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Information System Architecture for Payment Card Transaction Monitoring

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Abstract | **Original Research Article**

Digital payment systems involve the processing of large financial transactions with the help of payment cards, online commerce platforms, and mobile payment applications. Monitoring of financial transactions is essential to identify any unusual activity. This study examines an information system architecture designed for monitoring payment card transactions in digital financial environments. The proposed architecture integrates transaction data acquisition, database processing, monitoring modules, analytical models, and distributed infrastructure components within a unified monitoring framework. Transaction records are collected from multiple payment channels and stored in enterprise database systems that maintain historical transaction datasets. Monitoring engines evaluate transaction attributes such as transaction amount, location variation, and merchant category in order to identify abnormal patterns. Analytical models compute risk indicators and fraud probability estimates that support transaction classification and alert generation. Enterprise analytics platforms provide operational insights through monitoring dashboards that display transaction activity and system performance indicators. Distributed cloud infrastructure supports large-scale processing of transaction datasets and maintains system reliability during high transaction volumes. The results demonstrate that a structured monitoring architecture supports continuous transaction analysis and provides analytical capabilities for payment card transaction monitoring within modern financial information systems.

Keywords: Payment card transactions, transaction monitoring systems, financial information systems, fraud detection, information system architecture, transaction risk analysis, digital payment systems, and financial data analytics.

I. INTRODUCTION

Digital payment systems support a large share of global financial transactions. The use of payment cards, online banking, and electronic commerce requires complex architectures of information systems for the management of transaction processing, storage of data, and monitoring of security. As the number of electronic transactions grows, financial organizations face problems of fraud detection, data management, and reliability of the infrastructure. Research in financial analytics and fraud detection shows that transaction monitoring systems require analytical models and scalable data processing environments capable of examining large datasets and identifying irregular activity patterns within payment networks [1-3]. Recent studies emphasize the importance of information systems that support financial transaction analysis and operational monitoring. Secure data management frameworks play an important role in processing large financial datasets and supporting enterprise information systems used in banking and financial services [4]. Data quality management techniques also contribute to reliable financial reporting and monitoring functions within enterprise dashboards and analytical platforms [5]. Internal control mechanisms based on management information system logs assist organizations in detecting anomalies in financial operations and maintaining transparency in transaction records [6]. Infrastructure technologies also influence the performance of transaction monitoring platforms. Cloud computing environments provide computing capacity for large-scale financial systems and allow distributed processing of transaction data. Network monitoring architectures that integrate cloud services with IoT and analytics tools support system observation and operational monitoring across distributed environments [7], [8]. Hybrid cloud frameworks also contribute to system availability through backup and disaster recovery mechanisms designed for enterprise infrastructure [9]. These technologies support continuous operation of financial

systems that process large numbers of digital transactions. Analytical platforms also contribute to monitoring financial activities in organizational environments. Enterprise analytics frameworks support predictive analysis and operational evaluation in financial and business systems [10]. Machine learning techniques support forecasting models and analytical tools that examine operational performance indicators within enterprise platforms [11]. Research also examines the role of data management techniques such as SQL-based analytics and enterprise workload optimization within financial information systems [12,13]. Infrastructure reliability also depends on system monitoring tools and automated administrative platforms used in distributed computing environments [14,15].

Despite progress in financial analytics and monitoring technologies, the design of information system architectures for payment card transaction monitoring remains an important research area. Effective system architecture must integrate data processing, security monitoring, analytical models, and infrastructure management within a unified framework capable of processing high-volume transaction streams. Research that examines these components contributes to the development of monitoring systems that support financial institutions, payment networks, and digital commerce platforms.

The objective of this study is to examine the role of information system architecture in supporting payment card transaction monitoring systems. The research investigates technologies used in financial transaction analysis and fraud detection and evaluates architectural components required for scalable monitoring platforms. The study also explores the integration of data management systems, analytical tools, and monitoring infrastructures within payment processing environments. In addition, the research analyzes infrastructure considerations related to cloud computing, system monitoring, and reliability frameworks that support financial information systems. Another objective is to review analytical approaches used for transaction monitoring and operational evaluation in enterprise financial platforms. Finally, the study proposes a conceptual information system architecture that supports monitoring, analysis, and operational management of payment card transactions within modern digital financial environments.

II. Related Work

A. Credit Card Fraud Detection and Transaction Monitoring

Large numbers of digital transactions take place on a daily basis with the payment card systems, which increases the risks of fraudulent activities. Research in this area focuses on analytical models that identify suspicious patterns within transaction datasets. Cherif *et al.,* review major credit card fraud detection techniques and discuss the use of artificial intelligence and large-scale data processing within financial monitoring systems [1]. Ileberi *et al.,* present a machine learning framework that applies genetic algorithms for feature selection in fraud detection models [2]. Their results show that feature optimization can improve classification performance in transaction analysis. Jalil *et al.,* survey machine learning approaches applied to financial fraud detection and compare different analytical methods used in transaction monitoring environments [3]. These studies show the growing role of computational models in payment monitoring systems.

B. Financial Data Management and Information Systems

Information system architecture determines how financial data moves through monitoring platforms. Hasan examines scalable data management strategies used in enterprise finance and digital transaction systems [4]. The study discusses database design, storage structures, and security considerations related to large transaction datasets. Data quality also affects the reliability of financial analytics. Hasan presents SQL-based techniques that improve data accuracy within enterprise dashboards and reporting environments [5]. Akhter analyzes internal control mechanisms that use management information system event logs to detect irregular activity in financial operations [6]. Together, these studies describe how structured information systems support monitoring and analysis of financial transactions.

