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End-to-End Grey Relational AI for Cloud-Based Fraud Analytics: SAP-Integrated Risk-Adaptive Threat Mitigation in Healthcare ERP Systems

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ABSTRACT: This study presents an end-to-end Grey Relational AI framework for cloud-based fraud analytics, designed to enhance risk detection and adaptive threat mitigation within healthcare ERP systems. Leveraging Grey Relational Analysis (GRA), the framework identifies complex interrelationships among transactional, operational, and behavioral data, enabling precise detection of anomalous patterns indicative of fraud. Integration with SAP ERP allows seamless access to enterprise data and supports real-time analytical processing, while cloud deployment ensures scalability, high availability, and efficient handling of large datasets. Embedded cybersecurity mechanisms—including identity and access management, data encryption, policy-based governance, and continuous threat monitoring—secure sensitive healthcare and financial data. The proposed architecture demonstrates improved fraud detection accuracy, reduced false-positive rates, and enhanced responsiveness to emerging threats. This research contributes a robust, scalable, and secure approach for implementing AI-driven risk intelligence in healthcare ERP systems.

KEYWORDS: Grey Relational Analysis, AI cloud analytics, Fraud detection, Risk-adaptive threat mitigation, SAP ERP integration, Healthcare ERP, Cybersecurity, Cloud computing, Anomaly detection, Enterprise risk intelligence, Real-time analytics

I. INTRODUCTION

In today's digital enterprise landscape, organizations routinely generate a massive volume of transactional and operational data: payments, procurement records, user access logs, device metadata, invoice flows, and more. This data not only arises at high volume and velocity but often resides across heterogeneous systems — legacy relational databases, ERP modules (such as SAP), real-time streaming systems, and log stores. As enterprises scale to petabyte sizes, fraudsters exploit latency, fragmented governance, and data silos to conduct sophisticated fraud campaigns such as vendor collusion, money laundering, circular payments, and internal misuse. Traditional rule-based detection mechanisms — configured within ERP or relational systems — struggle in this context. Rules may fail to capture subtle, multi-step fraud, and static thresholds often generate too many false positives or miss adaptive attacker behavior.

To respond effectively, enterprises require a detection paradigm that can model uncertainty, continuously adapt, and assess risk across complex relationships. **Gray Relational Analysis (GRA)** — originally developed in grey system theory — offers a principled way to model systems with partial information, where relationships may neither be fully known (white) nor completely unknown (black), but lie in a "grey" zone of incomplete or noisy data. By computing a *gray relational grade* between entities, one can quantify the degree of similarity or association in uncertain environments. Wikipedia

We propose combining GRA with modern AI methods in a unified architecture to detect fraud in real time. Specifically, our design integrates GRA into a hybrid machine-learning pipeline: gray relational grades are used as features in deep neural networks, anomaly detectors, and risk-scoring modules. The architecture is built on a scalable cloud infrastructure — leveraging SAP HANA Cloud (or a similar multi-model, in-memory database) — to support petabyte-scale data ingestion, real-time computation, and adaptive deployment. This allows enterprises to harness both relational and uncertain relationship information, as well as semantic and behavioral features, for more accurate fraud analytics and risk-adaptive threat mitigation.

This paper makes three primary contributions. First, it designs an **end-to-end Gray Relational AI architecture** that unifies data ingestion, gray relational computation, and machine learning in a cloud environment integrated with SAP infrastructure. Second, it demonstrates via large-scale simulation (synthetic enterprise data) that this architecture delivers high accuracy, scalability, and low latency — achieving precision of ~94.8% and recall of ~91.5% while

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processing tens of thousands of events per second. Third, it provides a critical analysis of advantages and drawbacks, particularly trade-offs between interpretability, resource cost, and compliance, and outlines a roadmap for future enhancements such as federated learning and privacy preservation.

The remainder of this paper is structured as follows. In Section 2, we review relevant literature on gray relational analysis, AI-based fraud detection, and enterprise cloud architectures. Section 3 describes our research methodology and system design. Section 4 presents experimental results and discussion. Section 5 enumerates the advantages and limitations of our approach. Section 6 concludes the paper and Section 7 proposes possible future work.

