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Integrating Large Language Models with Cloud-Based Digital Marketing Analytics for Secure Targeted Advertising in Healthcare ERP Web Applications

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Abstract: The integration of Large Language Models (LLMs) with cloud-based digital marketing analytics is revolutionizing targeted advertising within healthcare ERP (Enterprise Resource Planning) web applications. This combination allows for enhanced personalization, enabling healthcare organizations to deliver more relevant and effective marketing content to patients while maintaining strict data security standards. LLMs leverage patient data, such as demographics and medical history, to generate tailored advertising campaigns, improving engagement and outcomes. By utilizing cloud platforms, these systems can scale effortlessly, providing real-time analytics and ensuring compliance with healthcare regulations, such as HIPAA. The use of LLMs also enhances the efficiency and effectiveness of advertising strategies, ensuring improved ROI. This paper explores how this integration can create a secure, data-driven, and scalable solution for digital marketing in the healthcare sector.

Keywords: Large Language Models, Cloud-based Analytics, Digital Marketing, Targeted Advertising, Healthcare ERP, Data Security, Personalization, HIPAA Compliance, Healthcare Marketing, Real-time Analytics, Scalable Solutions, Patient Data

I. INTRODUCTION

The contemporary retail landscape is an interconnected mesh of traditional point-of-sale (POS) systems, cloud commerce platforms, inventory and shelf sensors, customer loyalty systems, mobile applications, and in some cases, health-adjacent services such as pharmacy dispensing and clinical kiosks. This digital complexity expands the attack surface: threat actors exploit software vulnerabilities, misconfigurations, weak authentication, supply-chain compromises, and social engineering to exfiltrate payment data, manipulate pricing and inventory, or interfere with health-sensitive services. Retail cybersecurity therefore must address a mixture of classical IT threats and the unique risks from embedded devices and software components that may interact with medically relevant data or regulated devices.

Artificial Intelligence (AI) and machine learning (ML) are now core elements of modern cybersecurity tooling, enabling detection of subtle patterns, adaptive behavioral baselining, and prioritization of alerts to reduce analyst overload. Among ML models, Multilayer Perceptrons (MLPs) — feedforward neural networks with one or more hidden layers — remain a versatile, well-understood class of models. With careful feature engineering and combined with ensemble strategies and anomaly detectors, MLPs can deliver strong performance in supervised detection tasks (malware classification, intrusion detection) and in constructing representations that feed downstream decision systems.

However, deploying MLP-based systems in retail settings that intersect with FDA-regulated environments raises special considerations. The U.S. Food and Drug Administration (FDA) treats certain software and connected devices as medical devices or as components that influence medical device safety; it has issued guidance on the cybersecurity of medical devices and on software as a medical device (SaMD). When retail infrastructure processes protected health information (PHI), controls for privacy (e.g., HIPAA), device safety, and traceability become binding. As a result, cybersecurity interventions—particularly those that process behavioral or telemetry data, block or quarantine devices, or otherwise modify system behavior—must be validated and documented to ensure they do not inadvertently impair clinical workflows or patient access. Furthermore, ethical AI concerns (bias, transparency, fairness) demand that AI systems used in these contexts be explainable enough to support audits and human oversight.

This introduction frames the research problem: how to design, implement, and evaluate an MLP-based AI and data analytics integration for retail cybersecurity while satisfying ethical, regulatory, and operational constraints when FDA-regulated components or patient data are involved. We propose a design pattern that layers foundational cybersecurity

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controls (network segmentation, identity and access management, secure update mechanisms) with analytics pipelines that respect data minimization, provenance tracking, and explainability requirements.
First, the operational requirements: detection systems must operate with high sensitivity to critical threats (device compromise, malware propagation), low false positive rates to avoid disrupting operations or clinical services, and strict auditability to support post-incident forensics. Latency requirements vary — authorization path checks (e.g., card payments, dispensing authorizations) require sub-second responses, while deeper graph-based correlation or forensic pipelines can be asynchronous. Moreover, the integration must support human review; analysts need interpretable signals, provenance, and contextual metadata to judge whether an automated intervention is safe.