C. Cloud Infrastructure and System Monitoring

Modern monitoring systems often operate within distributed cloud environments. Afrin proposes a monitoring architecture that integrates cloud services with IoT and edge analytics to observe network behavior and system activity [7]. A related study examines cyber-resilient infrastructure for internet service providers and discusses automated threat detection mechanisms used in network security frameworks [8]. Farooq studies hybrid cloud environments and presents backup and disaster recovery strategies for distributed systems [9]. In addition, infrastructure analytics dashboards provide system administrators with visibility into computing resources and workload distribution across cloud platforms [10]. These technologies form the operational foundation of large-scale transaction monitoring systems.

D. Enterprise Analytics and Automated Monitoring

Enterprise analytics systems support operational monitoring within financial platforms. Hasan analyzes big-data analytics frameworks used in enterprise decision systems and discusses predictive models for operational evaluation [11]. Machine learning models also appear in KPI forecasting systems that analyze organizational performance metrics [12]. Cloud-based enterprise platforms support financial workload management and system monitoring across virtualized infrastructure [13]. System reliability also depends on

disaster recovery mechanisms within distributed computing environments [14]. Automated administration tools that apply artificial intelligence allow continuous observation of data center operations and system performance [15]. These approaches illustrate how monitoring technologies support large information system environments.

III. METHODOLOGY

A. Research Framework

This study adopts a conceptual system architecture approach to examine how information systems support payment card transaction monitoring in digital financial environments. The research framework focuses on the integration of financial transaction data, monitoring platforms, analytical models, and enterprise infrastructure within a unified information system architecture. Payment card networks generate continuous streams of transactional data that require structured data processing, security monitoring, and analytical evaluation. The methodology analyzes how these components interact within enterprise information systems designed for transaction monitoring. The framework considers the flow of payment transaction data across several operational stages, including data acquisition, processing, monitoring, analytics, and infrastructure management. Transaction data originates from payment terminals, online commerce platforms, and banking systems. These transactions are transmitted to centralized processing systems where monitoring platforms analyze transaction behavior and identify irregular activity patterns. Analytical tools then evaluate transaction records using statistical and machine learning techniques to support fraud detection and risk assessment. The research framework also incorporates infrastructure elements that support large-scale transaction monitoring environments. Cloud computing platforms, distributed databases, and system monitoring tools provide computational resources required for processing high-volume financial data streams. The framework therefore examines how architectural components interact to support transaction monitoring functions within modern payment systems. The conceptual design emphasizes modular architecture, which separates data processing, monitoring, analytics, and infrastructure layers. This separation supports scalability and system reliability in financial transaction monitoring platforms. Figure 1 presents the proposed architecture that illustrates the interaction between transaction data sources, monitoring modules, analytical components, and infrastructure systems.

B. Proposed Information System Architecture

The proposed information system architecture consists of five primary layers that manage payment card transaction monitoring across enterprise financial systems. Each layer performs specific operational functions within the monitoring platform.

1. Transaction Data Acquisition Layer

The transaction data acquisition layer is responsible for acquiring transactional data related to payment cards from various sources such as POS terminals, e-commerce sites, mobile payment apps, and banking systems. Each transactional record has various attributes such as the amount of the transaction, merchant id, time of the transaction, geographical location of the transaction, and id of the payment card used in the transaction. These data elements form the primary dataset used for monitoring and analysis. Data acquisition systems transmit transaction records to centralized monitoring platforms through secure communication protocols. Data validation procedures check transaction records for format consistency and completeness before processing.

2. Data Processing and Storage Layer

After acquisition, transaction data moves to the processing and storage layer where database systems organize and store transaction records. Structured database management systems store historical transaction data, while distributed storage frameworks manage large datasets generated from continuous payment activity. Data processing tasks include transaction normalization, timestamp synchronization, and aggregation of transaction records across merchants and cardholders. SQL analytics queries examine transaction patterns, compute statistical indicators, and prepare datasets for monitoring analysis.

3. Monitoring and Security Layer

The monitoring layer evaluates transaction behavior in real time and compares incoming transactions with historical activity patterns. Monitoring tools examine transaction frequency, location changes, merchant category variations, and transaction amounts. Security modules analyze these indicators to detect suspicious activity patterns that may indicate payment fraud. Alert generation mechanisms notify monitoring systems when transactions exceed predefined risk thresholds. Security dashboards provide administrators with system-wide monitoring capabilities and transaction risk indicators.

4. Analytics and Decision Layer

The analytics layer applies statistical models and analytical algorithms to evaluate transaction patterns and detect irregular activity. Analytical models estimate transaction risk scores and fraud probability values based on historical transaction behavior. Decision systems use analytical outputs to determine whether transactions require additional verification, rejection, or monitoring. These systems support operational decision making within payment processing platforms.

5. Infrastructure and Cloud Layer

The infrastructure layer provides computational resources that support large-scale transaction monitoring operations. Cloud computing platforms provide

distributed processing capabilities and scalable storage environments. Monitoring systems operate across virtualized infrastructure environments that support high-volume financial transaction workloads. Figure 1 illustrates the architecture of the proposed payment card transaction monitoring system.