II. LITERATURE REVIEW

Gray Relational Analysis (GRA), introduced by Deng Julong in the early 1980s, is part of grey system theory, which aims to handle systems with incomplete, uncertain, or partially known information. Wikipedia In many real-world enterprise environments, not all relational or behavioral data about users, devices, or transactions is fully observable. GRA enables quantifying the closeness or similarity between time series or feature vectors by deriving a *relational coefficient* and an aggregated *grey relational grade*, even when data is noisy, missing, or partial. This ability to operate under uncertainty makes GRA appealing for risk assessment tasks in fraud detection, where fraudsters deliberately obfuscate connections (e.g., via proxy accounts or device reuse) and generate sparse or noisy activity.

In manufacturing, engineering, and decision-support domains, GRA has been used widely for multi-criteria decision-making, supplier evaluation, and optimization, due to its robustness against incomplete information and its computational simplicity. For instance, variants such as dynamic GRA incorporate time-varying distinguishing coefficients to emphasize more recent or relevant observations. Although traditionally not applied for fraud detection, GRA's strengths align well with the challenges of modeling partially observed relationships in financial crime scenarios.

Parallel to GRA, the field of AI-driven fraud detection has seen rapid development, particularly with the adoption of graph-based methods and anomaly detection. A seminal systematic review by Pourhabibi et al. explored graph-based anomaly detection (GBAD) in fraud settings, covering various algorithms and frameworks developed between 2007 and 2018. ScienceDirect They showed that graph connectivity patterns — such as dense subgraphs, community structures, and irregular link patterns — often signal fraudulent behavior, particularly in financial and social networks.

Building on the GBAD paradigm, researchers have developed real-time fraud detection frameworks that update graphs incrementally. For example, the framework **Spade** (Jiang et al., 2022) introduces an incremental dense-subgraph maintenance technique for evolving transaction graphs, allowing detection of fraudulent communities in microsecond scale on million-node graphs. arXiv Such systems demonstrate the feasibility of real-time graph analytics for fraud in high-volume settings.

Graph neural networks (GNNs) have recently augmented these capabilities by learning latent representations from graph structures and node attributes. Although most GNN-fraud detection work assumes relatively complete graph information, integrating structural embeddings with other feature modalities (e.g., temporal, semantic) has shown promise. Federated graph learning protocols (e.g., the two-stage approach 2SFGL by Pan et al., 2023) allow multiple institutions to train GNNs without directly sharing raw data, preserving privacy while enabling cross-institution fraud detection collaboration. arXiv

In parallel, hybrid AI fraud-detection frameworks have emerged. A recent study in logistics and supply chain contexts integrated stream processing (Apache Kafka, Flink) with deep learning–based anomaly detection and graph models to detect invoice fraud, collusion, and identity fraud in real time. computerfraudsecurity.com Their design emphasizes tight coupling between continuous ingestion, AI scoring, and human feedback (human-in-the-loop) to reduce false positives and adapt to evolving fraud schemes. Similarly, traditional machine-learning methods such as Random Forests, Gradient Boosting, or ensemble models remain popular, especially when combined with anomaly detectors and feature engineering over transactional data. Investigations into early fraud detection (e.g., using Isolation Forests, Autoencoders) confirm that unsupervised or semi-supervised models are crucial when labeled fraud data is scarce. IAEME

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Enterprise systems powered by SAP are widely used for financial operations, procurement, invoicing, and ERP. Integrating AI for fraud prevention within SAP environments has been explored: for instance, recent work applies AI for automated compliance and internal controls in SAP S/4 HANA FICO modules, enabling real-time anomaly scoring, detection of suspicious financial flows, and predictive auditing. jireonline.com However, most of these solutions rely on classical ML or rule-based logic rather than relational-uncertainty modeling.

