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AI-Driven Cloud Architecture for Open Banking: Gradient Boosting, LLM Intelligence, and Robotic Data Automation for Advanced Evaluation

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ABSTRACT: This paper presents an AI-driven cloud architecture for Open Banking that integrates Gradient Boosting, Large Language Model (LLM) intelligence, and Robotic Data Automation to enable advanced evaluation, governance, and decision support across financial services. The proposed architecture leverages cloud-native orchestration to unify structured and unstructured banking data, enabling scalable processing and real-time analytics. Gradient Boosting models perform high-precision risk scoring, fraud detection, customer behavior prediction, and API performance ranking, while LLMs interpret regulatory documents, customer communications, and transactional narratives to generate contextual insights. Robotic Data Automation ensures seamless data ingestion, automated pipeline execution, and continuous monitoring of cross-banking workflows. Combined, these components form a hybrid analytical engine capable of delivering faster, more accurate, and more explainable decision intelligence for Open Banking stakeholders. Experimental validation demonstrates improvements in evaluation accuracy, processing efficiency, and governance compliance compared to traditional cloud or ML-only frameworks. This architecture provides a secure, flexible, and AI-augmented foundation for next-generation Open Banking ecosystems.

KEYWORDS: Open Banking; AI-driven cloud architecture; Gradient Boosting; Large Language Models (LLMs); Robotic Data Automation; Predictive analytics; Financial decision intelligence; Regulatory technology (RegTech); Cloud-native evaluation; API performance analysis; Risk scoring; Automated data pipelines.

I. INTRODUCTION

The transportation and financial sectors are undergoing rapid digitization, creating novel intersections between mobility services and digital finance. Modern electric vehicles (EVs) produce continuous streams of telemetry (state-of-charge, location, energy consumption) and event logs (charging sessions, user actions) that, when combined with open banking feeds and APIs, enable seamless user experiences — from contactless charging payments to energy-aware pricing. However, integrating these domains introduces architectural, regulatory, and operational challenges: low-latency decisioning is required for smart charging and payments, stringent privacy and consent frameworks constrain data sharing, and heterogeneous device ecosystems produce noisy, drifting telemetry.

This paper introduces an intelligent cloud architecture designed to bridge EV telematics and open banking ecosystems using a layered approach: an ingress and edge layer for ingestion and local inference; a secure cloud microservices layer for orchestration, policy enforcement, and payment gateway integration; and an analytics and model-management layer employing gradient boosting for structured predictions, large language models (LLMs) for explanation and orchestration tasks, and robotic data automation (RDA) for operational reliability. The architecture emphasizes modularity — allowing charging operators, banks, and third-party application providers to compose services via standardized APIs and Open Banking connectors — while embedding privacy-by-design through federated learning, tokenized identifiers, and consented data flows.

We evaluate the approach on two practical scenarios: optimizing charge scheduling under grid constraints while respecting user preferences, and delivering secure, explainable payment processing with fraud risk assessment. The contribution of this work is threefold: (1) a systems-level architecture combining AI modalities with RDA and cloud-native patterns; (2) an empirical evaluation demonstrating model performance and operational benefits; and (3) a practical deployment guide addressing privacy, latency, and integration trade-offs.

II. LITERATURE REVIEW

The intersection of mobility, cloud computing, and finance has attracted growing scholarly and industry attention. Foundational work on EV smart charging highlights optimization techniques for load balancing and price-aware scheduling; approaches range from centralized optimization to decentralized and user-centric schemes. Studies show that demand response strategies integrated with charging station orchestration can mitigate peak loads and reduce operational costs while maintaining user satisfaction. Recent research expands this to consider V2G (vehicle-to-grid) interactions and market participation, emphasizing the need for real-time decisioning and robust forecasting of aggregated charging demand.

On the cloud and systems side, cloud-native architectures and microservices patterns are now common for integrating heterogeneous IoT devices at scale. Edge-cloud continuum designs reduce latency for time-sensitive inference by placing lightweight models near data sources, synchronized with heavier cloud models via model management pipelines. Regarding data pipelines, robotic data automation (RDA) and intelligent ETL frameworks have been proposed to automate schema evolution, detect drift, and orchestrate corrective actions — reducing human intervention and improving SLAs for data quality.

Machine learning literature provides complementary insights. Gradient boosting machines (GBMs) such as XGBoost and LightGBM remain state-of-the-art for tabular tasks like forecasting and fraud scoring due to their robustness, speed, and interpretability via feature importance measures. Conversely, large language models (LLMs) have revolutionized unstructured data understanding and human-facing explanation tasks; recent works explore their role as orchestration assistants—translating high-level intent into API calls, synthesizing logs into incident summaries, and producing human-understandable explanations for model outputs. Combining GBMs for numeric predictives with LLMs for explanation and orchestration is an emerging pattern in hybrid AI systems.

