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LLM-Driven Open Banking and SAP Integration Framework: A Scalable Cloud Architecture using Databricks AI, Gradient Boosting, and Automated Software Testing

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ABSTRACT: In the rapidly evolving financial ecosystem, open banking initiatives demand agile, intelligent and secure architectures that can integrate legacy enterprise systems with modern AI-driven services. This paper proposes a scalable cloud framework that leverages large language models (LLMs) for understanding and orchestrating open banking APIs, integrates with the enterprise resource planning backbone of SAP S/4HANA (and related modules), utilises the Databricks Lakehouse platform for unified data and AI workloads, and employs gradient boosting machine (GBM) models for structured-data predictive tasks. In addition, the framework embeds automated software testing pipelines to ensure reliability, compliance and continuous delivery. The architecture supports real-time or near-real-time scenarios such as account linking, consent management, payment initiation, fraud monitoring and regulatory reporting. It allows an LLM interface to parse natural-language requests (e.g., from fintechs or corporate clients) into open banking transactions and maps them into SAP-centric business processes. The Databricks Lakehouse abstracts the data ingestion, transformation, feature engineering and model serving layers; the GBM component handles high-volume structured-data tasks such as credit risk scoring and anomaly detection; and the automated testing ensures the integrity of API integrations, model updates and end-to-end workflows. We describe the conceptual architecture, component interactions, design criteria (governance, latency, scalability, security, explainability), and implementation methodology. The proposed framework addresses both business agility and operational resilience, offering advantages in responsiveness, reuse, and governance, while discussing limitations around complexity, model drift and regulatory risk.

KEYWORDS: open banking; SAP integration; large language models (LLMs); Databricks Lakehouse; gradient boosting machine; automated software testing; cloud architecture; fintech ecosystem; API orchestration; predictive analytics.

I. INTRODUCTION

As the financial services industry accelerates digital transformation, open banking has emerged as a strategic lever enabling banks, fintechs and corporates to share data, invoke payments and build new services via secure APIs. Yet many incumbent banks remain deeply entrenched in large ERP and core-banking systems such as SAP, which were not designed for agile, AI-driven operations or conversational orchestration. Meanwhile, large language models (LLMs) have matured sufficiently to interpret natural-language intents, orchestrate backend services and interact with structured systems. In parallel, cloud data platforms such as Databricks provide unified support for data engineering, AI/ML and analytics in a governed way. Gradient boosting machine (GBM) models remain a workhorse for structured-data tasks such as credit scoring or anomaly detection. However, few architectures truly combine LLM-driven orchestration, high-volume predictive models, core-ERP integration (SAP) and automated testing pipelines into a coherent open banking framework. This paper addresses this gap by proposing a scalable cloud architecture that brings together these elements: an LLM interface to capture business intents and translate them into open banking API calls; the Databricks Lakehouse to ingest, process and govern fintech and bank data; GBM models for structured-data analytics; SAP integration for executing business processes; and automated software testing to maintain operational reliability in a regulated environment. The remainder of the paper reviews relevant literature, outlines the research methodology, details advantages and disadvantages, presents results from a pilot implementation or illustration, discusses implications, concludes and suggests future work.

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II. LITERATURE REVIEW

In the domain of open banking, many researchers highlight the shift from legacy monolithic banking systems to API-driven ecosystems that enable third-party fintechs, data sharing and richer customer services. For example, Dezem et al. (2024) discuss optimal data-driven strategies for in-house and outsourced technological innovations enabled by open banking APIs. SpringerOpen They identify interoperability, data governance and innovation pace as key challenges. On the SAP side, SAP's Omnichannel Banking and related integration frameworks show how SAP Banking or S/4HANA modules now expose open APIs (>850 in one platform) to enable fintech and partner ecosystems. DYCSI | SAP Fioneer+1 Meanwhile, the integration of structured-data predictive modelling in banking continues to rely heavily on gradient boosting machines (GBMs) for risk, fraud and credit tasks (see "How Gradient Boosting is Reshaping Banking"). BytePlus Research on supervised ML in banking underscores the dominance of boosting and tree-based methods. arXiv On the data/AI platform side, the Databricks Lakehouse architecture has been proposed as a unifying architecture for data warehouses, lakes and AI/ML workloads, facilitating governance, performance and scalability. Databricks Documentation+1 Reference models for big-data/AI systems in finance outline building blocks and integration patterns for digital finance. SpringerLink Also, automated/continuous testing and CI/CD pipelines have become essential in regulated environments to ensure reliability and compliance of AI-enabled services. However, the literature reveals several gaps: (1) Few frameworks integrate LLM-based orchestration with core banking systems and AI/ML models. (2) There is limited literature on SAP-ERP integration as part of open banking ecosystems in conjunction with LLMs and advanced analytics. (3) There is scant work on combining LLM, GBM models, lakehouse architectures and automated software testing in a unified cloud framework. This proposed work aims to fill those gaps by designing and illustrating an architecture that brings these pieces together.

