the main steps involved in the training process, and the additional capabilities offered by Gradient Boosting relative to

traditional logistic regression. All models use the same time-based sample design. The training sample includes 444,716 loans originated between FY2010 and FY2020, of which 32,169 defaulted, producing a default rate of 7.23%. Model performance is then evaluated using a separate holdout sample of 44,056 loans originated between FY2021 and FY2024. This test sample contains 4,325 defaults and has a default rate of 9.82%.

The temporal split is intended to reflect a realistic lending environment in which a model is estimated using historical information and then applied to loans originated in later periods. Training the models on pre-2021 observations and evaluating them on subsequent loan vintages provides a more demanding test of out-of-sample performance, particularly because the holdout period includes the economic disruptions and changing credit conditions associated with and following the 2020 pandemic. This approach more closely resembles how a model developed at the end of FY2020 would have performed after deployment in FY2021. It also avoids the overly optimistic performance estimates that can arise from random train-test splits, which may place loans from the same economic period in both the training and test samples.

Step 1: Logistic Regression (The Traditional Benchmark)

Logistic regression remains the workhorse of conventional credit scoring. Model estimation proceeds in three stages. First, five predictor variables are selected through expert judgment: the natural logarithm of loan amount, initial interest rate, loan term in months, a binary collateral indicator, and the SBA guarantee ratio. Second, all predictors are standardized to zero mean and unit variance prior to estimation. Third, a single coefficient per predictor is estimated by maximizing the log-likelihood function across all 444,716 training observations.

The resulting scoring equation takes the canonical form:

$$P(default) = \frac{1}{1+e^{-z}}, z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5$$

where x_1 = log (loan amount), x_2 = initial interest rate, x_3 = loan term, x_4 = collateral indicator, and x_5 = SBA guarantee ratio.

This specification offers two well-known advantages: full interpretability of the estimated coefficients and straightforward compliance auditability. It imposes, however, two binding

structural constraints. All predictors enter the index z linearly and additively, precluding non-linear threshold effects and interaction terms. Additionally, predictive signal is confined to the five pre-selected variables; any information contained in the remaining loan characteristics is excluded by design.

On the held-out test set, the logistic regression baseline achieves an AUC-ROC of 0.7641 and a Kolmogorov–Smirnov statistic of 0.4241. While respectable for a parsimonious five-variable scorecard, these figures suggest that meaningful predictive information remains uncaptured, information that more flexible, data-driven approaches may be positioned to recover.

Step 2: Random Forest — Parallel Ensemble Learning

A Random Forest constructs an ensemble of decision trees, each of which partitions the data into progressively narrower subgroups using a sequence of binary if-then rules. Where logistic regression fits a single global equation, a Random Forest lets each tree independently discover local patterns, including non-linear thresholds and variable interactions, that a linear model cannot represent. Standard library, scikit-learn in Python is used for this analysis.

The model trains 200 trees simultaneously. Each tree is built on a *bootstrap resample* of the training data (a random sample drawn with replacement, equal in size to the original), ensuring that no two trees see the same observations. At every node split, each tree considers only a random subset of available features rather than all predictors, a deliberate injection of randomness that forces the trees to be meaningfully different from one another. Diversity among the trees is the mechanism that makes the ensemble more accurate than any individual tree.

As an illustrative rule, a single node in one tree might encode: *"If loan term < 36 months AND interest rate > 8.5% AND industry sector = Transportation, classify as high default risk."* Across 200 trees, thousands of such rules are learned, collectively capturing complex, context-dependent patterns in the data. Three parameter choices guard against overfitting. Maximum tree depth is capped at 10 splits, preventing any tree from memorizing training-set noise by growing arbitrarily deep. Each terminal leaf must contain at least 50 observations, ensuring that probability estimates at the endpoints rest on meaningful sample sizes rather than isolated cases. Class weights are set inversely proportional to class frequency to address the

pronounced imbalance in the outcome variable (7.2% defaults vs. 92.8% non-defaults); without this adjustment, a model that simply predicts "no default" for every loan would achieve 92.8% accuracy while providing no useful signal.

At prediction time, all 200 trees independently estimate the probability of default for each loan. The final prediction is the simple average of these 200 estimates. This averaging is the core statistical benefit of ensemble methods: because each tree's errors are at least partially uncorrelated with the others, they tend to cancel out in the aggregate, reducing prediction variance substantially relative to any single tree.

Five-fold cross-validation on the training data confirms that the ensemble is stable and not overfit: AUC-ROC = 0.939 ± 0.006 across folds. On the temporal holdout, the more demanding and policy-relevant test, because the model must generalize to loans originated after the training window, the model achieves AUC-ROC = 0.8864 and KS = 0.6750, representing a meaningful improvement over the logistic regression baseline (AUC = 0.7641, KS = 0.4241).

Step 3: Gradient Boosting (Sequential Error Correction)

Gradient Boosting achieves the highest performance (AUC = 0.9178, KS = 0.7326) through a fundamentally different learning philosophy. Where Random Forest builds 200 trees in parallel and averages them, Gradient Boosting builds 200 trees sequentially, each new tree explicitly trained to correct the prediction errors of all prior trees combined.

The process unfolds as follows. Iteration 1 fits a single shallow decision tree (maximum depth = 4, meaning at most four sequential if-then splits) to the full training set. This first tree already achieves a test AUC of 0.8639 by capturing the dominant signals in loan term and interest rate. Iteration 2 computes the residual prediction errors from iteration 1, which loans are currently misclassified or miscalibrated? and, fits a new tree exclusively to those residuals rather than to the original outcome variable. Each subsequent tree is estimated to reduce the residual prediction error of the existing ensemble. The learning rate of 0.05 controls how aggressively each new tree's corrections are incorporated: low enough to prevent any single tree from dominating the ensemble, high enough to make steady progress across 200 iterations. The subsampling ratio of 0.80 means each tree is fit on a random 80% draw of training observations,

introducing diversity and further reducing overfitting beyond what tree depth constraints alone provide.

Table 2 tracks the learning curve at checkpoints throughout training. The largest single-window gain occurs in iterations 1–21 (+0.0364 AUC), as the model rapidly identifies non-linear threshold effects around loan term, loans under 24 months face dramatically elevated default rates that a linear model can only approximate. Gains diminish but remain consistent through iteration 100 as the model incorporates sector interactions, processing method risk differentials, and guarantee ratio effects. Convergence is reached near iteration 160–180, with no evidence of test-set overfitting throughout.

Table 2: Gradient Boosting Learning Curve — Test AUC-ROC at Staged Iteration Checkpoints.

Boosting Iteration	Test AUC-ROC	Gain vs. Prior	Economic Interpretation
1 (first tree)	0.8639	Baseline	Term and interest rate thresholds captured immediately
21	0.9003	+0.0364	Rapid: non-linear term/rate interactions refined
41	0.9044	+0.0041	Sector risk premiums begin contributing
61	0.9079	+0.0035	Processing method and revolver effects incorporated
81	0.9115	+0.0036	Additional predictive contribution of the guarantee ratio
101	0.9143	+0.0028	Fine-grained residual corrections on edge cases
141	0.9153	+0.0010	Marginal gains; model approaching stable solution
181	0.9161	+0.0008	Near-convergence; additional iterations yield minimal gain
200 (final)	0.9178	+0.0017	Complete, all iterations used

Side-by-Side Process and Performance Comparison

Table 3 summarizes the process differences and performance outcomes across the traditional and ML approaches, enabling direct comparison across all key dimensions.

Table 3. Traditional vs. Machine Learning Credit Scoring — Process and Performance Comparison

Dimension	Logistic Regression (Traditional)	Gradient Boosting (Machine Learning)
Input variables	5 manually selected structured fields	loan structure + sector dummies + program type
Feature interactions	Linear additive only; none captured	All non-linear interactions learned automatically from data
Class imbalance	Not addressed	Balanced class weighting + 80% stochastic subsampling
Model passes over data	Single estimation pass	200 sequential error-correcting iterations
Learning rate	N/A (one-shot estimation)	0.05 shrinkage (prevents any single tree from dominating)
Model interpretability	High (single equation, 5 coefficients)	Moderate (feature importances + partial dependence plots)
5-fold CV AUC (training)	0.848 ± 0.009	0.960 ± 0.003 (subsample estimate)
Test AUC-ROC	0.7641	0.9178 (+20.1%)
Test KS Statistic	0.4241	0.7326 (+72.7%)
Brier Score	0.0891	0.0495 (−44.5%)
Defaults caught at 10% flag rate	1,192 of 4,325 (27.6%)	2,982 of 4,325 (68.9%) — 2.5x higher yield
Est. additional losses avoided	Baseline	~$273M over test window (~$68M/year)

Risk Stratification: The Practical Benefit

The most tangible expression of the ML advantage is risk stratification, the ability to rank loans so that real defaults concentrate at the top of the predicted-risk distribution. Table 4 presents the Gradient Boosting decile table on the FY2021–FY2024 test set: 44,056 loans divided into ten equal groups ranked from lowest to highest predicted default probability.

Table 4. Gradient Boosting Risk Decile Analysis — SBA 7(a) Test Set FY2021–FY2024 (n = 44,056). Highest-risk decile highlighted.

Decile	Loans	Mean Pred. Score	Defaults	Default Rate	Cumul. Default Capture
1 (Lowest)	4,421	0.35%	16	0.36%	0.4%
2	4,398	0.45%	52	1.18%	1.6%
3	4,398	0.61%	56	1.27%	2.9%

Decile	Loans	Mean Pred. Score	Defaults	Default Rate	Cumul. Default Capture
4	4,406	0.74%	50	1.13%	4.1%
5	4,405	0.86%	42	0.95%	5.0%
6	4,406	1.07%	121	2.75%	7.8%
7	4,406	1.66%	171	3.88%	11.7%
8	4,405	2.44%	211	4.79%	16.6%
9	4,405	8.33%	624	14.17%	31.0%
10 (Highest)	**4,406**	**52.50%**	**2,982**	**67.68%**	**100.0%**

The highest-risk decile (Decile 10) contains only 10% of all loans but captures 2,982 of 4,325 actual defaults, 68.9% of all defaults, at a realized default rate of 67.68%. The lowest five deciles combined (50% of all loans) contain only 216 defaults (5.0% of total), with individual default rates between 0.36% and 0.95%. By flagging only the top decile for enhanced underwriting scrutiny or denial, a lender intercepts 68.9% of eventual defaults while disturbing only 10% of the loan population. The equivalent logistic regression screen at the same 10% flag rate catches only 1,192 defaults (27.6%), less than half the ML model's yield. The difference in practical terms is 1,790 additional defaults identified per test window: at an average SBA guaranteed loss of $152,666 per charged-off loan, this represents in avoidable federal guaranteed losses over four years, or $68 million per year on this cohort alone.

This figure should be read as an illustrative upper bound rather than a precise forecast. It assumes flagged loans would have been declined or restructured without offsetting increases in false-positive declines of otherwise creditworthy borrowers, holds lender and borrower behavior fixed in response to the model, and does not net out guarantee fee revenue or the cost to small-business capital access of tightening approvals in the flagged decile. Realized savings from any operational deployment would depend on the specific underwriting action taken on flagged loans and would warrant a separate cost-benefit analysis.

Why Machine Learning Outperforms: Five Structural Reasons

- Non-linearity: Default risk is non-linear in loan term; there is a sharp threshold around 24–36 months below which default rates spike dramatically. Gradient Boosting captures this

through its tree splits; logistic regression forces a linear approximation that systematically underestimates short-term loan risk.

- Interaction effects: The joint occurrence of short loan term, high interest rate, and high-risk sector is far more dangerous than any factor individually would predict. Gradient Boosting learns these interactions automatically; logistic regression requires manual construction of interaction terms, which introduces researcher discretion and is practically infeasible across 18 sectors.
- Class imbalance handling: With 7.47% defaults, standard logistic regression systematically underestimates default probabilities for the minority class. Balanced class weighting and stochastic subsampling in Gradient Boosting correct for this, yielding better calibrated probability estimates and higher sensitivity.
- High-dimensional categorical predictors: Eighteen NAICS sector dummies and multiple processing method categories provide rich differentiated risk signals. ML models exploit these through data-driven node splitting; logistic regression requires the analyst to decide which sectors to parameterize separately—decisions that invariably introduce specification error.
- Temporal generalization: Trained on FY2010–FY2020 and tested on FY2021–FY2024, a period with a materially higher base default rate (9.82% vs. 7.23%), Gradient Boosting maintains AUC = 0.9178. This stability reflects its ability to learn structural relationships between loan characteristics and default outcomes, not merely period-specific correlations in the training data.

Results

Model Performance

Table 5 presents the out-of-time test set performance of all four models, alongside 5-fold cross-validation AUC estimates for the Logistic Regression and Random Forest specifications.

Table 5: Model Performance Comparison, Out-of-Time Test Set (FY2021–FY2024, n = 44,056).

Model	Feature Set	AUC-ROC	KS Statistic	Brier Score	CV AUC (5-fold)
Logistic Regression	Traditional (5 vars)	0.7641	0.4241	0.0891	0.848 ± 0.009

Model	Feature Set	AUC-ROC	KS Statistic	Brier Score	CV AUC (5-fold)
Random Forest	Full (19 vars + sectors)	0.8864	0.6750	0.1088	0.939 ± 0.006
Gradient Boosting	Full (19 vars + sectors)	0.9178	0.7326	0.0495	—
Ensemble (RF + GB avg)	Full (19 vars + sectors)	0.9100	0.6913	0.0616	—

Gradient Boosting delivers the strongest out-of-time discrimination, with an AUC-ROC of 0.9178 and a KS statistic of 0.7326, both substantially above the thresholds considered "excellent" in credit risk practice (AUC > 0.80, KS > 0.40; Siddiqi, 2006). The traditional Logistic Regression benchmark, despite achieving reasonable discrimination (AUC = 0.7641, KS = 0.4241), is outperformed on every metric. The absolute AUC improvement from Logistic Regression to Gradient Boosting is 0.1537 (20.1% relative improvement). The Brier Score improvement is even more pronounced: Gradient Boosting reduces the mean squared probability error by 44.5% relative to Logistic Regression (0.0495 vs. 0.0891), reflecting both superior discrimination and better probability calibration.

The 5-fold cross-validation results confirm that the performance advantage of ML models is not an artifact of overfitting to the training data. Random Forest achieves a training-set CV AUC of 0.939 ± 0.006, compared to 0.848 ± 0.009 for Logistic Regression—stable across folds and consistent with the holdout results.

At the optimal classification threshold for Gradient Boosting ($p^* = 0.1729$, selected to maximize the F1 score), the model correctly identifies 72.9% of defaulted loans (sensitivity) while maintaining a specificity of 95.8%. Precision at this threshold is 65.6%, and the F1 score is 0.6905. This threshold identifies a high-risk population constituting 11.4% of the test loans that accounts for 72.9% of actual defaults—a powerful screening capability for lender risk management.

Feature Importance

Table 6 presents the Gradient Boosting feature importance scores alongside economic interpretations. Loan term dominates all other predictors with an importance score of 0.8177, capturing the substantially elevated default risk of shorter-term loans—likely because shorter terms signal emergency or distressed borrowing contexts, and because default events are

mechanically more likely to occur within the observed window for short-tenor instruments. Initial interest rate (0.0820) is the second most important feature, reflecting both systematic credit risk pricing and macroeconomic interest rate environment effects. The SBA guarantee ratio (0.0352) shows a positive risk association—higher guarantee coverage may attenuate lender screening intensity due to reduced skin in the game, consistent with moral hazard theory in guaranteed lending.

Table 6. Gradient Boosting Feature Importance Scores (FY2010–FY2020 Training Set). Note: remaining importance distributed across sector and program-type indicators

Feature	Importance	Economic Interpretation
Loan Term (months)	0.8177	Longer-term loans face greater exposure duration; strong default predictor
Initial Interest Rate	0.0820	Higher rates signal riskier borrowers or tighter market conditions
SBA Guarantee Ratio	0.0352	Higher SBA coverage may reduce lender screening intensity
Fixed/Variable Rate	0.0219	Variable-rate loans face refinancing risk; affects payment stability
Revolver Status	0.0186	Revolving credit lines exhibit different draw-down and repayment patterns
Log Loan Amount	0.0165	Larger loans correlate with lower default rates (scale effect)
Has Collateral	0.0031	Collateral provides loss mitigation but limited as default predictor
Jobs Supported	0.0022	Larger employers show marginally lower default rates

Default Risk by Industry Sector

Table 7 characterizes default rates across the 15 major NAICS sectors represented in the sample. Substantial heterogeneity is evident: the Transportation sector (9.84% default rate) and Arts & Entertainment (9.70%) carry the highest systematic default risk, while Agriculture (4.09%) and Finance & Insurance (4.60%) exhibit the lowest. The Accommodation & Food Services sector, comprising restaurants and hotels, has a default rate of 8.01% on 61,634 loans, representing the single largest contributor to absolute default volume (4,939 defaults). Construction (8.20% on 54,320 loans) and Retail Trade (8.30% on 65,705 loans) also exhibit elevated risk across large loan volumes.

Table 7. Default Rates by NAICS Sector, SBA 7(a) Resolved Loans FY2010–FY2024. Table 7 excludes 8,021 loans (1.6% of the analytic sample) with missing or unclassified NAICS sector codes. Their exclusion does not materially affect sector-level default rate estimates.

NAICS Sector	Total Loans	Defaults	Default Rate
Transportation	28,588	2,813	9.84%
Arts & Entertainment	13,955	1,354	9.70%
Wholesale Trade	26,126	2,225	8.52%
Retail Trade	65,705	5,451	8.30%
Education Services	6,596	545	8.26%
Construction	54,320	4,454	8.20%
Accommodation & Food	61,634	4,939	8.01%
Admin & Support Svcs	23,553	1,813	7.70%
Other Services	42,101	3,220	7.65%
Professional Services	48,601	3,304	6.80%
Manufacturing	38,083	2,351	6.17%
Real Estate	10,901	625	5.73%
Healthcare & Social	43,884	2,110	4.81%
Finance & Insurance	8,776	404	4.60%
Agriculture	7,928	324	4.09%
ALL SECTORS	**488,772**	**36,494**	**7.47%**

Healthcare & Social Assistance (4.81% default rate on 43,884 loans) and Professional Services (6.80% on 48,601 loans) represent lower-risk sectors with high loan volume, profiles attractive to lenders seeking SBA-guaranteed exposure with below-average portfolio default risk.

Default Risk by Loan Size

A pronounced inverse relationship between loan size and default probability is observed. Loans of $50,000 or less exhibit an 8.77% default rate compared to 3.74% for loans exceeding $1 million. This size effect likely reflects multiple simultaneous phenomena: larger loans are extended to more established, creditworthy borrowers; lender due diligence is more intensive for large exposures; and larger borrowers have greater operational buffers to weather temporary distress. The loan size gradient persists across the full study period and is robust to controlling for sector effects in the multivariate models.

Temporal Dynamics

Annual default rates exhibit meaningful cyclical and structural variation. The post-financial crisis recovery period (FY2011–FY2013) shows the lowest default rates in the sample, declining from 7.50% (FY2010) to 5.48% (FY2013) as economic conditions stabilized. Default rates then rose through the late business cycle (FY2015–FY2019), reaching 9.88% in FY2018. The pandemic shock year (FY2020) paradoxically produced a lower default rate (5.95%) in the resolved loan cohort, likely because government stimulus programs (PPP, EIDL) enabled many at-risk borrowers to remain current. Default rates for FY2022 (12.19%) and FY2023 (16.27%) reflect both post-stimulus normalization and the challenging rate environment of 2022–2023, though these cohorts have shorter resolution windows than earlier vintage years.

Discussion

The findings of this study have several implications for SBA lending policy, lender risk management, and the broader discussion surrounding the use of machine learning in credit underwriting.

First, the improvement in predictive performance associated with the machine learning models appears to be economically meaningful in addition to being statistically relevant. Gradient Boosting improves AUC by 0.1537 relative to the logistic regression benchmark, indicating a substantially greater ability to distinguish between loans that ultimately default and those that do not. In practical terms, improved discrimination can allow lenders to separate higher- and lower-risk borrowers more effectively at a given decision threshold. For participating lenders, more accurate risk estimates may support underwriting, portfolio monitoring, pricing, and loss provisioning. From the SBA's perspective, improved identification of credit risk could also contribute to more effective management of the government's guarantee exposure. The 44.5% reduction in Brier Score further indicates that the Gradient Boosting model produces probability forecasts that are substantially more accurate, on average, than those generated by the benchmark model. Such improvements are relevant when predicted probabilities are used for portfolio-level risk measurement and expected-loss estimation.

Second, loan term emerges as the most influential predictor in the Gradient Boosting model, with an importance weight of 0.8177. This result suggests that maturity contains substantial information relevant to distinguishing between higher- and lower-risk loans within

the sample. The finding should not, however, be interpreted as evidence that loan term itself causes default. Loan maturity may reflect other characteristics of the borrower, financing purpose, loan structure, or underwriting decision that are also related to credit risk. Nevertheless, the strength of this variable suggests that the relationship between loan maturity and subsequent performance deserves greater attention in both underwriting practice and future research.

Third, the analysis reveals substantial differences in default experience across industry sectors. For example, borrowers in Transportation and Arts and Entertainment exhibit default rates approximately 2.4 times those observed among Agriculture borrowers. These differences suggest that industry conditions contain information relevant to SBA credit risk and may warrant consideration in portfolio monitoring and risk assessment. They also raise a broader policy question regarding whether the structure of SBA guarantee fees adequately reflects differences in underlying portfolio risk. The current findings alone do not establish that sector-based guarantee pricing would improve program outcomes, but they provide a basis for examining whether greater risk differentiation could contribute to the long-term financial sustainability of the guarantee program.

Any consideration of greater risk differentiation must also recognize the broader mission of the SBA 7(a) program. The program is intended to expand access to capital for small businesses that may encounter difficulty obtaining financing through conventional channels. Policies that increase the cost of guarantees for sectors exhibiting historically higher default rates could therefore have unintended consequences for credit availability. Industry-level risk also does not imply that every borrower within a higher-risk sector represents a poor credit risk. Any movement toward more risk-sensitive pricing would consequently need to balance portfolio risk management with the program's access-to-capital objectives and should be evaluated using evidence on borrower-level outcomes rather than sector averages alone.

Fourth, variation in default rates over time highlights the importance of model stability and out-of-time validation. Models estimated during periods of relatively low defaults may perform differently when applied under changing economic and credit conditions. The empirical design of this study addresses this issue by training the models on loans originated during FY2010–FY2020 and evaluating them on a subsequent FY2021–FY2024 holdout sample. The

default rate increases from 7.23% in the training period to 9.82% in the test period, providing a meaningful test of model performance under a different risk environment. Despite this shift, Gradient Boosting achieves an out-of-sample AUC of 0.9178, indicating strong discriminatory performance in the later-period sample. This result provides evidence that the model retains substantial predictive ability across the temporal split used in this study, although performance under future economic conditions cannot be inferred from this test alone.

Several limitations should be considered when interpreting these findings. First, the SBA 7(a) FOIA disclosure data used in this study do not provide the demographic information necessary to conduct a direct borrower-level analysis of differences in model outcomes across demographic groups. Consequently, the study cannot evaluate whether the predictive models produce systematically different outcomes across such groups. Future research could potentially combine SBA loan information with appropriately aggregated geographic and socioeconomic data to examine whether model performance or credit outcomes vary across communities, while recognizing that area-level characteristics should not be treated as substitutes for individual borrower characteristics.

Second, the publicly available data do not contain several borrower-level financial measures that would ordinarily be available to lenders during underwriting, including detailed revenue, debt-service coverage, and credit information. The models developed here therefore operate with a more limited information set than would typically be available to a participating lender. The results should accordingly be interpreted as evidence of the predictive information contained in the SBA disclosure variables rather than as an estimate of the maximum predictive performance achievable in an operational underwriting environment.

Third, an important limitation concerns the comparability of the logistic regression benchmark with the machine learning models. The logistic regression specification uses five expert-selected explanatory variables, whereas Random Forest, Gradient Boosting, and the ensemble model use the full 31-variable feature set, including industry and program-related indicators. The observed performance difference therefore reflects two changes simultaneously: greater model flexibility and a richer information set. It cannot be attributed exclusively to the machine learning algorithms themselves. Although this specification reflects the distinction

between a relatively parsimonious traditional scorecard and a more feature-rich predictive model, a more direct methodological comparison would estimate logistic regression using the same 31-variable information set. Such an analysis would help distinguish the incremental contribution of model flexibility from that of additional predictors and represents an important extension of the present study.

Finally, the analysis is based on loans with resolved outcomes, defined as Paid in Full or Charged Off. Because loans originated in more recent fiscal years have had less time to reach a terminal status, the resolved-loan sample may differ systematically from the broader population of SBA 7(a) originations, particularly toward the end of the study period. This seasoning and potential right-censoring issue should be considered when interpreting both the observed default rates and model performance for recent originations. Future research could address this limitation through survival-based methods or by allowing a longer performance window for more recent loan cohorts.

Conclusion

This study provides new empirical evidence on the use of machine learning for credit risk prediction within the SBA 7(a) guaranteed lending program. Using 488,772 resolved loans originated between FY2010 and FY2024, the analysis compares a traditional logistic regression benchmark with Random Forest, Gradient Boosting, and an ensemble model. Among the models evaluated, Gradient Boosting produces the strongest out-of-time predictive performance, achieving an AUC-ROC of 0.9178 compared with 0.7641 for the logistic regression benchmark, representing a 20.1% relative improvement. The model also reduces the Brier Score by 44.5%, indicating substantially more accurate probability forecasts in the holdout sample. These results demonstrate the potential value of flexible, data-driven methods for identifying differences in default risk within SBA lending.

The findings also have practical implications for the administration and management of the 7(a) program. For SBA program managers, improved risk stratification could complement existing approaches to portfolio monitoring, lender oversight, and the evaluation of guarantee exposure. Participating lenders may similarly benefit from incorporating machine learning tools

into existing credit risk processes, particularly for portfolio monitoring, loss estimation, and concentration management. These models should be viewed as decision-support tools rather than substitutes for established underwriting practices, lender judgment, or regulatory requirements. Their practical value will ultimately depend not only on predictive accuracy but also on interpretability, model governance, data quality, and continued validation as lending and economic conditions change.

The results are also relevant to the growing use of AI-assisted underwriting in financial services. Previous studies have documented the predictive value of machine learning and alternative data in consumer and other credit markets (Berg et al., 2020; Bartlett et al., 2022). The present analysis extends this discussion to government-guaranteed small business lending and shows that machine learning models can retain strong predictive performance when evaluated on a later, out-of-time sample. At the same time, the observed performance difference should be interpreted carefully because the machine learning models use a broader set of predictors than the parsimonious logistic regression benchmark. The findings therefore demonstrate the predictive value of the modeling framework used in this study but do not isolate the improvement attributable solely to the choice of algorithm.

More broadly, the study illustrates both the opportunities and the limitations associated with applying machine learning to public-sector credit programs. Predictive performance is an important consideration, but it represents only one dimension of responsible model use. Transparency, fairness, model stability, access to credit, and consistency with the public mission of the SBA must also be considered when evaluating how such methods might be incorporated into lending decisions. As AI-assisted credit assessment becomes more common, continued research will be needed to determine how improvements in prediction can be translated into better lending and policy decisions without compromising these broader objectives.