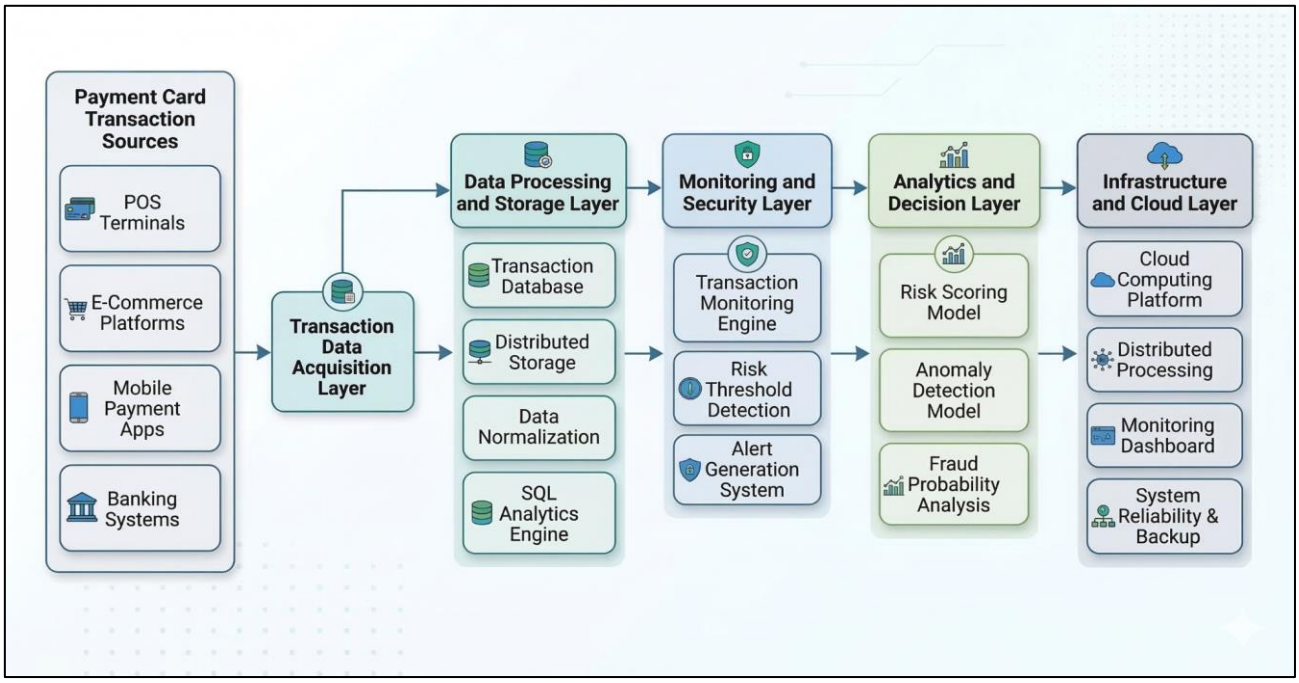

Figure 1: Proposed Payment Card Transaction Monitoring Architecture

C. Transaction Monitoring and Analytical Model

Analytical models support monitoring of payment card transactions through statistical evaluation of transaction attributes. These models generate risk indicators that assist monitoring systems in identifying irregular transaction behavior.

Transaction Risk Score Model

Transaction risk can be represented as a weighted function of several transaction attributes:

$$R_t = \sum_{i=1}^{n} w_i x_i$$

Where:

- R_t = risk score of transaction
- w_i = transaction attribute (amount, location change, merchant category, etc.)
- x_i = weight assigned to attribute i
- n = number of transaction attributes

Higher values of R_t indicate increased transaction risk. Monitoring systems compare the calculated risk score with predefined thresholds to determine whether the transaction requires additional review.

Anomaly Detection Model

Transaction anomaly detection evaluates deviations from historical transaction patterns. A common statistical anomaly detection approach calculates the standardized distance of a transaction value from the historical mean:

$$Z = \frac{x - \mu}{\sigma}$$

- x = observed transaction value
- μ = historical mean transaction value
- σ = standard deviation of transaction values

Large absolute values of Z indicate transactions that deviate significantly from normal activity patterns.

Fraud Probability Estimation

Fraud probability estimation models compute the likelihood that a transaction represents fraudulent activity. A logistic regression formulation can represent this probability:

$$P(Fraud) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}$$

Where:

- $P(Fraud)$ = probability of fraudulent transaction
- β_o = intercept parameter
- β_i = model coefficients
- x_i= transaction attributes

Monitoring systems use probability estimates to classify transactions into normal or suspicious categories.

D. Data Processing and Monitoring Workflow

Transaction monitoring platforms process financial transaction datasets through structured analytical workflows. Figure 2 illustrates the transaction monitoring workflow implemented within the proposed system architecture.