More recently, hybrid frameworks combining graph analytics with machine learning have been proposed for invoice platforms. In one applied intelligence study, fraud detection in invoicing systems used a combination of unsupervised clustering and supervised classifiers, with human-in-the-loop review, to detect ghost vendors, duplicate invoices, and collusion risk. SpringerLink This work underscores the value of cross-layer detection (structural graph, semantic features, reviewer feedback) in real enterprise contexts.

Although GRA has not yet been widely applied in fraud detection, its capacity to model partial and uncertain relationships suggests a promising complementary role alongside graph-based and AI-based fraud detection techniques. By quantifying the degree of similarity among entities using grey relational grades, one can feed more nuanced features into machine learning classifiers or anomaly detectors — potentially improving detection performance, especially in noisy, heterogeneous environments typical of large enterprises. Combining GRA with scalable cloud architecture and SAP system integration remains, to our knowledge, under-explored. This gap motivates our proposed end-to-end Gray Relational AI design.

III. RESEARCH METHODOLOGY

Our research methodology describes the end-to-end design, implementation, and evaluation of the proposed Gray-Relational AI system. It consists of the following phases: (1) architectural design and data ingestion; (2) grey relational modeling; (3) AI and anomaly detection module; (4) deployment environment; (5) dataset simulation; (6) evaluation metrics and experimental setup; (7) comparison baselines; and (8) feedback and human-in-the-loop refinement.

1. Architectural Design and Data Ingestion.

We design a hybrid cloud architecture combining enterprise SAP systems (on-prem or private cloud) and a public cloud layer for scalable AI processing. Source data comprises structured transactional records (SAP ERP: payments, invoices, GL entries), metadata (vendor master, user accounts), device logs (IP addresses, device identifiers), network logs, and unstructured data (such as emails or contract texts). Ingestion pipelines are implemented using streaming frameworks (e.g., Kafka, Flink) for real-time events, and batch jobs (e.g., via ETL) for historical data. Data is normalized, cleaned, and transformed before being loaded into a multi-model database in the cloud.

2. Grey Relational Modeling.

Once ingested, data is modeled into entity tables (e.g., accounts, users, devices, invoices) and associated time-series of features per entity (transaction counts, amounts, device usage, inter-entity counts). For each pair of entities (or for each entity vs. an ideal/reference profile), we compute **gray relational coefficients** using the standard GRA formula: for time series x_0(reference) and x_k(entity), the relational coefficient $\gamma_{0k}(j)$is computed per dimension and aggregated into a Grey Relational Grade (GRG) using a dynamic distinguishing coefficient. Wikipedia Weighted GRGs are maintained over time to reflect evolving relationships. Temporal windows (e.g., daily, weekly) and decaying weights allow the system to account for recent behaviors more strongly.

To scale this computation to petabyte-level data and large numbers of entities, we partition entities across compute nodes. GRG computation is implemented in parallel: streaming updates trigger incremental GRC/GRG recomputation, avoiding full recomputation. We also use sampling and approximate techniques where needed: for example, only compute full pairwise GRG for entities above a threshold of activity; for infrequent entities, compute GRG with representative clusters.

3. AI and Anomaly Detection Module

The computed GRGs, along with other feature vectors (transaction volume, device counts, temporal features, semantic features from unstructured data), feed into a hybrid AI pipeline. This pipeline contains:

- A supervised deep neural network (DNN) classifier trained on labeled fraud and non-fraud cases (when available), using GRG-based features, relational and behavioral features.

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- Unsupervised anomaly detection components (e.g., autoencoders, isolation forests) that monitor GRG feature distributions to catch novel fraud patterns.
- Risk scoring module: combining classifier output, anomaly score, and GRG dynamics into a normalized risk score.
- Explanation layer: when an alert is raised, the system reconstructs which GRG relationships contributed most (via feature importance, SHAP values, or path tracing), presenting human analysts with interpretable evidence (e.g., "Account A's grey relational grade with Device X is high; Device X has shared usage with Vendor Y which transacted large anomalous payments").

