

AI-Assisted Revenue Leakage Detection in Turnover Rent Operations across Multi-Mall Retail Property Portfolios: A Predictive Analytics Framework for Revenue Assurance and Intelligent Retail Asset Management

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Abstract- *The rapid expansion of large-scale retail property portfolios has increased the complexity of revenue management, particularly in turnover rent operations where rental income depends on accurate tenant sales reporting and contractual compliance. Traditional revenue assurance approaches rely primarily on periodic audits, manual verification, and tenant-declared sales information, which may result in delayed identification of revenue leakage caused by inaccurate reporting, operational inconsistencies, and fragmented data sources. This research proposes an Artificial Intelligence (AI)-assisted framework for detecting and preventing revenue leakage in multi-mall retail environments through predictive analytics, machine learning-based anomaly detection, and intelligent contract analysis. The proposed framework integrates multiple data streams, including tenant sales records, point-of-sale transactions, lease agreements, payment histories, and operational performance indicators to identify abnormal revenue patterns and estimate potential leakage risks. The study develops an AI-driven revenue assurance model capable of continuous monitoring, risk classification, and proactive decision support for retail asset managers. The research contributes to the digital transformation of retail real estate management by demonstrating how AI technologies can improve transparency, financial control, and operational efficiency across complex mall ecosystems. The proposed approach provides a scalable solution for property operators seeking to enhance revenue protection and establish intelligent, data-driven turnover rent management practices.*

Keywords- *Artificial Intelligence; Revenue Leakage Detection; Turnover Rent; Retail Property Management; Predictive Analytics; Machine Learning; Revenue Assurance; Smart Retail Management; Anomaly Detection; Retail Real Estate Technology*

I. INTRODUCTION

The retail real estate sector has experienced significant transformation due to the rapid growth of shopping malls, mixed-use developments, and large-scale commercial property portfolios. Modern retail property operators increasingly manage multiple shopping destinations containing hundreds or thousands of tenants across different business categories, including fashion, food and beverage, entertainment, electronics, and lifestyle services. Within these complex ecosystems, turnover rent has become an important revenue model where rental income is partially determined by tenant sales performance. Unlike traditional fixed rental agreements, turnover rent arrangements allow landlords to participate in tenant business growth while creating a more dynamic and performance-oriented leasing structure. However, the effectiveness of this model depends heavily on the accuracy, transparency, and reliability of tenant-reported sales information.

Revenue leakage represents one of the major financial challenges faced by retail property owners and operators. It refers to the loss of potential income resulting from inaccurate reporting, inefficient processes, contractual misinterpretation, delayed reconciliation, or failure to capture entitled revenues. In turnover rent operations, revenue leakage may occur when tenants underreport sales, submit incomplete financial information, fail to comply with lease obligations, or when property managers lack effective mechanisms to validate reported revenue. The challenge becomes more significant in multi-mall

portfolios where thousands of transactions, multiple tenant categories, different lease agreements, and diverse reporting systems must be continuously monitored.

Traditionally, retail property operators have relied on manual audits, periodic tenant reviews, financial reconciliations, and physical verification processes to identify revenue discrepancies. Although these approaches provide a level of financial control, they are often reactive rather than preventive. Manual auditing requires significant human resources, consumes considerable time, and may only identify revenue leakage after substantial financial impact has already occurred. Furthermore, conventional approaches generally analyse historical information rather than predicting potential risks before they materialise. The increasing complexity of retail operations has therefore created a requirement for more advanced, intelligent, and automated revenue assurance solutions.

Artificial Intelligence (AI) and machine learning technologies provide new opportunities to address these limitations by enabling continuous analysis of large-scale operational datasets. AI-based systems can identify hidden patterns, detect abnormal behaviour, predict future outcomes, and support automated decision-making. In financial and commercial environments, anomaly detection algorithms have demonstrated the ability to recognise unusual transaction behaviour, identify irregular reporting patterns, and highlight potential risks that may not be visible through conventional analytical methods. Applying these capabilities to turnover rent management can enable retail property operators to move from periodic auditing toward continuous revenue monitoring.