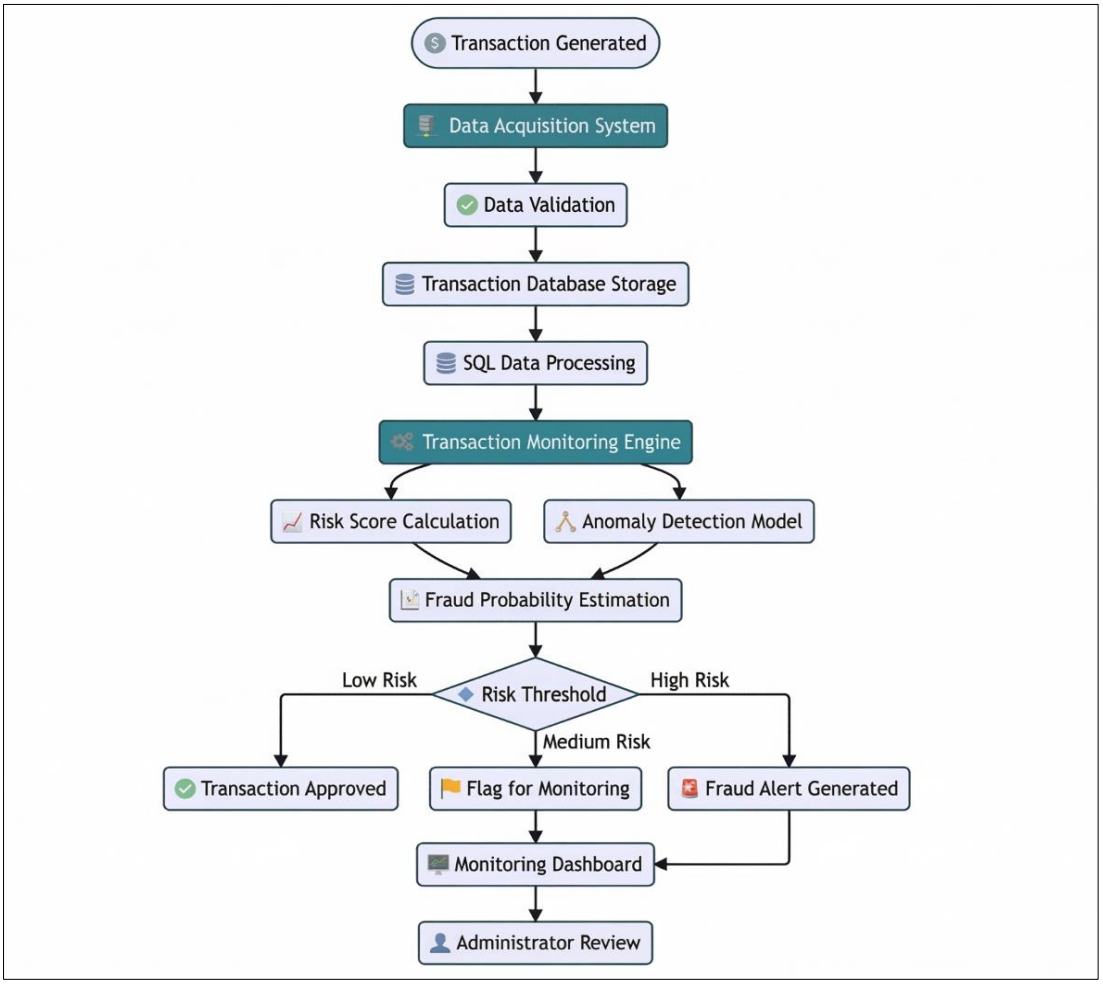

Figure 2: Transaction Monitoring Workflow

The workflow begins with the collection of transaction records from payment gateways and merchant systems. Data preprocessing procedures clean and standardize transaction records before storing them in enterprise databases. SQL analytics queries compute summary statistics, transaction frequencies, and merchant-level indicators. Monitoring dashboards visualize transaction metrics and system alerts. Analytical modules evaluate incoming transactions using risk scoring and anomaly detection models. Transactions that exceed risk thresholds trigger alerts that appear in monitoring dashboards for administrative review. Monitoring systems maintain audit logs that record transaction evaluations and alert responses. These logs support investigation processes and provide historical records for compliance and regulatory analysis.

E. Infrastructure and Deployment Environment

Payment transaction monitoring systems operate within distributed computing environments that support continuous processing of financial data streams. Cloud computing platforms provide scalable infrastructure capable of processing high volumes of transaction data generated by global payment networks. Distributed processing frameworks enable the parallel analysis of transactional datasets. Monitoring tools enable the collection of performance metrics of the system, such as CPU usage, memory consumption, and network bandwidth. These metrics enable the assessment of the performance of the infrastructure of the system. Reliability features of the system include backup systems, replication, and disaster recovery. The hybrid cloud infrastructure enables redundancy in the infrastructure of the system, thus ensuring the continuity of operations in the financial monitoring system.

F. Performance Evaluation Metrics

Evaluation of the proposed monitoring architecture requires measurement of system performance and analytical accuracy. Table 1 summarizes key metrics used to assess monitoring system performance.

Table 1. Performance Metrics for Transaction Monitoring Systems

Metric	Description
Detection Accuracy	Percentage of correctly identified fraudulent transactions
Anomaly Detection Rate	Ability to detect abnormal transaction patterns
False Positive Rate	Number of legitimate transactions incorrectly flagged
System Response Time	Time required to evaluate transaction risk
Scalability	Ability to process increasing transaction volumes
Infrastructure Utilization	Efficiency of computing resource usage

These metrics provide quantitative indicators used to evaluate monitoring system performance in financial transaction environments.

IV. DISCUSSION AND RESULTS

A. Performance Analysis of the Monitoring System

The proposed information system architecture was evaluated to determine its capability to process and monitor payment card transactions within digital financial systems. Payment networks generate large volumes of transaction records from point-of-sale systems, online payment platforms, and banking applications. Monitoring systems must process these records continuously while maintaining stable system performance. The architecture organizes transaction monitoring functions into several operational components including data acquisition, database processing, monitoring engines, and analytical modules. Transaction records are collected from payment systems and stored in database environments that maintain historical transaction data. Monitoring engines examine transaction attributes such as transaction amount, merchant category, geographic location, and transaction frequency. The monitoring system evaluates these attributes and assigns risk indicators to each transaction. Transactions that exceed defined risk thresholds are flagged for further inspection. Analytical modules compute statistical indicators that describe transaction activity patterns across the payment network. Figure 3 illustrates the performance evaluation structure of the monitoring system.