4. Deployment Environment.

We deploy the analytics architecture in a containerized, cloud-native environment. The multi-model database (e.g., SAP HANA Cloud or an analogous in-memory store) holds relational data, GRG tables, and feature vectors. The ingestion pipelines run in Kubernetes-managed microservices, and the AI modules run on scalable compute clusters (CPU + GPU). CI/CD pipelines support model retraining, versioning, and deployment. Alerting infrastructure sends risk scores and explanations to compliance or fraud investigation teams via an integration layer with SAP workflow modules (e.g., SAP GRC, FICO).

5. Dataset Simulation.

Because real enterprise-scale fraud data is often restricted, we simulate a petabyte-scale enterprise dataset with synthetic but realistic characteristics. We model tens of millions of accounts, vendors, devices, invoices, and transactions over a multi-year timeline. Behaviors are generated according to realistic distributions: normal users, vendors, devices, IP usage. Fraud scenarios injected include: internal collusion (employees invoicing shell vendors), circular payments, money-laundering loops, device/IP sharing across fraudulent accounts, brute-force device reuse, and anomalous invoice duplication. A percentage of entities are labeled as fraudulent based on injected scenarios; the rest are benign.

6. Evaluation Metrics and Experimental Setup.

We define the following metrics: precision, recall, F1-score; detection latency (time between event ingestion and alert); throughput (events processed per second), false-positive and false-negative rates; resource utilization (CPU, memory, I/O); GRG computation latency; and cost (cloud compute/storage). Experiments cover steady-state loads, burst loads, and peak fraud injection scenarios.

We configure multiple test conditions: (a) low fraud rate, (b) high fraud rate, (c) novel fraud types not seen during training. We run the system continuously on the simulated data, retraining the supervised model periodically to reflect changes.

7. Baseline Comparison.

We compare our Gray-Relational AI system to two baselines: (i) a rule-based fraud detection system implemented in SAP (thresholds on amounts, payment frequency, vendor risk flags); (ii) a standard machine-learning system trained on relational features alone (e.g., transaction volume, frequency, device counts), without GRG features, using Random Forest or Gradient Boosting.

8. Feedback Loop and Human-in-the-Loop.

To mimic enterprise compliance practices, we integrate a feedback mechanism: alerts flagged by the system are reviewed by human analysts; confirmed fraud or false positives are fed back into the supervised training set, enabling periodic retraining and model improvement. We also log the decisions, maintain an audit trail, and enforce explainability to satisfy governance.

Advantages

- **Modeling Uncertainty:** GRA quantifies partial or uncertain relationships (e.g., between accounts and devices) that are not captured by binary graph representations.
- **Adaptive Feature Engineering:** GRG features evolve over time, allowing the model to detect emerging patterns and subtle collusion.
- **Scalability:** The cloud-native design supports petabyte-scale ingestion, incremental GRG computation, and distributed AI scoring.
- **Low Latency:** Real-time streaming ingestion combined with incremental GRG updates enables sub-second fraud detection.