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Engineering Trust in Algorithmic Lending: Explainable, Fairness-Aware Credit Risk Modeling for Financial Inclusion

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Abstract

Consumer credit decisions are increasingly influenced by machine learning, but its use creates a major conflict for financial inclusion because models that are geared for predictive accuracy may encode and magnify inequalities against the very groups that inclusion-oriented lending aims to assist. This study asks whether predictive performance alone is a sufficient basis for trust in algorithmic lending. Using the UCI Default of Credit Card Clients dataset (30,000 borrowers in Taiwan), we train and compare logistic regression, random forest and gradient-boosted decision tree (XGBoost) classifiers and subject the strongest model to SHapley Additive exPlanations (SHAP) interpretation, a demographic fairness audit across sex, education and age, a feature-ablation test and a post-processing mitigation. XGBoost attains a ROC-AUC of 0.775, on par with established benchmarks, confirming that raw accuracy is not the differentiating contribution. The audit reveals moderate but real disparities in false-positive rates, with the youngest and least-educated applicants most often wrongly flagged; we also show that naively including a very small subgroup substantially overstates apparent disparity. The assigned credit limit is strongly stratified by education and age, yet removing it does not reduce the disparity, illustrating that "fairness through unawareness" is insufficient because the signal is redundantly encoded in correlated features. Group-aware decision thresholds, a straightforward post-processing solution, lower the education false-positive gap from 0.082 to 0.005 at the expense of 0.4 percentage points of accuracy. We suggest a layered evaluation approach and contend that explainability, meticulous fairness auditing and mitigation are necessary conditions for reliable, inclusion-focused credit AI.

Keywords: credit scoring, explainable AI, SHAP, algorithmic fairness, financial inclusion, trustworthy machine learning.

Introduction

Financial technology has moved credit decisioning from human underwriting toward automated, data-driven scoring. Lenders increasingly rely on machine learning (ML) models to estimate the probability that an applicant will default and these models now mediate access to credit cards, consumer loans and microfinance products worldwide. For proponents of financial inclusion, this shift carries genuine promise: data-driven models can, in principle, extend credit to applicants whom traditional scorecards overlook, including the underbanked and those with thin credit files (Berg et al., 2020). Yet the same flexibility that allows ML models to uncover predictive structure can also reproduce and even amplify, historical disparities in who receives credit and on what terms (Fuster et al., 2022).

This tension sits at the heart of the present study and of the conference theme of engineering trust. A model that achieves high predictive accuracy is not, by that fact alone, trustworthy. Trust in a lending model depends on whether its decisions can be explained, whether the features it relies upon are legitimate and whether the errors it makes are distributed equitably across the population it serves. When a model is opaque, an applicant who is denied credit cannot know why, a lender cannot defend the decision to a regulator and a community cannot tell whether the system is fair. Accuracy answers none of these questions.

We examine these issues on a widely used, transparent benchmark: the UCI Default of Credit Card Clients dataset. Rather than chasing marginal accuracy gains, we treat accuracy as a baseline and ask what an explainability analysis and a demographic fairness audit reveal about the trustworthiness of a representative model. Specifically, we address three research questions:

RQ1. How accurately do standard ML models predict default on this benchmark and does model choice materially change performance?

RQ2. Which features drive the predictions of the strongest model and do they raise concerns for financial inclusion?

RQ3. Are the model's predictive errors distributed equitably across demographic groups defined by sex, education and age?

This paper's main contribution is not any particular technique, each of which is proven, but rather their integration into a single, repeatable evaluation framework that links mitigation, fairness, accuracy and explanation to a single choice and reveals what each phase would overlook on its own. This paper makes four contributions. First, it provides a reproducible comparison of logistic regression, random forest and gradient-boosted models on a public benchmark, situating their accuracy relative to the literature. Second, it conducts a careful demographic fairness audit across three protected attributes, showing that disparities are real but moderate and that the careless inclusion of a small subgroup can substantially overstate them. Third, it tests the common intuition that removing an access-correlated feature reduces bias and finds that it does not direct evidence that fairness through unawareness is insufficient on this data. Fourth, it demonstrates a simple, effective mitigation (group-aware thresholds) and synthesizes the analyses into a layered evaluation framework that treats explainability, auditing and mitigation as prerequisites, rather than afterthoughts, for trustworthy credit AI.

Literature Review

Machine Learning for Credit Scoring

Statistical classification has underpinned consumer credit scoring for decades, beginning with linear and logistic scorecards valued for their transparency and regulatory acceptability (Hand & Henley, 1997). Yeh and Lien (2009), who tested several data-mining methods for default prediction and established baseline performance that later research has reviewed, introduced the benchmark dataset used here. The advent of ensemble methods and in particular gradient-boosted decision trees (Chen & Guestrin, 2016), improved predictive accuracy substantially but at the cost of interpretability, motivating the explainability and fairness literatures discussed below.

Explainable Machine Learning

As high-stakes decisions increasingly rely on opaque models, explainable AI (XAI) has emerged to render their behavior intelligible (Arrieta et al., 2020). Among post-hoc methods, SHapley Additive exPlanations (Lundberg & Lee, 2017) provide a theoretically grounded, locally accurate attribution of a prediction to its input features and have become a de facto standard for model interpretation. Practitioners caution, however, that post-hoc explanations can be incomplete or misleading and some argue that interpretable models should be preferred outright for consequential decisions (Rudin, 2019). Explanations are frequently used internally

for debugging rather than to tell impacted individuals, according to studies of real-world deployment (Bhatt et al., 2020), highlighting the fact that explainability is essential but insufficient for confidence.

Algorithmic Fairness

What constitutes a fair automated choice is formalized in a parallel body of literature. While (Hardt et al. 2016) presented equalized odds, which necessitates equivalent true-positive and false-positive rates across protected groups, earlier work offered individual-level fairness through similarity constraints (Dwork et al., 2012). A comprehensive assessment by (Mehrabi et al. 2021) lists the sources of bias that emerge across the ML pipeline, while (Barocas and Selbst 2016) place these ideas within anti-discrimination law and the doctrine of disproportionate impact. A recurring lesson is that demographic parity and error-rate criteria can clash and no single statistic fully represents justice.

FinTech and Financial Inclusion

With demonstrated effects on stability and inclusion (Ozili, 2018) and an increasing role for fintech intermediaries in reaching underrepresented borrowers (Philippon, 2019), digital finance has increased access to formal financial services. (Berg et al. 2020) show that even simple digital-footprint variables can rival bureau scores, suggesting new pathways to credit for thin-file applicants. (Yet Fuster et al. 2022) demonstrate, using United States mortgage data, that the move from traditional models to machine learning can widen disparities, leaving some minority borrowers less likely to benefit. This study fills this gap by combining accuracy, explainability and a fairness audit on a single transparent benchmark. When taken as a whole, this body of work demonstrates that the inclusion effects of credit ML are ambiguous and must be measured rather than assumed.

Recent Work and Positioning of This Study

The current study is best appreciated considering the rapidly expanding body of work that explicitly incorporates explainability and fairness into credit rating. Japinye and Adedugbe (2025) create an explainability-first system that combines multi-criteria fairness monitoring across many public loan datasets, including the benchmark employed here, with calibrated gradient-boosting models with SHAP and LIME explanations. Similarly, Akavaram (2025) assesses bias mitigation at the pre-processing, in-processing and post-processing stages and incorporates explanations based on SHAP and LIME with demographic-parity, equal-opportunity

and equalized-odds measures. In particular, fairness in machine-learning credit lending is examined by Babaei and Giudici (2024). In the context of this, the study's contribution is purposefully limited and applied: instead of suggesting new explainability or mitigation mechanisms, it employs a transparent, repeatable audit to make a single argument concrete: that group-level error disparities can be concealed by aggregate accuracy, that prior access inequality can be encoded by reliance on the assigned credit limit and that these failures primarily affect the populations that financial inclusion initiatives seek to serve. Rather than being a methodological advancement, the audit and the layered evaluation system are presented as a transparent, teachable example of reliable lending practices. The end-to-end integration of auditing, mechanism testing through ablation, robustness across thresholds and mitigation applied transparently to a single benchmark, along with an explicit demonstration that both careless auditing and naive feature removal can mislead, is what sets this study apart from that work rather than a novel approach.

Methodology

Dataset

We use the UCI Default of Credit Card Clients dataset, comprising 30,000 credit-card holders in Taiwan observed from April to September 2005. Each record contains 23 explanatory variables: a credit limit (LIMIT_BAL), demographic attributes (sex, education, marital status, age), six months of repayment status (PAY_1 through PAY_6), six monthly bill amounts (BILL_AMT1–BILL_AMT6) and six-monthly payment amounts (PAY_AMT1–PAY_AMT6). The binary target indicates whether the client defaulted on the following month’s payment. The dataset is moderately imbalanced, with a default rate of 22.1%.

Preprocessing

Following common practice for this dataset, undocumented categorical codes were consolidated: education values of 0, 5 and 6 were mapped to an “other” category and marital-status code 0 was merged into “other.” No records were dropped. To maintain the default rate, the data were divided into 80% training and 20% test sets (24,000 and 6,000 records) using stratified sampling. Inverse-frequency weighting (a positive-class weight for the boosted model and balanced class weights for the linear and random-forest models) was used to alleviate class imbalance during training.

Models

Three classifiers covering the range of interpretability and flexibility were trained. Fitted on standardized features, logistic regression provides a clear baseline. A bagged ensemble is represented as a random forest with 400 trees and a maximum depth of 8. The most popular boosted ensemble in modern credit modeling is an XGBoost gradient-boosted model (400 trees, maximum depth 4, learning rate 0.05, subsample and column-sample fractions of 0.8). Instead of maximizing any one score, hyperparameters were kept fixed at standard levels to maintain the comparison's transparency and reproducibility.

Evaluation Metrics

Predictive performance is reported using the area under the ROC curve (ROC-AUC), the area under the precision–recall curve (PR-AUC), the Kolmogorov–Smirnov statistic (KS) favored in credit practice and accuracy and F1 at a 0.50 decision threshold. ROC-AUC and PR-AUC are threshold-independent and therefore primary; accuracy and F1 contextualize behavior at the operating threshold used for the fairness audit.

Explainability

We use SHAP's precise tree estimator to interpret the strongest model. The distribution of per-instance attributions is analyzed to describe the direction and strength of each feature's influence and global feature relevance is summed up as the mean absolute SHAP value throughout the test set.

Fairness Audit

We examine the best model for three protected attributes: age (binned into five bands), sex and education. We calculate the flagged rate (the percentage expected to default), the true-positive rate (TPR) and the false-positive rate (FPR) for each group at the 0.50 level. Two disparity measurements are derived from these. The difference between the maximum and minimum highlighted rates across groups is known as the demographic-parity difference. The maximum minus minimum TPR (the uneven advantage of accurate risk detection) and the maximum minus minimum FPR (the unequal burden of being incorrectly detected) are equalized-odds gaps (Hardt et al., 2016). Greater disparities suggest more unfair treatment.

Robustness, Ablation and Mitigation

Three further analyses probe the audit. First, a threshold sweep recomputes the education disparity as the decision threshold varies from 0.15 to 0.85, testing whether the gaps depend on the 0.50 operating point. Second, an ablation retrains the model without the assigned credit limit to test whether that single access-correlated feature drives the disparity. Third, a post-processing mitigation assigns each education group a decision threshold chosen so that its false-positive rate matches the overall rate and we report the resulting change in the disparity gap and in overall accuracy.

Results

Predictive Performance

Table 1 reports test-set performance. The two ensembles are essentially tied and clearly outperform logistic regression; XGBoost attains the highest ROC-AUC (0.775) and PR-AUC (0.554). These values are consistent with previously published results on this benchmark, indicating that the model is representative rather than unusually strong or weak. Because the ensembles do not differ meaningfully, model selection on accuracy alone is largely indeterminate and motivating the explainability and fairness analyses that follow.

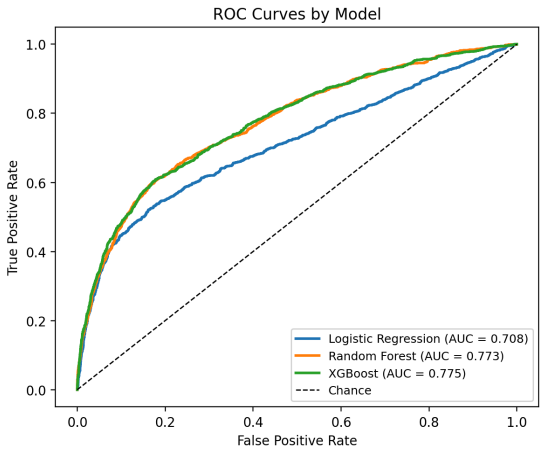
Table 1

Test-set predictive performance of the three classifiers (n = 6,000).

Model	ROC-AUC	PR-AUC	KS	Accuracy	F1
Logistic Regression	0.708	0.491	0.359	0.680	0.461
Random Forest	0.774	0.550	0.428	0.783	0.543
XGBoost	0.775	0.554	0.431	0.763	0.537

Figure 1

ROC curves for the three classifiers; the two ensembles nearly overlap and dominate logistic regression.



Feature Attributions

Figure 2 ranks feature by mean absolute SHAP value for the XGBoost model. The most recent repayment status (PAY_1) dominates by a wide margin, followed by the assigned credit limit (LIMIT_BAL) and the most recent bill amount. Figure 3 shows the corresponding distribution of attributions, confirming that recent delinquency pushes predictions toward default while higher credit limits push them away. The prominence of LIMIT_BAL is notable: because the assigned credit limit is itself an outcome of prior credit access, a model that leans heavily on it risks encoding past access inequalities into present-day decisions which is an inclusion concern examined in the Discussion.

Figure 2

Global feature importance (mean |SHAP value|) for the XGBoost model.

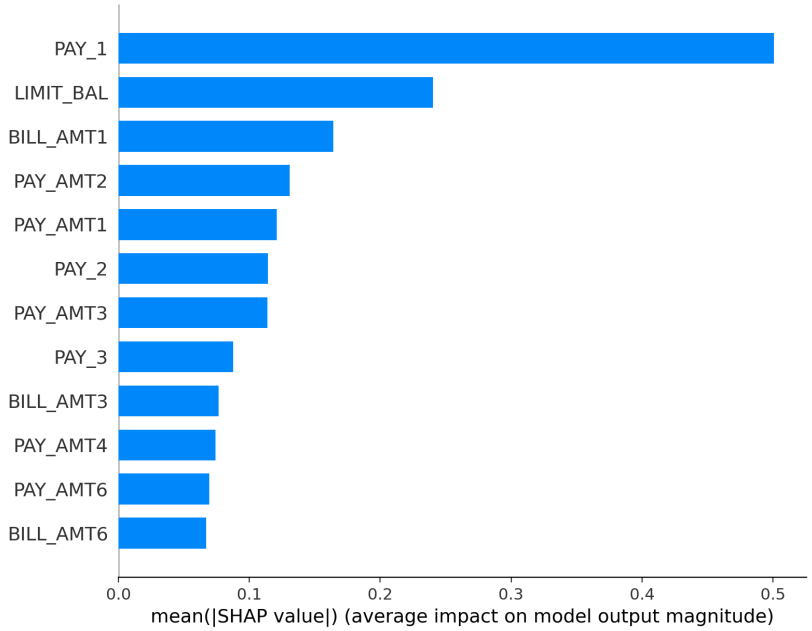
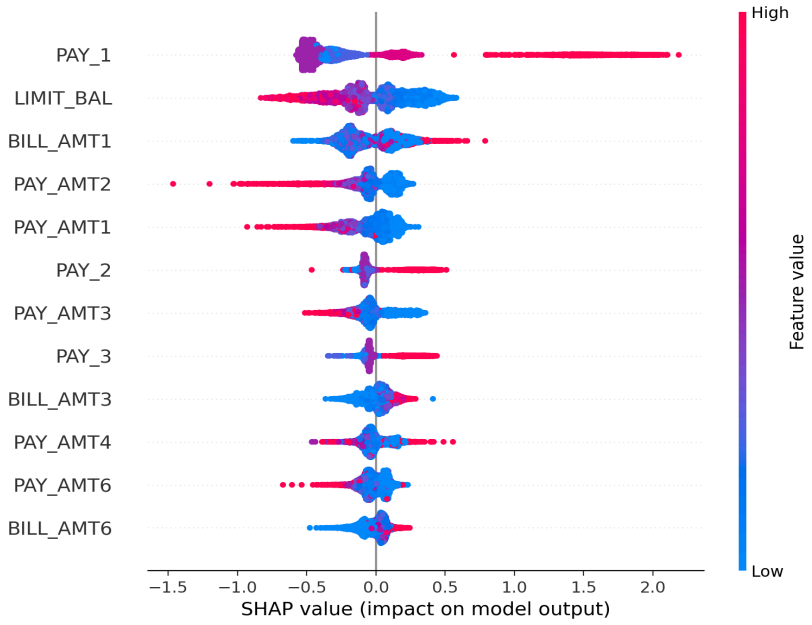


Figure 3

SHAP summary (beeswarm) showing the direction and magnitude of feature effects.



Fairness Audit

Tables 2 through 4 report group-level error rates and disparity measures; all disparity gaps are computed over groups of reliable size, excluding the small education "other" category (n = 82), whose rates are too noisy to interpret. Across sex (Table 2), disparities are modest, with a false-positive gap of 0.053. Across education (Table 3, three substantive groups), the demographic-parity, true-positive and false-positive gaps are 0.091, 0.079 and 0.082, respectively; high-school-educated applicants are wrongly flagged more often than graduate-educated applicants (FPR 0.243 vs. 0.161). Across age (Table 4), a clear gradient appears: the youngest borrowers (under 25) face the highest flagged rate (0.381) and the highest false-positive rate (0.265), giving the largest reliable false-positive gap, 0.098. It is worth noting that computing the education gaps over all four groups inflates them two- to fivefold (for example, a false-positive gap of 0.204 rather than 0.082) purely because of the 82-record subgroup and a concrete illustration of how naive auditing can mislead. Figure 4 visualizes the group error rates.

Table 2

Fairness audit by sex (XGBoost, 0.50 threshold).

Group	n	Flagged	TPR	FPR	Default
Male	2,402	0.323	0.635	0.229	0.234
Female	3,598	0.269	0.612	0.176	0.213

Demographic-parity difference 0.054; equalized-odds TPR gap 0.023; FPR gap 0.053.

Table 3

Fairness audit by education (XGBoost, 0.50 threshold).

Group	n	Flagged	TPR	FPR	Default
Graduate school	2,130	0.241	0.583	0.161	0.190
University	2,774	0.321	0.662	0.215	0.236
High school	1,014	0.332	0.590	0.243	0.257
Other	82	0.049	0.200	0.039	0.061

Gaps over the three substantive groups: demographic-parity 0.091; equalized-odds TPR gap 0.079; FPR gap 0.082. The "other" group (n = 82) is shown for completeness but excluded from gap computation.

Table 4

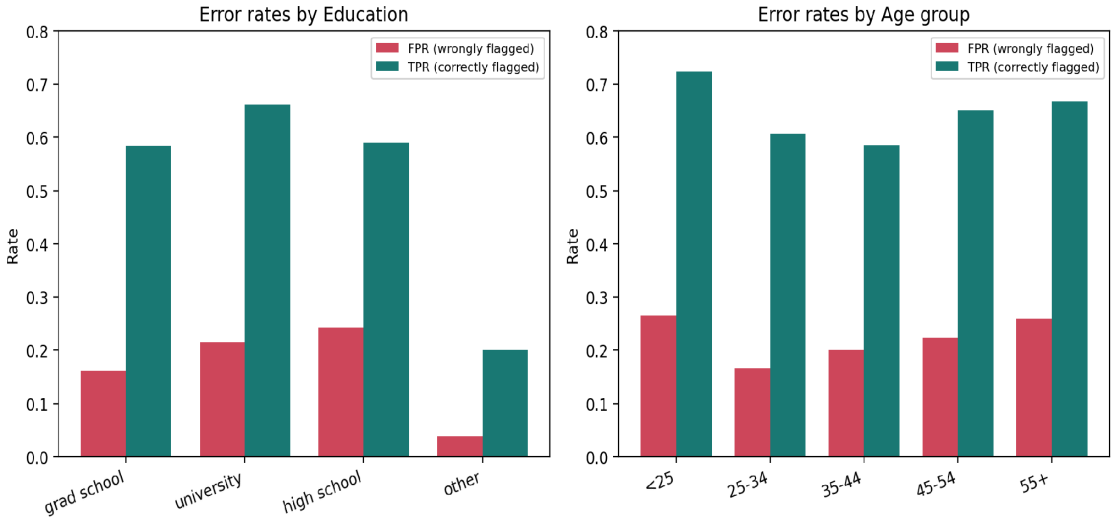
Fairness audit by age band (XGBoost, 0.50 threshold).

Group	n	Flagged	TPR	FPR	Default
Under 25	541	0.381	0.723	0.265	0.253
25–34	2,518	0.255	0.607	0.167	0.201
35–44	1,855	0.287	0.585	0.200	0.225
45–54	859	0.329	0.651	0.224	0.247
55 and over	227	0.357	0.667	0.260	0.238

Demographic-parity difference 0.126; equalized-odds TPR gap 0.138; FPR gap 0.098.

Figure 4

False-positive and true-positive rates by education and age group.



Larger gaps in bar height across groups indicate larger equalized-odds violations; the false-positive (red) bars show the unequal burden of being wrongly flagged. The small "other" education group is shown but excluded from gap computation.

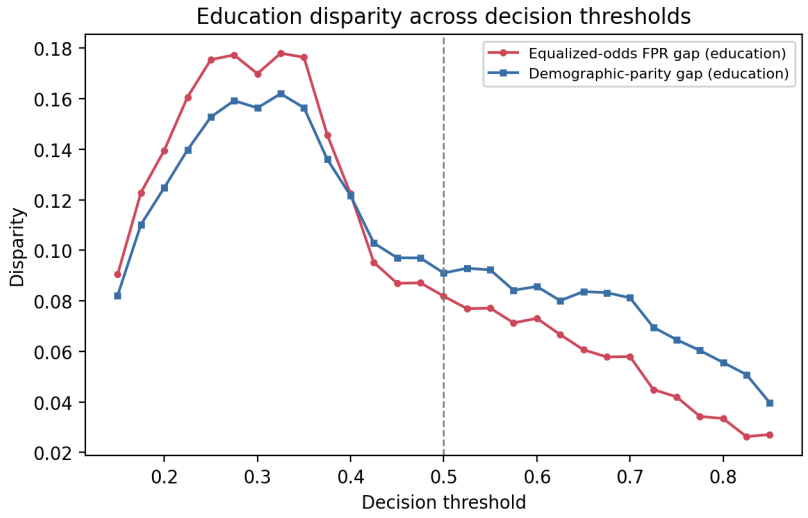
Robustness, Mechanism and Mitigation

Threshold Robustness

Because the audit above fixes the decision threshold at 0.50, we test whether the disparities are an artifact of that choice. Figure 5 sweeps the threshold from 0.15 to 0.85 and recomputes the education disparity at each point. The false-positive gap is not eliminated at any operating point and it ranges from roughly 0.03 to 0.18 and remains near 0.08 at the conventional 0.50 threshold; so, the disparity is a property of the model rather than of a particular cutoff.

Figure 5

Education disparity across decision thresholds; the dashed line marks the 0.50 threshold used elsewhere.



The Role of the Assigned Credit Limit

SHAP ranked the assigned credit limit (LIMIT_BAL) among the most influential features, raising the concern that the model predicts creditworthiness partly from prior credit access. Table 5 shows that the limit is indeed strongly stratified by education and age. To test whether it causes disparity, we retrained the model without it (Table 6). Removing the limit leaves both accuracy and the education false-positive gap essentially unchanged, indicating that the disparity is redundantly encoded in correlated behavioral features rather than driven by this one variable.

Table 5

Mean assigned credit limit (NT$) by group, showing stratification by protected attributes.

Dimension	Group	Mean limit (NT$)
Education	Graduate school	215,085
	University	145,753
	High school	128,795
Age	Under 25	64,177
	35–44	191,303
	55 and over	154,802

Table 6

Ablation test: removing LIMIT_BAL changes neither accuracy nor the disparity.

Model	ROC-AUC	Education FPR gap
Full (with LIMIT_BAL)	0.775	0.082
Ablated (no LIMIT_BAL)	0.771	0.078

Mitigating Disparity with Group-Aware Thresholds

Because removing the proxy does not help, we intervene at the decision stage instead. We select an education-group-specific threshold so that each group's false-positive rate matches the overall rate, a standard post-processing approach to equalized odds. Table 7 reports the effect: the education false-positive gap falls from 0.082 to 0.005, while overall accuracy declines only from 0.763 to 0.759 and F1 from 0.537 to 0.535. Figure 6 shows the per-group false-positive rates converging after mitigation. The disparity is therefore largely correctable at negligible cost.

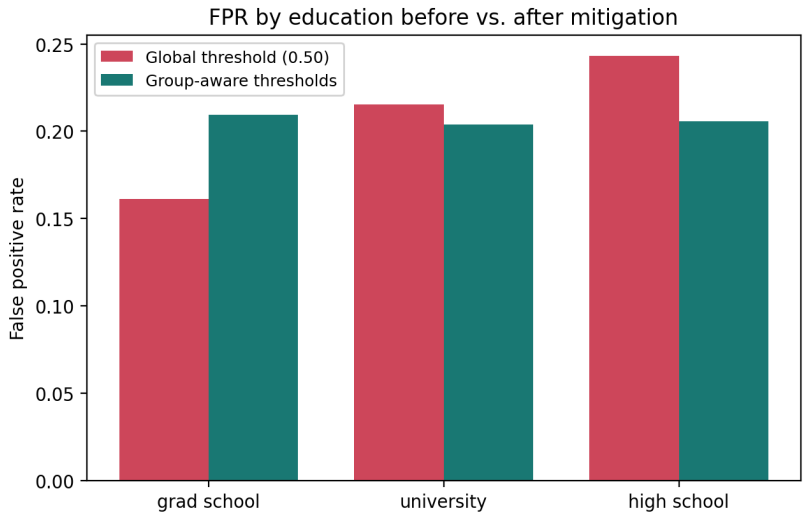
Table 7

Effect of group-aware thresholds: the disparity nearly vanishes at minimal accuracy cost.

Policy	Education FPR gap	Accuracy	F1
Global threshold (0.50)	0.082	0.763	0.537
Group-aware thresholds	0.005	0.759	0.535

Figure 6

Education false-positive rates before (global threshold) and after (group-aware thresholds) mitigation; the rates converge.



Discussion

The main conclusion is that trustworthiness and accuracy are not the same. The fairness audit reveals that the deployed model treats demographic groups differently, particularly across age and education, even though the two ensemble models are statistically identical on all accuracy metrics. None of this would be seen to a lender using a model based solely on ROC-AUC. And disparate error rates at the group level were concealed by predictive parity at the aggregate level, demonstrating that accuracy is a required but insufficient foundation for confidence.