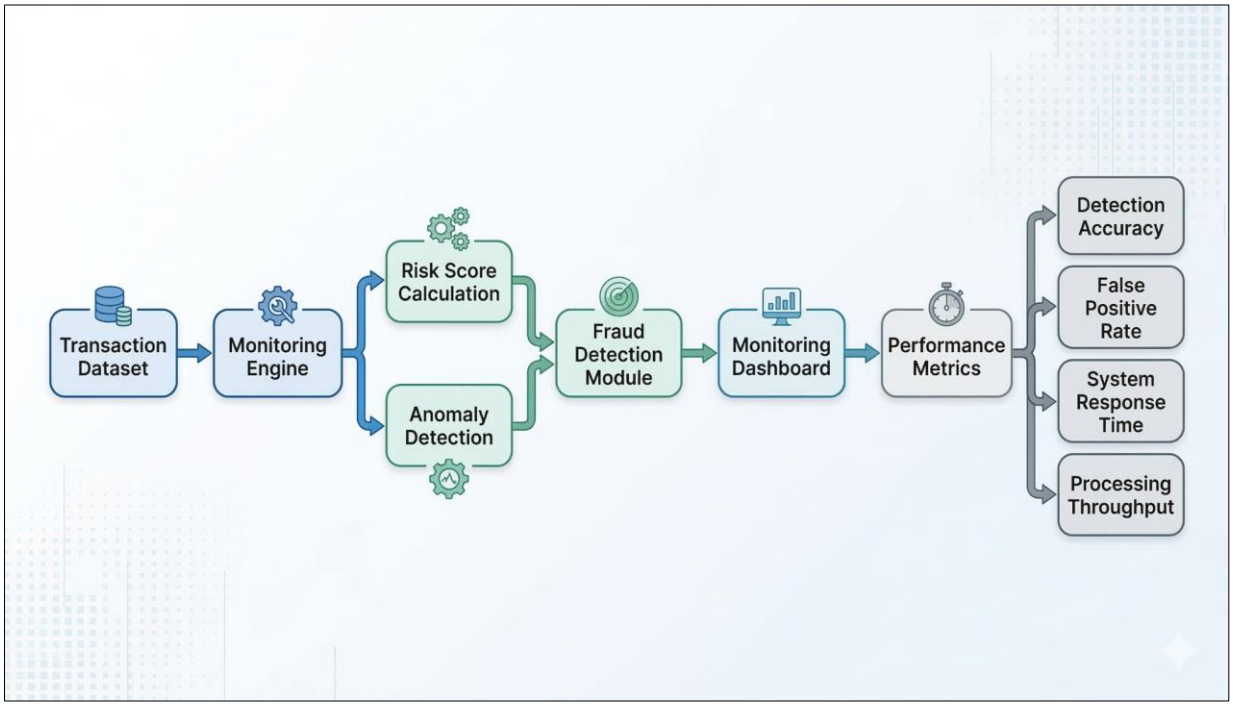

Figure 3. Performance Evaluation of the Payment Card Transaction Monitoring System

Monitoring dashboards show system performance indicators, for example, the accuracy of the detection system, the processing capabilities of the system, and the generation of alerts by the system. These indicators allow administrators to evaluate monitoring performance and identify abnormal transaction behavior.

B. Transaction Monitoring and Fraud Detection Results

Transaction monitoring relies on analytical models that evaluate transaction attributes and identify suspicious activity patterns. These models compute statistical indicators that represent transaction risk levels.

A transaction risk score model calculates risk indicators based on weighted transaction attributes:

$$R_t = \sum_{i=1}^{n} w_i x_i$$

Were

- R_t = risk score of transaction
- w_i = transaction attribute (amount, location change, merchant category, etc.)
- x_i = weight assigned to attribute i
- n = number of transaction attributes

Higher values of R_t indicate greater deviation from normal transaction patterns. Monitoring systems compare this score with predefined thresholds to identify suspicious transactions.

An anomaly detection model measures deviation from historical transaction activity:

$$Z = \frac{x - \mu}{\sigma}$$

Where,

- x = observed transaction value
- μ = historical mean transaction value
- σ = standard deviation of transaction values

Large values of Z indicate abnormal transaction behavior.

Fraud probability estimation is calculated using a logistic probability function:

$$P(Fraud) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}$$

Where,

- $P(Fraud)$ = probability of fraudulent transaction
- β_o = intercept parameter
- β_i = model coefficients
- x_i = transaction attributes

Transactions with high fraud probability are flagged for investigation. Figure 4 illustrates the fraud detection process used in the monitoring system.