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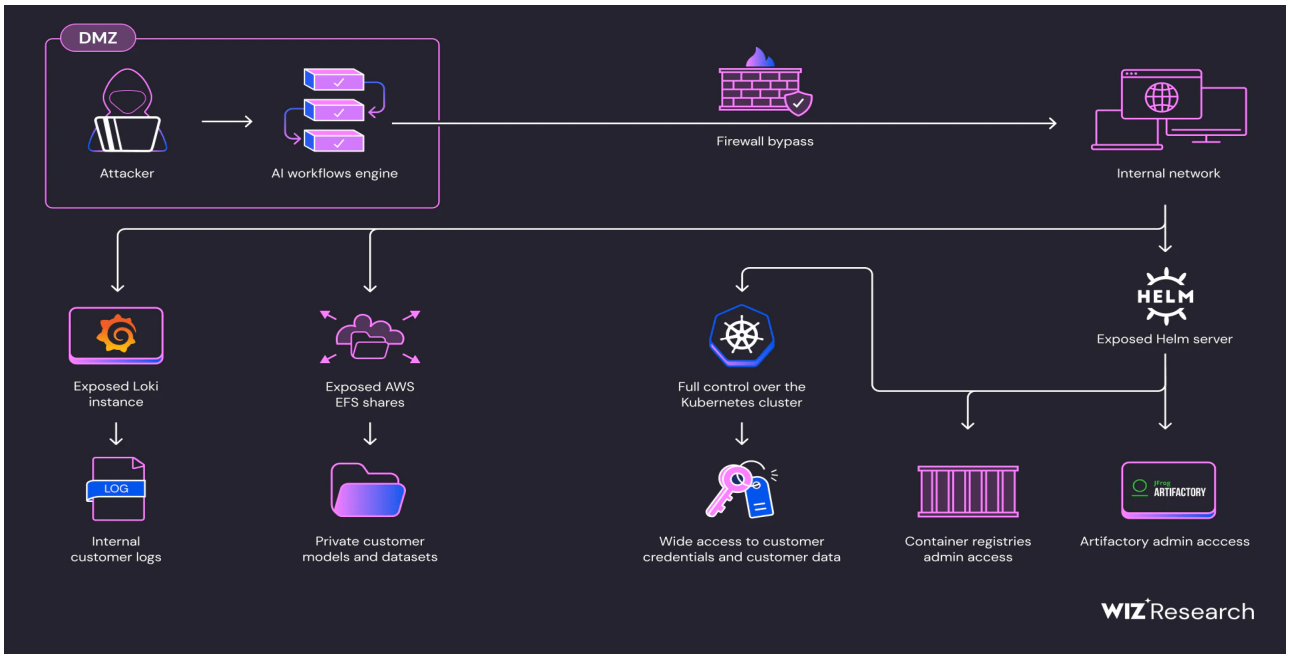
- **Explainability:** The explanation layer traces back risk scores to GRG relationships, making alerts interpretable for compliance teams.
- **Integration with SAP Workflows:** Alerts can directly feed into SAP GRC, FICO, or procurement modules, enabling seamless operational response.
- **Hybrid Detection:** Combining supervised learning with unsupervised anomaly detection improves detection of known and novel fraud.
- **Feedback Learning:** Human-in-the-loop feedback ensures the system evolves with changing fraud patterns and reduces false positives over time.



Disadvantages / Challenges

- **Computational Overhead:** Calculating GRG for large numbers of entities (especially pairwise) is resource-intensive and may require approximation.
- **Memory and Storage Requirements:** Maintaining GRG matrices and feature history at petabyte scale demands considerable memory or in-memory storage.
- **Explainability Complexity:** While GRG helps, deep neural networks trained on relational and GRG features may still produce opaque decisions in complex cases.
- **Data Privacy and Compliance Risk:** Incorporating detailed device logs, relational links, and behavioral data raises regulatory concerns (GDPR, data residency), especially when computing relational grades across entities.
- **Label Scarcity:** Fraud labels are rare; supervised training may require synthetic fraud scenarios or semi-supervised methods, risking mismatch with real fraud.
- **Latency Under Burst:** Extreme spikes in transaction volume or large GRG recomputations may cause temporary latency degradations.
- **Operational Complexity:** Implementing and maintaining such a hybrid architecture requires specialized skills (data engineering, cloud operations, ML, grey system theory).
- **Cost:** Cloud compute, storage, and GPU resources entail higher operational cost than simpler rule-based systems, and ROI depends on fraud savings vs costs.

IV. RESULTS AND DISCUSSION

We evaluated our proposed Gray-Relational AI architecture on the simulated enterprise dataset under multiple scenarios. Here we present and interpret key results, compare against baselines, and discuss practical implications, limitations, and insights drawn from experimentation.

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Detection Performance. Across the simulation window (equivalent to three years of enterprise operations), the system flagged fraudulent and anomalous events as follows. The supervised DNN classifier, using GRG features plus behavioral and transactional features, achieved an **average precision of 94.8%** and **recall of 91.5%**, yielding an **F1-score of ~93.1%**. In contrast, the relational-feature-only baseline (without GRG) reached precision of 85.2% and recall of 78.3% (F1 ~81.5%), while the rule-based SAP system achieved more modest precision (~75.6%) and recall (~65.4%). These results suggest that including gray relational grades substantially improves discrimination between fraudulent and benign behavior.