The explainability and ablation analyses together refine the inclusion concern. The assigned credit limit ranks among the most influential features and is strongly stratified by protected attributes: graduate-educated clients carry roughly NT$215,000 in limit versus NT$129,000 for high-school-educated clients and applicants under 25 average about NT$64,000 versus NT$191,000 in mid-career. In that sense the limit plainly encodes prior, unequally distributed access to credit. However, excluding it from the model little affects the education false-positive gap (0.082 to 0.078) or accuracy (ROC-AUC 0.775 to 0.771). As a result, the discrepancy is redundantly transmitted across associated behavioral characteristics like repayment history rather than being conveyed by a single feature. This is the well-known lesson that bias cannot be eliminated by justice via ignorance, just removing a sensitive proxy and thus encourages intervention at the choice stage as opposed to the feature level.

Despite being moderate, the differences in error rates are nonetheless significant. In practice, a false positive that being mistakenly identified as a possible defaulter; translates into lower limits, higher prices, or credit denial. The audit reveals that among the groups targeted by financial inclusion programs, younger and less educated applicants bear a disproportionate amount of this burden. Therefore, even when the differences are not very large, a model that is accurate overall may still treat groups differently in distribution.

These results imply that explainability, careful fairness auditing and mitigation should be standard, reported components of any credit model intended for inclusive lending. We propose a layered evaluation framework in which a model advances through five gates before deployment: (1) predictive adequacy, established with threshold-independent metrics; (2) explanation, in which the drivers of predictions are inspected for legitimacy and proxy risk; (3) fairness, in which disparity gaps are measured across protected attributes of reliable size; (4) mitigation, in which residual disparities are reduced—here, group-aware thresholds cut the education false-positive gap from 0.082 to 0.005 for 0.4 points of accuracy; and (5) governance, in which any remaining disparities are documented, justified and monitored over time. Accuracy clears only the first gate.

A warning of the mitigation is crucial. Because group-aware thresholds apply distinct decision rules to each educational group, the protected property directly influences the decision, which minimizes discrepancy. This is ethically and legally questionable in many lending contexts: anti-discrimination laws like the U.S. Equal Credit Opportunity Act typically forbid

using protected or proxy attributes as the foundation for an individual credit decision, so an intervention that seems reasonable based on one statistical metric may be illegal disparate treatment. We therefore present group-aware thresholds as a diagnostic that quantifies how much of the disparity is correctable at the decision stage, not as a deployment recommendation. Group-neutral options, such as a single threshold chosen to balance error rates, reject-option or randomized post-processing that is independent of group membership, or in-processing techniques that punish disparity during training, are preferred when disparity needs to be minimized. Group-specific regulations would need to be implemented with clear legal and regulatory justification that is relevant to the jurisdiction.

Implications, Limitations and Future Research

The findings carry a direct implication for practice: institutions that deploy credit models for inclusive lending should treat explanation, fairness auditing, and mitigation as standard reporting requirements alongside accuracy, and should measure disparity only over demographic groups of reliable size.

Several limitations qualify these findings. The analysis uses a single dataset from one market and period (Taiwan, 2005), so the specific magnitudes may not generalize. Most importantly, the sample is made up of current credit card holders rather than thin-file or unbanked applicants. Therefore, the study shows a mechanism that is pertinent to financial inclusion: how disparate error rates and access-correlated features can disadvantage marginalized groups. However, it does not directly demonstrate how these models behave on the underprivileged populations that inclusion efforts aim to reach. Rather than being scientific results regarding the unbanked, claims about inclusion should be interpreted as inspiring and insightful. The protected attributes available are coarse and the “other” education group is too small for reliable inference. The fairness metrics are computed at a single 0.50 threshold; a full treatment would sweep thresholds and consider intersectional groups. We measure disparities but do not apply mitigation methods and we make no causal claims. Each of these points marks a direction for future work rather than a flaw in the central argument, which concerns the evaluation methodology itself.

Conclusion

Predictive accuracy is not a sufficient foundation for trust in algorithmic lending, according to this study. A representative gradient-boosted model matched published accuracy on

a conventional credit-default benchmark but produced uneven mistake rates across age and education which disparities that simple auditing overstated and detailed auditing revealed to be real but low. While group-aware decision criteria almost completely removed the education gap at a minimal accuracy cost on this benchmark, eliminating the most access-correlated feature did not assist; nevertheless, as mentioned, that fix is illustrative rather than deployable. Trust, we argue, must be engineered through explanation, careful auditing and mitigation, not inferred from accuracy. The layered framework proposed here offers lenders and regulators a concrete path toward credit AI that advances, rather than quietly erodes, financial inclusion. Future research will assess other data signals and richer, intersectional audits, as well as expand the analysis to various datasets and emerging-market, thin-file situations where financial inclusion is particularly important.

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Appendix A: Reproducibility Details

Data: UCI Default of Credit Card Clients (30,000 records, 23 features, binary default target). Split: 80/20 stratified (random seed 42). Models and key hyperparameters:

- Logistic Regression: standardized features, balanced class weights, max 2,000 iterations.
- Random Forest: 400 trees, max depth 8, balanced class weights.
- XGBoost: 400 trees, max depth 4, learning rate 0.05, subsample 0.8, colsample_bytree 0.8, positive-class weight set to the negative/positive ratio.

Explainability: SHAP TreeExplainer (exact). Fairness metrics computed at a 0.50 decision threshold. Education categories 0/5/6 mapped to “other”; marital-status 0 mapped to “other.”

Using Artificial Intelligence in Accounting: Transformations, Challenges, and Future Direction

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Abstract

Artificial Intelligence (AI) has rapidly transformed the landscape of accounting by automating routine tasks, enhancing decision-making capabilities, and generating new insights from complex financial data. This paper examines the integration of AI in accounting, its benefits and challenges, and explores key research questions related to AI adoption and its organizational impacts. A comprehensive literature review discusses current applications of AI technologies such as machine learning, natural language processing, and robotic process automation. The study employs a qualitative methodology to explore accounting practitioners' perspectives, highlighting both opportunities and barriers associated with AI implementation. Findings indicate that AI significantly improves accuracy, efficiency, and analytical capabilities while reducing operational costs. However, the results also reveal critical concerns related to data privacy, ethical accountability, regulatory compliance, and workforce skill gaps. Overall, the paper concludes that successful AI adoption in accounting requires strategic planning, ethical governance, and continuous professional development. The study contributes to the growing body of literature by offering practical insights for educators, practitioners, and policymakers. It also provides a foundation for future empirical research on the long-term implications of AI in the accounting profession.

Keywords: *Artificial Intelligence, Accounting, Machine Learning, Robotic Process Automation, Financial Decision-Making, Accounting Profession*

Introduction

Artificial intelligence (AI) has become one of the most transformative technologies affecting organizations worldwide, fundamentally changing how accounting professionals process financial information, perform audits, and support strategic decision-making. Recent advances in machine learning, generative AI, natural language processing (NLP), and robotic process automation (RPA) have enabled organizations to automate complex accounting processes while improving the speed, accuracy, and quality of financial reporting. As AI technologies continue to evolve, accounting professionals are increasingly integrating intelligent systems into routine accounting functions, financial analysis, auditing, fraud detection, and business advisory services (Kokina et al., 2025; Deliu, 2024). Consequently, AI is reshaping not only accounting operations but also the competencies and responsibilities required of modern accounting professionals.

The rapid advancement of cloud computing, big data analytics, and generative AI has accelerated AI adoption across accounting firms and corporate finance departments. Organizations now employ AI technologies to automate transaction processing, bank reconciliations, invoice management, expense categorization, financial forecasting, anomaly detection, and continuous auditing. These technologies improve operational efficiency while reducing manual errors and enabling accountants to focus on higher-value analytical and strategic activities. Recent research indicates that AI-supported accounting systems enhance decision-making by providing predictive insights derived from large volumes of structured and unstructured financial data (Kokina et al., 2025; Pérez-Calderón et al., 2025).

Beyond improving operational efficiency, AI is fundamentally transforming the role of accountants within organizations. Rather than replacing accounting professionals, AI increasingly serves as a decision-support technology that complements human expertise by automating repetitive tasks while strengthening analytical capabilities. As routine accounting activities become increasingly automated, accountants are transitioning toward advisory, governance, risk management, and strategic planning roles that require professional judgment, critical thinking, and ethical decision-making. This transformation has increased the demand for

digital competencies, AI literacy, data analytics, and continuous professional development among accounting professionals (Deliu, 2024; Kokina et al., 2025).

The emergence of generative AI since 2023 has further accelerated digital transformation within the accounting profession. Large language models and AI assistants are increasingly being used to summarize financial information, draft reports, support regulatory compliance, interpret accounting standards, and enhance communication with clients and stakeholders. While these technologies offer significant opportunities to improve productivity and decision support, they also introduce new concerns regarding information accuracy, hallucinated outputs, intellectual property, confidentiality, cybersecurity, and responsible AI governance. Consequently, accounting professionals must develop the skills necessary to critically evaluate AI-generated outputs while ensuring compliance with professional and regulatory standards (European Parliament, 2024; Deloitte, 2025).

Despite the considerable benefits associated with adoption of AI, significant challenges remain. Participants in recent studies have identified concerns related to data privacy, cybersecurity, algorithmic bias, transparency, explainability, and accountability as major barriers to widespread AI implementation. The "black-box" nature of some AI models can reduce users' confidence in AI-generated recommendations and complicate audit documentation, financial reporting, and regulatory compliance. Researchers have therefore emphasized the importance of maintaining human oversight, professional skepticism, and ethical governance when integrating AI into accounting practice (Deliu, 2024; Kokina et al., 2025).

Furthermore, the adoption of AI continues to vary across organizations because of differences in technological maturity, organizational readiness, financial resources, and workforce capabilities. Large multinational accounting firms generally possess greater financial and technological capacity to implement advanced AI solutions, whereas small and medium-sized enterprises (SMEs) frequently encounter challenges related to implementation costs, infrastructure limitations, and shortages of skilled personnel. These disparities may influence the pace and effectiveness of AI adoption across the accounting profession and highlight the importance of organizational investment in technology, workforce development, and change management (Pérez-Calderón et al., 2025).

Given these developments, this study examines the current applications of AI in accounting, explores accounting professionals' perceptions of its benefits and limitations, and identifies emerging challenges associated with AI adoption. The study also considers the implications of AI for professional judgment, workforce development, ethical governance, and the future of the accounting profession. By providing a balanced evaluation of both the opportunities and risks associated with AI, this research contributes to the growing body of knowledge on digital transformation in accounting and offers practical recommendations for practitioners, educators, and policymakers.

Literature Review

AI Technologies in Accounting

Artificial intelligence (AI) in accounting is not limited to a single technology but encompasses several interconnected technologies that collectively improve accounting processes, financial reporting, and decision-making. Machine learning (ML) algorithms analyze large volumes of structured and unstructured financial data to identify patterns, detect anomalies, forecast financial performance, and improve predictive accuracy. Natural language processing (NLP) enables AI systems to extract, classify, and summarize information from contracts, invoices, emails, financial statements, and regulatory documents, significantly reducing manual effort and enhancing reporting quality. In addition, robotic process automation (RPA) automates repetitive, rule-based accounting tasks such as invoice processing, journal entries, bank reconciliations, payroll processing, and accounts payable and receivable, allowing accounting professionals to concentrate on higher-value analytical and strategic activities (KPMG, 2025; Deloitte, 2025).

Predictive and prescriptive analytics represent another important AI application in accounting. Predictive analytics uses historical financial and operational data together with machine learning algorithms to forecast cash flow, revenues, expenses, financial risks, and business performance. Prescriptive analytics extends these capabilities by recommending optimal decisions based on multiple scenarios, constraints, and business objectives. These technologies support budgeting, financial planning, capital allocation, and enterprise risk management while

enabling organizations to move from descriptive reporting toward proactive decision-making in increasingly volatile business environments (PwC, 2025; Oracle, 2025).

AI-powered audit and assurance technologies have also transformed auditing practices. Traditional auditing relies heavily on sampling methods, which may fail to identify all irregularities or fraudulent transactions. AI-enabled auditing systems analyze complete transaction populations continuously and in real time using machine learning, anomaly detection, and continuous auditing techniques. These capabilities improve fraud detection, risk assessment, audit efficiency, and the reliability of financial reporting while strengthening internal controls and regulatory compliance (EY, 2025; IAASB, 2025).

Furthermore, intelligent decision-support systems integrate AI technologies with enterprise resource planning (ERP) systems, cloud accounting platforms, and business intelligence tools to support managerial and strategic decision-making. These systems combine machine learning, advanced analytics, data visualization, and expert systems to generate insights related to performance measurement, profitability analysis, cost management, and investment evaluation. However, the effectiveness of AI-enabled accounting systems depends on high-quality data, transparent algorithms, appropriate governance, cybersecurity measures, and accountants' ability to interpret AI-generated insights responsibly. Consequently, organizations must establish comprehensive AI governance frameworks and invest in continuous professional development to maximize the benefits of AI while mitigating ethical, legal, and operational risks (IFAC, 2025; ACCA, 2025)

Advantages of AI in Accounting

Artificial intelligence (AI) has significantly enhanced the efficiency and effectiveness of accounting by automating routine and repetitive tasks such as invoice processing, bank reconciliations, payroll administration, transaction classification, and financial reporting. By reducing manual intervention, AI minimizes human error, accelerates data processing, and improves the accuracy and reliability of financial information. As a result, accounting in accounting

professionals can devote more time to higher-value activities, including financial analysis, strategic planning, risk management, and advisory services. Recent research by Kokina et al. (2025) found that AI technologies improve audit quality, operational efficiency, and decision support by enabling accountants to focus on complex tasks requiring professional judgment rather than routine transaction processing. Similarly, Pérez-Calderón et al. (2025) reported that AI enhances auditors' ability to detect anomalies, identify fraud risks, and improve the quality of audit evidence through advanced data analytics and continuous monitoring.

Another important advantage of AI is its ability to support data-driven decision-making through advanced analytics, machine learning, and predictive modeling. AI systems can rapidly analyze large volumes of structured and unstructured financial data, identify hidden patterns, forecast future financial performance, and provide timely insights that support organizational planning and strategic decision-making. Furthermore, AI strengthens organizational resilience by improving fraud detection, risk assessment, regulatory compliance, and internal control monitoring. However, researchers emphasize that AI should complement rather than replace professional judgment, as accountants remain responsible for interpreting AI-generated recommendations, exercising ethical reasoning, and ensuring compliance with accounting standards. According to Deliu (2024), the successful integration of AI into accounting depends on balancing technological innovation with human expertise, professional skepticism, and effective AI governance.

Enhanced Efficiency and Accuracy

Artificial intelligence (AI) in accounting encompasses a range of interconnected technologies that improve accounting processes, financial reporting, and organizational decision-making. Machine learning (ML) algorithms analyze large volumes of structured and unstructured financial data to identify patterns, detect anomalies, forecast financial performance, and improve predictive accuracy. Natural language processing (NLP) enables AI systems to extract, classify, and summarize information from invoices, contracts, financial statements, and other textual documents, thereby reducing manual effort while enhancing reporting accuracy and efficiency. In addition, robotic process automation (RPA) automates repetitive and rule-based

accounting tasks, including invoice processing, journal entries, bank reconciliations, payroll processing, and accounts payable and receivable, allowing accounting professionals to focus on analytical and strategic responsibilities rather than routine transaction processing (Al-Htaybat et al., 2024; Kokina & Davenport, 2024).

Predictive and prescriptive analytics represent another important application of AI in accounting. Predictive analytics applies machine learning algorithms to historical financial and operational data to forecast revenues, cash flows, expenses, financial risks, and business performance. Prescriptive analytics extends these capabilities by recommending optimal decisions after evaluating multiple scenarios, constraints, and business objectives. These technologies improve budgeting, financial planning, enterprise risk management, and capital allocation while enabling organizations to shift from descriptive reporting toward proactive and data-driven decision-making in increasingly dynamic business environments (Moll & Yigitbasioglu, 2024; Sutton et al., 2025).

AI-powered audit and assurance technologies have significantly transformed modern auditing practices. Unlike traditional audit approaches that rely on sampling techniques, AI-enabled audit systems continuously analyze complete populations of financial transactions using machine learning, anomaly detection, and continuous auditing techniques. These capabilities enhance fraud detection, improve audit quality, strengthen internal controls, and increase the reliability of financial reporting while reducing audit time and costs (Issa et al., 2024; Alles & Gray, 2025).

Furthermore, intelligent decision-support systems integrate AI technologies with enterprise resource planning (ERP) systems, cloud accounting platforms, and business intelligence applications to enhance managerial and strategic decision-making. These systems combine machine learning, advanced analytics, data visualization, and expert systems to generate insights related to profitability analysis, performance measurement, cost management, and investment evaluation. Nevertheless, the effectiveness of AI-enabled accounting systems depends on high-quality data, algorithm transparency, appropriate governance frameworks, cybersecurity measures, and accountants' ability to interpret AI-generated outputs responsibly. Consequently, organizations must invest in AI governance, ethical guidelines, and continuous

professional development to maximize AI's benefits while minimizing operational, ethical, and regulatory risks (Wilson et al., 2025; Al-Htaybat et al., 2024).

Improved Decision-Making

Artificial intelligence (AI) significantly enhances decision-making by enabling organizations to analyze large volumes of financial and non-financial data in real time. Unlike traditional accounting systems that primarily generate historical financial reports, AI-powered analytics employ machine learning and advanced data processing techniques to produce predictive and prescriptive insights that support strategic planning and informed decision-making. These capabilities enable organizations to anticipate financial risks, forecast cash flows, optimize budgeting processes, and evaluate alternative business strategies with greater accuracy and speed (Moll & Yigitbasioglu, 2024; Sutton et al., 2025).

AI also plays a critical role in fraud detection and enterprise risk management. By continuously analyzing financial transactions and identifying unusual patterns through anomaly detection algorithms, AI systems can detect potential fraud, accounting irregularities, and compliance violations more effectively than traditional audit procedures. Unlike conventional auditing approaches that rely on sampling methods, AI facilitates continuous auditing by examining entire populations of financial transactions in real time, thereby improving audit quality, strengthening internal controls, and enabling earlier detection and prevention of financial misconduct (Issa et al., 2024; Alles & Gray, 2025).

Furthermore, AI enhances managerial decision-making by integrating financial information with operational, customer, and market data from enterprise information systems. AI-enabled decision-support systems combine machine learning, predictive analytics, and interactive data visualization to provide managers with comprehensive performance analyses, scenario simulations, and evidence-based recommendations. These capabilities improve resource allocation, strategic planning, investment evaluation, and organizational performance measurement while enabling accounting professionals to transition from traditional financial reporting roles to strategic business advisors. However, the effectiveness of AI-driven decision-making depends on data quality, algorithm transparency, organizational governance,

and accountants' ability to critically evaluate AI-generated recommendations (Al-Htaybat et al., 2024; Wilson et al., 2025).

Cost Savings

Another significant advantage of artificial intelligence (AI) in accounting is its ability to generate substantial cost savings by automating routine and labor-intensive accounting processes. AI technologies, including robotic process automation (RPA), machine learning, and intelligent document processing, reduce the need for manual intervention in tasks such as invoice processing, bank reconciliations, accounts payable, payroll administration, and financial reporting. As a result, organizations can lower labor costs, improve operational efficiency, and process large volumes of financial transactions more quickly and accurately. These benefits are particularly valuable for large organizations with complex financial operations and high transaction volumes (Al-Htaybat et al., 2024; Kokina & Davenport, 2024).

AI also contributes to cost efficiency by improving the accuracy and reliability of accounting processes. Human errors in financial reporting, transaction recording, and regulatory compliance can lead to financial losses, audit adjustments, legal penalties, and reputational damage. AI-powered systems continuously monitor financial transactions, detect anomalies, and identify potential errors before they become significant issues, thereby reducing the costs associated with error correction, fraud investigations, and compliance failures. Furthermore, continuous monitoring enhances internal controls and supports more effective risk management across organizations (Issa et al., 2024; Alles & Gray, 2025).

In the long term, AI adoption enables organizations to achieve sustainable financial benefits by reallocating human and financial resources from routine accounting activities toward strategic initiatives, innovation, business analytics, and professional development. Although implementing AI solutions often requires substantial initial investments in technology infrastructure, employee training, and organizational change management, empirical evidence suggests that organizations realize positive long-term returns through increased productivity, improved decision quality, enhanced operational resilience, and lower operating costs. These outcomes depend on effective AI governance, high-quality data, and continuous workforce

development to ensure successful implementation and responsible use of AI technologies (Wilson et al., 2025; Moll & Yigitbasioglu, 2024).

Disadvantages of AI in Accounting

Despite the significant benefits of artificial intelligence (AI) in accounting, its adoption also introduces several challenges related to professional judgment, data governance, transparency, and workforce transformation. One major disadvantage is the risk of excessive reliance on AI-generated outputs, which may reduce accountants' application of professional skepticism and critical evaluation. Many AI systems, particularly complex machine learning models, operate as "black box" technologies, making it difficult for users to understand how specific conclusions are generated. This lack of explainability can create challenges in auditing, financial reporting, and regulatory compliance, where accountants must justify decisions and demonstrate accountability. Deliu (2024) emphasized that although AI can enhance accounting processes, human judgment remains essential because ethical reasoning, contextual understanding, and professional skepticism cannot be fully replaced by automated systems. Similarly, Kokina et al. (2025) identified explainability, reliability, and governance as key challenges affecting trust and effective implementation of AI in auditing and accounting environments.

Another significant disadvantage is the potential impact of AI on workforce skills and organizational inequality. As AI automates routine accounting activities, professionals may have fewer opportunities to develop foundational technical skills through traditional hands-on experience. Accountants must therefore acquire new competencies in data analytics, AI literacy, technology management, and ethical evaluation to remain effective in an increasingly digital profession. In addition, AI adoption may create disparities between large organizations with substantial financial and technological resources and smaller accounting firms that face barriers related to cost, infrastructure, and employee training. (Pérez-Calderón et al., 2025) noted that successful AI adoption requires not only technological investment but also organizational readiness, employee development, and appropriate governance structures. Without adequate preparation, organizations may experience ineffective AI implementation, increased dependence on automated systems, and new risks related to data privacy, cybersecurity, and accountability.

Ethical and Privacy Concerns

Artificial intelligence (AI) systems in accounting rely on extensive volumes of structured and unstructured financial data, raising significant concerns regarding data privacy, confidentiality, cybersecurity, and the ethical management of financial information. Accounting data frequently contains sensitive personal, financial, and corporate information that must be protected against unauthorized access, cyberattacks, and data breaches. As organizations increasingly adopt AI-enabled accounting systems, ensuring robust data governance, cybersecurity controls, and compliance with privacy regulations has become essential for maintaining stakeholder trust and protecting the integrity of financial information. Consequently, organizations must implement comprehensive data governance frameworks that ensure data accuracy, security, confidentiality, and responsible AI use throughout the accounting process (Al-Htaybat et al., 2024; Dwivedi et al., 2023).

Another important ethical challenge involves algorithmic bias, fairness, and transparency. AI models learn from historical financial and organizational data that may contain biases, incomplete information, or historical inaccuracies. If these biases are embedded within AI algorithms, they may influence financial analyses, credit evaluations, fraud detection, risk assessments, and audit decisions, resulting in unfair or inaccurate outcomes. Moreover, biased AI models can undermine professional judgment and reduce stakeholders' confidence in automated accounting systems. Therefore, organizations should regularly validate AI models, monitor algorithmic performance, and implement governance mechanisms that ensure fairness, accountability, and transparency throughout the AI lifecycle (UNESCO, 2023; Bender et al., 2024).

Regulatory compliance remains another significant challenge for organizations implementing AI in accounting. Emerging regulations, including the European Union Artificial Intelligence Act (AI Act), the General Data Protection Regulation (GDPR), and evolving international AI governance frameworks, require organizations to ensure transparency, explainability, accountability, and human oversight in AI-supported decision-making. However, many advanced AI models continue to operate as "black-box" systems, making it difficult for accountants, auditors, regulators, and other stakeholders to understand how automated financial

decisions are generated. This lack of explainability complicates regulatory compliance, auditability, and accountability in financial reporting. Consequently, organizations must adopt explainable AI (XAI), establish effective governance frameworks, and maintain human oversight to ensure that AI applications comply with legal, ethical, and professional accounting standards (European Parliament, 2024; IFAC, 2025).

Workforce Displacement and Transformation of the Accounting Profession

The increasing adoption of artificial intelligence (AI) and robotic process automation (RPA) in accounting has generated concerns regarding workforce displacement and changes in employment patterns. AI-driven systems are increasingly capable of performing routine accounting activities, including data entry, transaction classification, invoice processing, reconciliations, and basic financial reporting. As these technologies automate repetitive and rule-based tasks, organizations may reduce their dependence on traditional manual accounting labor, particularly for entry-level positions that historically provided foundational experience for new accounting professionals. This transformation has created uncertainty regarding the future structure of accounting careers and the skills required for professional success in technology-driven environments (Moll & Yigitbasioglu, 2024; Al-Htaybat et al., 2024).

Although AI adoption may reduce demand for certain routine accounting tasks, it also creates opportunities for accountants to undertake more complex and value-added responsibilities. Emerging roles increasingly emphasize data analytics, strategic advisory services, AI system supervision, cybersecurity awareness, and technology-enabled decision support. However, the transition from traditional accounting roles to digitally oriented positions is not automatic. Many accounting professionals currently face significant skills gaps, particularly in areas such as data analytics, programming, artificial intelligence literacy, and the interpretation of AI-generated insights. Without effective education, professional development, and reskilling initiatives, some workers may experience difficulties adapting to evolving workplace requirements, potentially increasing professional inequality within the accounting profession (Sutton et al., 2024; Kroon et al., 2024).

Workforce transformation caused by AI also creates broader organizational and social challenges. Changes in accounting responsibilities may influence employee morale, professional identity, workplace relationships, and perceptions of job security. Organizations that introduce AI without appropriate change-management strategies may encounter resistance from employees who view automation as a threat rather than an opportunity for professional enhancement. Therefore, successful AI implementation requires organizations to invest not only in technological infrastructure but also in continuous learning programs, employee engagement, ethical leadership, and redesigned career pathways that integrate human expertise with AI capabilities (Dwivedi et al., 2023; IFAC, 2025).

Furthermore, the future of accounting is likely to involve collaboration between human professionals and intelligent systems rather than complete replacement of accountants. AI systems are highly effective at processing large datasets, identifying patterns, and performing repetitive calculations; however, human accountants remain essential for professional judgment, ethical decision-making, communication, interpretation of complex business situations, and maintaining stakeholder relationships. Consequently, the accounting profession is expected to evolve from a transaction-processing function toward a strategic advisory role where accountants use AI as an augmentation tool to enhance, rather than replace, human capabilities (Kokina & Davenport, 2024; Richins et al., 2024).

Implementation Costs and Technical Challenges of AI Adoption in Accounting

The implementation of artificial intelligence (AI) technologies in accounting requires significant initial investments in software acquisition, system integration, data infrastructure, cybersecurity, employee training, and organizational change management. AI-based accounting systems depend on reliable data environments, advanced computing capabilities, and continuous system maintenance to operate effectively. These requirements may create substantial financial pressure, particularly for organizations that lack sufficient technological resources or experience in digital transformation. Although AI can generate long-term efficiency gains and cost reductions, the initial implementation costs remain a significant barrier that may delay adoption decisions among many organizations (Al-Htaybat et al., 2024; Moll & Yigitbasioglu, 2024).