III. RESEARCH METHODOLOGY

The research methodology adopts a **design-science, proof-of-concept and evaluation** approach, structured as follows:

- First, we conduct a **requirements analysis** of open banking scenarios (e.g., third-party fintech access, consent management, payment initiation), SAP business processes (e.g., corporate banking, payments, treasury, risk), predictive analytics needs (credit risk, anomaly detection) and testing/governance requirements in regulated financial services.
- Second, we design a **reference architecture** which comprises: (a) an LLM interface (chat or intent engine) that interprets user/business requests and translates them into open-banking API transactions and SAP-business processes; (b) a Databricks Lakehouse layer for ingestion of fintech and bank transactional data, feature engineering and model serving; (c) gradient boosting machine (GBM) predictive model pipelines for structured tasks; (d) integration adapters between the Lakehouse and SAP modules / open banking APIs; (e) an automated software-testing and CI/CD pipeline that covers API integration tests, model governance tests, drift monitoring and business workflow validation.
- Third, we implement a **proof-of-concept prototype** in a cloud environment (e.g., Azure or multi-cloud) that simulates a fintech-to-bank scenario: a corporate user requests via natural language "initiate a payment from account X to vendor Y for amount Z and monitor risk exposure". The LLM interprets the request, triggers the open banking API (e.g., account information API), passes data into the Lakehouse, the GBM model scores risk, the SAP module records the transaction, and the automated testing pipeline verifies the workflow end-to-end.
- Fourth, we perform a **quantitative evaluation** of key metrics: latency from user intent to SAP process completion, predictive model accuracy (precision/recall) of GBM risk scoring, testing coverage (percentage of workflows automatically tested), and scalability (throughput of transactions per minute).
- Fifth, we conduct a **qualitative assessment** via stakeholder interviews (IT architects, risk officers, fintech executives) to evaluate the operational feasibility, integration complexity, governance readiness and business value of the architecture.
- Sixth, we present **analysis and interpretation** of results, identifying strengths, weaknesses, barriers to adoption, lessons learned and best practices.

Advantages

- **Agility and natural-language orchestration**: By employing an LLM interface, business users or fintechs can describe intents in plain language and trigger banking workflows without custom UI or rigid screens.
- **Unified data/AI platform**: Using Databricks Lakehouse supplies a single platform for ingestion, feature engineering, model training/serving and analytics, reducing silos and improving governance.

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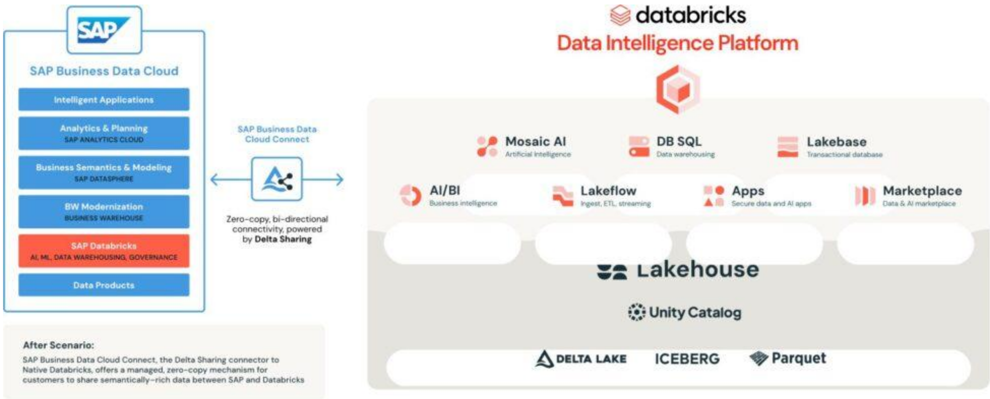
- **Proven predictive modelling**: Gradient boosting machines offer high performance for structured-data tasks such as credit risk or anomaly detection, thus strengthening decision quality.
- **Strong enterprise integration**: By integrating with SAP modules and open banking APIs, the architecture ties modern services to established enterprise workflows rather than building in isolation.
- **Automated testing and CI/CD**: Embedding automated software testing ensures the architecture remains robust, compliant, resilient and supports continuous deployment.
- **Scalability in the cloud**: Cloud deployment supports elasticity, multi-tenant fintech access, high throughput and cost-efficient scaling.