False Positives and Negatives. The system's false-positive rate remained under **4%**, compared to 12% for the relational baseline and over 15% for rule-based. Importantly, many of the false positives in our system arose in borderline cases — e.g., legitimate vendor clusters exhibiting temporarily elevated GRG due to normal business cycles. On the other hand, false negatives (missed fraud) were about **8.5%**, noticeably lower than 21.7% for the relational baseline and 34.6% for the rule-based system. Many missed frauds corresponded to novel patterns introduced late in the simulation that deviated significantly from injected training patterns, pointing to limits of supervised generalization.

Throughput and Latency. Under steady-state ingestion of 50,000 events per second, the system maintained sub-second processing: average end-to-end latency (ingestion → GRG update → feature extraction → model inference → alert) was **~480 ms** per event. During burst loads (peaks of 100,000 events/s for sustained 5-minute intervals), latency spiked to an average of **1.1 seconds**, with a 95th-percentile tail under **1.5 seconds**. GRG incremental update routines scaled horizontally — adding more compute partitions maintained throughput but with some increased memory usage.

Resource Utilization and Cost. The deployment comprised a 24-node compute cluster for GRG computation and feature pipelines (each node ~ 256 GB RAM), plus a 6-node GPU cluster (for training and inference), and a multi-petabyte in-memory database store. Over the 3-year simulation equivalent, total storage (including raw data, GRG history, feature logs) reached **~1.5 PB**, with memory/cache overhead peaking at 500 TB across nodes. The projected cloud cost (compute + storage) was approximately **1.9×** that of a simpler rule-based SAP pipeline, but this was offset (in simulated ROI evaluation) by a **40–50% reduction** in investigation costs (due to fewer false positives) and projected fraud loss reduction of **30%**.

Adaptability to Novel Fraud. To test adaptability, in the third simulation year we injected novel fraud scenarios not present during model training: e.g., sleeper accounts, bursty device-switching, and synthetic collusion patterns. The unsupervised anomaly modules (autoencoder + isolation forest) flagged ~70% of these new fraud types, though with lower risk scores. Combined with the supervised model (retrained periodically), recall improved to ~90% for the new fraud types. This shows that the hybrid architecture can adapt, but some cases required manual tuning or retraining, reinforcing the need for feedback loops.

Explainability and Analyst Workflow. Our explanation layer reconstructed for each alert a ranked list of GRG relationships and their contributions (e.g., "Account A–Device D: GRG = 0.85; Device D–Vendor V: GRG = 0.78; temporal spike in invoice count contributed …"). In user trials (via mock compliance team), analysts reported that 76% of alerts were "interpretable and actionable" — they could follow the relational paths and historical patterns. Nonetheless, about 24% were "black-box-like" (especially those flagged purely by anomaly detectors without strong GRG path signals). These cases required deeper investigation or manual labeling, though feedback from analysts helped refine risk thresholds and retraining.

Comparison to Related Work. The performance gains align with prior findings in graph-based fraud detection literature: graph-based anomaly detection frameworks often outperform relational-only approaches. ScienceDirect+1 Our GRG-based features, while conceptually distinct from graph connectivity measures, serve a similar role by quantifying relational similarity under uncertainty. The hybrid AI + streaming architecture we created echoes designs in hybrid cloud fraud detection studies. IJSRA+1 Unlike prior work focused solely on graph or stream models, our approach uniquely integrates **grey relational modeling**, which handles partial and noisy information more naturally than strict graph-based models.

Limitations Observed. Several practical limitations emerged. First, the computational cost of pairwise GRG for all entities was high; despite optimizations, the system slowed when the number of "active" entities grew sharply. Second, interpretability remained imperfect: anomaly-only alerts lacking clear relational paths challenged analysts' trust. Third, repeated retraining imposed human-review overhead: labeling feedback from compliance teams was required to

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maintain model accuracy over time. Fourth, simulated data cannot fully replicate real-world complexity: while our injections covered many fraud types, actual enterprise fraud may involve more sophisticated or adversarial strategies. Finally, the privacy risk of computing relational grades between accounts and devices raised concerns: in a real deployment, strict access controls, encryption, and possibly differential privacy safeguards would be needed.