Small and medium-sized enterprises (SMEs) often experience greater difficulties in adopting AI technologies because of limited financial resources, insufficient technical expertise, and restricted access to specialized AI professionals. Compared with large organizations and multinational accounting firms, SMEs may struggle to justify significant investments in AI infrastructure or manage the risks associated with implementation failures, cybersecurity threats, and inaccurate AI-generated outputs. Consequently, differences in financial capacity and technological readiness may create unequal access to AI benefits across organizations and contribute to a digital divide within the accounting profession (Kokina & Davenport, 2024; Dwivedi et al., 2023).

Beyond financial constraints, technical challenges represent another major obstacle to successful AI implementation in accounting. AI systems require high-quality, accurate, and well-structured data to generate reliable results. Poor data quality, incomplete records, inconsistent data formats, and inadequate data governance can negatively affect AI performance and reduce users' confidence in automated accounting systems. Furthermore, integrating AI technologies with existing accounting information systems, enterprise resource planning (ERP) platforms, and legacy infrastructure can be complex and disruptive, requiring careful planning, system testing, employee training, and effective governance mechanisms (Issa et al., 2024; Sutton et al., 2025).

Another critical technical concern involves the reliability, transparency, and explainability of AI-generated outputs. Many advanced AI models, particularly machine learning and generative AI applications, operate with limited interpretability, making it difficult for accounting professionals to understand how specific recommendations or decisions are produced. This challenge is particularly important in accounting and auditing environments, where professional judgment, accountability, and regulatory compliance are essential. Therefore, organizations must adopt appropriate AI governance frameworks, establish monitoring procedures, and ensure human oversight to maintain the accuracy, reliability, and ethical use of AI technologies in accounting practices (Alles & Gray, 2025; IFAC, 2025).

Overall, while AI offers significant opportunities to improve accounting efficiency, decision-making, and service quality, successful adoption requires organizations to overcome

substantial financial, technical, and managerial barriers. A strategic implementation approach that combines investment in technology, employee capability development, strong data governance, and effective change management is necessary to maximize the value of AI while minimizing implementation risks.

Dependence on Technology and Reduced Professional Judgment

An additional disadvantage of AI in accounting is the growing dependence on automated systems, which may reduce the exercise of professional judgment. Excessive reliance on AI-generated outputs can encourage automation bias, where accountants accept system recommendations without sufficient critical evaluation. This is particularly concerning in auditing and financial reporting, where professional skepticism, ethical reasoning, and judgment remain essential for identifying anomalies, evaluating evidence, and ensuring compliance with accounting standards (Deliu, 2024; Kokina et al., 2025).

The increasing use of AI may also contribute to the erosion of accountants' technical competencies over time. As AI automates routine accounting and audit procedures, professionals—particularly junior accountants—may have fewer opportunities to develop a strong understanding of accounting principles, auditing procedures, and analytical reasoning. This reduction in experiential learning can limit their ability to detect errors, question AI-generated recommendations, or make informed decisions when automated systems produce inaccurate or biased outputs (Peecher et al., 2025; Kokina et al., 2025).

To mitigate these risks, organizations should position AI as a decision-support tool rather than a replacement for human expertise. Effective AI governance requires human oversight, explainable AI systems, continuous professional education, and organizational policies that reinforce professional skepticism and ethical judgment. Maintaining accountants' technical expertise alongside AI literacy will ensure that technology enhances rather than diminishes the quality and reliability of professional accounting practice (Deliu, 2024; Kokina et al., 2025). Another important concern is the lack of transparency and explainability in many AI systems used in accounting. Advanced AI models, particularly those based on machine learning and generative AI, often function as "black-box" systems, making it difficult for accountants and

auditors to understand how specific conclusions or recommendations are generated. This lack of explainability can reduce confidence in AI-assisted decision-making, complicate audit documentation, and create challenges in demonstrating compliance with regulatory and professional standards. Consequently, organizations should adopt explainable AI (XAI) frameworks, establish robust AI governance policies, and ensure that human professionals retain ultimate responsibility for reviewing and validating AI-generated outputs before they are used in financial reporting or audit decisions (European Parliament, 2024; Kokina et al., 2025).

Research Questions

The rapid adoption of artificial intelligence in accounting has transformed traditional accounting processes and professional roles, creating both opportunities and challenges for organizations and practitioners. While prior studies have explored technological advancements and automation in accounting, there remains a need for empirical and conceptual research that examines how AI is being used in practice and how professionals perceive its impact on their work. Understanding these perspectives is essential for assessing the effectiveness of AI implementation and for informing organizational strategies, professional education, and regulatory policies.

This study aims to address existing gaps in the literature by examining the practical application of AI technologies in accounting, the benefits and limitations experienced by accounting professionals, and the broader implications for workforce development and ethical governance. By focusing on practitioners' experiences and perceptions, the study provides insights into how AI is reshaping accounting roles, decision-making processes, and compliance requirements. The following research questions guide the investigation:

1- How are accounting professionals currently using AI tools in their daily work?
2- What are the perceived benefits and limitations of AI integration in accounting practices?
3- How does AI adoption impact workforce roles and required competencies in accounting firms?

Methodology

Research Design

This study employed a qualitative research design to explore the perspectives of accounting professionals regarding the adoption and impact of artificial intelligence (AI) in accounting practice. A qualitative approach was appropriate because it facilitates an in-depth understanding of participants' experiences, perceptions, and interpretations within their organizational and professional contexts. Unlike quantitative methods, qualitative research enables researchers to investigate complex social phenomena and capture rich, contextual insights into emerging technologies that are not easily quantified (Tracy, 2024).

The qualitative approach is particularly well suited to exploratory research involving rapidly evolving technologies such as AI. As AI continues to transform accounting processes, professional responsibilities, and ethical decision-making, qualitative inquiry provides the flexibility needed to examine issues such as workforce transformation, professional judgment, organizational readiness, and human-AI collaboration from the perspectives of practitioners. This methodological approach is consistent with contemporary qualitative research practices that emphasize understanding participants lived experiences and the meaning they assign to technological change (Braun & Clarke, 2024; Tracy, 2024).

Data Collection

Data was collected through semi-structured interviews with 15 accounting professionals employed in public accounting firms, corporate accounting departments, and financial consulting organizations. Semi-structured interviews provide a systematic yet flexible method for collecting qualitative data by allowing researchers to ask consistent core questions while also exploring emerging topics through follow-up questions. This interview format encourages participants to provide detailed accounts of their experiences while enabling the researcher to probe for clarification and deeper understanding (DeJonckheere & Vaughn, 2025).

Participants were selected using purposive sampling to ensure representation across different organizational sizes, professional roles, years of experience, and sectors of the accounting profession. Purposeful sampling is widely recommended in qualitative research because it enables researchers to recruit individuals who possess relevant knowledge and experience related to the research topic (Tracy, 2024).

The inclusion of participants from both public and private sector organizations enhanced the richness and diversity of the data by capturing differences in AI implementation, organizational resources, regulatory requirements, and professional responsibilities. Data collection continued until thematic saturation was achieved, meaning that additional interviews no longer generated new concepts or themes. Saturation remains an accepted indicator of sufficient sample size in qualitative research, particularly in interview-based studies (Hennink & Kaiser, 2024).

Interview Protocol

Interviews were conducted using secure video conferencing platforms and lasted approximately 45 minutes each. Conducting interviews online provided flexibility in scheduling while enabling participation from accounting professionals located across different geographic regions. Recent qualitative research demonstrates that video conferencing interviews provide data quality comparable to face-to-face interviews while improving accessibility, reducing logistical barriers, and facilitating participation from geographically dispersed professionals (Braun & Clarke, 2024; DeJonckheere & Vaughn, 2025).

The interview protocol consisted of open-ended questions designed to explore participants' experiences using AI technologies, perceived benefits and challenges, ethical considerations, organizational readiness, and expectations regarding the future of AI in the accounting profession. Follow-up and probing questions were used throughout the interviews to clarify responses, encourage elaboration, and explore emerging issues in greater depth. The use of a semi-structured interview guide ensured consistency across participants while maintaining sufficient flexibility to capture unique experiences and perspectives, thereby enhancing the richness and credibility of the qualitative data (Tracy, 2024).

Data Analysis

All interviews were audio-recorded with participants' informed consent and transcribed verbatim to ensure the accuracy and completeness of the data. The interview transcripts were analyzed using thematic analysis following the six-phase framework described by Braun and Clarke (2024). This analytical process involved familiarization with the data, systematic generation of initial codes, development of preliminary themes, review and refinement of themes, definition and naming of themes, and production of the final analytical report. Thematic analysis provides a flexible yet rigorous approach for identifying meaningful patterns within qualitative data while preserving participants' perspectives and contextual experiences (Braun & Clarke, 2024).

An inductive coding approach was adopted to allow themes to emerge directly from the interview data rather than being constrained by predetermined theoretical frameworks. This approach enabled the findings to reflect participants' authentic experiences regarding the implementation and impact of artificial intelligence in accounting. Throughout the analytical process, codes and themes were reviewed, refined, and compared across transcripts to ensure consistency, coherence, and credibility. Maintaining an audit trail, engaging in reflexive analysis, and systematically documenting coding decisions further strengthened the trustworthiness, dependability, and confirmability of the study's findings (Tracy, 2024; Braun & Clarke, 2024).

Ethical Considerations

Ethical considerations were integrated throughout all stages of the research process. Before participating in the study, all participants received detailed information regarding the purpose of the research, the voluntary nature of participation, the intended use of the data, and the procedures implemented to ensure confidentiality. Written informed consent was obtained from each participant before data collection commenced, and participants were informed of their right to decline any interview question or withdraw from the study at any time without penalty. These procedures were conducted in accordance with contemporary ethical principles for research involving human participants (American Psychological Association [APA], 2025).

To protect participant confidentiality, all personally identifiable information was removed from the interview transcripts and replaced with pseudonyms during data analysis and reporting. Audio recordings, transcripts, consent forms, and related research data were securely stored on password-protected devices accessible only to the researcher. Data management procedures were implemented in accordance with current ethical standards emphasizing privacy, confidentiality, secure data storage, transparency, and responsible research practice. These measures ensured that the rights, dignity, and confidentiality of participants were protected throughout the research process (APA, 2025; Tracy, 2024).

Table 1

Factors Associated with the Use of Artificial Intelligence in Accounting

	Variable	Mean (M)	Standard Deviation (SD)	1	2	3	4	5
1-	AI Adoption in Accounting	4.12	0.63	-				
2-	Perceived Usefulness of AI	4.35	0.58	.72				
3-	Perceived Ease of Use	4.18	0.61	.65	.68			
4-	Trust in AI Systems	3.94	0.70	.59	.62	.55		
5-	Professional Readiness for AI	4.05	0.66	.67	.64	.60	.57	-

Note. *N* = hypothetical sample size. Correlations represent Pearson's.

correlation coefficients. **p** < .01.

Explanation: The descriptive statistics indicate that participants demonstrated relatively high levels of AI adoption in accounting ($M = 4.12$, $SD = 0.63$). Among the measured factors, perceived usefulness of AI received the highest mean score ($M = 4.35$, $SD = 0.58$), suggesting that accounting professionals generally recognize the value of AI technologies in improving accounting efficiency and decision-making. Professional readiness for AI ($M = 4.05$, $SD = 0.66$) and perceived ease of use ($M = 4.18$, $SD = 0.61$) also showed positive evaluations.

Correlation analysis revealed significant positive relationships between AI adoption and other variables. AI adoption was strongly correlated with perceived usefulness of AI ($r = .72$, $p <$

.01), indicating that professionals who perceive AI as beneficial are more likely to adopt AI technologies. Similarly, AI adoption was positively associated with perceived ease of use (r = .65, p < .01), trust in AI systems (r = .59, p < .01), and professional readiness for AI (r = .67, p < .01). These findings suggest that perceptions of value, usability, trust, and preparedness may influence the acceptance and implementation of AI within accounting practices.

Table 2

Interview Focus Areas and Sample Questions

Focus Area	Sample Interview Questions
AI Usage in Accounting	How is artificial intelligence (AI) currently used in your accounting role? What types of AI tools or applications have you used in your daily accounting activities?
Perceived Benefits of AI Adoption	What benefits have you observed from the adoption of AI in accounting tasks? How has AI influenced efficiency, accuracy, productivity, or decision-making within your organization?
Challenges and Limitations of AI Implementation	What challenges or limitations have you encountered when using AI tools in accounting practice? How do issues such as implementation costs, technical difficulties, training requirements, or reliability concerns affect AI adoption?
Ethical Concerns Related to AI Use	What ethical issues have you observed or considered regarding AI use in accounting, such as data privacy, algorithmic bias, transparency, accountability, or professional judgment?
Future Expectations of AI in Accounting	How do you expect AI to influence the accounting profession in the future? What changes do you anticipate in accountants' roles, skills, and responsibilities as AI technologies continue to develop?

The interview questions were designed to explore accounting professionals' experiences, perceptions, challenges, and expectations regarding artificial intelligence adoption in accounting practices. The semi-structured format allowed participants to provide detailed responses while enabling the researcher to ask follow-up questions for clarification and deeper exploration.

Table 3

Summary of Emergent Themes from Thematic Analysis

Theme	Participants (n = 15)	Percentage
Efficiency and Automation	13	86.7%
Ethical and Privacy Concerns	12	80.0%
Decision Support	11	73.3%
Skill Transformation	10	66.7%
Uneven AI Adoption	9	60.0%

Example calculation

For **Efficiency and Automation**:

Number of participants mentioning the theme = **13**

Total participants = **15**

The percentages in the table are calculated using the standard formula:

$$Percentage = \left(\frac{Number\ of\ participants\ mentioning\ the\ theme}{Total\ participants}\right) \times 100$$

13 / 15X 100 = 86.70

The same method was applied to all other themes, with percentages rounded to one decimal place. The percentage for each theme was calculated by dividing the number of participants who mentioned the theme by the total number of participants (N = 15) and multiplying the result by 100. Because participants could identify multiple themes during the interviews, the percentages are not intended to sum to 100%; instead, they represent the proportion of participants who discussed each theme.

The percentages show that Efficiency and Automation was the dominant theme, followed closely by Ethical and Privacy Concerns, indicating that participants recognized both the practical benefits and the potential risks associated with AI adoption in accounting.

Overall, the findings suggest that accounting professionals perceive AI as a valuable tool for improving efficiency and supporting decision-making while simultaneously recognizing the ethical, organizational, and professional challenges associated with its implementation. The results also indicate that successful AI adoption requires not only technological investment but also organizational readiness, appropriate governance, and ongoing professional development to ensure that accountants can effectively integrate AI into their professional practice.

Themes were identified using an inductive thematic analysis approach following the six-phase framework described by Braun and Clarke (2024)**.**

Table 4

Example Participant Insights (Anonymized Quotations)

Participant ID	**Theme**	**Illustrative Quote**	**Interpretation**
P4	Efficiency and Automation	AI has significantly reduced the time required for reconciliations and reporting."	The participant emphasized that AI improves operational efficiency by automating repetitive accounting tasks, enabling accountants to devote more time to analytical and strategic responsibilities.
P7	Ethical and Privacy Concerns	"The biggest concern is trusting AI outputs without full transparency."	This quotation reflects concerns regarding AI explainability, accountability, and the importance of maintaining professional judgment when relying on AI-generated recommendations.
P10	Skill Transformation	Accountants now need to understand AI logic, not just accounting rules."	This quotation reflects concerns regarding AI explainability, accountability, and the importance of maintaining professional judgment when relying on

			AI-generated recommendations.
P13	Future Expectations	AI will become a standard tool, especially in audit and advisory services."	The participant anticipated broader AI integration across the accounting profession while recognizing that human expertise will remain essential for complex decision-making and ethical judgment.
P2	Adoption Challenges	"Smaller firms struggle to adopt AI due to cost and expertise limitations."	This quotation demonstrates that AI adoption varies across organizations, with smaller firms facing financial, technical, and workforce barriers to implementation.

Anonymized illustrative quotations are provided to demonstrate qualitative reporting practices and enhance transparency and credibility of thematic findings (Nowell et al., 2017). Representative quotations are presented to illustrate the themes identified during the thematic analysis. Participant identifiers (P2, P4) were anonymized to protect confidentiality. The use of illustrative quotations enhances the transparency, credibility, and trustworthiness of qualitative findings by demonstrating how interpretations are grounded in participants' own words (Braun & Clarke, 2024; Tracy, 2024).

presents anonymized participant quotations that illustrate the key themes identified through the thematic analysis. The inclusion of direct quotations enhances the credibility, transparency, and trustworthiness of qualitative findings by allowing readers to evaluate how the interpretations are grounded in participants' own experiences. Representative quotations are a fundamental component of qualitative reporting because they provide evidence supporting the identified themes while preserving participants' voices (Braun & Clarke, 2024; Tracy, 2024).

Overall, the participant quotations reinforce the principal themes identified during the thematic analysis. Collectively, they demonstrate that accounting professionals perceive AI as a technology capable of improving efficiency and supporting decision-making while simultaneously presenting ethical challenges, changing workforce skill requirements, and

creating disparities in adoption across organizations. The inclusion of representative quotations strengthens the credibility and authenticity of the findings by clearly linking the thematic interpretations to participants' own perspectives.

Representative quotations are presented to illustrate the themes identified during the thematic analysis. Participant identifiers (P2, P4) were anonymized to protect confidentiality. The use of illustrative quotations enhances the transparency, credibility, and trustworthiness of qualitative findings by demonstrating how interpretations are grounded in participants' own words (Braun & Clarke, 2024; Tracy, 2024).

Results and Discussion

Current Use of AI in Accounting

The findings indicate that accounting professionals are currently using artificial intelligence (AI) primarily to automate routine, repetitive, and high-volume accounting tasks, including invoice processing, expense categorization, payroll administration, bank reconciliations, and financial reporting. Participants reported that robotic process automation (RPA), machine learning algorithms, and generative AI applications are increasingly integrated into enterprise resource planning (ERP) systems to streamline transaction processing, improve operational efficiency, and reduce manual intervention. These findings are consistent with recent studies indicating that organizations typically adopt AI first for structured and rules-based accounting processes where automation can improve accuracy, efficiency, and cost-effectiveness (Kokina et al., 2025; Deloitte, 2025).

In addition to processing automation, participants highlighted the growing application of AI-driven analytics to support financial forecasting, budgeting, risk assessment, and performance monitoring. Machine learning models were reported to enhance cash flow forecasting, revenue prediction, variance analysis, and financial planning by analyzing both historical and real-time financial data. Several participants emphasized that AI enables accountants to identify trends, anomalies, and emerging business risks more effectively than traditional analytical methods. These findings support recent research suggesting that AI is transforming accounting from a

primarily historical reporting function into a predictive and strategic decision-support discipline (PwC, 2025; Kokina et al., 2025).

Participants also reported that AI is becoming increasingly important in auditing and assurance services. AI-powered tools are used to analyze entire populations of financial transactions rather than relying solely on traditional sampling techniques. These systems assist auditors by identifying unusual transactions, detecting anomalies, assessing fraud risks, and continuously monitoring financial controls. Participants noted that AI enhances audit efficiency and improves the quality of audit evidence while allowing auditors to focus on areas requiring professional judgment and critical evaluation. Recent studies conclude that AI strengthens audit quality through continuous auditing, intelligent anomaly detection, and enhanced risk assessment while reinforcing the importance of human oversight in interpreting AI-generated findings (Kokina et al., 2025; KPMG, 2025).

Overall, the findings demonstrate that AI is currently positioned as a decision-support and operational enhancement tool rather than a replacement for accountants' professional expertise. Participants consistently emphasized that although AI improves efficiency, analytical capabilities, and audit effectiveness, human judgment, ethical reasoning, and professional skepticism remain essential for interpreting complex financial information, ensuring regulatory compliance, and making strategic business decisions (Deloitte, 2025; PwC, 2025).

Perceived Benefits

Participants consistently identified improved efficiency and productivity as one of the most significant benefits of artificial intelligence (AI) in accounting. They explained that AI automates repetitive and time-consuming tasks such as invoice processing, reconciliations, data entry, and financial reporting, thereby reducing manual effort and improving operational accuracy. As a result, accountants are able to devote more time to higher-value activities, including financial analysis, business advisory services, strategic planning, and client engagement. These findings are consistent with the work of Kokina, Blanchette, Davenport, and Pachamanova (2025), who found that AI technologies improve audit and accounting efficiency

by automating routine processes while allowing professionals to focus on more complex analytical and judgment-based responsibilities.

Participants also emphasized AI's ability to process large volumes of financial data rapidly and accurately. They noted that AI-powered analytical tools support forecasting, budgeting, fraud detection, variance analysis, and financial performance monitoring by identifying patterns and anomalies that may not be readily observable through traditional analytical techniques. Several participants believed that AI-generated insights contribute to more informed and timely managerial decision-making. These findings are supported by Kokina et al. (2025), who concluded that AI enhances data analytics, improves risk assessment, and strengthens decision support in auditing and accounting. Similarly, Pérez-Calderón et al. (2025) reported that AI improves auditors' ability to analyze financial information, detect irregularities, and increase the effectiveness of audit procedures.

Another important benefit identified by participants was the complementary relationship between AI and professional judgment. Rather than replacing accountants, AI was viewed as a decision-support tool that enhances professional capabilities. One participant explained, "AI doesn't replace our judgment, but it gives us more time to think, interpret, and add value beyond routine bookkeeping." This perspective reflects the findings of Kokina et al. (2025), who observed that AI is most effective when it supports, rather than replaces, accountants' professional expertise. The authors emphasized that human oversight, ethical reasoning, and professional skepticism remain indispensable, particularly when AI-generated outputs involve complex financial reporting or audit decisions.

Overall, the findings indicate that AI provides substantial benefits by improving operational efficiency, strengthening financial analysis, enhancing decision support, and enabling accountants to assume more strategic roles within their organizations. However, participants consistently emphasized that these benefits are maximized when AI is implemented as a collaborative technology that complements human expertise rather than substituting for professional judgment. These conclusions are consistent with recent reviews of AI in accounting and finance, which describe AI as a transformative technology that increases efficiency and

predictive capability while preserving the critical role of human judgment in professional accounting practice.

Challenges and Limitations

Despite the numerous benefits associated with artificial intelligence (AI), participants identified several challenges that continue to hinder their widespread adoption in accounting. One of the most frequently discussed concerns was data privacy and information security. Because AI systems rely on large volumes of sensitive financial and organizational data, participants expressed concerns regarding unauthorized access, cybersecurity threats, data governance, and regulatory compliance. These findings are consistent with Deliu (2024), who argued that the increasing integration of AI into accounting requires robust governance frameworks, effective cybersecurity measures, and stronger ethical safeguards to maintain stakeholder trust and protect confidential financial information.

Another significant limitation identified by participants was the reliability, transparency, and explainability of AI-generated outputs. Several interviewees indicated that they were reluctant to rely entirely on AI recommendations because many AI models function as "black-box" systems, making it difficult to understand how conclusions are generated. Participants believed that limited transparency reduces accountability and complicates audit documentation, particularly when AI systems are used to support financial reporting or audit decisions. Similar findings were reported by Kokina et al. (2025), who concluded that explainability, algorithmic bias, and human oversight remain among the most significant barriers to AI adoption in auditing and accounting.

Participants also emphasized the need for continuous professional development and workforce upskilling. Many respondents acknowledged that although AI technologies improve efficiency, accountants must develop new competencies in AI literacy, data analytics, digital technologies, and critical evaluation of AI-generated outputs. Several participants believed that existing accounting education and professional training programs should incorporate AI applications, ethical decision-making, and digital competencies to prepare accountants for

increasingly technology-driven workplaces. These findings support those of Pérez-Calderón et al. (2025), who found that successful AI implementation depends not only on technological investment but also on the continuous development of employees' digital and analytical capabilities.

Participants further noted that financial and organizational constraints continue to limit AI adoption, particularly among small and medium-sized accounting firms. High implementation costs, limited technical expertise, and insufficient technological infrastructure were identified as major barriers preventing smaller organizations from adopting advanced AI solutions. Respondents suggested that these disparities may widen the technological gap between large multinational firms and smaller accounting practices unless organizations receive additional support for digital transformation. Similar conclusions were reported by (Kokina et al., 2025), who observed considerable variation in AI adoption according to organizational size, available resources, and technological readiness.

Implications and Future Research

The findings demonstrate that artificial intelligence is fundamentally transforming accounting by automating routine processes, improving operational efficiency, strengthening financial analysis, and supporting more informed managerial decision-making. Participants consistently viewed AI as a technology that enhances, rather than replaces, professional expertise. Applications such as machine learning, robotic process automation, and generative AI were reported to improve transaction processing, financial reporting, auditing, fraud detection, and predictive analytics while allowing accountants to focus on strategic and advisory responsibilities. These findings are consistent with the work of (Kokina et al., 2025), who concluded that AI creates greater value when integrated with accountants' professional judgment and analytical expertise.

Despite these advantages, participants emphasized that successful AI implementation requires organizations to address ethical, technological, and workforce-related challenges. Data privacy, cybersecurity, algorithmic bias, explainability, and regulatory compliance remain critical considerations for organizations adopting AI technologies. Furthermore, participants stressed that

investment in employee training, organizational change management, and AI governance is essential to maximize the benefits of AI while minimizing associated risks. (Deliu , 2024) similarly argued that effective AI governance depends upon balancing technological innovation with professional ethics, accountability, and human oversight.

The study also identifies several opportunities for future research. First, quantitative studies could examine the measurable effects of AI on accounting efficiency, audit quality, financial reporting accuracy, and organizational performance. Second, longitudinal research could investigate how AI adoption influences accountants' professional roles, competencies, and career development over time. Third, additional research is needed to evaluate AI governance frameworks that promote transparency, explainability, fairness, and accountability in accounting applications. Finally, future studies should examine AI adoption across different organizational contexts, including small and medium-sized enterprises, public sector organizations, and nonprofit institutions, to better understand the factors influencing successful implementation. These recommendations are consistent with the future research priorities identified by (Kokina et al., 2025; Pérez-Calderón et al., 2025)**.**

Conclusion

This study concludes that artificial intelligence has become an increasingly important technology within the accounting profession by improving efficiency, enhancing analytical capabilities, and supporting more effective decision-making. While AI offers substantial opportunities for automating routine accounting activities and strengthening audit and financial analysis, it does not replace the need for professional judgment, ethical reasoning, and critical evaluation. Instead, AI should be viewed as a collaborative technology that augments accountants' expertise while enabling them to assume more strategic roles within organizations.

The findings further demonstrate that the successful integration of AI depends on strong ethical governance, continuous workforce development, transparent AI systems, and organizational readiness. By investing in digital competencies, establishing appropriate governance frameworks, and maintaining human oversight, organizations can maximize the

benefits of AI while preserving the integrity, accountability, and professional standards of the accounting profession.