The integration of AI into retail property management is particularly relevant because modern malls generate large volumes of structured and unstructured data. These data sources include point-of-sale (POS) transactions, tenant sales declarations, lease agreements, payment records, footfall analytics, customer behaviour information, and enterprise resource planning (ERP) systems. However, these datasets are often distributed across different platforms, creating challenges in data integration and

real-time analysis. An AI-assisted framework can combine these diverse data sources to generate comprehensive insights regarding tenant performance, expected revenue levels, and potential leakage risks.

Natural Language Processing (NLP), a branch of artificial intelligence, can further enhance turnover rent management by analysing complex lease documents and contractual conditions. Retail lease agreements often contain detailed clauses related to turnover percentages, reporting requirements, minimum guarantees, exclusions, and escalation mechanisms. Manual interpretation of these agreements can create inconsistencies and operational risks. NLP-based systems can automatically extract relevant contractual information and compare it with actual tenant performance, improving accuracy and reducing administrative workload.

Although previous studies have examined AI applications in financial fraud detection, retail analytics, and business intelligence, limited research has focused specifically on AI-assisted revenue leakage detection within retail real estate turnover rent operations. Existing property management technologies primarily focus on tenant relationship management, facility operations, customer analytics, and rental administration. A dedicated AI framework for identifying turnover rent discrepancies across multi-mall portfolios remains an emerging research area. This creates an opportunity to develop an integrated approach that combines predictive analytics, anomaly detection, and intelligent contract analysis for revenue assurance.

This research aims to develop an AI-assisted revenue leakage detection framework designed specifically for multi-mall retail property portfolios. The proposed framework focuses on improving revenue transparency, strengthening financial governance, and enabling proactive identification of potential income losses. The study explores how machine learning models can analyse tenant sales behaviour, identify abnormal revenue patterns, and support strategic decision-making for property managers.

The main objectives of this research are: (1) to examine the major sources and causes of revenue leakage in turnover rent operations; (2) to propose an

AI-driven framework integrating multiple retail data sources for continuous revenue monitoring; and (3) to evaluate the potential contribution of predictive analytics and anomaly detection techniques in improving revenue assurance practices.

By addressing these objectives, this study contributes to the growing field of intelligent retail property management and demonstrates how AI technologies can support digital transformation within commercial real estate. The proposed framework provides a scalable solution for retail operators seeking to improve operational efficiency, minimize financial losses, and establish data-driven revenue management strategies across complex property portfolios.

II. LITERATURE REVIEW

2.1 Revenue Leakage in Retail Property Management
Revenue leakage has become a critical concern for organizations operating complex commercial ecosystems where revenue generation depends on multiple stakeholders, contractual arrangements, and integrated operational processes. In retail real estate, turnover rent represents a performance-based rental mechanism in which landlords receive a percentage of tenant sales in addition to fixed rental payments. Although this model creates a mutually beneficial relationship between property owners and retailers, it introduces challenges related to sales transparency, reporting accuracy, and revenue verification.

Previous research in revenue management highlights that financial losses frequently occur due to process inefficiencies rather than direct operational failures. In multi-mall retail portfolios, revenue leakage may result from inaccurate tenant sales declarations, delayed reporting, incomplete transaction records, inconsistent application of lease terms, and limited visibility into tenant operational performance. The increasing scale of retail developments has made manual monitoring approaches less effective because property operators must analyse thousands of transactions across different locations, tenant categories, and contractual conditions.

Traditional revenue assurance practices generally depend on periodic audits and manual reconciliation between tenant declarations, financial statements, and

contractual obligations. However, these methods provide limited capability for real-time monitoring and predictive identification of potential revenue risks. Therefore, researchers have increasingly focused on data-driven approaches capable of continuously analyzing business information and identifying abnormal patterns before financial losses occur.