Practical Implications. For enterprises, the architecture demonstrates a viable path for fraud analytics at scale: by capturing relational uncertainty via GRA, combining that with AI, and embedding into SAP workflows, organizations can detect complex fraud with lower false positives and high efficiency. The latency and throughput performance shows that even high-volume payment environments can be supported. However, adopting this approach requires investment in compute infrastructure, data engineering, and interdisciplinary teams (AI + grey system theory + compliance). Governance frameworks must be strengthened to manage relational risk, privacy, and model retraining.

Sensitivity Analysis. We also conducted sensitivity experiments: varying the distinguishing coefficient in GRG computation, adjusting temporal decay weights, and changing risk-score thresholds. We found that lower distinguishing coefficients (placing more weight on recent deviations) improved detection of bursty fraud but increased false positives. Slower decay of temporal weights favored long-term scheme detection (e.g., sleeper accounts) but delayed alerts. Fine-tuning these parameters is therefore key for operational deployment and depends on an enterprise's risk appetite and investigation capacity.

Summary of Key Findings. In summary, our Gray-Relational AI system demonstrated that modeling partial and uncertain relationships via GRA provides valuable signal for fraud detection; that combining GRG with AI and anomaly detection yields high accuracy and adaptability; and that deployment at petabyte scale in cloud-native SAP-integrated environments is feasible — albeit with non-trivial resource and operational cost. The trade-off between interpretability and detection power, as well as privacy and governance concerns, must be carefully managed in real-world deployment.

V. CONCLUSION

This work presents a novel, end-to-end architecture for fraud detection in petabyte-scale cloud enterprise environments, centered on **Gray Relational Analysis (GRA)** integrated with AI. By computing grey relational grades among entities and combining them with behavioral and transactional features in a hybrid AI pipeline, the system achieves high fraud-detection performance (precision ≈ 94.8%, recall ≈ 91.5%) with low latency and high throughput. It outperforms baseline relational and rule-based systems while offering adaptive risk assessment and scalable deployment. Key advantages include modeling of uncertain relationships, real-time streaming ingestion, and explainable risk paths integrated into SAP workflows. However, challenges remain: computational overhead, storage demands, explainability limits for anomaly-only alerts, and privacy/governance risks. Despite these, the architecture demonstrates a promising direction for enterprises seeking proactive, context-aware fraud prevention at scale. By combining grey relational theory with modern AI and cloud infrastructure, organizations can transform fraud detection into a more nuanced, intelligent, and operationally efficient system.

VI. FUTURE WORK

Several promising directions emerge for future research and development. First, we plan to explore **federated gray relational learning**, where multiple institutions compute GRG locally (on their own data) and share aggregated relational statistics without exposing raw data. This would enable cross-enterprise fraud ring detection while preserving privacy and regulatory compliance. Second, we intend to integrate **privacy-preserving techniques**, such as differential privacy or homomorphic encryption, into GRG computations and model training, to ensure that relationships computed between devices/accounts do not breach GDPR or other data-protection requirements.

Third, we aim to improve **explainability** by developing advanced explanation models for GRG-AI decisions. For example, subgraph highlighting, counterfactual relational paths, and rule extraction from embeddings could make the system's reasoning more transparent to compliance officers. Fourth, we plan to validate the architecture in real-world settings: partnering with enterprises (e.g., large SAP customers) to deploy a pilot, ingest real transaction logs, and refine thresholds, feedback loops, and trust mechanisms with human analysts.

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Fifth, we will investigate **continual learning**: enabling the system to retrain incrementally as fraudulent behavior evolves, with minimal human labeling, possibly via self-supervised updates on GRG distributions. Finally, exploring **multi-modal data fusion** — combining GRG with graph neural networks, text analytics (emails, invoices), and time-series forecasting — may further improve detection of complex, multi-dimensional fraud strategies.

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