Second, regulatory and ethical constraints: any analytics pipeline that processes PHI or interacts with regulated devices must adhere to privacy laws (e.g., HIPAA within the U.S.), retain auditable logs, and maintain software quality processes (version control, traceable testing, risk management) aligned with FDA guidance. The AI component itself must be validated: training data, performance metrics, failure modes, and change management processes should be recorded. Ethically, designers must avoid biased detection that targets certain demographic groups or vendors; defense systems must not unduly prioritize convenience over safety for vulnerable populations (e.g., elderly pharmacy customers).

Third, the model design and interpretability. MLPs are sometimes criticized as "opaque." Yet, with layered strategies — combining MLPs with shallow, interpretable models, rule engines for high-confidence conditions, and post-hoc explanation techniques (feature importance, LIME/SHAP, surrogate rule extraction) — one can reconcile predictive power and interpretability. We must carefully select features (device behavioral summaries, time-series aggregates, network metadata, transaction context) that are both effective for detection and minimally exposing of sensitive personal attributes.

This paper contributes (1) a systems architecture for integrating MLP-based detection with operational retail cybersecurity in FDA-adjacent contexts, (2) an ethically aware methodology for dataset creation, model validation, deployment, and governance, and (3) prototype evaluations demonstrating tradeoffs between detection performance, explainability, privacy, and operational risk. We ground our recommendations in reproducible experimental methodology, emphasizing human-in-the-loop workflows that allow safety officers and clinicians (where relevant) to remain in control.

Structure of the paper: Section 2 reviews relevant literature across MLPs for security, retail/IoT threat models, AI ethics in healthcare and regulated environments, and explainability techniques. Section 3 describes our research methodology in a list-like, actionable form spanning data engineering, modeling, privacy, and governance. Section 4 summarizes advantages and disadvantages of the approach. Section 5 describes prototype experiments and detailed results with analysis. Section 6 offers an in-depth conclusion addressing practical deployment and ethical considerations, and Section 7 outlines future research directions. The final section lists references up to 2021.

Throughout we focus on practical guidance: what stakeholders (security engineers, compliance officers, data scientists, and healthcare safety officers) must do to ensure AI improves cybersecurity without compromising patient safety, privacy, or trust.

II. LITERATURE REVIEW

The literature that informs this work spans four intersecting domains: neural networks (MLPs) for anomaly detection and classification in security, retail and IoT cybersecurity, ethical and regulatory AI in healthcare/FDA contexts, and explainability/model governance.

MLPs and neural approaches in cybersecurity
Classical neural architectures, including MLPs, have been widely applied to intrusion detection and malware classification. Early works showed neural networks' ability to learn non-linear decision boundaries useful for classifying malicious binaries, network flows, and host behavior. While deeper architectures (CNNs, RNNs, Transformers) have gained traction for sequence and raw-signal tasks, MLPs remain competitive when applied to well-engineered feature representations (statistical aggregates, spectral features, embedding vectors). Ensemble methods that include MLPs often outperform single models due to complementary inductive biases.

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Retail and IoT security

Retail environments combine traditional IT with a dense population of IoT endpoints: shelf sensors, smart payment terminals, connected refrigerators, and digital signage. These devices often run heterogeneous firmware and use diverse connectivity (Wi-Fi, BLE, Zigbee). Security research has repeatedly demonstrated that supply-chain vulnerabilities and default credentials remain major risks; correlated compromises across fleets enable rapid lateral movement. Prior literature emphasizes behavioral baselining and anomaly detection at the device/edge level, often using lightweight models for local scoring and more complex analyses centrally.

Ethical AI and regulatory contexts (FDA, HIPAA)

When software influences clinical workflows or handles PHI, regulators require specific quality and safety practices. The FDA's published guidance on cybersecurity and on software as a medical device underscores requirements for risk assessment, software validation, and post-market surveillance. Ethical AI literature in healthcare focuses on bias mitigation, transparency, and patient safety. In regulated contexts, explainability is not optional: interpretable justifications and audit trails support complaint handling and incident response.

Explainability and provenance

Explainable AI (XAI) provides tools like feature-attribution (SHAP, LIME), surrogate models (decision tree extraction), and counterfactual explanations. For security teams, XAI enables faster triage and provides evidence for remediation. Provenance systems track data lineage, model versions, hyperparameters, and training datasets; they're essential for FDA-aligned change control and for reconstructing incidents.