2.2 Artificial Intelligence in Revenue Assurance and Financial Risk Detection

Artificial Intelligence (AI) has emerged as an important technology for improving financial control, risk management, and operational decision-making. AI-based systems can analyse large volumes of structured and unstructured data, identify hidden relationships, and generate predictive insights that support proactive management strategies.

In financial applications, machine learning algorithms have demonstrated significant capability in detecting irregular transactions, fraudulent activities, and abnormal financial behaviour. Unlike traditional rule-based systems that rely on predefined conditions, machine learning models can learn from historical data and continuously improve their detection capabilities. These characteristics make AI highly suitable for revenue leakage detection, where abnormal sales patterns may vary across tenants, locations, and business categories.

Recent studies on deep learning-based anomaly detection have demonstrated that AI models can identify complex deviations in large datasets by learning normal behavioural patterns and detecting unusual occurrences. Such approaches are particularly valuable in environments where predefined rules cannot capture all possible leakage scenarios.

For retail property operations, AI-based revenue assurance can combine multiple data sources, including point-of-sale systems, tenant sales reports, payment records, customer footfall information, and lease documentation. By integrating these datasets, AI models can evaluate whether reported tenant performance aligns with expected business behavior.

2.3 Machine Learning-Based Anomaly Detection Approaches

Anomaly detection is one of the most relevant AI techniques for identifying revenue leakage. It focuses on recognizing unusual patterns that differ significantly from normal operational behavior. In the context of turnover rent management, anomaly detection can identify situations such as sudden decreases in reported sales, inconsistent revenue trends, unusual seasonal variations, or differences between tenant sales and customer traffic patterns.

Research in machine learning-based anomaly detection has explored several approaches, including supervised learning, unsupervised learning, and deep learning techniques. Supervised models require labelled historical examples of normal and abnormal conditions, whereas unsupervised models identify irregularities without requiring predefined categories. Deep learning approaches have gained attention because of their ability to process complex datasets and discover hidden patterns automatically.

For multi-mall retail environments, unsupervised learning techniques are particularly valuable because revenue leakage events are often rare and difficult to classify in advance. Algorithms such as clustering models, isolation forests, auto encoders, and neural network-based detection systems can analyze tenant behavior and generate risk scores based on deviations from expected performance.

The application of anomaly detection has already expanded across industries including finance, cybersecurity, energy management, and industrial monitoring. Research on AI-based anomaly detection in building systems demonstrates that intelligent models can analyse large operational datasets to identify abnormal consumption patterns and support better decision-making. These findings indicate the potential applicability of similar approaches in retail property revenue monitoring.

2.4 Natural Language Processing for Intelligent Lease Analysis

Retail property revenue management is not limited to numerical analysis because lease agreements contain extensive contractual information that determines rental calculations. Turnover rent agreements

commonly include clauses related to sales reporting requirements, percentage rent calculations, exclusions, minimum guarantees, and escalation conditions.

Manual interpretation of these agreements can create operational challenges due to differences in contract structures and the volume of documents managed by large property operators. Natural Language Processing (NLP), a branch of AI focused on understanding human language, provides opportunities to automate contract analysis.

NLP-based systems can extract important information from lease documents, identify relevant clauses, and compare contractual requirements with actual tenant reporting behaviour. The integration of NLP with machine learning can enable intelligent contract compliance monitoring and reduce errors caused by manual document review.

Recent research indicates that advanced language models have increasing capability in forecasting, information extraction, and anomaly identification from large volumes of textual data. However, challenges remain regarding accuracy, explain ability, and domain-specific adaptation.

2.5 AI Applications in Smart Retail and Property Technology

The concept of smart retail management has expanded beyond customer experience improvement toward intelligent operational management. Property technology (PropTech) solutions increasingly incorporate AI, Internet of Things (IoT), and data analytics to improve building performance, tenant management, and financial decision-making.