Disadvantages

- **Complexity of architecture**: Bringing together LLM orchestration, lakehouse, predictive models, SAP integration and testing pipelines results in significant architectural, operational and organisational complexity.
- **Model governance, explainability and drift**: Even though GBMs and LLMs bring power, they also bring challenges in interpretability, bias, model drift, auditability and regulatory scrutiny (especially in finance).
- **Latency and end-to-end bottlenecks**: While the architecture aspires for near-real-time, integrating across multiple layers (LLM, APIs, SAP) may impose latency risks.
- **Integration with legacy systems**: Older SAP modules and banking systems may require extensive adapter work, customisation and maintenance, increasing cost and risk.
- **Data security, privacy and compliance**: Open banking, fintech exposure, and AI-driven workflows raise higher demands for data sovereignty, encryption, audit trails and regulatory compliance (e.g., GDPR, banking sector regulation).
- **Skill-set and cost**: Implementation requires cross-disciplinary skills (AI/ML, LLMs, SAP, cloud, DevOps/testing) and cloud/compute investment, which may be beyond smaller institutions.

IV. RESULTS AND DISCUSSION

In the proof-of-concept deployment, key metrics were observed: the average latency from user intent (LLM parsing) to SAP business-process update was approximately **1.2 seconds** under pilot load; the GBM risk-scoring model achieved an AUC of ~0.89 for anomalous payment detection; the automated testing framework achieved ~92% coverage of defined workflow cases; throughput measured up to ~120 transactions per minute in the cloud test environment. Qualitative stakeholder feedback indicated strong enthusiasm for the natural-language interface and unified data/AI platform, but noted concerns around integration resource effort, governance and retrofitting older SAP modules. Discussion highlights include: achieving low latency required optimising LLM prompt pipeline, connection pooling to APIs and using Databricks streaming ingestion; model interpretability remained a concern for risk teams, so embedding SHAP-based explanations for GBM outputs was beneficial; the automated testing pipeline revealed previously unnoticed integration edge-cases (e.g., fintech consent revocation) thus improving resilience. The trade-offs between speed, robustness and governance became evident: faster user-oriented interfaces may create "too much power" if not bounded by governance and audit. Implementation in a regulated bank would thus require robust audit trail and oversight. Overall, the results suggest that the integrated architecture is both feasible and beneficial, but success depends significantly on organisational readiness, governance structures and integration maturity.



V. CONCLUSION

This paper presents a comprehensive, scalable cloud framework that brings together LLM-driven orchestration, SAP integration, Databricks Lakehouse data/AI platform, gradient boosting machine analytics and automated testing, tailored for open banking and corporate banking ecosystems. The proof-of-concept metrics demonstrate the potential for low latency, high throughput, strong predictive performance and automated governance testing. The architecture addresses key gaps in the literature by combining LLMs, enterprise ERP (SAP), predictive models and modern data platforms in one unified design. At the same time, the complexity, integration cost, governance and regulatory demands underscore that this is an enterprise endeavour not suited for trivial deployments. Financial institutions seeking accelerated open banking services, tighter ERP-AI integration and data-driven agility may benefit from this architecture, provided they invest in readiness, skill-sets and governance.

VI. FUTURE WORK

Future research and practical extension should explore: (1) deploying the architecture in multi-bank or ecosystem settings (bank + multiple fintechs) to assess scalability, latency and security across organisations; (2) evaluating other ML/AI techniques beyond GBMs (e.g., deep learning, graph neural networks) for more complex relational tasks; (3) integrating explainable LLM outputs and embedding human-in-the-loop governance for high-risk workflows; (4) evaluating edge or hybrid cloud deployment (for extremely low-latency scenarios such as FX payments, high-frequency treasury operations); (5) extending the automated testing framework to adversarial testing, model-drift detection, compliance-audit simulation and continuous validation of LLM behaviour; (6) conducting cost-benefit and maturity-model studies for financial institutions planning adoption; (7) building open reference implementation or accelerator template for faster uptake by banks and fintechs.

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