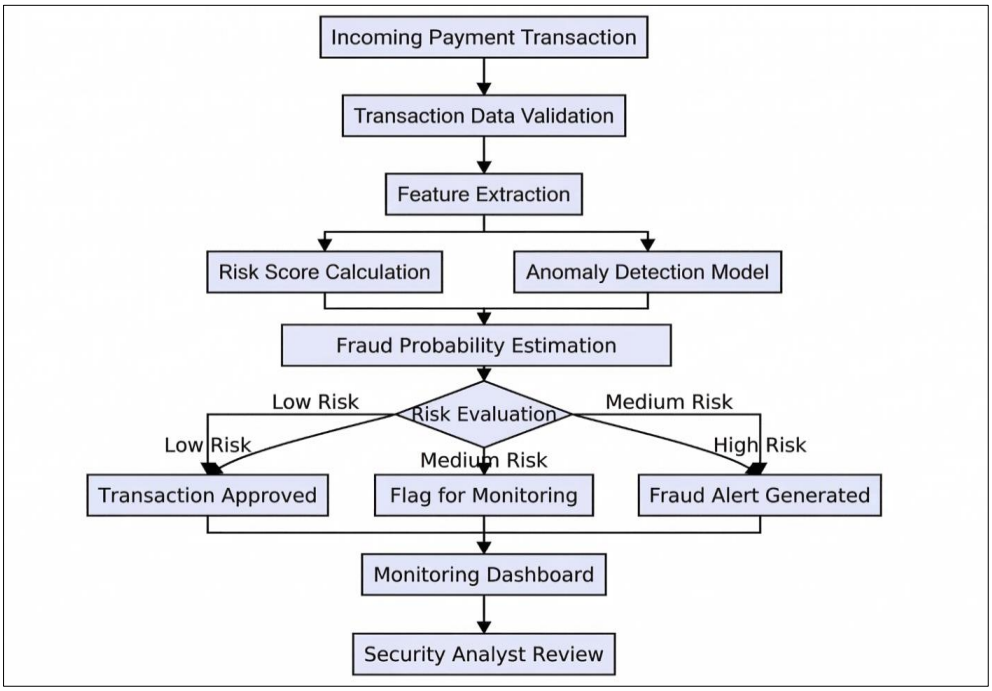

Figure 4: Fraud Detection Process in Payment Card Transaction Monitoring

C. Analytical Insights from Monitoring Data

Monitoring platforms generate analytical insights from historical transaction datasets. Enterprise analytics systems analyze patterns concerning the number of transactions, the merchants, and the spending of the cardholders. Monitoring dashboards display various indicators, for example, the total number of transactions, the average value of the transactions, and the geographic distribution of the transactions. These indicators allow analysts to observe irregular transaction patterns. SQL-based analytics queries also calculate aggregated transaction statistics. These queries generate indicators such as daily transaction totals and merchant transaction frequencies. The analysis of historical transactions enables analysts to identify patterns concerning fraudulent activities.

D. Infrastructure Scalability and System Reliability

Payment monitoring systems operate within distributed infrastructure environments that support continuous transaction analysis. Cloud computing platforms provide scalable computing resources capable

of processing large transaction datasets. Distributed processing frameworks divide analytical workloads across multiple computing nodes. Each node processes a subset of the transactions, hence enhancing the system's performance. Infrastructure monitoring tools monitor system metrics, for instance, processor utilization, memory utilization, and network utilization. These metrics enable the evaluation of the system's infrastructure. Replication and backup mechanisms support system reliability. Distributed storage systems maintain multiple copies of transaction datasets. If infrastructure failure occurs in one location, transaction monitoring continues in another computing node.

E. Comparison with Existing Monitoring Approaches

Traditional payment monitoring systems rely on rule-based detection methods that examine predefined transaction rules. These systems often identify known fraud patterns but may fail to detect new fraud behaviors. The architecture proposed in this study integrates statistical models with monitoring engines. Analytical models evaluate transaction attributes and generate risk indicators that represent transaction behavior. These indicators allow the system to identify suspicious patterns beyond simple rule-based detection. Another difference relates to system scalability. Traditional monitoring systems operate within centralized environments, which may experience performance limitations during high transaction volumes. Distributed infrastructure environments support analysis of larger transaction datasets and maintain system stability.

F. Implications for Financial Information Systems

The proposed monitoring architecture provides a framework for financial institutions that process digital payment transactions. Financial organizations require monitoring systems capable of analyzing transaction datasets while maintaining stable system performance. Distributed infrastructure environments allow monitoring systems to analyze transaction data across multiple locations. Analytical models generate indicators that assist analysts in identifying suspicious transaction activity. Digital commerce platforms also benefit from transaction monitoring systems that analyze payment activity across merchant networks.

G. Limitations of the Study

This study presents a conceptual architecture for payment card transaction monitoring. The research does not include experimental validation using real financial transaction datasets due to privacy and security restrictions. Another limitation relates to system deployment. The architecture describes system components and operational workflows but does not include full implementation within a production payment network. Future research may evaluate monitoring architectures using anonymized transaction datasets and examine system performance under real operational conditions.

V. CONCLUSION

This study examined an information system architecture designed for monitoring payment card transactions in digital financial environments. The architecture integrates transaction data acquisition, database processing, monitoring modules, analytical models, and distributed infrastructure components within a unified monitoring platform. Analytical models evaluate transaction attributes and generate risk indicators that assist monitoring systems in identifying irregular transaction behavior. The results show that a layered monitoring architecture supports continuous transaction analysis, operational visibility, and scalable processing of high-volume payment data. The interaction between monitoring engines, enterprise analytics systems, and distributed computing environments provides a structured framework for analyzing transaction activity across payment networks. These findings indicate that information system architecture plays an important role in organizing transaction monitoring operations and supporting analytical evaluation of payment card transactions within financial information systems.

Future research may examine implementation of transaction monitoring architectures using real or anonymized financial transaction datasets in order to evaluate analytical model performance under operational conditions. Additional studies may investigate advanced analytical techniques such as machine learning models and behavioral analytics for detecting evolving fraud patterns in payment networks. Further work may also examine optimization of distributed processing environments that support extremely large transaction volumes within global financial systems. These directions may contribute to improved monitoring methods and more reliable financial information systems within digital payment infrastructures.