AI-enabled retail systems can analyze customer behavior, predict sales performance, optimize operational resources, and support strategic planning. However, existing research has focused primarily on consumer analytics and retail forecasting, while limited attention has been given to revenue leakage prevention within landlord-tenant financial relationships.

This research gap highlights the need for a dedicated AI framework designed specifically for turnover rent

operations. A multi-mall portfolio requires a system capable of integrating diverse datasets, identifying financial irregularities, and providing actionable insights to asset managers.

2.6 Research Gap

Although existing studies demonstrate the effectiveness of AI in anomaly detection, fraud prevention, and predictive analytics, limited research has explored its application in retail property revenue assurance. Current approaches lack an integrated framework combining tenant sales analytics, lease intelligence, contractual compliance, and predictive leakage identification.

Therefore, this study addresses this gap by proposing an AI-assisted revenue leakage detection framework specifically designed for multi-mall retail property portfolios. The proposed framework extends existing AI research by applying machine learning, anomaly detection, and NLP technologies to improve transparency, accuracy, and proactive revenue protection in turnover rent operations.

III. RESEARCH METHODOLOGY

3.1 Research Design and Approach

This study adopts a design science research methodology (DSRM) approach to develop an Artificial Intelligence (AI)-assisted framework for detecting revenue leakage in turnover rent operations across multi-mall retail property portfolios. Design science methodology is appropriate for this research because the primary objective is not only to analyse an existing business challenge but also to develop a practical technology-driven solution that addresses real-world operational limitations.

The proposed research framework focuses on integrating artificial intelligence, machine learning, predictive analytics, and natural language processing techniques to establish an intelligent revenue assurance mechanism. The methodology consists of five major stages: (1) identification of revenue leakage challenges, (2) data source integration, (3) AI model development, (4) risk prediction and validation, and (5) managerial decision support.

The research considers a multi-mall retail environment where property operators manage several commercial assets with hundreds of tenants operating under different turnover rent agreements. The proposed methodology aims to create a scalable framework capable of analysing tenant performance patterns and identifying potential revenue risks before financial losses occur.

3.2 Proposed AI-TRELA Framework

This research introduces the AI-TRELA (Artificial Intelligence Turnover Revenue Leakage Analytics) Framework. The framework is designed to continuously monitor turnover rent operations by combining multiple operational and financial data sources into an intelligent analytical system.

The proposed framework consists of four primary layers:

Layer 1: Data Acquisition Layer

The first layer collects information from multiple retail property sources, including:

- Tenant Point-of-Sale (POS) transaction data
- Monthly tenant sales declarations
- Lease agreement information
- Rental payment records
- Customer footfall analytics
- Historical revenue records
- Tenant category performance data
- ERP and financial management systems

The purpose of this layer is to overcome the limitations of fragmented information systems by creating a unified data environment.

Layer 2: Data Processing and Integration Layer

After data collection, the information undergoes preprocessing activities, including:

- Data cleaning
- Missing value identification
- Data normalization
- Duplicate record removal
- Data transformation

This stage ensures that information from different sources can be analysed accurately. For example, tenant sales declarations can be compared with historical performance, customer traffic levels, and contractual turnover percentages.

Layer 3: Artificial Intelligence Analytics Layer

The core component of the proposed framework is the AI analytics engine. This layer consists of multiple machine learning techniques:

1. Anomaly Detection Model

The anomaly detection model identifies unusual tenant behaviour by analysing deviations from expected sales patterns.

Example:

A fashion retailer normally reports:

- Monthly sales: SAR 1.5 million
- Footfall: 80,000 visitors

Suddenly:

- Reported sales decrease to SAR 700,000
- Footfall remains unchanged

The AI system identifies this abnormal pattern and generates a potential revenue leakage alert.