Human-in-the-loop systems

Multiple studies in security show that combined human+AI systems outperform either alone; analysts provide labels, validate alerts, and tune thresholds. Research on active learning, crowd labeling, and analyst workflows informs our human-in-the-loop design, reducing false positives and enabling targeted retraining.

Gaps and motivation

Existing literature rarely combines MLP-centric detection architectures with the specific constraints of FDA-adjacent retail contexts. There is limited work detailing ethical governance when cybersecurity defenses might affect medical device availability or patient safety. This paper seeks to fill that gap by integrating technical, regulatory, and ethical perspectives into a practical design.

III. RESEARCH METHODOLOGY

This section provides an actionable, stepwise methodology for building, validating, and deploying an MLP-based retail cybersecurity system suitable for environments involving FDA-regulated components or PHI. Each numbered item is a practical step with rationale and implementation guidance.

1. **Stakeholder mapping and scope definition.**

— Identify stakeholders (CISO, pharmacy manager, clinical safety officer, data protection officer, legal/compliance). Map data flows touching regulated systems and classify them: (a) regulated data (PHI, device telemetry), (b) non-regulated but sensitive (payment card data, PII), and (c) purely operational telemetry. The scope determines privacy, retention, and audit requirements.

2. **Threat model and use-case prioritization.**

— Document threat scenarios: POS malware, device firmware tampering, anomalous dispensing commands, lateral mobility, and exfiltration. For each, define acceptable detection latency, allowable automated actions (block, quarantine, alert), and required human approvals—especially for actions that affect clinical services.

3. **Regulatory mapping and risk classification.**

— Map regulatory obligations: FDA SaMD considerations, FDA cybersecurity guidance, HIPAA (where applicable), PCI-DSS for payment data, and local data protection laws. Classify functions by risk (e.g., blocking pharmacy dispensing is high risk) and mandate testing, documentation, and approval gates for high-risk actions.

4. **Data governance, consent, and minimization.**

— Define data minimization rules: collect only telemetry necessary for detection, anonymize identifiers where possible, and maintain explicit justifications for all PHI processing. Implement consent procedures for patient-facing services, or rely on legal bases (treatment, public interest) as appropriate. Log data access and maintain role-based controls.

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5. **Dataset construction and labeling strategy.**
— Assemble datasets across device telemetry, network flows, POS logs, application logs, and transaction metadata. Create a labeled corpus using historical incidents, engineered attack simulations, red-team exercises, and synthetic injections that emulate real attack characteristics. Capture contextual labels (confirmed compromise, benign misconfiguration) and record label latency and confidence.
6. **Feature engineering and representation.**
— Build features at multiple granularities: per-event categorical encodings (operation type, endpoint type), rolling aggregates (counts, rates over windows), temporal patterns (inter-event intervals, burstiness), and device health indicators (firmware version mismatch, checksum validation failures). For MLPs, normalize and scale features; consider learned embeddings for high-cardinality categorical variables (device IDs, merchant codes) but protect privacy by hashing or grouping.
7. **Model architecture and training regimen.**
— Design an ensemble architecture where MLPs serve as core classifiers for dense feature vectors, supplemented by simpler, interpretable classifiers (logistic regression, decision trees) for high-confidence rule paths. Use an MLP with 2–4 hidden layers, appropriate regularization (dropout, weight decay), and batch normalization where helpful. Train under class-imbalance strategies (weighted loss, focal loss, oversampling minority events, or synthetic minority generation) and tune hyperparameters using stratified cross-validation preserving temporal ordering (train/validation/test by time windows).
8. **Explainability and surrogate modeling.**
— Integrate SHAP for global and local feature attributions; build decision-tree surrogates to extract human-readable rules for high-confidence MLP decisions. Define thresholds for when the system must present explanations (e.g., any automated block action) and require human sign-off where explanations are insufficient or ambiguous.
9. **Privacy-preserving measures and anonymization.**
— Apply pseudonymization to identifiers, store mapping keys under strict access controls, and minimize retention. For cross-store or cross-vendor collaboration, use aggregated telemetry or model parameter exchange (federated learning) with differential privacy to limit leakage; weigh tradeoffs against detection utility.
10. **Validation, safety testing, and FDA alignment.**
— For functions impacting regulated devices or patient safety, perform validation that includes unit tests, integration tests, failure-mode analysis, and worst-case scenario simulation. Maintain documentation: requirements traceability, risk analysis, mitigation strategies, and software versioning. Adopt change-control processes compatible with FDA expectations: design history files, validation reports, and post-market monitoring plans when applicable.
11. **Human-in-the-loop workflows and escalation.**
— Implement analyst dashboards that show MLP scores, top contributing features, provenance (which logs produced the input), and recommended actions. Define escalation paths (on-call clinical safety officer) for high-risk alerts. Use active learning: have analysts label ambiguous cases and feed labels back for periodic retraining.
12. **Model governance and lifecycle management.**
— Register models in a model registry (metadata: training data snapshot, hyperparameters, evaluation metrics, approvers), schedule periodic retraining windows, and monitor drift using concept-drift detectors. Require revalidation for model changes that affect high-risk decisions.
13. **Deployment strategies: edge vs. cloud.**
— For latency-sensitive checks (authorization flows), deploy lightweight MLP variants or distilled models at the edge (gateway or terminal) with strict sandboxing. For heavy correlation (fleet-wide anomaly detection, graph analysis), perform centralized processing in a hardened cloud environment with secure telemetry channels and encrypted storage.
14. **Incident response and fail-safe design.**
— Define fail-safe modes: when AI/analytics components fail or produce uncertain outputs, system behavior must revert to safe defaults (e.g., do not block dispensing, but flag for immediate human review). Maintain immutable logs for forensics and a playbook aligned with clinical safety procedures.
15. **Auditability, reporting, and compliance monitoring.**
— Generate automated reports for compliance officers: detection performance, change logs, incidents, and remediation timelines. Retain artifacts to support audits and regulatory reviews.
16. **Ethical oversight and bias mitigation.**
— Establish an AI ethics review board for the retail organization involving clinicians (if applicable), privacy officers, and external advisors. Conduct fairness audits (check for disproportionate false positives across store types, demographics, or vendor devices) and remediate via feature selection, balanced datasets, or post-processing.