REFERENCES

1. Akhter, T. (2025, October 6). Algorithmic internal controls for SMEs using MIS event logs. *TechRxiv*. https://doi.org/10.36227/techrxiv.175978941.15848264.v1
2. Afrin, S. (2025). Cloud-integrated network monitoring dashboards using IoT and edge analytics. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2298–2307. https://doi.org/10.5281/zenodo.17536343
3. Cherif, A., Badra, F., Aloulou, M. A., & Amiri, H. (2023). Credit card fraud detection in the era of disruptive technologies: A systematic review. *Journal of King Saud University – Computer and Information Sciences, 35*(1), 145–174. https://doi.org/10.1016/j.jksuci.2022.11.008
4. Afrin, S. (2025). Cyber-resilient infrastructure for public internet service providers using automated threat detection. *World Journal of Advanced Engineering Technology and Sciences*, 17(02), 127–140. https://doi.org/10.30574/wjaets.2025.17.2.1475

5. Farooq, H. (2025). Cross-platform backup and disaster recovery automation in hybrid clouds. *International Journal of Science and Innovation Engineering*, 2(11), 220–242. https://doi.org/10.70849/IJSCI02112025025
6. Farooq, H. (2025). Resource utilization analytics dashboard for cloud infrastructure management. *World Journal of Advanced Engineering Technology and Sciences*, 17(02), 141–154. https://doi.org/10.30574/wjaets.2025.17.2.1458
7. Hasan, E. (2025). Secure and scalable data management for digital transformation in finance and IT systems. *Zenodo*. https://doi.org/10.5281/zenodo.17202282
8. Ileberi, E., Sun, Y., & Wang, Z. (2022). A machine learning based credit card fraud detection using the GA algorithm for feature selection. *Journal of Big Data, 9*, 33. https://doi.org/10.1186/s40537-022-00573-8
9. Hasan, E. (2025). Big data-driven business process optimization: Enhancing decision-making through predictive analytics. *TechRxiv*. https://doi.org/10.36227/techrxiv.175987736.61988942.v1
10. Hasan, E. (2025). Machine learning-based KPI forecasting for finance and operations teams. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2139–2149. https://doi.org/10.5281/zenodo.17926746
11. Jalil, M. A., Razak, S. A., Othman, S. H., *et al.,*(2022). Financial fraud detection based on machine learning: A systematic literature review. *Applied Sciences, 12*(19), 9637. https://doi.org/10.3390/app12199637
12. Hasan, E. (2025). SQL-driven data quality optimization in multi-source enterprise dashboards. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2150–2160. https://doi.org/10.5281/zenodo.17926758
13. Hasan, E. (2025). Optimizing SAP-centric financial workloads with AI-enhanced CloudOps in virtualized data centers. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2252–2264. https://doi.org/10.5281/zenodo.17926855
14. Joarder, M. M. I. (2025). Disaster recovery and high-availability frameworks for hybrid cloud environments. *Zenodo*. https://doi.org/10.5281/zenodo.17100446
15. Joarder, M. M. I. (2025). Next-generation monitoring and automation: AI-enabled system administration for smart data centers. *TechRxiv*. https://doi.org/10.36227/techrxiv.175825633.33380552/v1
16. Mirza, S. B. (2026). Predictive reliability engineering for cloud-scale business intelligence platforms through anomaly detection, capacity optimization, and proactive support automation. *Zenodo*. https://doi.org/10.5281/zenodo.18968909
17. Rahman, M. (2025). Design and implementation of a data-driven financial risk management system for U.S. SMEs using federated learning and privacy-preserving AI techniques. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 1041–1052. https://doi.org/10.5281/zenodo.17769869
18. Tabassum, M., Rokibuzzaman, M., Islam, M. I., & Bristy, I. J. (2025). Data-driven financial analytics through MIS platforms in emerging economies. *Saudi Journal of Engineering and Technology*, 10(9), 440–446. https://doi.org/10.36348/sjet.2025.v10i09.007
19. Zaman, S. U. (2025). Enhancing security in cloud-based IAM systems using real-time anomaly detection. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2292–2304. https://doi.org/10.5281/zenodo.17926883
20. Rahman, T. (2026). Financial risk intelligence: Real-time fraud detection and threat monitoring. *Zenodo*. https://doi.org/10.5281/zenodo.18176490
21. Nahar, S., Rahman, M., Alam, M. S., & Al Sany, S. M. A. (2026). Intelligent data governance and ethical AI framework for enterprise information systems. Zenodo. https://doi.org/10.5281/zenodo.18839122
22. Sharan, S. M. M. I., Fahim, M. A. I., & Farooq, H. (2026). Cloud-native fintech analytics platform for IoT-enabled retail networks. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 089–104. https://doi.org/10.30574/wjaets.2026.18.1.1582
23. Rahman, M. A., Bristy, I. J., Islam, M. I., & Tabassum, M. (2025). Federated learning for secure inter-agency data collaboration in critical infrastructure. *Saudi Journal of Engineering and Technology*, 10(9), 421–430. https://doi.org/10.36348/sjet.2025.v10i09.005
24. Rahman, M. A., Islam, M. I., Tabassum, M., & Bristy, I. J. (2025). Climate-aware decision intelligence: Integrating environmental risk into infrastructure and supply chain planning. *Saudi Journal of Engineering and Technology*, 10(9), 431–439. https://doi.org/10.36348/sjet.2025.v10i09.006
25. Tabassum, M., Islam, M. I., Bristy, I. J., & Rokibuzzaman, M. (2025). Blockchain and ERP-integrated MIS for transparent apparel and textile supply chains. *Saudi Journal of Engineering and Technology*, 10(9), 447–456. https://doi.org/10.36348/sjet.2025.v10i09.008
26. Enam, M. M. R., Joarder, M. M. I., Taimun, M. T. Y., & Sharan, S. M. I. (2025). Framework for smart SCADA systems: Integrating cloud computing, IIoT, and cybersecurity for enhanced industrial automation. *Saudi Journal of Engineering and Technology*, 10(4), 152–158.
27. Hossain, M. T., Nabil, S. H., Razaq, A., & Rahman, M. (2025). Cybersecurity and privacy in IoT-based electric vehicle ecosystems. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(2), 921–933. https://doi.org/10.5281/zenodo.17246184
28. Islam, R. (2025). AI and big data for predictive analytics in pharmaceutical quality assurance. *SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5564319
29. Islam, R. (2025). Integration of IIoT and MIS for smart pharmaceutical manufacturing. *TechRxiv*. https://doi.org/10.36227/techrxiv.176049811.10002169
30. Haque, S. (2025). Effectiveness of managerial accounting in strategic decision making. *Preprints*. https://doi.org/10.20944/preprints202509.2466.v1