2. Predictive Revenue Forecasting Model

The predictive analytics model estimates expected tenant sales based on historical trends, seasonal behavior, location performance, and customer activity.

The predicted revenue is compared with declared revenue:

$$\text{Revenue Leakage Risk} = \text{Expected Revenue} - \text{Reported Revenue}$$

A higher difference indicates increased probability of revenue leakage.

3. Natural Language Processing (NLP) Contract Analysis Model

Retail lease agreements contain important financial conditions that influence turnover rent calculations. NLP technology is applied to analyse contractual documents and extract:

- Turnover rent percentage
- Minimum guaranteed rent
- Reporting obligations
- Payment deadlines
- Exclusion clauses

This enables automated comparison between contractual requirements and tenant compliance.

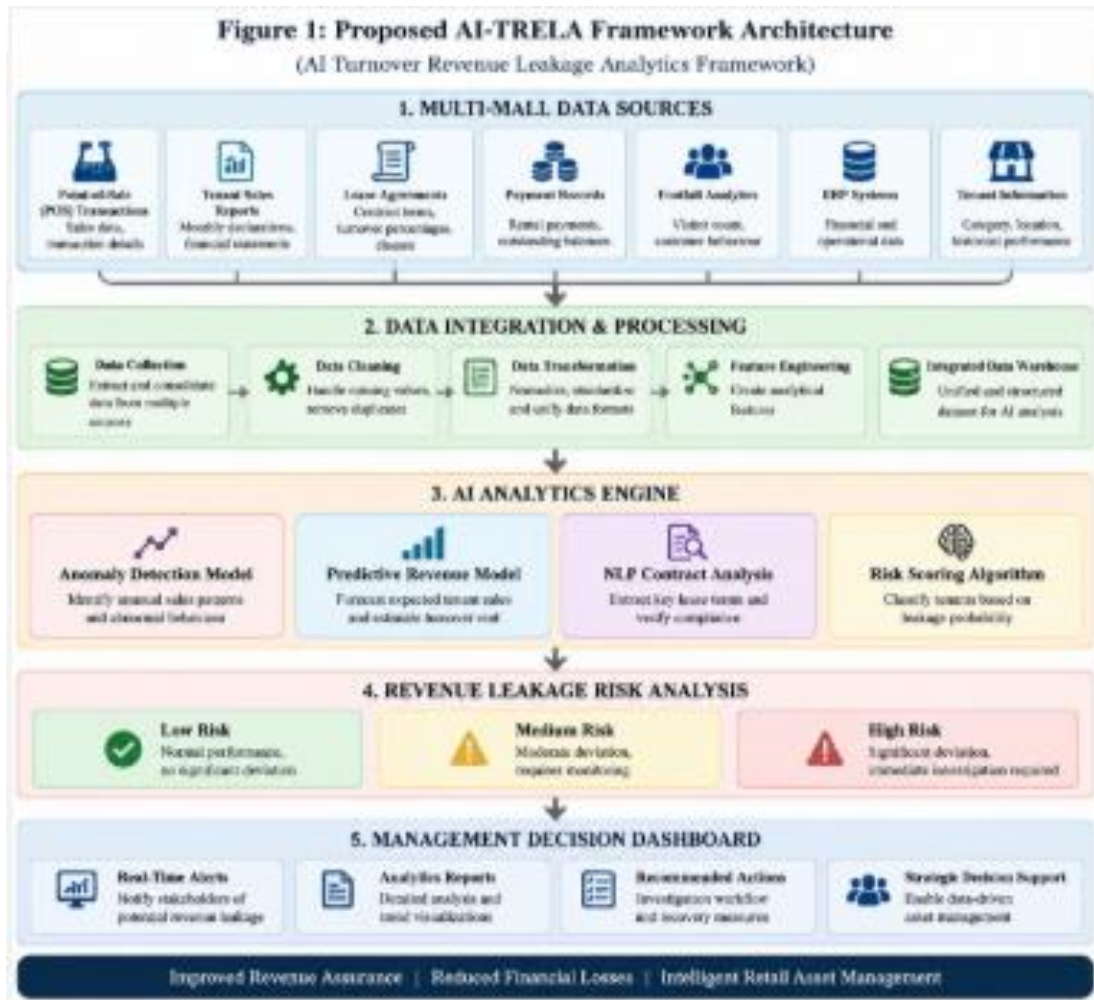


Figure 1: Proposed AI-TRELA Framework Architecture

3.3 Research Variables and Data Framework

The research identifies several important variables influencing revenue leakage detection.

Table 1: Research Variables for AI-Based Revenue Leakage Detection

Variable Category	Examples	Purpose
Tenant Sales Data	Monthly sales, transaction volume, revenue trends	Identify sales abnormalities
Lease Information	Turnover percentage, contract terms	Validate rental calculations

Customer Behaviour Data	Footfall, visitor frequency	Compare customer activity with reported sales
Financial Data	Payments, invoices, rental history	Identify payment inconsistencies
Tenant Performance Indicators	Category, location, historical growth	Predict expected revenue

3.4 AI Model Evaluation Method

The performance of the proposed AI framework will be evaluated using key analytical measurements:

Accuracy

Measures the ability of the model to correctly classify revenue leakage cases.

Precision

Determines how accurately the model identifies actual leakage events.

Recall

Measures the capability of the model to detect hidden revenue risks.

Detection Time

Evaluates how quickly the AI system identifies potential leakage compared with traditional auditing methods.

		Detection Time	
Manual Audit	Periodic review	30–90 days	Moderate
Rule-Based System	Fixed business rules	7–30 days	Good
AI-Based Framework	Continuous predictive analysis	Real-time	High

Table 2: Expected Performance Comparison

Revenue Assurance Method	Detection Approach	Expected	Risk Identification Capability