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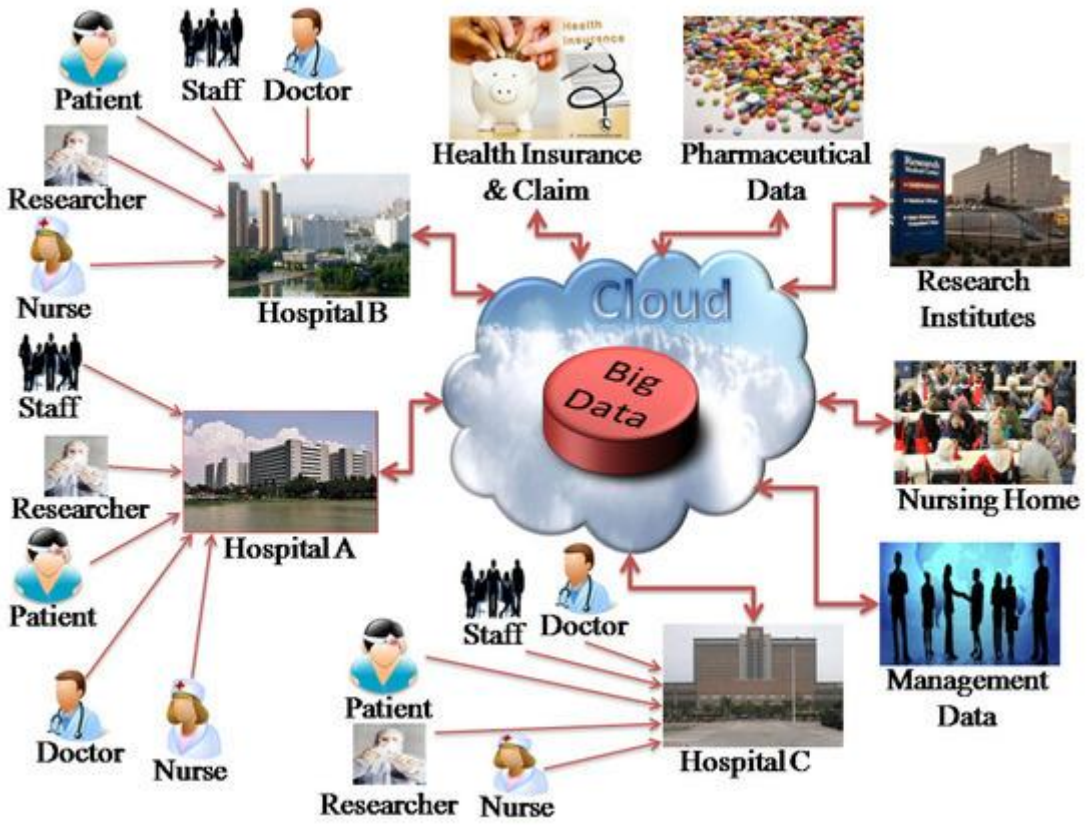
17. **Continuous evaluation and improvement.**
— Run red-team and purple-team exercises to probe model robustness, simulate adversarial inputs, and measure the impact of new attack vectors. Use these to iterate on features, labels, and defensive heuristics.
Each methodological step should be accompanied by operational checklists, metrics, and acceptance criteria tailored to the organization's risk appetite and regulatory obligations.