31. Al Sany, S. M. A. (2025). The role of data analytics in optimizing budget allocation and financial efficiency in startups. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2287–2297. https://doi.org/10.5281/zenodo.17536325
32. Haque, S., Al Sany, S. M. A., & Rahman, M. (2025). Circular economy in fashion: MIS-driven digital product passports for apparel traceability. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 1254–1262. https://doi.org/10.5281/zenodo.17276038
33. Al Sany, S. M. A., Haque, S., & Rahman, M. (2025). Green apparel logistics: MIS-enabled carbon footprint reduction in fashion supply chains. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 1263–1272. https://doi.org/10.5281/zenodo.17276049
34. Islam, K. S. A. (2025). Implementation of safety-integrated SCADA systems for process hazard control in power generation plants. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2321–2331. https://doi.org/10.5281/zenodo.17536369
35. Fahim, M. A. I., Sharan, S. M. M. I., & Farooq, H. (2025). AI-enabled cloud-IoT platform for predictive infrastructure automation. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 431–446. https://doi.org/10.30574/wjaets.2025.17.3.1574
36. Islam, K. S. A., Zaidi, S. K. A., Afrin, S., & Zaman, S. U. (2026). Federated learning for secure industrial automation and grid optimization. *Global Journal of Engineering and Technology Advances*, 26(01), 025–040. https://doi.org/10.30574/gjeta.2026.26.1.0360
37. Sharan, S. M. M. I. (2025). Integrating human-centered design with agile methodologies in product lifecycle management. *International Journal of Science and Innovation Engineering*, 2(10), 1019–1034. https://doi.org/10.70849/IJSCI02102025115
38. Farabi, S. A. (2025). AI-augmented OTDR fault localization framework for resilient rural fiber networks in the United States. *arXiv*. https://arxiv.org/abs/2506.03041
39. Farabi, S. A. (2025). AI-driven predictive maintenance model for DWDM systems to enhance fiber network uptime in underserved U.S. regions. *Preprints*. https://doi.org/10.20944/preprints202506.1152.v1
40. Farabi, S. A. (2025). AI-powered design and resilience analysis of fiber optic networks in disaster-prone regions. *ResearchGate*. https://doi.org/10.13140/RG.2.2.12096.65287
41. Jasem, M. M. H. (2025). An AI-driven system health dashboard prototype for predictive maintenance and infrastructure resilience. *Authorea*. https://doi.org/10.22541/au.176617579.97570024/v1
42. Islam, M. A. (2026). Native scalable student information systems and admission test automation with peak load architecture database performance optimization and observability driven reliability. *Zenodo*. https://doi.org/10.5281/zenodo.18987480
43. Mim, M. A. (2026). Cybersecurity risk mitigation in educational and healthcare IT environments. *Zenodo*. https://doi.org/10.5281/zenodo.18988585
44. Dukkipati, S. S. N. C. (2026). Design and implementation of scalable AI-driven conversational systems for enterprise-level feedback intelligence and decision support. *SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=6263818
45. Rahman, F. (2025). Data science in power system risk assessment and management. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 295–311. https://doi.org/10.30574/wjaets.2025.17.3.1560
46. Rahman, F. (2025). Advanced statistical models for forecasting energy prices. *Global Journal of Engineering and Technology Advances*, 25(03), 168–182. https://doi.org/10.30574/gjeta.2025.25.3.0350
47. Karim, F. M. Z. (2025). Integrating quality management systems to strengthen U.S. export-oriented production. *Global Journal of Engineering and Technology Advances*, 25(03), 183–198. https://doi.org/10.30574/gjeta.2025.25.3.0351
48. Fazle, A. B. (2025). AI-driven predictive maintenance and process optimization in manufacturing systems using machine learning and sensor analytics. *Global Journal of Engineering and Technology Advances*, 25(03), 153–167. https://doi.org/10.30574/gjeta.2025.25.3.0349
49. Rahman, F., Nahar, S., & Mim, M. A. (2026). Cloud-native enterprise resource management for multi-sector operations. *Global Journal of Engineering and Technology Advances*, 26(01), 126–141. https://doi.org/10.30574/gjeta.2026.26.1.0012
50. Mim, M. A., Sharif, M. M., Rahman, F., & Nahar, S. (2026). Smart IoT infrastructure for workplace efficiency and energy savings. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 140–156. https://doi.org/10.30574/wjaets.2026.18.1.0026