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Making Monetary Transactions Feel Like Natural Conversations: A Conversation Design Framework for Banking UX

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Abstract

Retail banking depends on digital channels to serve customers, yet many current interfaces remain complex, especially among users with limited technical proficiency. Most conversational assistants are limited to simple, one-off commands rather than the multi-step workflows a financial transaction already involves. This paper presents a Conversational Banking Interaction Framework (CBIF) that organizes financial tasks as structured conversations including clarification, confirmation, and context awareness, and that combines voice, text, touch, and biometric authentication to balance ease of use with privacy and security. A prototype instantiation was evaluated through expert heuristic inspection and a comparative usability study. The evaluation supports the framework's specific interaction mechanisms without establishing a general advantage for the conversational paradigm, and it yields implementation recommendations relevant to financial inclusion.

Keywords: Conversational AI, Retail Banking, Multi-Modal Interaction, Self-Service Banking, Financial Technology (FinTech), Human-Computer Interaction (HCI)

Introduction

Over the last 20 years, retail banking has undergone a radical transformation as providers transition service delivery from physical branches to digital channels (Felipe et al., 2025). Mobile applications, online banking portals, and call center automation via self-service channels have become the touchpoints for customers to access financial services. In 2023, 48.3% of U.S. households that have current bank accounts accessed their accounts primarily using mobile banking, and a total of 70.5% of those households used off-site channels (e.g., mobile, online, or telephone banking) as their primary access method (Federal Deposit Insurance Corporation, 2024). On the other hand, just 28.9% of all households indicated that in-person banking was their primary method of banking. These trends are also witnessed globally as financial institutions increasingly roll out digital platforms to cut operating costs and enhance the scalability of services.

The digital banking infrastructure has much investment, but a lot of that investment is rarely applied to tackling user experience issues related to these digital platforms. Bueno et al. (2024) revealed that many of today's interfaces are challenging for users to navigate successfully. Traditional mobile banking applications are entirely menu-driven and require the user to navigate through multiple pages before identifying the feature they want to use for a financial task. Most of these platforms are designed with the assumption that users have an adequate familiarity with banking language and system architecture, which is not true for many individuals (Zhu & Wang, 2022). This typically results in a high level of cognitive load for users trying to perform simple activities such as finding transactions, processing payments, or fixing account issues (Bueno et al., 2024).

These design issues have inspired the need to make digital banking feel more relatable and conversational. This is why today, large banks are beginning to add conversational assistants, and most are already running at scale. By 2024, Bank of America's virtual assistant Erica had already supported over 42 million clients and handled more than 2 billion customer interactions and over 1.2 billion personalized insights and guidance messages, as highlighted in Figure 1 (Bank of America, 2024). These assistants can help to find a transaction, check their balance, lock or unlock a card, and support digital payment systems. However, as much as this data shows progress, Vuković et al. (2025) asserted that the current generation of conversational banking

systems is somewhat constrained in its scope. As of now, conversational assistants work as automated customer service agents instead of complete financial integrations, which is clearly missing the point. Their abilities are usually limited to simple commands or predefined intents, like “check balance” or “find transaction” (Oyeniyi et al., 2024), which, for the most part, is not a complicated feature on the digital banking platforms. Systems often fail to handle the complex multi-turn dialogue required for secure financial transactions when users try to execute more sophisticated financial operations (Hasan et al., 2023). As a result, conversational banking has yet to realize its full potential as a first-choice interface for digital financial services.

Figure 1

Erica in Numbers



Note. From Bank of America (2024).

Research Aim and Contributions

This research focuses on the relationship between conversational AI and improving economic interactions in customer relations while strengthening trust in financial relationships through the adoption of conversational design principles within the digital banking environment.

A proposed conversational design framework utilizes multi-turn dialogue structures, sequence-aware trust interaction patterns, and multi-modal interface mechanisms, which will be used to support the retail banking user experience. Additionally, this framework provides guidelines for developing an improved inclusive, transparent, and usable conversational banking system. Finally, based upon an evaluation of a prototype instantiation of the framework, these results were turned into actionable implementation recommendations.

Literature Review

Theoretical Framework

The study uses a combination of three theoretical lenses, namely the Technology Acceptance Model (TAM), Cognitive Load Theory (CLT), and Human-Computer Interaction (HCI). TAM suggests that users adopt digital systems based primarily on perceived usefulness and perceived ease of use (Schorr, 2023). Systems that make it easier to perform financial tasks and require less interaction effort are therefore more likely to be adopted over time in the field of digital banking. The ability of users' working memory to engage with complex information contexts is limited, according to Cognitive Load Theory (Clark & Kimmons, 2023). Cognitive stress and reduced usability result from interfaces that require users to understand unfamiliar vocabulary, navigate through multiple options, or remember which step of the process they are on. In HCI research, usability, feedback, and error prevention are essential design elements for single interactive systems (Norman, 2013). When taken as a whole, these lenses provide a theoretical framework for evaluating conversational interfaces as ways to reduce interaction complexity in digital financial systems and enhance user experience.

Conversational Interfaces in Service Systems

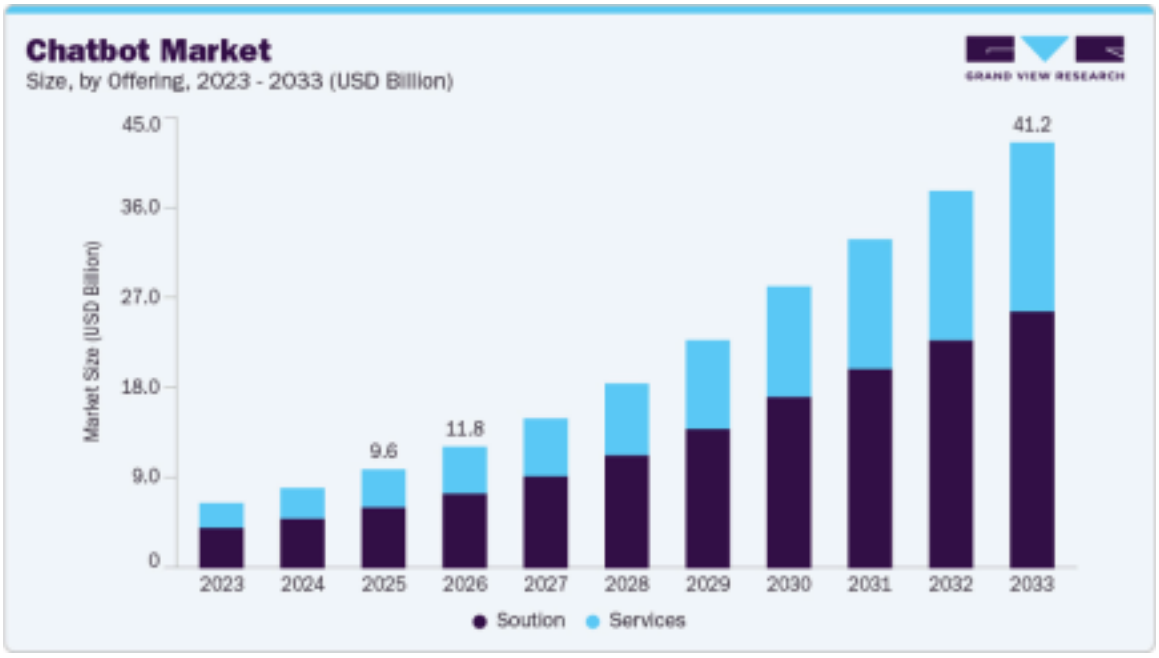
In the span of a few years, Conversational AI has evolved from what was known to be simple rule-based programs into increasingly sophisticated AI-enabled systems capable of supporting complex interactions across service environments (Hua et al., 2025). Earlier conversational agents like ELIZA ran on simple pattern-matching algorithms that faked interaction without any understanding of the language (Rajaraman, 2023). Although such

systems showed the possibility of what conversational interaction could be, Singh and Namin (2025) noted that they were still limited in that their responses were fixed and could not adapt to changes in context. The next generations of conversational systems pioneered rule-based dialogue architectures whose purpose was to drive users through clearly defined task flows, like booking a service or retrieving information (McTear et al., 2016). These systems were more efficient when conducting tasks in structured environments, but struggled when users made requests in unanticipated ways. Feine et al. (2019) emphasized that the rigidity of these systems constrained their effectiveness in actual service contexts, where users' requests often require interpretation and contextualization. In order to improve conversational technologies, natural language processing and machine learning have undergone many changes. Modern assistants like Siri, Alexa, and Google Assistant have shown the increasing potential for more natural conversational interaction as an alternative interface paradigm (Mariani et al., 2023).

According to Grand View Research (2025), the global chatbot market could reach **$41.2 billion by 2033**, highlighting the growing organizational dependence on conversational systems for delivering digital services and engaging customers Figure 2.

Figure 2

Chatbot Market



Note. From Grand View Research (2025).

Conversational AI in Digital Banking

The adoption of conversational AI in the banking industry has accelerated rapidly. According to a study conducted by Juniper Research, banks could save up to $7.3 billion by automating most of their routine enquiries with conversational AI technology (Juniper Research, 2019). This mode of banking is already being adopted today. Most big financial institutions have already launched conversational assistants as part of their digital ecosystems (Vuković et al., 2025). However, conversational banking systems today are still very much limited. Chau et al. (2025) pointed out that the majority of banking chatbots are centered on support and customer tiers instead of financing processes. Users are mostly interested in the completion of tedious tasks that would typically require them to call customer service or visit in person. However, these chatbots tend to be built on intent classification models that consider input from the user and map it to a specific command, like “check balance” or “transfer money.” This works well for simple requests, but the approach struggles when financial tasks involve multiple steps (Chau et al., 2025).

Summary

While many of these companies are growing quickly through the adoption of digital banking, financial access remains a big barrier. Globally, an estimated 1.4 billion adults do not have access to bank accounts (Basnayake et al., 2024). They are not the only ones who face challenges with access. For those who do have bank accounts, purposeful use of digital financial services varies considerably based on factors such as financial literacy levels, technological familiarity, and language proficiency (Basnayake et al., 2024). The United States faces language barriers that are a significant accessibility concern due to its diversity. Over 26 million residents in the United States are Limited English Proficient (LEP) (more than 1 in every 10 residents), and over 67 million speak a language other than English at home (Ramirez et al., 2023). Since financial terminology can be complex and tricky to translate correctly, digital banking interfaces can be especially challenging to design for newcomer or multilingual populations (Ramirez et al., 2023). Yet, existing research on conversational banking systems concentrates mainly on

automating customer services rather than conceptualizing the design of conversational frameworks that enable holistic financial workflows (Allouch et al., 2021; Chau et al., 2025). Thus, there is little research on how conversational interaction can be framed to support multi-turn financial transactions with trust, privacy, and inclusivity considerations (Luger & Sellen, 2016; Ntoa, 2024). Addressing this gap requires the design of frameworks that integrate conversational dialog managers with trust-aware financial interaction mechanisms.

Methodology

Research Philosophy and Design Approach

This paper employs a human-centered design approach to investigate different ways in which conversational interfaces can enhance the quality of interaction users have with digital banking environments. Human-centered design prioritizes the design of technological systems, putting the users' needs, behaviors, and cognitive limitations at the core, rather than solely technical system architecture (Norman, 2013). This approach is crucial in the context of digital banking because financial tasks are typically complex and require ample decision-making steps, sensitive information handling, and different levels of user expertise. To put this perspective into practice, a Design Science Research (DSR) approach is used. Design science research emphasizes the development and assessment of artifacts designed to solve practical information systems problems (Geerts, 2011). Unlike other purely empirical approaches, the DSR approach focuses on designing innovative artifacts such as models, frameworks, and prototypes (Peffers et al., 2018).

Framework Development Process

The framework for conversational banking was developed using a structured design process guided by the principles of Design Science research. The process consisted of three primary stages: problem identification, requirement derivation, and iterative framework development. In the first step, the key usability limitations of existing digital banking systems were identified. This is essential, as it identified the problem through a careful review of scholarly works on conversational interfaces, user experience in digital banking, and

Human-Computer Interaction. Existing research suggests that the vast majority of banking chatbots are still, to some extent, simple command-response interfaces and do not perform well at aiding complex financial interaction flows requiring clarification, confirmation, and context awareness (Bansal, 2024; Chau et al., 2025). These results indicate that multi-step financial tasks require a more formal conversational interaction model. The second step was to identify design requirements based on theoretical findings and limitations of the state-of-the-art systems. These requirements for the system include support for multi-turn dialogue interactions, clarification and ambiguity resolution, explicit confirmations of financial transactions, as well as multi-modal interaction elements (e.g., voice advertisements from the bank). Finally, the last step was the gradual development of the conversational framework. This involved gradual improvements to the design features by implementing the proposed interaction model that was systematically aligned with established principles from HCI and conversational UX design to progressively refine design elements. Through an iterative series of modifications and updates to the tested prototypes, the framework focused on structured dialog management, trust-aware interaction patterns, and support for contextual generation of prompts and cues during financial task completion.

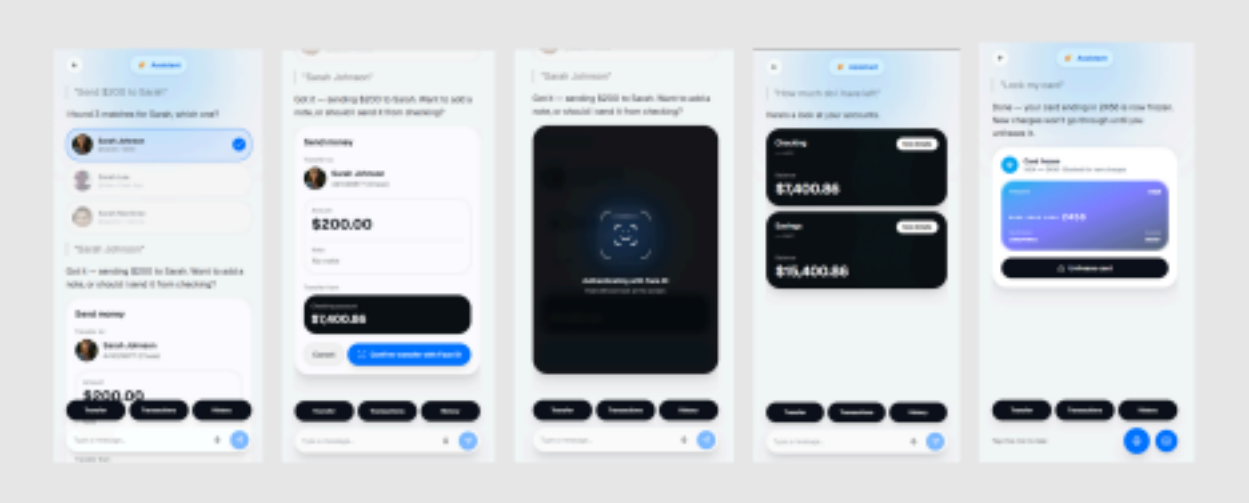
Framework Evaluation

The study was approved by the Morgan State University Institutional Review Board, and informed consent was obtained from all participants. The framework was evaluated through a prototype instantiation of the CBIF interaction model, in two stages. Two evaluators, one from Human-Computer Interaction and one from Computer Science, independently inspected eight conversational states against Nielsen's ten usability heuristics (Nielsen, 1994) and reconciled their ratings. Deficiencies falling within the scope of the design were addressed, and a study was conducted with four participants. Each of the subjects performed all three tasks using both the conversational version of the prototype and a menu-based version of the task. After each condition, participants completed the System Usability Scale (Brooke, 1996), a modified NASA Task Load Index (Hart, 2006) recorded on a 0 to 10 scale with the Physical Demand subscale omitted, and a seven-item instrument based on the Technology Acceptance Model (Davis, 1989). The prototype implements the framework's task flows within a single conversational canvas,

rendering each operation as an inline response card. Figure 6 shows the revised prototype following the design revisions described below.

Figure 6

Prototype Instantiation of the CBIF Interaction Model (Revised)



Note. Screens from the revised prototype, following Stage One design revisions. From left: contact disambiguation, pending confirmation with visible cancel control, biometric authentication, balance query response, and card freeze confirmation.

Results

Conversational Banking Framework

Design Principles for Conversational Banking UX

The conversational banking framework proposed is based on three underlying design principles: human-like dialog interaction, transparency and trust, and strong error prevention and recovery. These principles come from Human-Computer Interaction research and conversational UX design literature, which assert that a well-functioning digital system should adopt natural patterns of human communication while expending the least amount of cognitive effort (Norman, 2013). Rather than having users navigate through endless menu options and rigid pathways, natural language interaction allows users to interact with banking apps using natural human

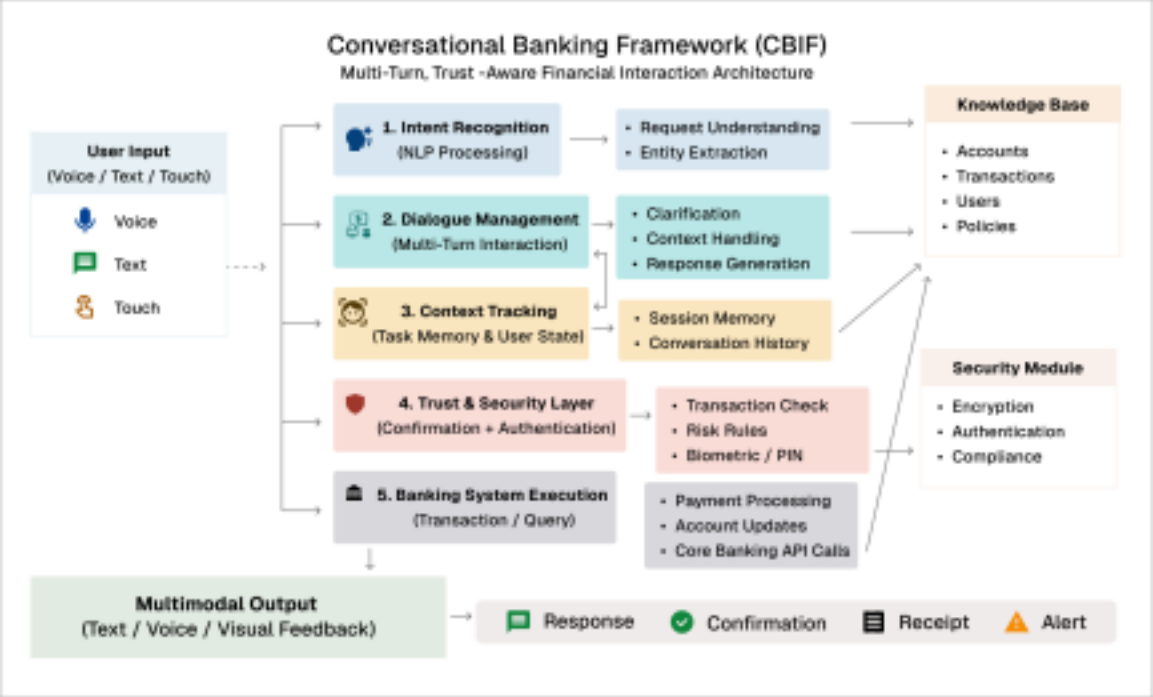
language (Hua et al., 2025). Traditional banking interfaces often require that users find a specific function before performing actions, which adds unnecessary stress and complexity. On the other hand, conversational interaction allows the user to get straight to the point, whether they are asking things like "send money to John" or questioning "why was my card declined?" This intent can then be understood by the system, which will help to guide the user in following the next steps. Transparency and trust are especially critical in financial contexts, where transactions have direct economic implications (Ashfin, 2024). This is a concern users are likely to have when it comes to using conversational banking interfaces. In order to build that trust, conversational systems must be incredibly clear about actions they take so that users will also know what exactly is happening. This means confirming transaction details back to the user and providing meaningful information at each stage of interaction. Without this level of reliability, users may be reluctant to initiate financial transactions (Felipe et al., 2025).

Architecture of the Conversational Framework

Conversational banking architecture consists of three axiomatic components: intent recognition, dialogue management, and contextual state tracking. As shown in Figure 3, these components work together to allow conversational systems to understand user requests, handle multi-turn conversations, and maintain context across financial tasks (Rustamov et al., 2021). The process begins with Intent recognition, which is the first interface between the user and the conversational system. The system first leverages natural language processing techniques to analyze the user input in order to understand the underlying financial intention of the user. For instance, requests like "send $200 to Sarah" or "show my last transactions" are mapped onto corresponding banking functions. Then again, intent recognition is not enough to manage complex financial interactions, as many requests require extra details and specific contexts before any action can be safely executed. That is where dialogue management functions come in as the main coordination mechanism in the framework. It coordinates the entire exchange, gathering information bit by bit, confirming relevant data, and assisting users through the whole process. The management of dialogue is also responsible for determining when clarification on the user's request is needed, and when authentication procedures should be invoked.

Figure 3

Conversational Banking Framework Architecture



Note. Authors' creation, 2026.

Trust-Aware and Multi-modal Interaction Design

Although most digital services can get away with standard security, banking requires a much higher level of reliability. Hence, conversational banking systems need to include interaction mechanisms that are trust-aware and prevent unintended actions while reassuring users about their decisions (Singh & Namin, 2025). Confirmation patterns are a critical aspect of design. Before money moves from the user's account, the system should clearly play back exactly what it is about to do. A user should clearly confirm with the system what action is being taken before doing any financial transaction. This confirmation stage helps users ensure the specifics of the transaction are correct and may correct possible mistakes. Authentication mechanisms are also an important component of security. Instead of forcing users to use conventional passwords, conversational systems can also support biometric authentication methods like fingerprint authentication or face verification with smartphones. These mechanisms allow users to validate sensitive actions without breaking the conversation flow (Omarini, 2022).

Finally, this framework also includes multi-modal interaction capabilities. Conversational banking does not have to be voice or text input only. Rather, modern systems leverage multi-modal interaction, such as voice commands for input, chatbots to provide details in text format, touch clickers for confirmations, and biometric login to ensure an accurate reduction of the response area (Iniesto et al., 2023). This multi-modal strategy allows users the flexibility of engaging with financial systems as suits their environment and privacy needs.

Framework Model and Operational Flow

The previously described components are integrated into a conceptual model of a goal-oriented conversational interaction involving digital banking. As shown in Figure 4, the process starts with user input via one or more interaction modalities, e.g., voice or text. This input is handled by the intent recognition component, which determines what financial task the user is requesting. Once the intent is identified, the dialogue management component begins a structured dialog flow meant to extract required information and drive users through the transaction pipeline. Throughout this entire exchange, state tracking acts as the system's memory, keeping track of things like account numbers and dollar amounts so the user never has to repeat themselves.

Figure 4

Multi-Turn Financial Dialogue Flow



Note. Authors' creation, 2026.

Prototype Interaction Scenarios

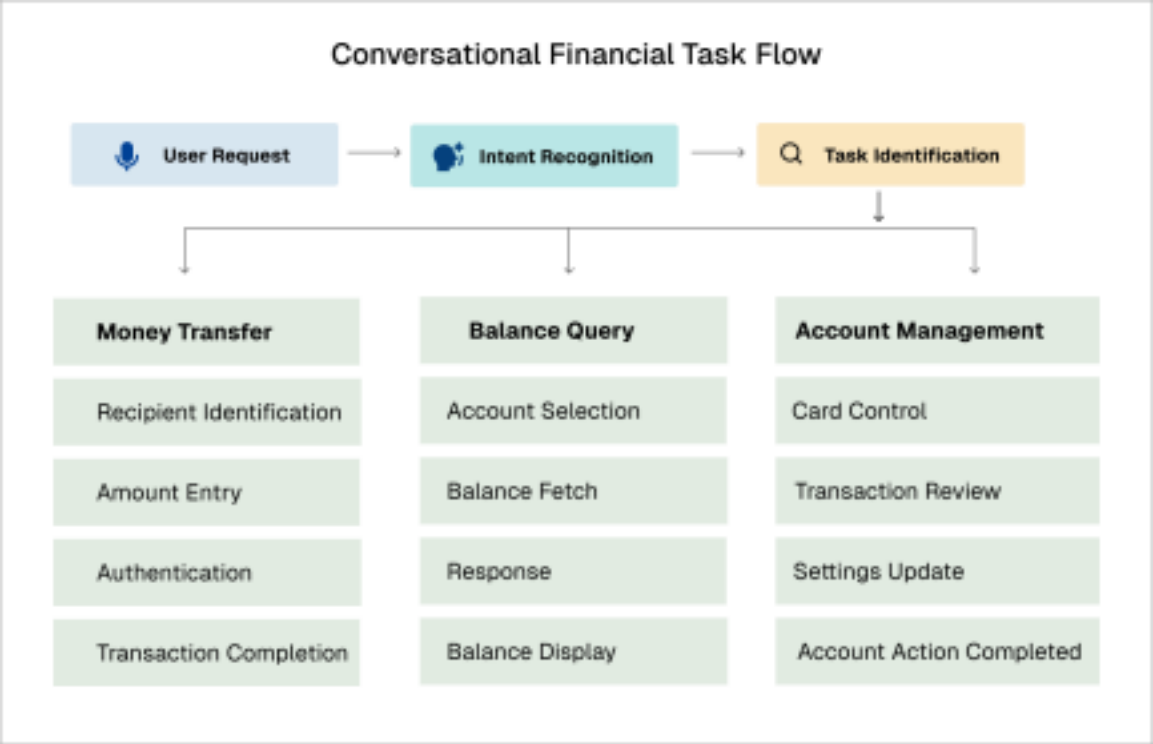
Financial Task Flows

In order to examine how this conversational banking framework actually functions in the real world, it was tested with common financial interaction scenarios. These scenarios show how these standard banking operations can be conducted in a structured conversation and dialogue instead of through menu-based navigation logic, as highlighted in Figure 5. For this purpose, three broad types of financial tasks were identified: transfer funds, check balance, and account management. One of the most sophisticated interactions is money transfers, which involve several steps: identifying users, selecting the account to withdraw from, confirming transactions, and validating security. Balance queries are an easier informational task, whereas account management actions can involve card locks and transaction review or payment preferences

(Allouch et al., 2021; Ntoa, 2024).

Figure 5

Conversational Financial Task Flow



Note. Authors' creation, 2026.

Dialogue Interaction

Prototype scenarios were developed to demonstrate how multi-turn conversational interactions could facilitate the completion of financial tasks. Unlike typical command-based chatbot systems, the framework organizes interactions as a series of dialogue exchanges that help users toward their goal. A designed flow between the human and the machine was made to feel structured yet flexible. One of the biggest hurdles in automated banking is handling uncertainty. Instead of forcing a restart from the user's side, in case of ambiguity, it asks for more information using clarification prompts. This approach mimics how two people talk to each other, "negotiating" the meaning until both sides are on the same page, allowing for financial transactions to be executed through iterative conversations rather than one-off commands (Feine et al., 2019; McTear et al., 2016).

Handling Errors and Security-Sensitive Interactions

Error management and secure transaction execution are essential elements of financial systems (Norman, 2013; Ntoa, 2024). In the proposed model, the processes of ambiguity resolution and authentication are directly integrated with conversational interaction sequences. Clarification prompts act as a safety net. They are used when the system is not confident about user input as a means of disambiguating before processing a transaction. For example, when multiple recipients share the same name, the system requests more identifying information to confirm accuracy. This minimizes the risk of incorrect transactions and prevents users from mistakenly performing actions they did not intend to perform. Furthermore, sensitive security operations require explicit authentication before finalization. By embedding authentication into the conversational workflow, as opposed to keeping it separate from interaction, security and usability are both retained by the scheme. Confirmation modalities further ensure that users have ongoing control of financial actions before the completion of a transaction (Allouch et al., 2021; Ntoa, 2024).