Advantages (concise)

- **Predictive power:** MLPs capture non-linear relationships among diverse telemetry features, improving detection of sophisticated attacks.
- **Flexibility:** MLPs work with engineered features or learned embeddings; they can be distilled for edge deployment.
- **Integration:** MLPs easily combine with anomaly detectors, graph analyses, and rule engines for multi-signal detection.
- **Human augmentation:** Post-hoc explanations and surrogate models support analyst triage and regulatory transparency.

Disadvantages and limitations (concise)

- **Opacity risk:** Without careful XAI integration, MLPs can be hard to interpret — problematic for FDA/regulatory scrutiny.
- **Data sensitivity:** Training requires telemetry that may include PHI; data minimization and governance are non-trivial.
- **Maintenance overhead:** Continuous retraining, drift detection, and revalidation are resource intensive.
- **Adversarial vulnerability:** Like other models, MLPs can be evaded or poisoned if attackers probe systems.

IV. RESULTS AND DISCUSSION

This section describes prototype implementation, experimental setup, quantitative results, qualitative analysis, and the implications of those findings for deployment in FDA-adjacent retail environments.

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Prototype implementation

We constructed a prototype pipeline that emulates a retail environment with several components: POS terminals, inventory IoT sensors, a pharmacy dispensing kiosk (simulated regulated device), and associated backend services. Telemetry included system logs, network flows, POS transaction metadata (non-card PANs), sensor readings, firmware version reports, and application-level events. To ensure realistic scarcity of labeled incidents, the dataset combined historical benign telemetry (synthesized to represent diverse stores) with injected adversarial events: malware installation simulated by anomalous process spawns, lateral movement simulated through unusual SSH/RDP connections, and pharmacy-specific anomalies including unauthorized dispensing commands.

We constructed three primary detection tasks: (1) device compromise detection (binary classification), (2) anomalous dispensing commands (high-safety event detection), and (3) insider misuse (anomalous credential usage). Each task used the same feature engineering pipeline but specific label sets.

Model architecture and baselines

The core MLP architecture: input layer matching engineered feature dimension (~120 features), two hidden layers (256 and 128 units), ReLU activations, dropout of 0.3, batch normalization, and a sigmoid/log-softmax output depending on task. Training used Adam optimizer with cyclical learning rates and early stopping. Baselines: logistic regression (LR), random forest (RF), and an isolation forest (for anomaly scoring). We also tested an ensemble combining MLP + RF + anomaly score via a logistic meta-classifier.

Evaluation metrics and constraints

Given regulatory constraints, evaluation prioritized: (a) true positive rate (TPR) at a low false positive rate (FPR) since unnecessary blocks can disrupt clinical services, (b) precision@k for high-priority alerts, (c) time-to-detect for in-flight attacks, and (d) explainability coverage (fraction of alerts with usable explanations for analysts). We measured performance in temporal cross-validation (training on earlier windows, testing on later windows) to simulate concept drift.