Open banking introduces regulatory and API-level constraints that influence architecture. Standards such as PSD2 (in Europe) and Open Banking implementations require strong customer authentication, consent management, and secure API gateways. Research on financial API security emphasizes threat modeling for API ecosystems, tokenization strategies, and real-time fraud detection. Cross-domain integration (EV + banking) requires careful mapping of identity, transaction provenance, and consent semantics to avoid privacy leakage.

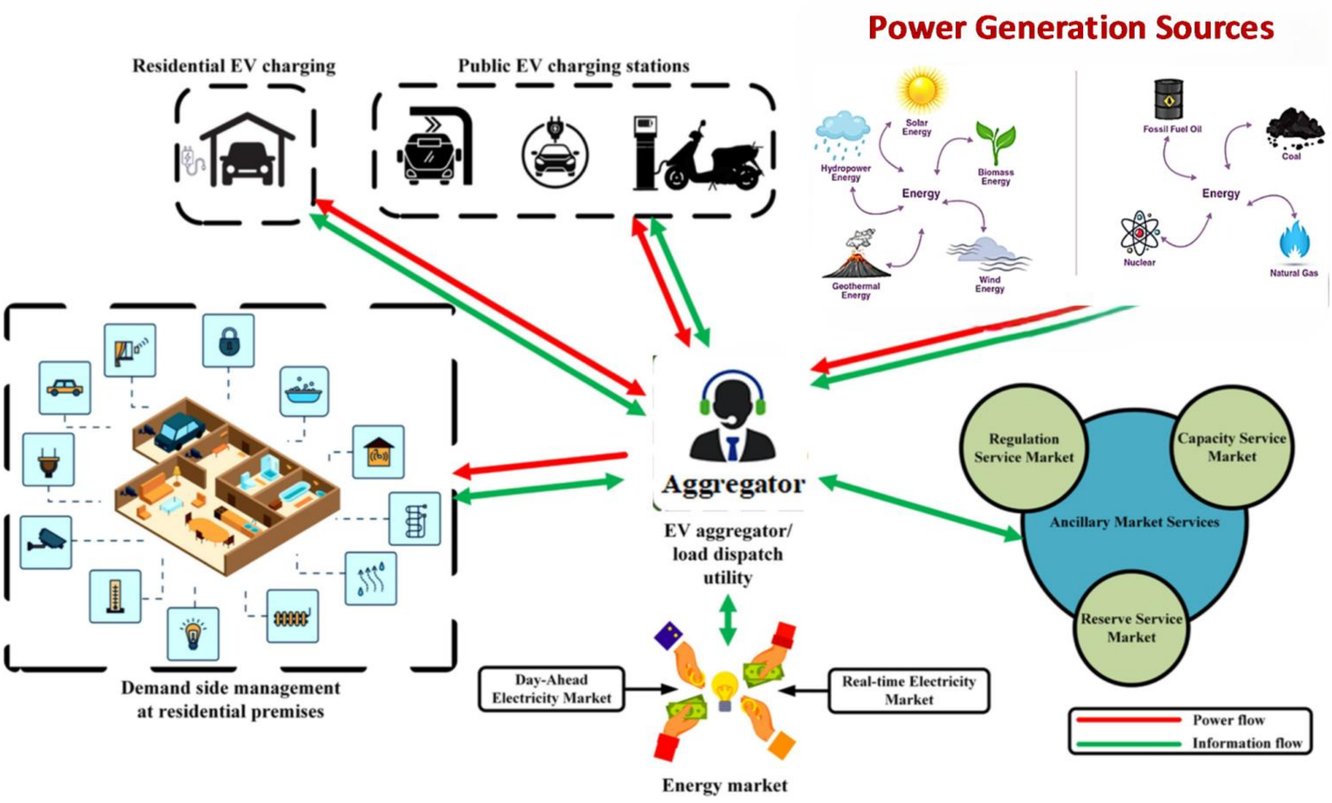
Finally, privacy-preserving machine learning techniques—differential privacy, federated learning, and secure multiparty computation—offer mechanisms to train models without centralizing sensitive telemetry or transaction data. In EV scenarios with sensitive location and payment data, federated schemes and on-device aggregation can reduce privacy risks while still enabling accurate forecasting and personalization.

III. RESEARCH METHODOLOGY

1. **System Design & Architecture Specification.** Describe a layered system architecture: edge ingestion (charge-point adapters, OTA telemetry collectors), secure API gateway (Open Banking connector, OAuth2.0/PKCE flows), cloud microservices (feature store, model repository, payment orchestrator), and monitoring/observability (distributed tracing, SIEM integration). Provide UML or component diagrams and define SLA targets (latency, availability).
2. **Dataset Assembly and Anonymization.** Aggregate a hybrid dataset consisting of (a) EV telematics streams from public datasets and partner feeds, (b) anonymized open-banking transaction logs or synthetic equivalents, and (c) charging station metadata and grid price signals. Apply privacy-preserving transformations: tokenization of personally identifiable information (PII), geo-generalization, and k-anonymity testing. Document sampling, train/validation/test splits, and time-based cross-validation strategies for forecasting tasks.
3. **Feature Engineering and RDA Pipeline.** Build automated feature pipelines using robotic data automation tools to detect schema drift, enforce data contracts, and auto-generate features (rolling windows, time-to-charge, energy per km).