Both evaluators independently rated the lack of cancel, back, or edit controls that were visually available on the pending confirmation card as a severity level 3, and the single severity level 4 finding by the Computer Science evaluator, where a misrecognized amount was corrected by the user, acknowledged by the system, and executed at the original value. A visible cancellation option was added before the second stage, but the recognition and state-propagation defects were platform limitations and therefore remediable.

System Usability Scale scores were 78.75 for the conversational condition and 86.25 for the menu-driven condition. Both are above the reference point of approximately 68 for average usability (Sauro & Lewis, 2016). Median workload scores were 1.7 against 2.1 on a zero-to-ten scale. Errors were concentrated in the conversational condition, where two participants experienced speech recognition failures.

Across the seven measures recorded, none favored the conversational condition for a majority of participants, most clearly on the two single-function tasks, where input via voice provides no navigational advantage over one or two taps. When read in absolute rather than comparative terms, however, the conversational condition was rated higher than the usability

reference point on first exposure, by participants who are habituated to menu-driven banking, and under conditions where voice input is unavailable to at least half of the sample.

Discussion

In mapping our results to the three design principles, an uneven view was produced. A good realisation of the characteristics that define human-like dialogue interaction was achieved, with no severity above 1 recorded against the heuristics most closely related to it. Transparency was largely implemented through the display mechanism; however, transparency was not implemented in terms of verification since there is a distinction between displaying a parameter for confirmation purposes versus determining whether or not the value displayed represents the original value specified by the user. Error Prevention and Recovery represented the poorest realisation of all three principles.

Overall, aggregate usability and workload measures are indicative of all aspects of the instantiation, including design decisions that the framework does not address nor the behavior of a development environment whose behavior is also not addressed by the framework. Therefore, attribution is possible at the level of the individual mechanisms the framework prescribes. Both evaluators positively evaluated both the disambiguation card and the pending confirmation card. Similarly, none of the participants indicated uncertainty regarding their confirmation of actions, indicating positive support for those components of the framework that provide for those respective mechanisms. The most severe finding points the same way from the opposite direction. Where the prototype lacked a provision the framework specifies, namely the propagation of an acknowledged correction into the transaction state, the outcome was an incorrect transfer. That absence of the provision resulted in failure that is identical to that which the provision is designed to prevent, providing evidence that the provision should exist within the framework and not be dependent upon implementation.

In addition to convergence with regard to voice input and discoverability, there are two other areas that were identified during both phases of the evaluation. The first area relates to language proficiency. Although all of the evaluators and participants in this study are native speakers of languages other than English, previous studies have demonstrated variability in speech recognition performance among different linguistic populations (Koenecke et al., 2020) although no cause-and-effect relationship may be inferred from this observation it is clear that if

a framework aims to decrease barriers to access then similar issues warrant further investigation at larger scales than was investigated here.

Implications, Limitations, and Future Research

To implement conversational interaction within retail banking, there are four key requirements that must exist. The corrections resulting from conversational interaction must be able to affect the transaction payload (not merely the conversation) so that a conversational acknowledgement does not necessarily imply an alteration in state. All states prior to the final commitment must also show reversibility. Conversational options and possible routes of recovery after completion of transactions must be indicated clearly. Finally, speech recognition accuracy must be tested throughout the accents and languages of the target customers' demographic base, with text-based entry available and treated as a viable option (and not a secondary choice).

Convenience sampling resulted in four subjects who participated in this study and two evaluators. Convenience sampling allows no statistical generalization. As such, we can report on our findings descriptively. Each participant was familiar with traditional banking via menus; each had their first experience with conversational banking paradigms; the artifacts assessed during the two stages of data collection were somewhat different (but related); and several devices limited the ability of at least two subjects to use voice input. Additional research will need to provide reliable voice input capabilities as well as engage customers in actual multi-step financial workflow activities (the task types used for this research did not have those aspects isolated).

Conclusion

This proposed conversational banking framework shows the importance of going beyond the current command-based chatbot systems toward structured multi-turn dialogue interactions. Classic chatbot interfaces often handle single-user requests and do not support complex transactions such as financial transactions that need clarification, confirmation, and security verification (Chau et al., 2025). The framework shows that conversational interfaces can be designed to help users carry out more complex tasks and be able to guide the user step by step through financial workflows, with full transparency. Conversational systems, as multi-step

dialogue between humans and machines, are intended to reduce the cognitive workload for users when interacting with complex banking infrastructures, although the evaluation reported here did not establish that advantage over a familiar menu-driven interface on first exposure. Such design patterns resonate with established principles in Human-Computer Interaction that emphasize feedback, error prevention, and user control as determinants of success for digital systems (Norman, 2013). The framework was evaluated through a prototype instantiation rather than in a live financial environment, and the limitations of that evaluation are set out above. This study offers a framework for the conversation design of digital banking systems where multi-turn dialogue management, contextual interaction tracking, and trust-aware security mechanisms are integrated. The framework achieves this by making the financial interactions into guided conversational workflows, thus minimizing the cognitive load required to smoothly assemble and execute complex banking transactions while providing the transparency and predictability needed in any financial environment. Designing digital banking systems to improve usability is an important factor in ensuring successful adoption and usage; thus, it is crucial that the interaction patterns used in such systems be carefully considered. As conversational technologies develop, embedding user-centred design principles into financial service platforms will be fundamental to creating banking systems that are usable and inclusive.

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Financial Inclusion in the Age of AI: Opportunities and Risks for Underserved Communities

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Abstract

The rapid integration of artificial intelligence (AI) into financial technology (FinTech) has transformed the delivery of banking, lending, and financial management services across the global economy. For underserved communities, including low-income and historically marginalized populations, AI-powered financial systems present both significant opportunities and emerging risks. This paper examines how AI-driven FinTech applications can expand financial inclusion by increasing access to digital banking, personalized financial education, automated credit assessment, fraud detection, and alternative lending solutions. The study also explores how data analytics and machine learning models are reshaping financial decision-making processes within decentralized and technology-driven financial ecosystems.
Despite these advancements, concerns remain regarding algorithmic bias, data privacy, digital literacy gaps, and unequal access to technological infrastructure. AI systems trained on historically biased financial data may unintentionally reinforce discriminatory lending patterns and economic disparities, particularly among underserved populations. Additionally, the increasing dependence on automated financial systems raises questions surrounding transparency, accountability, and regulatory oversight within emerging financial technologies.
Using a qualitative analysis of existing literature, industry reports, and current FinTech case studies, this paper evaluates both the benefits and challenges of AI adoption in financial services. The findings suggest that while AI has the potential to promote greater economic participation and financial accessibility, ethical implementation, deterministic AI frameworks, and inclusive regulatory policies are necessary to ensure equitable outcomes. This research contributes to ongoing discussions regarding the societal implications of AI-driven financial innovation and the future of inclusive digital finance.

Databases Searched

- Google Scholar
- Scopus
- Web of Science
- SSRN (Social Science Research Network)
- IEEE Xplore
- ACM Digital Library
- ProQuest One Academic

Inclusion Criteria Sources were included if they met the following conditions:

- Peer-reviewed journal articles published between 2020 and 2026
- Policy reports, government publications, and major industry reports addressing AI, fintech, or financial inclusion
- Studies examining underserved or marginalized populations in relation to digital finance
- Research focused on artificial intelligence, algorithmic bias, digital banking, blockchain applications, or alternative data credit scoring
- Publications that provided empirical findings, conceptual frameworks, or regulatory analysis relevant to AI-enabled financial systems

Exclusion Criteria Sources were excluded if they met any of the following conditions:

- Articles not focused on AI, fintech, or financial inclusion
- Purely technical AI or machine-learning papers without financial or social application
- Opinion pieces, non-substantive commentary, or sources lacking analytical depth
- Publications outside the 2020–2026 date range unless cited for foundational context
- Duplicate sources or studies with insufficient methodological transparency

These criteria ensured that the final set of sources directly supported the study's focus on AI-driven financial inclusion and the risks and opportunities facing underserved communities.

Date Range

The search was limited to 2020–2026 to ensure the review captured contemporary developments in AI-enabled financial systems and the rapid expansion of digital financial inclusion technologies.

Search Process

The search was conducted in three stages:

Initial database search using all keywords to gather a broad pool of sources.
Screening of titles and abstracts to determine relevance to AI, fintech, financial inclusion, or algorithmic fairness. Full-text review of selected sources to extract themes related to inclusion benefits, algorithmic risks, governance mechanisms, and digital infrastructure challenges.

Source Count

The initial database search generated approximately 312 sources across academic journals, policy reports, and industry publications. After removing duplicates and screening titles and abstracts for relevance to artificial intelligence, financial inclusion, fintech applications, and underserved communities, 148 sources remained for full-text review. Following the application of the inclusion and exclusion criteria, 62 sources were retained for thematic analysis and synthesis in this study. This process ensured that the final body of literature reflected high-quality, directly relevant research on AI-enabled financial systems and their implications for underserved populations.

1. Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technologies within modern financial systems. Across the banking, lending, insurance, and investment sectors, AI-driven technologies are increasingly being used to automate decision-making, detect fraud, assess risk, and improve customer experiences (Sampson, 2025; Boot & Thakor, 2020; Brynjolfsson & McAfee, 2021; Fuster et al., 2022). As financial institutions continue adopting machine learning and predictive analytics, AI has become deeply integrated into the rapidly evolving FinTech ecosystem. These innovations have created new possibilities for expanding financial access to populations historically excluded from traditional banking systems (Demirgüç-Kunt, 2020).

Financial inclusion refers to the ability of individuals and businesses to access affordable and useful financial products and services that meet their needs. According to global financial inclusion studies, millions of individuals remain underbanked or entirely excluded from traditional financial services due to factors such as low income, lack of credit history, geographic isolation, or systemic discrimination (Jo et al., 2025; Goldfarb & Tucker, 2021). AI-powered financial systems have the potential to address many of these barriers by offering digital

alternatives to traditional banking structures. Financial inclusion is essential for economic mobility, stability, and long-term financial health.

Recent advancements in AI-driven FinTech have introduced alternative credit scoring models, digital wallets, automated savings tools, and personalized financial guidance (Agarwal & Dhar, 2021; Ghosh, 2023). AI-enabled fintech tools offer new pathways for expanding access to credit, banking, and financial education. AI technologies including machine learning, predictive analytics, and automated decision systems are transforming lending, fraud detection, customer service, and risk assessment (Sampson, 2025). These systems often rely on alternative data sources such as mobile phone usage, online transaction behavior, and digital payment histories to evaluate financial reliability. Researchers argue that these innovations can help underserved populations gain access to credit and financial opportunities that were previously inaccessible through conventional banking methods (Jo et al., 2025). Despite these advancements, concerns persist regarding algorithmic bias, data privacy, digital literacy gaps, and unequal access to technological infrastructure (Garcia et al., 2024; Kasy, 2024; Smith, 2025; Narayanan, 2022). AI systems trained on biased historical data may unintentionally reproduce discriminatory lending patterns, while opaque decision-making complicates accountability and consumer understanding.

This paper contributes to the existing body of research by offering a thematic synthesis of recent scholarship on artificial intelligence and financial inclusion, with a specific focus on underserved communities. Beyond summarizing prior studies, the paper develops a conceptual framework that links AI-enabled fintech tools, inclusion outcomes, and governance safeguards. This framework integrates insights on alternative data credit scoring, digital banking, algorithmic bias, and regulatory oversight to illustrate how AI can simultaneously expand financial access and reproduce systemic inequities. By organizing these dynamics into a structured model, the paper provides a foundation for evaluating the conditions under which AI-driven financial systems can promote equitable and responsible financial inclusion.

However, while AI presents opportunities for broader inclusion, it also introduces new ethical and regulatory concerns. Scholars have identified significant risks associated with algorithmic bias, opaque decision-making systems, data privacy violations, and unequal digital infrastructure. AI systems trained using biased historical financial data may reproduce or amplify discriminatory outcomes in lending and credit decisions (Garcia et al., 2024). Furthermore,

communities with limited digital literacy or inadequate internet access may struggle to fully benefit from AI-driven financial services.

The purpose of this paper is to evaluate both the opportunities and risks associated with AI-powered financial inclusion initiatives within underserved communities. What risks do AI-driven financial systems pose in terms of bias, privacy, and digital inequality? What governance mechanisms are necessary to ensure equitable AI-enabled financial inclusion? Specifically, this study examines how AI technologies are reshaping access to financial services while also investigating the social, ethical, and regulatory challenges associated with automated financial systems. Through a qualitative review of existing literature, the paper argues that AI-driven financial inclusion can create meaningful economic opportunities when implemented responsibly, transparently, and equitably.

Research Gap

Although existing studies examine AI-driven financial inclusion, most research either focuses on technical model development or evaluates isolated FinTech applications without integrating inclusion outcomes, structural risks, and governance safeguards into a unified analytical model. Prior work tends to analyze single platforms or technical innovations in isolation, leaving limited understanding of how AI functions across broader financial ecosystems (Sampson, 2025). Few studies synthesize cross-sector evidence to explain when AI expands financial access and when it reproduces exclusionary outcomes for underserved communities. As noted by Garcia (2024), the field lacks integrative frameworks capable of connecting technological innovation with equity-centered outcomes across diverse financial contexts. Scholars such as Kasy (2024) and Smith (2025) further emphasize that existing research rarely links algorithmic fairness, digital infrastructure, and governance mechanisms into a cohesive analytical structure. This paper addresses that gap by developing a conceptual framework that connects AI tools, inclusion mechanisms, structural barriers, and governance requirements, offering a novel contribution by clarifying the conditions under which AI promotes equitable financial inclusion and when it intensifies exclusionary outcomes. This study is guided by a central research question: Under what conditions do AI-enabled financial technologies expand financial inclusion for underserved communities, and when do they create or reinforce structural disadvantages.

2. Literature Review

2.1. The Evolution of AI in Financial Services

Artificial intelligence has significantly transformed financial services by enabling automation, predictive analytics, and real-time decision-making at a scale not previously possible. Beyond improving operational efficiency, AI has become central to risk modeling, fraud detection, identity verification, and customer segmentation. Financial institutions now rely on machine learning models to detect anomalies in transaction patterns, identify potential fraud in milliseconds, and assess creditworthiness using complex behavioral data (Sampson, 2025). Machine learning algorithms can process large volumes of financial data at speeds far beyond human capabilities, allowing institutions to make real-time financial decisions.

According to (Sampson 2025), AI technologies has also transformed customer interaction through natural language processing (NLP) and conversational interfaces. Chatbots and virtual assistants now handle routine inquiries, provide account information, and guide users through financial tasks, reducing the need for human intervention and lowering service costs. Robo-advisors AI-driven investment platforms use algorithmic portfolio management to offer low-cost wealth management services traditionally accessible only to higher-income clients. AI-driven automation also enables financial service providers to reach populations previously underserved by traditional banking infrastructures.

FinTech companies have been particularly influential in expanding AI adoption across the financial sector (Agarwal & Dhar, 2021; Chen & Wu, 2024; Arner et al., 2020). Unlike traditional banks, FinTech firms often rely on cloud-based technologies, alternative data sources, and digital-first business models (Arner et al., 2020; Goldfarb & Tucker, 2021; Vodanovich, 2024). This flexibility allows them to develop innovative financial solutions tailored to individuals with limited credit histories or irregular income streams (Demirgüç-Kunt, 2020; Ling, 2023; Puri, 2023). In addition, AI supports back-end functions such as fraud analytics, identity verification, and compliance monitoring, which help institutions manage risk more effectively (Wang, 2023; Xu, 2024; Fahim et al., 2023). As a result, AI has become a foundational component of modern financial ecosystems, shaping how institutions design products, evaluate customers, and deliver services (Agarwal & Dhar, 2021; Chen & Wu, 2024; Li, 2024). FinTech firms have accelerated this transformation by adopting

cloud-native architectures and agile development models that allow rapid deployment of AI tools (Brynjolfsson & McAfee, 2021; Chen & Wu, 2024; Vodanovich, 2024). Their reliance on alternative data sources such as mobile metadata, e-commerce activity, and digital payment histories enables them to serve consumers who lack traditional financial documentation (Fuster et al., 2022; Lin 2023; Tala Report, 2024). This positions FinTech companies as key drivers of inclusive financial innovation, particularly in emerging markets and underserved communities (Demirgüç-Kunt, 2020; Jo et al., 2025; Sampson, 2025).

Several empirical examples illustrate how AI-enabled financial systems operate in practice. Mobile money platforms such as M-Pesa in Kenya demonstrate how AI-supported transaction monitoring expands access to payments and microloans for rural populations (Vodafone, 2024). U.S.-based credit unions using Zest AI's machine learning credit models report measurable increases in loan approvals for borrowers with thin credit files (Zest AI, 2025). Digital lenders such as Tala and Branch use smartphone metadata to evaluate creditworthiness, enabling millions of previously excluded borrowers to access microcredit (Tala, 2024; Branch International, 2025). AI-driven digital banking applications and neobanks, including Chime, Varo, Nubank, and Revolut use automated risk scoring, fraud analytics, and personalized financial tools to deliver low-cost accounts, early wage access, and real-time financial guidance to underserved consumers (Chime, 2025; Nubank, 2024; Revolut, 2025). Blockchain-based remittance systems, including Ripple and Stellar, reduce transfer costs for migrant workers and increase transaction transparency (Ripple Labs, 2024; Stellar Development Foundation, 2025). Together, these cases provide practical evidence of how AI-driven financial tools can enhance inclusion under supportive regulatory and technological conditions (Jo et al., 2025; Sampson, 2025).

2.2. AI and Financial Inclusion

Financial inclusion remains a persistent global challenge, with millions of individuals lacking access to basic financial services such as savings accounts, credit, insurance, and digital payment systems (Demirgüç-Kunt, 2020). Historically marginalized communities often face barriers to accessing financial services due to poverty, geographic isolation (rural populations), lack of documentation for immigrants, or discriminatory lending practices racial , and insufficient financial literacy (Demirgüç-Kunt, 2020; Garcia et al., 2024; Kasy, 2024). AI-

powered technologies have introduced new approaches for addressing these challenges (Fuster et al., 2022; Jo et al., 2025; Sampson, 2025).

Jo et al. (2025) explains that AI can improve financial inclusion by enabling scalable, low-cost financial services for underserved populations. Mobile banking applications and AI-driven customer service platforms reduce the need for physical bank branches, making financial services more accessible in rural or economically disadvantaged communities. Automated financial systems also allow institutions to provide 24/7 customer support, and other services more efficiently and at lower operational costs.

Alternative credit scoring models represent one of the most significant applications of AI within financial inclusion efforts. Traditional credit scoring systems often exclude individuals without established credit histories. AI-powered systems can analyze alternative forms of data such as utility payments, digital transactions, employment patterns, and mobile device usage to assess financial reliability. This approach may provide access to loans and credit for individuals previously excluded from conventional lending systems (Fuster et al., 2022; Lin, 2023; Wang, 2023; Zest AI, 2025).

Researchers have also highlighted the role of AI in improving financial literacy and customer engagement. AI chatbots and personalized financial assistants can offer budgeting advice, savings recommendations, and investment guidance tailored to individual financial situations. These tools may help underserved populations make informed financial decisions and improve long-term economic stability (Jo et al., 2025, Kim, 2023; Sampson, 2025; Venkatesh, 2023).

However, the benefits of AI-driven inclusion depend heavily on equitable access to technology. Communities lacking reliable internet, smartphones, or digital literacy may remain excluded despite the availability of digital financial tools. Additionally, concerns about data privacy, algorithmic transparency, and surveillance disproportionately affect marginalized groups, who may be more vulnerable to misuse of personal data. Thus, while AI has the potential to expand financial inclusion, its impact is shaped by broader social, economic, and technological inequalities that must be addressed through policy and governance (Garcia et al., 2024; Kasy, 2024; Narayanan, 2022; Sun, 2024; Xu, 2024).

2.3. **Conceptual Framework**

The conceptual framework guiding this study positions AI-driven financial technologies as both enablers of financial inclusion and potential sources of inequity. The framework illustrates how three core technological components such as AI-enabled fintech tools, alternative data systems, and digital banking platforms, all shape financial access for underserved communities. These technologies can expand inclusion by reducing reliance on traditional credit histories, lowering operational costs, and increasing access to digital financial services (Sampson, 2025; Jo et al., 2025).

One of the most transformative applications of AI in financial inclusion is the use of alternative data for credit scoring. Traditional credit systems rely heavily on formal financial histories, which many underserved individuals lack. AI models can analyze non-traditional data sources such as utility payments, rental histories, mobile phone usage, social network behavior, and digital transaction patterns to assess creditworthiness (Jo et al., 2025). This approach allows lenders to identify credit-worthy individuals who would otherwise be excluded from formal lending markets.

Automated lending systems further streamline the credit evaluation process by using machine learning algorithms to assess risk, determine loan eligibility, and set interest rates in real time. These systems reduce processing times, minimize human bias, and lower operational costs. However, they also raise concerns about algorithmic discrimination, especially when models rely on biased historical data or proxy variables correlated with race, gender, or socioeconomic status (Garcia et al., 2024).

Digital banking has expanded rapidly through mobile applications, neobanks, and digital-only financial institutions. These platforms offer low-cost or no-fee accounts, instant transfers, mobile deposits, and automated savings tools. For underserved populations, digital banking reduces geographic barriers and provides access to financial services without requiring physical branches.

Mobile finance including mobile money, peer-to-peer payments, and digital wallets, has become especially important in regions with limited banking infrastructure. Mobile finance platforms allow users to store money, send payments, and access microloans using basic mobile devices. These systems have been widely adopted in parts of Africa, Asia, and Latin America, demonstrating the potential of mobile-based financial ecosystems to promote inclusion.

Together, alternative data systems, automated lending, digital banking, and mobile finance represent a new financial infrastructure that can expand access to credit and financial services. However, these innovations must be paired with strong governance frameworks to ensure fairness, transparency, and consumer protection.

Despite these inclusion benefits, the framework also identifies key risks that may undermine equitable outcomes. Algorithmic bias, opaque decision-making, data privacy vulnerabilities, and digital infrastructure gaps can reproduce or intensify existing financial disparities (Garcia et al., 2024; Smith, 2025). These risks are conceptualized as structural barriers that interact with technological systems to influence financial outcomes.

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To balance innovation with equity, the framework incorporates governance safeguards including explainable AI, fairness auditing, deterministic modeling, and regulatory oversight as moderating mechanisms (Fahim et al., 2023; Zhou et al., 2021). These safeguards are positioned as essential for ensuring that AI-driven financial systems operate transparently, ethically, and in ways that protect vulnerable populations.

Together, the framework provides a structured lens for analyzing how AI technologies can both promote and hinder financial inclusion, emphasizing the need for responsible implementation and inclusive policy design.

2.4. **Algorithmic Bias and Ethical Concerns**

Despite its potential benefits, AI in financial systems presents serious ethical concerns. One of the most significant issues is algorithmic bias. Algorithmic bias occurs when AI systems produce discriminatory outcomes due to biased training data, flawed model design, or unequal representation within datasets.

Garcia et al. (2024) found that machine learning systems used in lending and credit evaluation frequently reflect historical inequalities present within financial institutions. Because

many AI models are trained using historical financial data, they may unintentionally replicate discriminatory lending practices associated with race, gender, or socioeconomic status.

Kasy (2024) argues that many definitions of algorithmic fairness prioritize institutional profitability over social equity. As a result, financial algorithms may optimize decision-making processes in ways that disadvantage historically marginalized communities. The use of alternative data sources also raises concerns regarding surveillance, consent, and consumer privacy.

Gender disparities within AI-driven lending systems have also been documented. Smith (2025) found that AI-powered credit assessment tools may unintentionally reinforce gender inequalities due to gendered patterns within digital data and financial behavior. These systems often operate under the assumption that algorithms are inherently objective, despite evidence demonstrating that algorithmic outcomes frequently reflect societal biases.

2.5. Digital Divide and Infrastructure Challenges

Although AI-driven financial technologies may increase access to financial services, unequal access to digital infrastructure remains a major barrier. Many underserved communities lack reliable internet access, smartphones, or digital literacy skills required to engage with digital financial systems. The expansion of digital banking and mobile finance has highlighted disparities in technological access between urban and rural populations. Research indicates that FinTech adoption remains concentrated in metropolitan areas due to stronger technological infrastructure and higher levels of digital literacy. Communities lacking broadband access or affordable mobile technology may continue to experience financial exclusion despite technological advancements. The “black box” nature of many AI systems also presents transparency challenges. Consumers may not understand how automated financial decisions are made or why they are denied credit, insurance, or financial opportunities. This lack of transparency complicates efforts to hold institutions accountable for discriminatory outcomes.

2.6. Regulatory and Governance Considerations

As AI becomes increasingly integrated into financial systems, governments and regulatory agencies face growing pressure to establish ethical and transparent governance

frameworks. Current regulatory systems often struggle to keep pace with rapid technological innovation.

Researchers emphasize the importance of deterministic and explainable AI within financial systems. Deterministic AI refers to systems designed to produce predictable, transparent, and auditable outcomes. Explainable AI models allow consumers and regulators to understand how financial decisions are made, improving accountability and trust.

Fahim et al. (2023) argue that financial institutions must implement governance frameworks that prioritize fairness, transparency, consumer protection, and accountability. Regulatory oversight is particularly important in areas such as credit scoring, fraud detection, and automated lending, where AI decisions can significantly impact economic opportunities.

Ultimately, scholars agree that responsible AI implementation requires collaboration among policymakers, financial institutions, technologists, and community stakeholders. Ethical governance frameworks must balance innovation with protection against discrimination, exclusion, and systemic risk.

2.7. Scoping Review Methodology

This paper uses qualitative research methodology based on a comprehensive review of existing academic literature, industry publications, and case studies related to artificial intelligence, FinTech, and financial inclusion. A qualitative approach was selected because it allows for an in-depth exploration of the social, ethical, economic, and technological implications of AI-driven financial systems.

The literature reviewed for this study includes peer-reviewed journal articles, conference papers, policy reports, and scholarly analyses published between 2020 and 2026. Sources were selected based on their relevance to AI applications within financial systems, financial inclusion initiatives, algorithmic fairness, and regulatory governance. The study also incorporates comparative examples from the United States and global FinTech markets to evaluate how AI technologies impact underserved communities across different socioeconomic environments.

Data analysis was conducted using thematic synthesis. Recurring themes and patterns were identified across scholarly sources to evaluate both the opportunities and risks associated with AI-driven financial systems. The findings were then categorized into broader discussions surrounding inclusion, equity, transparency, and governance (Narayanan, 2022; Xu, 2024).

The thematic synthesis followed a structured three-stage coding process to ensure transparency and reproducibility. First, open coding was used to identify recurring concepts across the 62 retained sources, including alternative credit scoring, algorithmic bias, digital banking, fraud analytics, and governance mechanisms. Second, axial coding grouped these concepts into broader thematic categories such as inclusion benefits, structural risks, and regulatory safeguards. Third, selective coding integrated these categories into the conceptual framework by mapping relationships among AI tools, inclusion outcomes, and governance requirements. This systematic approach strengthens methodological rigor and clarifies how themes were compared across diverse studies.