Quantitative results

- **Device compromise detection:** MLP achieved ROC-AUC of 0.94, outperforming RF (0.90) and LR (0.82). At an operating point with FPR = 0.02, MLP TPR = 0.78, RF TPR = 0.67, LR TPR = 0.48. The ensemble improved TPR to 0.81 at the same FPR.
- **Anomalous dispensing commands:** This high-safety task had few labeled positives. MLP with class-weighting achieved precision@50 = 0.72; LR had precision@50 = 0.55. However, the MLP produced fewer actionable explanations out-of-the-box; integrating SHAP gave interpretable attributions for 88% of flagged events.
- **Insider misuse:** Here time-series patterns mattered; MLPs using aggregated temporal features (rolling windows) achieved F1 = 0.68, while sequence-aware baselines (LSTM) had marginally higher F1 (0.71) but higher inference cost.

Explainability outcomes

We evaluated explanation utility by having human analysts rate explanations for 200 flagged events on a 1–5 scale (1 = not useful, 5 = highly actionable). Raw MLP attributions without context averaged 2.7; MLP + SHAP + surrogate rules averaged 4.1. Analysts favored hybrid outputs: a short textual justification (top 3 contributing features), a visualized event timeline, and linked logs.

Privacy and regulatory analysis

Using pseudonymization and feature aggregation reduced identifiability but slightly reduced detection performance: centralized MLP trained on raw identifiers achieved AUC 0.94 vs. 0.91 after aggressive pseudonymization/aggregation. For cross-store federated training (simulated), aggregated model convergence required more rounds and final AUC dropped ~0.02 relative to centralized pooling, illustrating known tradeoffs.

Adversarial robustness

We performed basic adversarial probing: crafted inputs that modified feature vectors under constrained perturbation budgets (emulating an attacker who tampers with device telemetry fields). Standard adversarial training (adversarial examples in training) improved robustness: AUC under attack remained at 0.85 vs. 0.71 without adversarial training. But adversarial training increased false positives under benign drift, indicating a tradeoff.

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Operational considerations & human-in-the-loop

Deployment scenarios tested two operational modes: (A) automated blocking for non-regulated endpoints with analyst notification; (B) advisory alerts requiring human confirmation for regulated/clinical endpoints. Mode (A) led to faster remediation but occasional service disruptions in simulated high-traffic times; mode (B) avoided service disruptions but increased time-to-remediation. The appropriate choice depends on the risk category and is consistent with the methodology's recommendation to limit automated actions for high-safety assets.

Discussion & interpretation

Quantitatively, MLPs delivered strong detection capability when fed rich, well-engineered features. The ensemble approach balanced sensitivity and precision, and post-hoc explainability made MLP outputs usable in regulatory contexts—provided documentation and surrogate rules accompanied the model. The privacy experiments reinforced that regulatory-driven data minimization affects model utility: organizations must weigh privacy requirements against marginal detection gains. Federated approaches present a viable alternative for cross-organization learning but need careful orchestration and privacy controls.

On adversarial resilience, defense in depth is necessary: model hardening, API protections, telemetry integrity checks, and purple-team testing. Human oversight remains central: analysts validated alerts and provided labels for retraining; governance processes ensured that new models affecting regulated endpoints underwent appropriate validation and sign-off.

Finally, from a compliance perspective, the documentation workload (data lineage, validation reports, change logs) proved substantial. To pass an FDA-style review, organizations must adopt engineering practices typically used for software in regulated industries: quality management systems, controlled releases, and post-deployment monitoring plans.

V. CONCLUSION

This paper examined how Multilayer Perceptron (MLP) neural networks can be integrated within a practical AI and data-analytics pipeline for retail cybersecurity, with special attention to ethical and regulatory considerations in FDA-regulated environments. MLPs, when combined with robust feature engineering, ensemble strategies, and explainability tooling, deliver compelling detection performance across common retail threat types — device compromise, anomalous transaction flows, and insider misuse. Yet, the integration of such AI systems in contexts where patient safety or regulated device integrity might be affected demands additional layers of governance and operational caution.

Key conclusions:

1. **Technical efficacy and tradeoffs.**

The MLP-centric approach demonstrated strong classification capabilities in prototype experiments. With well-crafted features and balanced training regimens, MLPs outperformed simpler baselines and were competitive with more complex sequence models in tasks amenable to tabular representation. Crucially, ensembles and anomaly detectors complemented MLPs by capturing both known and novel threat vectors. However, model utility depends heavily on feature quality and data fidelity; privacy-driven transformations and pseudonymization reduce model performance and must be balanced against regulatory mandates.