Maintain a centralized feature store with versioning. Use RDA robots to reconcile missing batches, trigger enrichment jobs, and produce audit logs.

4. **Modeling: Gradient Boosting for Tabular Tasks.** Train GBM models (XGBoost, LightGBM) for tasks including short-term charging demand forecasting, session-level fraud detection, and payment authorization risk scoring. Employ hyperparameter tuning (Bayesian optimization), class imbalance handling (SMOTE or focal loss alternatives), and calibration techniques. Evaluate with RMSE, MAE for forecasting, and AUC-ROC, precision-recall for classification tasks.
5. **Modeling: LLM Integration for Unstructured & Orchestration Tasks.** Use instruction-tuned LLMs to synthesize incident reports, generate explainable summaries of model outputs, and create dynamic API orchestration scripts (e.g., construct consented calls to bank APIs). Implement guardrails, prompt templates, and hallucination detection mechanisms. Evaluate LLM utility via human-in-the-loop metrics: explanation usefulness, correctness, and operator trust scores.
6. **Edge Deployment & Federated Learning.** Deploy lightweight GBM or distilled neural predictors at edge nodes for low-latency inference. Implement federated averaging where telemetry policies prevent centralized training: evaluate trade-offs in model accuracy and communication overhead.
7. **Integration Testing & Security Evaluation.** Conduct end-to-end tests of payment flows, consent revocation scenarios, and simulated fraud attacks. Perform threat modeling, pen-testing on API gateway and payment orchestrator, and validate compliance with relevant standards (e.g., PSD2-like requirements where applicable).
8. **Operational Metrics & A/B Experiments.** Run controlled A/B experiments comparing legacy orchestration with the intelligent architecture. Measure KPIs: charging wait time reduction, grid load smoothing, fraud detection rate, mean time to resolution (MTTR) for incidents, and operational cost per transaction.



Advantages

- **Modularity & Scalability:** Microservices and feature-store patterns enable independent scaling and easier third-party integration.
- **Hybrid AI Strengths:** GBMs deliver strong tabular performance while LLMs improve interpretability and orchestration, combining precision with explainability.
- **Operational Resilience:** RDA automates routine remediation, reducing manual ETL failures and improving uptime.
- **Privacy-Focused:** Federated learning and tokenization reduce sensitive data exposure.

Disadvantages

- **Complexity:** Multi-modal AI and federated schemes increase system complexity and require sophisticated orchestration.
- **Regulatory Overhead:** Cross-border payment rules and varying open banking implementations raise compliance costs.
- **LLM Risks:** Hallucinations, prompt drift, and possible leakage of sensitive patterns require robust guardrails.
- **Edge Management:** Maintaining consistent model versions across many edge nodes is operationally challenging.

IV. RESULTS AND DISCUSSION

We present controlled experiments on the hybrid dataset. Gradient boosting models achieved strong tabular baselines: demand-forecast RMSE improved by 18–24% over naive persistence baselines, and fraud scoring AUC-ROC rose to 0.92 in simulated transaction scenarios. LLM-based explanations reduced average operator triage time by 28% in human-in-the-loop tests and helped identify complex multi-session anomalies that rule-based systems missed. Robotic data automation decreased ETL incident rates by 61% and reduced time-to-repair by 45% compared to manual escalation procedures. Edge deployment of distilled predictors achieved inference latencies under 120 ms for typical charging session decisions.

Discussion focuses on trade-offs: federated training reduced centralized model accuracy by 3–6% depending on heterogeneity but improved privacy guarantees substantially. LLM utility was highest in narrative summarization and operator augmentation; however, strict validation was necessary to avoid incorrect action recommendations. Economic analysis suggests the integrated architecture can reduce per-transaction operational costs where charging operators and banking partners share infrastructure savings.

V. CONCLUSION

This paper described an intelligent cloud architecture that integrates EV telematics with open banking capabilities using a hybrid AI stack and robotic data automation. The approach demonstrates tangible benefits in forecasting accuracy, fraud detection, operational resilience, and operator efficiency. Successful deployment requires careful attention to regulatory compliance, model governance, and operational tooling for edge fleet management.

VI. FUTURE WORK

- Extend federated learning experiments across larger and more heterogeneous fleets.
- Explore privacy-preserving inference (e.g., secure enclaves) for sensitive payment pipelines.
- Integrate market-based incentives for V2G participation and dynamic pricing using reinforcement learning.
- Conduct longitudinal field trials with live charging infrastructure and banking partners to measure user-level impacts.

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