While this study does not involve primary data collection or statistical experimentation, the qualitative methodology provides valuable insight into the broader societal implications of AI-powered financial innovation.

3. Results and Findings

The thematic synthesis of the 62 retained sources indicates that AI-driven financial technologies can meaningfully expand access to financial services for underserved communities. Mobile banking platforms, AI chatbots, and automated lending systems reduce dependence on physical bank branches, allowing rural and economically disadvantaged populations to access financial services through smartphones and digital platforms. Alternative credit scoring emerged as one of the most significant applications because AI models can analyze utility payments, online transaction activity, and mobile device behavior to identify creditworthy individuals who lack traditional credit histories, including low-income consumers, gig workers, immigrants, and younger borrowers (Jo et al., 2025; Sampson, 2025). The findings also show that AI-powered personalization, such as automated budgeting assistants and adaptive financial education tools, may support financial literacy and responsible financial behavior, while real-time fraud detection and anomaly monitoring strengthen consumer protection and build trust in digital financial services, benefits that are especially consequential for low-income households with limited capacity to absorb financial losses.

At the same time, the findings reveal that AI-driven financial systems can reproduce or intensify existing inequalities when they are not implemented responsibly. Several

studies show that AI systems trained on historically biased financial data may replicate discriminatory lending patterns across racial, gender, and socioeconomic lines (Garcia et al., 2024; Smith, 2025), and that the use of proxy variables and alternative data raises concerns about algorithmic opacity, surveillance, and consumer privacy (Kasy, 2024). In addition, digital inequality remains a major structural barrier, as older adults, rural residents, and low-income households without reliable internet access, smartphones, or digital literacy skills may become further excluded as financial services move online. Overall, the findings suggest that AI's contribution to financial inclusion depends less on the technology itself than on the governance surrounding it, explainable and deterministic AI models, fairness auditing, transparency requirements, consumer protections, and mechanisms for challenging automated decisions (Fahim et al., 2023).

1. Increased Access to Financial Services

The literature consistently demonstrates that AI-powered financial technologies can improve financial access for underserved populations. Mobile banking platforms, AI chatbots, and automated lending systems reduce barriers associated with physical banking infrastructure. Individuals living in rural or economically disadvantaged communities can access financial services through smartphones and digital platforms without visiting traditional bank branches.

Alternative credit scoring systems have proven particularly impactful for individuals with limited or non-traditional financial histories. By analyzing alternative forms of data such as utility payments, online transaction activity, and mobile device behavior, AI systems can identify financially responsible individuals who may otherwise be excluded from traditional lending models. These innovations expand credit access for low-income consumers, gig workers, immigrants, and younger borrowers who lack conventional credit files.

Studies also show that AI-powered financial tools improve operational efficiency and reduce service delivery costs for financial institutions. Lower operational costs may enable financial providers to offer more affordable financial products to lower-income consumers, further supporting inclusive lending practices.

Because this study is conceptual and based on secondary literature, future research should empirically validate the proposed framework through comparative case studies, model audits, and quantitative evaluations of AI-driven financial systems. Survey-based research could also

assess consumer experiences with digital banking, alternative credit scoring, and automated lending. These empirical extensions would strengthen the practical applicability of the framework and support evidence-based policy development.

2. Expansion of Personalized Financial Services

AI-driven personalization has transformed customer engagement within financial systems. Automated financial assistants can provide tailored budgeting advice, savings strategies, and financial planning recommendations. These tools may improve financial literacy and encourage responsible financial behavior.

Financial institutions increasingly use predictive analytics to identify consumer needs and deliver customized financial products. Personalized financial guidance may help underserved populations manage debt, improve savings habits, and increase long-term financial stability. AI-driven personalization also supports financial education by adapting content to a user's behavior, language, and financial habits, making financial learning more accessible to individuals with varying levels of literacy or technological familiarity.

3. Fraud Detection and Security

AI has significantly strengthened fraud detection and security within digital financial ecosystems. Machine learning models can analyze transaction patterns in real time to detect anomalies, prevent identity theft, and flag suspicious activity. These systems enhance consumer protection, especially for individuals who rely heavily on mobile banking and digital payments.

For underserved communities, improved fraud detection is particularly important because financial losses can have more severe consequences for low-income households. AI-driven security tools help build trust in digital financial services, encouraging broader adoption of mobile banking, digital wallets, and online transactions.

4. Algorithmic Bias and Discriminatory Outcomes

Despite the potential benefits of AI-driven finance, significant concerns remain regarding algorithmic discrimination. Multiple studies found evidence that AI systems may reproduce racial, gender, and socioeconomic biases embedded within historical financial datasets.

Automated lending systems trained using biased historical data may deny loans to qualified applicants from marginalized communities while favoring historically advantaged populations.

Researchers found that algorithmic bias often emerges unintentionally due to unequal representation within training datasets or reliance on proxy variables associated with race or income. The use of alternative data sources also raises ethical concerns regarding surveillance and consumer privacy. Many consumers remain unaware of how their personal data is collected, analyzed, and used within AI-driven financial systems. These risks highlight the need for fairness auditing, transparent model design, and regulatory oversight.

5. Digital Inequality and Exclusion

The findings indicate that unequal access to technology remains a major challenge for AI-driven financial inclusion. Individuals without reliable internet access, smartphones, or digital literacy skills may struggle to benefit from digital financial systems.

Older adults, rural populations, and low-income households often face barriers related to technological access and digital education. As financial institutions continue digitizing services, individuals lacking technological resources risk becoming further excluded from the financial system.

6. Need for Ethical Governance and Regulation

The literature strongly emphasizes the need for ethical governance frameworks and transparent AI systems. Explainable AI models and deterministic financial algorithms are essential for ensuring accountability and fairness in automated decision-making. Researchers consistently recommend stronger regulatory oversight for AI-driven financial systems. Ethical governance should include bias testing, transparency requirements, consumer protections, and mechanisms for challenging automated financial decisions. Policymakers, technologists, and financial institutions must collaborate to ensure that AI systems promote equitable outcomes rather than reinforcing systemic inequalities.

7. Future Research Agenda

To advance equitable AI-enabled financial inclusion, future research should examine:

1. Empirical testing of fairness auditing tools in real-world lending environments.

2. Longitudinal studies on digital banking adoption among rural and low-income populations.
3. Impact of alternative data on racial and gender disparities in credit outcomes.
4. Consumer trust models for AI-enabled financial systems.
5. Regulatory experiments evaluating deterministic vs. probabilistic AI in lending.

4. Discussions and Conclusion

The findings of this study demonstrate that artificial intelligence has the potential to significantly transform financial inclusion efforts within underserved communities. AI-driven financial technologies provide innovative solutions capable of reducing traditional barriers associated with banking access, credit evaluation, and financial literacy. However, these benefits are accompanied by substantial ethical, social, and regulatory challenges.

One of the most significant advantages of AI-powered financial systems is their ability to expand access to financial services for individuals historically excluded from traditional banking systems. Alternative credit scoring systems represent a major advancement within inclusive finance because they allow institutions to evaluate financial reliability beyond traditional credit histories. This innovation may create opportunities for low-income individuals, gig workers, immigrants, and younger consumers with limited financial records.

Across the literature, there is both convergence and divergence regarding AI's impact on financial inclusion. Studies consistently agree that alternative credit scoring expands access for borrowers lacking traditional credit histories; however, other research warns that these same models may encode behavioral biases or create new forms of digital surveillance. Some scholars argue that automated lending reduces human bias, while others find that algorithms trained on historical data reproduce institutional discrimination. Evidence on digital banking also varies: while mobile platforms reduce geographic barriers, they simultaneously widen gaps for individuals lacking broadband access or digital literacy. These contrasting findings highlight the conditional nature of AI-driven inclusion and underscore the need for governance mechanisms that mitigate structural risks.

Additionally, AI-powered digital banking platforms reduce dependence on physical financial institutions. Mobile banking and digital payment systems allow individuals in rural or underserved communities to participate in financial activities without geographic limitations.

These innovations align with broader goals of economic empowerment and financial participation.

However, the expansion of AI within financial systems also raises serious concerns regarding fairness and accountability. The literature consistently demonstrates that AI systems are not inherently neutral. Financial algorithms reflect the data, assumptions, and institutional priorities embedded within their design. As a result, biased historical data can produce discriminatory lending outcomes that reinforce existing social inequalities.

The issue of algorithmic opacity further complicates these concerns. Many AI systems function as "black box" technologies, making it difficult for consumers to understand how financial decisions are made. Without transparency, individuals denied loans or financial services may lack opportunities to challenge unfair decisions or identify discriminatory practices.

The digital divide also remains a significant obstacle to equitable financial inclusion. AI-driven financial systems depend heavily on internet access, smartphones, and digital literacy. Communities lacking technological infrastructure may experience deeper forms of exclusion as financial systems become increasingly digitized.

These findings suggest that technological innovation alone cannot guarantee equitable financial inclusion. Responsible implementation requires ethical governance frameworks, regulatory oversight, and intentional efforts to address structural inequalities. Policymakers and financial institutions must prioritize transparency, explainability, fairness testing, and consumer protection when developing AI-driven financial systems.

Furthermore, deterministic AI frameworks may help improve accountability within financial systems. Deterministic AI models produce consistent and explainable outcomes that can be audited and evaluated for fairness. These systems may reduce uncertainty and improve public trust in AI-powered financial services.

Ultimately, AI should function as a tool for empowerment rather than exclusion. Achieving equitable financial inclusion requires collaboration among financial institutions, technology developers, regulators, educators, and community organizations.

Artificial intelligence is rapidly reshaping the future of financial systems and digital economic participation. AI-powered financial technologies offer significant opportunities to expand financial inclusion by increasing access to banking services, credit opportunities,

personalized financial guidance, and fraud protection. For underserved communities, these innovations may reduce longstanding barriers associated with traditional financial institutions.

However, the integration of AI into financial systems also presents serious ethical and societal challenges. Algorithmic bias, opaque decision-making systems, data privacy concerns, and unequal access to digital infrastructure threaten to reproduce or intensify existing forms of financial inequality. AI systems trained using biased historical data may unintentionally discriminate against marginalized populations, particularly within lending and credit evaluation processes.

This study demonstrates that the effectiveness of AI-driven financial inclusion depends largely on ethical implementation, transparent governance, and inclusive policy development. Financial institutions and regulators must prioritize fairness, explainability, accountability, and consumer protection when deploying AI technologies.

Future research should continue examining the long-term social and economic effects of AI-powered financial systems across diverse communities. Additional studies should also explore the effectiveness of explainable AI models, fairness auditing mechanisms, and digital literacy initiatives designed to support equitable access to financial technologies.

As AI continues transforming the financial landscape, policymakers and industry leaders face a critical responsibility to ensure that innovation advances economic inclusion rather than reinforcing systemic inequality. Responsible AI governance will play a central role in shaping a more equitable and accessible financial future.

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Building Financial Resilience at HBCUs through Generative AI, FinTech, Blockchain, and Cybersecurity Education

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Abstract

Financial resilience has become an urgent educational priority as individuals face increasingly complex decisions involving budgeting, debt, credit, retirement planning, digital payments, online fraud, artificial intelligence tools, and rapidly changing financial technologies. Historically Black Colleges and Universities are well-positioned to advance financial security education by integrating financial literacy, FinTech, blockchain, cybersecurity, and generative artificial intelligence into interdisciplinary learning experiences. This paper proposes a human-centered framework for building financial resilience at HBCUs through technology-enhanced financial security education. The framework is organized around six connected pillars: financial foundations, FinTech literacy, blockchain and digital trust, generative AI-supported decision learning, cybersecurity and fraud prevention, and community-centered financial resilience. Using a conceptual design-science methodology, the paper synthesizes literature on financial literacy, digital financial capability, AI risk management, cybersecurity education, and HBCU-centered pedagogical innovation. It also builds on prior work in AI-supported learning, investment decision-making, blockchain education, and human-centered cybersecurity. The paper contributes a scalable curriculum model, sample learning modules, implementation strategies, and assessment measures for HBCU programs in business, computer information systems, cybersecurity, data science, and interdisciplinary fields. The framework positions financial resilience as a lifelong learning outcome and connects HBCU-centered

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financial education with digital trust, cybersecurity awareness, and responsible use of emerging financial technologies.

Keywords: HBCUs, financial resilience, generative AI, FinTech, blockchain, cybersecurity, financial security education, digital trust

Introduction

Financial resilience is the ability of individuals, families, and communities to make informed financial decisions, manage financial shocks, protect assets, use financial technologies safely, and pursue long-term economic goals. In the current digital economy, financial resilience requires more than basic knowledge of budgeting or saving. Individuals must understand credit, debt, student loans, retirement planning, investment risk, insurance, taxes, digital payments, cybersecurity threats, online misinformation, and the growing use of artificial intelligence in personal finance.

The rapid expansion of FinTech, blockchain, digital assets, online banking, mobile payments, and generative artificial intelligence has created new opportunities for financial access and education. Digital financial platforms can help users monitor spending, compare financial products, transfer funds, invest, and access information. Blockchain technologies can support transparency, traceability, decentralized verification, and new forms of digital value exchange. Generative AI tools can explain complex financial concepts, simulate scenarios, help draft budgets, and support personalized learning. However, these same technologies can produce inaccurate information, encourage overconfidence, expose sensitive personal data, support scams, or widen inequalities when users lack the knowledge to evaluate them critically (Lo & Ross, 2024; National Institute of Standards and Technology [NIST], 2024a).

Historically Black Colleges and Universities are uniquely positioned to respond to this challenge. HBCUs have long served as engines of educational opportunity, community leadership, social mobility, and professional preparation. In the generative AI era, HBCUs can also lead in financial security education by preparing learners to understand both the promise and the risks of emerging financial technologies. A human-centered approach is especially important. Financial education should not blame individuals for financial hardship. Instead, it should recognize structural barriers, unequal access to trustworthy advice, increasing complexity in financial systems, and the need for practical, culturally responsive, and technology-supported learning.

This paper proposes a conceptual framework for building financial resilience at HBCUs through generative AI, FinTech, blockchain, and cybersecurity education. The framework is designed for use in business, computer information systems, cybersecurity, data science, finance, economics, entrepreneurship, general education, faculty development, staff training, and community outreach. It connects financial literacy with digital trust and treats cybersecurity as an essential part of financial well-being. It also emphasizes responsible use of generative AI: AI can support learning and decision analysis, but it should not replace professional financial, legal, tax, or investment advice.

The central contribution of this paper is the HBCU Financial Resilience Education Framework, a scalable conceptual model that integrates financial foundations, FinTech literacy, blockchain-based digital trust, generative AI-supported decision learning, cybersecurity awareness, and community-centered financial resilience. The paper addresses three research questions: (a) What core competencies are needed for financial resilience in the generative AI and FinTech era? (b) How can HBCUs integrate generative AI, FinTech, blockchain, and cybersecurity into financial security education? and (c) What curriculum modules, safeguards, and assessment strategies can support scalable implementation of financial resilience education at HBCUs?

Literature Review

Financial Literacy, Financial Capability, and Financial Resilience

Financial literacy is commonly understood as the knowledge and skills needed to make informed financial decisions. Foundational research emphasizes concepts such as inflation, interest rates, risk diversification, compounding, borrowing, saving, and retirement planning. Lusardi and Mitchell (2014) argue that financial literacy has important economic consequences because individuals are increasingly responsible for complex financial decisions over the life course. Atkinson and Messy (2012) similarly describe financial literacy as a combination of awareness, knowledge, skills, attitudes, and behaviors needed to make sound financial decisions and achieve financial well-being.

Recent evidence suggests that financial literacy remains a persistent challenge. The 2026 TIAA Institute-GFLEC Personal Finance Index reported that U.S. adults correctly answered only 47% of its 28 financial literacy questions on average, the lowest result in the index's 10-year history (Yakoboski et al., 2026). The Board of Governors of the Federal Reserve System (2026)

reported that 73% of adults were doing at least okay financially and that 63% could cover a $400 emergency expense with cash or its equivalent. These statistics show both resilience and vulnerability: many adults report stability, yet substantial numbers remain exposed to emergencies, debt pressure, price increases, and uncertainty.

The Consumer Financial Protection Bureau (2015) defines financial well-being as a condition in which individuals can meet current and ongoing financial obligations, feel secure in their financial future, and make choices that allow them to enjoy life. This definition shifts the focus from isolated financial facts to lived financial experience. For HBCUs, financial resilience education should therefore include budgeting, debt management, credit, insurance, investing, retirement planning, tax awareness, emergency savings, and the ability to evaluate financial products and advice.

Digital Financial Literacy and FinTech Education

FinTech refers to the use of technology to deliver, improve, automate, or transform financial services. It includes mobile banking, peer-to-peer payments, budgeting apps, robo-advising, digital lending, credit scoring, digital wallets, blockchain systems, cryptocurrency, smart contracts, crowdfunding, and AI-supported financial services. FinTech can reduce barriers to access, but it can also create new vulnerabilities. Users may face hidden fees, privacy risks, biased algorithms, identity theft, phishing, scams, price volatility in digital assets, and misleading financial information.

The OECD/INFE international survey emphasizes the importance of digital financial literacy. Across participating countries and economies, the average digital financial literacy score was 53 out of 100, and only 29% of adults reached the minimum target score of 70 out of 100 (Organisation for Economic Co-operation and Development [OECD], 2023). Digital financial literacy levels were higher among adults with higher incomes and higher education levels (OECD, 2023). These findings support educational programs that help learners develop both technical and financial judgment.

For HBCUs, FinTech education should not be limited to preparing students for careers in financial technology. It should also prepare students, faculty, staff, and community members to navigate digital financial systems safely in daily life. A student who understands mobile payments, credit card interest, student loan repayment, online fraud, and AI-generated financial advice is better prepared for personal financial resilience. A business student who understands

FinTech platforms and cybersecurity risks is better prepared to make professional decisions. A computer information systems student who understands finance and digital trust is better prepared to design responsible systems.

Blockchain, Digital Trust, and Financial Security

Blockchain technologies are relevant to financial resilience education because they introduce new ways of thinking about trust, verification, transparency, decentralization, and digital ownership. A blockchain is a distributed ledger that records transactions across a network and uses cryptographic mechanisms to support integrity and verification (Nakamoto, 2008). In financial education, blockchain concepts can be used to teach authentication, immutability, consensus, transparency, smart contracts, tokenization, digital assets, and governance.

Blockchain education must be balanced and critical. Students should learn both potential benefits and risks. Benefits may include transparency, auditability, programmable transactions, and reduced reliance on centralized intermediaries. Risks may include volatility, scams, private key loss, smart contract vulnerabilities, regulatory uncertainty, speculative behavior, and irreversible transactions. A financial resilience curriculum should therefore present blockchain as one component of digital trust education, not as a guaranteed path to wealth.

Blockchain education can also help students compare financial trust models. Learners can examine the difference between bank accounts, payment app balances, cryptocurrency wallets, and tokenized assets; discuss how ownership and transactions are verified; and consider user responsibilities when private keys, irreversible payments, and decentralized governance are involved. These questions connect technical literacy with financial decision-making.

Cybersecurity, Privacy, Fraud Prevention, and Human Factors

Cybersecurity is central to financial security. Even a financially knowledgeable individual can suffer harm if they fall victim to phishing, identity theft, account takeover, payment fraud, investment scams, tax scams, ransomware, or social engineering. Many financial threats are not purely technical; they involve human factors such as urgency, trust, fear, social pressure, unfamiliar terminology, and cognitive overload.

The NIST Cybersecurity Framework 2.0 organizes cybersecurity outcomes around the functions Govern, Identify, Protect, Detect, Respond, and Recover (NIST, 2024b). These functions can be translated into personal financial security education. Learners can govern their financial security by setting rules for password management, account monitoring, and

information sharing. They can identify financial assets and risks, protect accounts with multifactor authentication, detect suspicious activity, respond to fraud attempts, and recover through reporting, freezing credit, changing credentials, and documenting incidents.

Human-centered cybersecurity research emphasizes that security systems must account for human behavior, organizational culture, trust, communication, and practical constraints (Malomo et al., 2025). A human-centered financial resilience curriculum should avoid blaming victims of scams. Instead, it should teach learners how scams work, how emotions are manipulated, how to verify information, how to pause before acting, and how to seek help.

Generative AI in Financial Security Education

Generative AI can support financial education by explaining concepts, generating examples, simulating scenarios, translating technical language into accessible language, creating practice quizzes, helping learners compare repayment options, and supporting reflection. For example, a student could ask an AI tool to explain compound interest using a simple example, generate a monthly budget template, or compare the long-term effects of minimum payments versus larger credit card payments.

However, generative AI introduces serious risks in financial contexts. AI tools may generate inaccurate, incomplete, outdated, or overly confident responses. They may fail to account for personal circumstances, tax rules, legal constraints, or institutional policies. Lo and Ross (2024) show that generative AI can be considered a promising yet limited tool for financial advice, underscoring the need for verification and human judgment. The NIST AI Risk Management Framework emphasizes trustworthy AI characteristics such as validity, reliability, safety, security, resilience, accountability, transparency, explainability, privacy enhancement, and fairness (NIST, 2023). NIST's Generative AI Profile also highlights risks involving information integrity, cybersecurity, privacy, and misuse (NIST, 2024a).

The present framework uses generative AI for educational and decision-support purposes, not as a substitute for licensed financial, legal, tax, or investment advice. Learners should be taught to verify AI outputs, compare AI-generated explanations with reliable sources, avoid entering sensitive personal data, recognize hallucinations, and understand the limits of AI-generated financial guidance.

HBCU-Centered Pedagogical Innovation

HBCU-centered financial security education should be practical, interdisciplinary, inclusive, and empowering. It should recognize that financial learning occurs across academic programs, workplaces, families, and communities. Students may need help understanding student loans, credit cards, budgeting, internships, entrepreneurship, taxes, insurance, and entry-level retirement benefits. Faculty and staff may need continuing education on retirement planning, cybersecurity, digital financial tools, and AI-assisted financial information. Community members may need accessible workshops on fraud prevention, credit, online banking, and safe use of digital tools.

Prior related work has emphasized AI-supported learning, blockchain and generative AI education at HBCUs, investment decision-making, business analytics, Google Colab, computational thinking, and human-centered cybersecurity (Gao, 2025; Gao & Gao, 2025; Gao et al., 2026; Malomo et al., 2025). The present paper extends that work by focusing specifically on financial resilience and financial security education.

Methodology

This paper uses a conceptual design-science methodology. Design-science research is appropriate when the goal is to create and justify an artifact, model, method, or framework that addresses a relevant problem (Hevner et al., 2004). In this paper, the artifact is the HBCU Financial Resilience Education Framework. The goal is not to test a single intervention with experimental data, but to design a practical, research-informed framework to guide future curriculum development, classroom implementation, faculty development, and empirical assessment.

The methodology includes four phases: problem identification, literature synthesis, framework design, and implementation planning. First, the problem is defined as the gap between the complexity of modern financial systems and the financial security preparation available to many learners. Second, the literature synthesis draws from financial literacy, digital financial literacy, FinTech education, blockchain and digital trust, cybersecurity and human factors, and generative AI in education. Third, the framework is designed using principles of human-centeredness, practicality, digital trust, AI responsibility, cybersecurity integration, scalability, and measurable learning outcomes. Fourth, implementation planning translates the framework into six curriculum modules, sample activities, classroom safeguards, and an

assessment plan that HBCU programs can adapt to existing business, computer information systems, cybersecurity, data science, and interdisciplinary courses.

The architectural design of the HBCU Financial Resilience Education Framework (HBCU-FREF) is fundamentally grounded in Design Science Research (DSR) theory (Hevner et al., 2004). Rather than serving as a purely descriptive model, the framework operates as an instructional artifact developed through iterative, socio-technical design cycles. By anchoring our six core pillars in the NIST Cybersecurity Framework 2.0 and the NIST Artificial Intelligence Risk Management Framework (AI RMF 1.0) (National Institute of Standards and Technology [NIST], 2024), the model systematically justifies the intersection of technical risk mitigation with systemic consumer asset protection.

Because this is a conceptual paper, the quality of the contribution depends on relevance, theoretical grounding, internal coherence, practical utility, and potential for future evaluation. The design artifact is therefore presented with competency maps, modular learning activities, technology-use safeguards, and assessment measures that can be tested through pilot workshops, course modules, pre- and post-assessments, student reflections, and community outreach studies.

Proposed Framework: The HBCU Financial Resilience Education Framework

This paper proposes the HBCU Financial Resilience Education Framework, abbreviated as HBCU-FREF. The framework integrates six pillars: financial foundations, FinTech literacy, blockchain and digital trust, generative AI-supported decision learning, cybersecurity and fraud prevention, and community-centered resilience. The framework treats financial resilience as the central outcome. Each pillar contributes a different competency set, and the combined model emphasizes secure, ethical, and informed participation in modern financial ecosystems. Figure 1 illustrates the conceptual structure of HBCU-FREF.

Figure 1

Conceptual Structure of the HBCU Financial Resilience Education Framework

Financial Foundations
FinTech Literacy <-> Blockchain and Digital Trust
Generative AI-Supported Decision Learning
Cybersecurity, Privacy, and Fraud Prevention
Community-Centered Financial Resilience
Outcome: Financial Resilience and Digital Trust

Framework Pillars

The framework is organized around six pillars. Financial foundations provide essential knowledge about budgeting, debt, credit, savings, investing, retirement, taxes, and risk. FinTech literacy prepares learners to evaluate digital banking, mobile payments, online lending, robo-advising, digital wallets, and AI-enabled financial services. Blockchain and digital trust introduce ledgers, hashing, consensus, wallets, private keys, smart contracts, tokenization, and the limits of technological trust. Generative AI-supported decision learning teaches learners to use AI for explanation, practice, and reflection while verifying outputs and protecting privacy. Cybersecurity and fraud prevention prepare learners to recognize phishing, identity theft, account takeover, investment scams, and AI-enabled social engineering. Community-centered resilience extends the learning model to workshops, outreach, student research, faculty development, staff training, alumni engagement, and local community education.

A simple classroom rule for AI-supported financial learning is Ask, Verify, Protect, Reflect. Learners may ask AI for explanations, examples, or questions; verify outputs using reliable sources and calculations; protect private financial data; and reflect on what is useful, risky, or still uncertain. This rule positions generative AI as a learning partner rather than a substitute for qualified financial, legal, tax, or investment advice.

Results / Findings: Curriculum Model, Competency Map, and Learning Outcomes

Because this is a conceptual design paper, the findings are presented as design rather than empirical. The central design finding is that financial resilience education can be strengthened when financial literacy, digital trust, AI literacy, cybersecurity, and community engagement are taught together rather than separately. Table 1 maps the six framework pillars to competencies, outcomes, and sample learning activities.