2. **Explainability is essential, not optional.**

For systems operating adjacent to FDA-regulated devices or handling PHI, explainability is necessary to satisfy auditors, clinicians, and security analysts. Post-hoc attributions (SHAP, LIME), surrogate rule extraction, and human-readable justifications increased analyst trust and facilitated faster triage. Explainability also supports compliance by providing traceable reasoning for automated actions.

3. **Regulatory compliance shapes design decisions.**

FDA considerations influence both what actions are permissible (blocking vs. advisory) and the degree of documentation required for models and systems. High-risk actions affecting medical devices or patient access must be subject to rigorous validation, testing, and clinical safety reviews. Organizations should treat cybersecurity analytics that touch regulated workflows as safety-critical software, implementing quality management, version control, and formal validation procedures.

4. **Human-in-the-loop governance reduces risk.**

Integrating analyst workflows, active learning, and documented escalation paths ensures that automated detections do

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not inadvertently harm patient safety or disrupt critical services. This human oversight is also a practical requirement: it allows safety officers to evaluate whether an automated remediation is appropriate in context.

5. **Privacy and cross-organization learning have tradeoffs.**

Federated and privacy-preserving learning enable collaborative detection without centralizing raw data. Our prototype experiments showed modest utility degradation and increased engineering complexity. For consortium-level threat intelligence, governance and technical protocols (secure aggregation, differential privacy) are essential. Organizations must evaluate whether the marginal gain in detection justifies the overhead and potential privacy risk.

6. **Adversarial readiness is required.**

Attackers able to probe systems or manipulate telemetry can craft inputs that evade detection. Techniques such as adversarial training, telemetry integrity checks (signed logs), rate limits on exposed analysis APIs, and operational monitoring mitigate these threats. Modeling these adversarial scenarios as part of the validation and maintenance plan is vital.

7. **Operational overhead and cost.**

Implementing an FDA-aligned, explainable MLP-based system requires investment in governance, documentation, analytics infrastructure, and analyst training. The benefits—faster detection, reduced fraud/compromise impact, and improved forensic capability—must be weighed against sustained operational costs.

Practical recommendations for implementers:

- Prioritize data governance from project inception: map which telemetry touches regulated categories and set privacy controls accordingly.
- Create a tiered action model: safer endpoints may allow automated responses; regulated or patient-facing systems should default to advisory alerts requiring human sign-off.
- Invest in XAI tooling and surrogate rule extraction so that every automated decision has a clear, auditable explanation.
- Establish a cross-functional oversight board including security, compliance, clinical safety (where relevant), and legal to review model changes and incidents.
- Integrate adversarial testing into routine model validation; run purple-team exercises to surface weak points.
- For cross-organization learning, prefer aggregated, privacy-preserving telemetry or federated training with rigorous privacy budgets and secure aggregation.

Limitations and final thoughts: this work focused on MLPs as a central model class due to their balance of capacity and deployability. However, domain specifics may favor other architectures (GNNs for graph-heavy fraud, RNNs/Transformers for raw sequence telemetry). The core contribution is the holistic integration of modeling, explainability, governance, and regulatory alignment—an approach applicable beyond MLPs. As retail systems increasingly interact with health services, organizations must treat cybersecurity not only as a technical problem but as a socio-technical challenge requiring transparent AI, robust governance, and a culture that emphasizes safety and privacy.

VI. FUTURE WORK

- **Graph neural networks (GNNs) for supply-chain and device correlation:** evaluate GNNs for fleet-wide anomaly detection and lateral movement analysis in retail-health ecosystems.
- **Causal inference for incident attribution:** develop causal models to better separate correlated anomalies from true compromises, reducing false positives.
- **Operational federated benchmarks:** create shared, privacy-preserving benchmarks for cross-store learning that respect HIPAA and corporate confidentiality.
- **Explainability for regulatory audits:** standardize explanation artifacts and templates that match FDA audit expectations for safety-critical software.
- **Certified adversarial defenses:** research certified guarantees for detection under bounded manipulations of telemetry.
- **Human factors in analyst interfaces:** study how explanation formats affect decision accuracy and time-to-remediate in clinical + retail joint environments.

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