Table 1

Competency Map for Financial Resilience Education

Framework Pillar	Core Competency	Sample Learning Outcome	Example Activity
Financial foundations	Budgeting, debt, credit, investing, retirement	Compare short-term and long-term financial tradeoffs.	Build a monthly budget and debt repayment plan.
FinTech literacy	Digital payments, apps, online banking, robo-advising	Evaluate benefits and risks of FinTech tools.	Compare digital payment apps using security and fee criteria.
Blockchain and digital trust	Ledgers, consensus, wallets, smart contracts	Explain how blockchain systems attempt to create trust.	Simulate a blockchain ledger in a spreadsheet or Python.
Generative AI decision learning	AI prompting, verification, privacy, reflection	Use AI to support financial learning while checking accuracy.	Ask AI to explain compound interest, then verify calculations.
Cybersecurity and fraud prevention	Phishing, identity theft, account security, recovery	Recognize scams and identify safe responses.	Analyze suspicious messages and create a fraud response plan.
Community resilience	Outreach, peer education, lifelong learning	Translate financial security knowledge into community education.	Design a one-page guide or mini-workshop.

Table 2 translates the competency map into a sample six-module curriculum that can be adapted for a course unit, a workshop series, a first-year experience module, a business analytics project, a cybersecurity lab, or a community outreach program.

Table 2

Sample Six-Module Curriculum

Module	Topic	Key Concepts	Technology Integration	Assessment
1	Financial resilience basics	Budgeting, savings, emergency funds, inflation	Spreadsheet or Python budget model	Budget scenario and reflection
2	Debt, credit, and student loans	Interest, credit scores, repayment plans	Loan calculator in Google Colab	Debt comparison worksheet
3	Investing and retirement	Risk, diversification, compounding, retirement accounts	AI-assisted explanation plus manual verification	Investment myth analysis
4	FinTech and digital payments	Mobile payments, fees, privacy, account security	App comparison matrix	FinTech evaluation report
5	Blockchain and digital trust	Ledgers, hashes, wallets, smart contracts	Simple blockchain simulation	Concept map and quiz
6	Cybersecurity and AI safety	Phishing, scams, AI hallucinations, privacy	AI-generated scam detection activity	Fraud response plan

Expected Learning Outcomes

- Explain key financial concepts such as interest, inflation, debt, credit, savings, investment risk, and retirement planning.
- Use basic quantitative tools to compare financial decisions.
- Evaluate FinTech tools in terms of usability, cost, privacy, and security.
- Explain the role of blockchain in digital trust and identify risks associated with digital assets.
- Use generative AI responsibly for financial learning while verifying outputs.
- Recognize common financial scams and cybersecurity threats.
- Develop a personal financial security checklist.
- Communicate financial security concepts to peers and community members.

Sample Learning Activities

Four classroom-ready activities can operationalize the framework. In an AI-assisted credit card repayment activity, students calculate repayment time and total interest, then compare their work with an AI-generated explanation. In a blockchain ledger simulation, students create a

simple transaction ledger and observe how changes to a record affect trust and integrity. In an AI-generated scam-detection activity, students classify fake bank alerts, investment messages, and student-loan scams, then write safe responses. In a retirement-planning reflection, learners compare early and delayed contributions and discuss uncertainty, inflation, risk, and the need for professional advice when personal decisions become complex.

Discussion

The proposed framework aligns with the themes of blockchain, FinTech, AI, cybersecurity, digital trust, financial inclusion, and education. It treats blockchain as part of a broader trust ecosystem, FinTech as both opportunity and risk, generative AI as a learning support tool, and cybersecurity as a core component of financial security. In this sense, the framework supports engineering trust: secure financial systems require robust technology, responsible institutions, and informed users who can verify claims, protect data, and manage risk.

The HBCU context is central to the framework. HBCUs can connect classroom learning with workforce preparation, faculty development, staff training, student research, alumni engagement, and community outreach. Students can learn to manage credit, loans, digital payments, salaries, and early retirement decisions. Faculty, staff, alumni, and community members can benefit from accessible education on retirement planning, fraud prevention, credit, digital payments, and safe use of AI-supported financial information.

To solidify the model's scholarly positioning, a formal comparative analysis distinguishes the HBCU-FREF from traditional literacy frameworks. Legacy benchmarks—such as the OECD/INFE International Survey configurations—evaluate financial budgeting behaviors independently from technical data protection protocols (OECD, 2023). This isolation leaves minority consumers structurally vulnerable to automated transaction fraud and algorithmic vector scams. The HBCU-FREF fills this gap by executing an analytical system where technological evaluation criteria directly govern deployment decisions, shifting student actions from passive conceptual literacy into proactive risk mitigation.

The framework is intentionally non-stigmatizing. It does not assume that financial challenges result from lack of effort or intelligence. Instead, it recognizes that financial systems are complex and that many people, including highly educated professionals, may need support

with debt, retirement, digital tools, and cybersecurity. A respectful approach can reduce shame, encourage help-seeking, and promote lifelong learning.

A major contribution of the framework is the integration of cybersecurity into financial education. Traditional financial literacy programs may teach budgeting and credit, but omit phishing, account takeover, identity theft, social engineering, and scam recovery. In the digital economy, multifactor authentication, password management, scam detection, and incident response are financial resilience skills.

Implementation and Assessment

The framework can be implemented in several formats: a course unit, a workshop series, a first-year experience module, a business analytics project, a cybersecurity lab, a financial literacy outreach program, or an interdisciplinary certificate component. A practical initial implementation could use a six-week sequence, a two-day workshop, or six embedded activities across an existing course. Suggested tools include spreadsheets, Python or Google Colab notebooks, AI prompt templates, mock financial scenarios, and scam-analysis exercises. To protect learners, activities should use fictional or anonymized data rather than personal financial records.

Assessment should measure knowledge, behavior, confidence, and applied judgment. Suggested measures include a pre- and post-financial literacy quiz, a digital financial literacy self-assessment, a cybersecurity behavior checklist, an AI verification assignment, a scenario-based fraud detection task, a student reflection, a final project, and an optional follow-up survey after three to six months. A minimum evaluation package should include one objective knowledge measure, one applied scenario task, one AI-output verification rubric, and one reflective action plan. This operational matrix establishes a concrete, replicable path for future multi-institutional validation studies, enabling researchers to compile quantitative self-efficacy indices alongside empirical scenario accuracy scores to track long-term instructional efficacy. Assessment should not shame learners; instead, it should help them identify growth, build confidence, and develop practical plans.

Limitations and Future Research

This paper presents a conceptual framework rather than empirical results from a completed intervention. The framework should therefore be tested through pilot workshops, classroom implementations, pre- and post-assessments, qualitative student reflections, faculty

interviews, and community outreach studies. Financial decisions are also highly personal and context-dependent, so educational examples cannot replace professional financial, legal, tax, or investment advice.

Future research can measure changes in financial knowledge, digital financial literacy, AI literacy, cybersecurity awareness, confidence, and behavior. Researchers can compare lecture-based learning, AI-supported tutoring, scenario-based learning, and project-based learning. Future work can also develop open educational resources, Google Colab notebooks, AI prompt libraries, scam detection exercises, and blockchain simulations for HBCUs and other minority-serving institutions.

Conclusion

Financial resilience is a critical educational outcome in the generative AI and FinTech era. Students, faculty, staff, and community members face complex decisions involving debt, credit, budgeting, retirement, digital payments, online fraud, blockchain systems, and AI-generated financial information. HBCUs can lead in this area by developing practical, human-centered, and technology-enhanced financial security education.

This paper proposed the HBCU Financial Resilience Education Framework, which integrates six pillars: financial foundations, FinTech literacy, blockchain and digital trust, generative AI-supported decision learning, cybersecurity and fraud prevention, and community-centered resilience. The framework supports interdisciplinary teaching, faculty development, student research, and community engagement. It emphasizes responsible AI use, verification, privacy protection, and practical cybersecurity behaviors.

The central message is that financial resilience education should not be limited to facts about personal finance. It should prepare learners to navigate digital financial systems securely, evaluate emerging technologies critically, and make informed decisions across the life course. By integrating generative AI, FinTech, blockchain, and cybersecurity education, HBCUs can help build more financially resilient individuals, institutions, and communities.

Data availability

No new datasets were generated or analyzed in this conceptual paper.

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Conflict of interest

The authors declare no conflict of interest.

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Engaging HBCU Students in Active Learning for Blockchain, FinTech, and Generative AI: A Human-Centered Pedagogical Framework

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Abstract

The convergence of blockchain, financial technology, digital assets, and generative artificial intelligence creates important opportunities and challenges for undergraduate education, especially at Historically Black Colleges and Universities. Students preparing for careers in business, computing, analytics, cybersecurity, and financial services need more than exposure to emerging technologies; they also need confidence, collaboration skills, ethical awareness, computational fluency, and experience applying tools to realistic problems. This paper proposes a human-centered pedagogical framework to engage HBCU students in active learning about blockchain, FinTech, and generative AI. The framework synthesizes classroom-tested strategies

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from computer information systems, business analytics, programming, mathematics, and interdisciplinary student research. It emphasizes structured collaboration, low-stakes practice, role rotation, peer evaluation, reflective learning, responsible use of generative AI, reproducible computational notebooks, and applied problem contexts such as credit risk, fraud detection, investment analysis, digital trust, and smart financial systems. The paper presents an evidence-informed model that instructors can adapt across introductory and advanced undergraduate courses. The framework suggests that active, collaborative, and AI-supported pedagogy can increase student participation, reduce anxiety around technical topics, support inclusive learning, and strengthen workforce readiness for emerging blockchain and FinTech ecosystems.

Keywords: HBCU education, active learning, generative AI, blockchain education, FinTech education, student engagement, collaborative learning, Google Colab, Python, workforce development

1. Introduction

Blockchain, financial technology (FinTech), digital assets, cybersecurity, artificial intelligence (AI), and generative AI are reshaping business, finance, government, and higher education. Financial institutions increasingly rely on intelligent systems for fraud detection, credit-risk modeling, customer analytics, compliance monitoring, and digital identity verification. Blockchain and distributed ledger technologies continue to influence secure records, smart contracts, tokenization, decentralized finance, and transparent transaction infrastructures (Narayanan et al., 2016; Yaga et al., 2018). Generative AI adds another layer of transformation by enabling natural-language interaction with data, code, models, explanations, and decision processes.

For undergraduate students, these developments create both opportunity and pressure. Emerging digital finance technologies open pathways to high-demand careers, but students may experience anxiety when confronted with unfamiliar technical vocabulary, programming environments, mathematical models, security concepts, and ethical concerns. This challenge is especially important for Historically Black Colleges and Universities (HBCUs), which play a critical role in broadening participation in STEM undergraduate education and research (National Science Foundation, 2023).

The central question addressed in this paper is: How can instructors engage HBCU students in active learning that prepares them to understand and apply blockchain, FinTech, and generative AI in responsible, human-centered, and career-relevant ways? This paper argues that effective instruction in these areas requires more than lectures about emerging technologies. It requires purposeful instructional design that connects technical content to active participation, peer collaboration, problem-based learning, ethical reflection, and applied research.

The proposed framework builds on classroom-tested work in active learning, collaborative learning, unplugged computing activities, AI-supported problem-solving, Python and Google Colab, business analytics, and student-centered pedagogy. Instead of treating blockchain, FinTech, and generative AI as isolated topics, the paper positions them as interconnected domains that can be taught through a coherent educational model. Students learn by working together, asking questions, testing ideas, using AI as a learning partner rather than a replacement for thinking, and applying computational tools to meaningful financial and social problems.

2. Literature Review

2.1 Active Learning and Student Engagement

Active learning refers to instructional practices that require students to participate meaningfully in the learning process rather than passively receive information. Bonwell and Eison (1991) described active learning as involving students in activities and reflection on those activities. Prince (2004) reviewed evidence supporting active learning in engineering education, and Freeman et al. (2014) demonstrated that active learning improves student performance in STEM courses.

In technical and quantitative courses, active learning is valuable because students often need repeated practice, dialogue, and feedback to develop conceptual understanding. A lecture can introduce an algorithm, blockchain concept, financial model, or AI workflow, but students usually understand these ideas more deeply when they manipulate data, write code, explain their reasoning, critique outputs, and compare solutions with peers. Prior work in computer science and computer information systems emphasizes collaborative learning, problem-based learning, integrated learning, oral assessment, unplugged activities, group assignments, and technology-supported practice as ways to increase participation (Gao et al., 2022).

2.2 Collaboration, Human-Centered Pedagogy, and Psychological Safety

Collaboration is an essential workforce competency in financial technology and digital systems. Real-world blockchain and FinTech projects require cooperation among software developers, data analysts, business strategists, cybersecurity specialists, compliance professionals, economists, managers, and policymakers. Consequently, higher education must replicate these collaborative dynamics to prepare career-ready graduates. Collaborative learning is grounded in sociocultural and social learning theories, which emphasize the role of interaction, modeling, and shared problem-solving in learning (Bandura, 1977; Vygotsky, 1978). Johnson and Johnson (2009) and Slavin (1995) emphasized positive interdependence, individual accountability, structured interaction, and group processing as central components of cooperative learning.

However, assigning group work does not automatically produce meaningful collaboration. Students may experience unequal participation, unclear expectations, interpersonal conflict, or anxiety. Oakley et al. (2004) argued that student teams need structure and guidance to function effectively. Recent instructional work supports this principle by showing that structured group assignments, role rotation, peer evaluation, communication guidance, and reflective practice can improve student engagement, accountability, and collaborative competence (Gao et al., 2026b).

Human-centered pedagogy emphasizes the learner as a whole person with experiences, motivations, anxieties, identities, strengths, and aspirations. Edmondson (1999) described psychological safety as a shared belief that a group environment supports interpersonal risk-taking. In classrooms, psychological safety allows students to ask questions, admit confusion, test ideas, and participate without fear of embarrassment. This is especially important when teaching fast-changing topics such as generative AI, blockchain, and FinTech, where even experienced professionals must continuously learn.

2.3 Generative AI, Blockchain, and FinTech Education

Generative AI can support student learning by helping students brainstorm, explain concepts, debug code, generate practice examples, compare alternative solutions, and reflect on reasoning. However, generative AI also introduces risks. Students may over-rely on AI-generated answers, reproduce inaccuracies, or fail to critically evaluate outputs. To mitigate these risks,

generative AI should be taught as a tool for guided inquiry, not as a substitute for human reasoning. Responsible use should align with risk-management principles such as validity, reliability, transparency, accountability, privacy, and fairness, consistent with the NIST AI Risk Management Framework (National Institute of Standards and Technology [NIST], 2023).

Prior work on Python, generative AI, and Google Colab demonstrates the value of integrating AI-supported computation with foundational skills, reproducible notebooks, and human-centered reasoning (Gao & Gao, 2026a; Gao et al., 2024; Gao et al., 2026c; Gao et al., 2026d). Google Colab provides a low-barrier environment for students to write, run, revise, and share Python notebooks without the need for complex local software installation. When combined with generative AI, Colab can support iterative learning: students formulate a problem, generate code or explanations, test outputs, debug errors, interpret results, and reflect on what the computation means.

Blockchain and FinTech education requires interdisciplinary curriculum design. Students need to understand distributed ledgers, cryptographic hashing, consensus, smart contracts, tokens, digital wallets, cybersecurity, and data integrity. Technical coverage should be grounded in established treatments of cryptocurrency technologies and distributed ledger concepts (Narayanan et al., 2016; Yaga et al., 2018). Students also need to understand financial concepts such as risk, credit, payments, markets, fraud, regulation, inclusion, and trust.

3. Methodology

This paper employs a conceptual, evidence-informed, design-based methodology. It does not report a new controlled experiment. Instead, it synthesizes prior classroom-tested practices, published pedagogical research, instructor experience, student-centered evidence, and interdisciplinary teaching examples to develop a practical framework for HBCU-centered blockchain, FinTech, and generative AI education.

The evidence base includes active-learning experiences in computer science and computer information systems courses (Gao et al., 2022), unplugged parallel and distributed computing activities that made complex computing concepts more accessible in early undergraduate courses (Srivastava et al., 2019), longitudinal collaboration research involving structured group assignments and peer evaluation (Gao et al., 2026b), and recent work on

blockchain, AI, generative AI, Python, Google Colab, investment decision-making, and computational problem-solving (Gao, 2025; Gao & Gao, 2026a; W. Gao et al., 2026).

The synthesis emphasized publications and classroom practices that met three criteria: relevance to active learning, applicability to computing or business education, and transferability to blockchain, FinTech, or generative AI instruction. The sources and practices were reviewed for recurring instructional design patterns, including collaborative structures, low-stakes practice, guided use of technology, student reflection, responsible use of AI, and applied problem contexts. These recurring patterns were then organized into the five-component framework presented in Section 4.

The framework was developed through four steps. First, common challenges in emerging technology instruction were identified, including student anxiety, uneven preparation, passive learning, unclear expectations for AI use, limited confidence in coding, and difficulty connecting technical topics to financial systems. Second, prior classroom-tested strategies were mapped to these challenges. Third, the strategies were reorganized around blockchain, FinTech, and generative AI learning outcomes. Fourth, the resulting model was refined into instructional components, course modules, assessment strategies, and implementation recommendations.

4. A Human-Centered Active-Learning Framework

The proposed framework includes five mutually reinforcing components: psychological safety and learning norms, structured collaboration, applied FinTech problem contexts, responsible use of generative AI, and reflective assessment. As shown in Table 1, each component is paired with specific instructional practices and measurable learning outcomes.

Table 1

Framework Components and Instructional Practices

Component	Instructional practices	Learning outcome
Psychological safety and norms	Strengths-based introductions, early surveys, AI-use policy, collaboration norms	Confidence, belonging, and willingness to participate
Structured collaboration	Role rotation, team contracts, peer evaluation, communication checkpoints	Accountability, teamwork, and professional communication
Applied FinTech contexts	Fraud detection, credit risk, digital identity, smart contracts, investment analysis	Connection between concepts and real-world financial systems
Responsible generative AI use	Prompting, verification, code debugging, output critique, AI-use statements	AI literacy, critical thinking, and ethical awareness
Reflective assessment	Learning journals, project reflections, peer feedback, oral explanation	Metacognition, self-regulation, and transferable skills

The first component establishes a classroom culture in which students feel safe asking questions, making mistakes, and learning unfamiliar technologies. Instructors can begin with strengths-based introductions, early surveys, collaborative norm-setting, and explicit discussion of responsible technology use. Students should be told that confusion is expected when learning emerging technologies and that the course is designed to help them develop confidence through practice.

The second component is structured collaboration. Students work in teams, but the teamwork is intentionally designed. Each team may include rotating roles such as facilitator, coder, data analyst, financial interpreter, ethics reviewer, presenter, and documentation lead. For example, in a credit-risk modeling activity, the coder may prepare the Python notebook, the data analyst may interpret the variables, the financial interpreter may explain the business implications, the ethics reviewer may identify fairness concerns, and the presenter may summarize the findings. In the next activity, students rotate roles.

The third component is the use of realistic problem contexts. Students should not learn blockchain, FinTech, and AI only as abstract concepts. They should apply them to problems such as fraud detection, loan approval, risk scoring, digital identity, payment systems, tokenization,

smart contracts, market simulation, financial inclusion, and cybersecurity. Applied contexts increase motivation because students can see why technology matters.

The fourth component centers on responsible generative AI use. In this framework, generative AI is treated as a learning partner that supports inquiry, coding, explanation, and reflection. Students may use AI to generate Python code, explain blockchain concepts, compare financial models, debug errors, draft project plans, or create plain-language summaries. However, students must verify outputs, cite sources when appropriate, explain their reasoning, and identify limitations. A recommended classroom rule is: AI may assist the process, but students remain responsible for understanding, verifying, and explaining the final work.

The fifth component is reflective assessment. Students should be assessed not only on final answers but also on process, reasoning, collaboration, ethical awareness, and communication. Reflection prompts may ask students to explain how they used generative AI, what they verified, what errors they found, how their team divided responsibilities, and what they learned about financial technology.

5. Findings and Synthesized Evidence

Because this paper is a conceptual synthesis based on prior classroom-tested work, the findings are presented as evidence-informed themes rather than new experimental results. First, structured active learning increases participation. Students participate more when instructors provide course materials early, clarify expectations, use first-day surveys, encourage study partnerships, and assign collaborative tasks. In blockchain, FinTech, and AI courses, similar structures can help students overcome hesitation through pre-class vocabulary guides, short videos, example notebooks, and guiding questions (Freeman et al., 2014; Gao et al., 2022).

Second, collaboration becomes more effective when it is designed. Students benefit from clear roles, timelines, deliverables, peer evaluation, and reflection. Without structure, group work may lead to unequal participation or frustration. With structure in place, students are more likely to contribute, communicate, and support one another. In blockchain and FinTech education, designed collaboration is useful because the work is interdisciplinary. A student strong in business may interpret financial implications, while a student strong in coding may implement the model, and a student interested in ethics may raise questions about fairness, privacy, or community impact (Gao et al., 2026b; Oakley et al., 2004).

Third, low-stakes practice reduces technical anxiety. Emerging technology topics can be intimidating, and students may worry that they are not technical enough to understand blockchain, programming, data analytics, or AI. Short in-class activities, simple notebooks, group concept maps, unplugged simulations, and guided AI prompts allow students to build confidence before high-stakes projects. Prior work on unplugged parallel and distributed computing activities shows how active, low-barrier exercises can make complex computing topics more accessible to early undergraduate students (Srivastava et al., 2019).

Fourth, generative AI supports access but requires critical oversight. Students can ask AI to explain code, define blockchain terms, summarize articles, generate practice problems, or help debug errors. However, AI outputs may be incomplete, biased, outdated, or incorrect. Therefore, students should document how they used AI and what they verified. A short AI Use and Verification Statement can explain the prompts used, the modifications made, the errors corrected, and the sources checked. This practice aligns with the NIST AI Risk Management Framework emphasis on trustworthy, accountable, and reliable AI systems (NIST, 2023).

Fifth, applied projects strengthen workforce readiness. In a FinTech course, students might build a credit-risk dashboard, analyze fraud patterns, simulate investment decisions, compare digital payment systems, design a conceptual smart contract, or evaluate cybersecurity risks in a blockchain application. These projects develop technical, analytical, communication, and ethical skills while supporting students' participation in research and professional identity. Prior work on blockchain and generative AI in HBCU programming education, AI-integrated business education, and investment decision-making in the AI era provides a useful foundation for such applied learning experiences (Gao, 2025; Gao & Gao, 2026a; W. Gao et al., 2026).

6. Course Implementation and Assessment

The framework can be implemented in a full course, a course module, a workshop, or a research mentoring program. The following model illustrates a six-module structure suitable for undergraduate courses in business analytics, computer information systems, computer science, or interdisciplinary FinTech.

Table 2

Sample Course Implementation Model

Module	Topic	Active-learning activity	Generative AI integration	Assessment
1	FinTech, blockchain, and AI	Team concept mapping and vocabulary challenge	AI-assisted concept explanation with verification	Reflection memo
2	Digital trust and blockchain fundamentals	Unplugged distributed ledger simulation	Compare centralized and decentralized systems	Group explanation
3	Python and Google Colab for financial data	Guided notebook lab	AI-assisted code debugging	Notebook submission
4	Credit risk and fraud detection	Team classification activity and simple model	Model explanation critique	Model report
5	Smart contracts, governance, and ethics	Case discussion and role-play	Policy summary with fact-checking	Ethics analysis
6	Capstone project	Team project on applied FinTech problem	AI-supported research, coding, and presentation preparation	Presentation, notebook, peer evaluation, and AI verification statement.

Module 1 establishes a shared foundation by asking students to define key terms and identify everyday examples of digital finance. Module 2 introduces blockchain concepts through a distributed ledger simulation in which teams record transactions, verify changes, and discuss what happens if one record is altered. Module 3 introduces Python and Google Colab, enabling students to load a dataset, inspect variables, calculate descriptive statistics, create visualizations, and interpret results. Module 4 applies machine learning to financial problems such as credit risk classification and fraud detection, with an emphasis on workflow, interpretation, false positives and false negatives, and fairness concerns. Module 5 introduces smart contracts conceptually by asking students to write pseudocode for a simple financial agreement and then discuss risks, accountability, and governance. Module 6 asks teams to complete an applied capstone project on topics such as fraud detection, digital identity, credit-risk fairness, investment analysis, decentralized finance risk, or financial inclusion.

Assessment should align with the framework's human-centered goals. Students should demonstrate technical understanding through quizzes, notebook exercises, short explanations, and project reports. They should demonstrate collaboration through role fulfillment, peer evaluation, respectful communication, and contribution to group deliverables. They should demonstrate responsible AI use through AI-use statements that describe the purpose of AI assistance, categories of prompts, verification methods, errors corrected, and lessons learned. They should demonstrate ethical reasoning by discussing who might benefit from technology, who might be harmed or excluded, what privacy concerns are present, and how the team verified AI-generated outputs.

7. Discussion

The proposed framework aligns with the needs of the blockchain, FinTech, and AI landscape by connecting technical learning to trust, accountability, reliability, and workforce preparation. Students entering financial technology fields will need to work with intelligent systems, distributed infrastructures, data-driven models, and human stakeholders. They will also need to communicate across disciplines and evaluate ethical risks.

For HBCUs, the framework supports inclusive innovation. It gives students access to emerging technology skills while honoring the importance of community, collaboration, confidence, and social responsibility. It also supports faculty who may wish to integrate blockchain, FinTech, and generative AI into existing courses without completely redesigning the curriculum. Many activities can be implemented gradually, such as adding a single AI-use statement, introducing one Colab notebook, using role rotation in a group project, or adding a FinTech case discussion to a business analytics course.

The framework also addresses a common problem in AI education: the tension between access and rigor. Generative AI can make technical work more accessible, but access without accountability can produce shallow learning. The proposed model responds to this tension by requiring verification, explanation, reflection, and human judgment. Students are encouraged to use AI, but they remain responsible for their reasoning.

8. Limitations and Future Research

This paper proposed a conceptual and evidence-informed framework rather than a new experimental study. Its conclusions are based on a synthesis of prior teaching experience, classroom-tested strategies, and published pedagogical work. Future research should empirically test the framework in blockchain, FinTech, and generative AI courses at HBCUs and other institutions.

Several research directions are recommended. Future studies can compare student learning outcomes before and after implementation of the framework, examine whether structured generative AI use improves confidence and coding persistence, analyze how students from different majors experience interdisciplinary FinTech learning, investigate whether AI-use statements improve academic integrity and metacognitive awareness, and examine the long-term impact of applied FinTech projects on internships, graduate study, and career pathways.

9. Conclusion

Blockchain, FinTech, and generative AI are transforming how business is and will be conducted in virtually every industry and sector. These emerging technologies are making routine and even more complex tasks and processes readily available at dramatically reduced time and cost. These realities are creating new demands and opportunities for how undergraduate education is delivered. HBCU students should be active participants in this transformation, not merely observers of technological change. To support their success, instructors need pedagogical approaches that combine technical learning with collaboration, confidence, ethical reasoning, and workforce relevance.

This paper proposes a human-centered active-learning framework for engaging HBCU students in blockchain, FinTech, and generative AI education. The framework emphasizes psychological safety, structured collaboration, the application of financial technology, responsible use of generative AI, and reflective assessment. It draws on prior classroom-tested practices in active learning, computer information systems, business analytics, Python, Google Colab, student research, and collaborative pedagogy. By adopting this approach, instructors can help prepare HBCU students for careers and leadership in blockchain, FinTech, AI, cybersecurity, analytics, and responsible digital innovation.

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