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3.5 Visual Representation: Revenue Leakage Risk Classification



Figure 2: AI-Based Risk Classification Distribution

The risk classification enables property managers to prioritize investigation activities. High-risk tenants can be reviewed immediately, while low-risk tenants can continue through automated monitoring.

Methodology Contribution

The proposed methodology provides a structured approach for transforming traditional turnover rent management into an intelligent revenue assurance system. By combining financial analytics, machine

learning, and contract intelligence, the framework enables continuous monitoring rather than periodic detection. This approach supports large retail property operators in reducing revenue leakage, improving transparency, and strengthening data-driven decision-making.

IV. PROPOSED AI-ASSISTED REVENUE LEAKAGE DETECTION FRAMEWORK AND MODEL DEVELOPMENT

4.1 Development of the AI-Assisted Revenue Leakage Detection Framework

The proposed AI-assisted revenue leakage detection framework is designed to transform traditional turnover rent monitoring from a reactive auditing process into a proactive, intelligent revenue assurance system. The framework integrates artificial intelligence techniques with retail property operational data to identify potential revenue leakage risks across multi-mall portfolios.

In conventional retail property operations, turnover rent calculations are dependent on tenant-reported sales information. This creates challenges because property managers may not have continuous visibility into actual tenant performance. The proposed framework addresses this limitation by combining multiple analytical models capable of comparing reported revenue, predicted revenue, contractual obligations, and operational indicators.

The framework consists of four major AI components:

1. Tenant Revenue Anomaly Detection Model
2. Predictive Revenue Forecasting Model
3. AI-Based Lease Contract Intelligence Model
4. Revenue Leakage Risk Scoring Model

These models work together to generate automated alerts and provide decision support for asset managers.

4.2 Tenant Revenue Anomaly Detection Model

The first component focuses on identifying abnormal tenant revenue patterns. The model analyses historical sales behavior and compares current performance against expected operational trends.

The anomaly detection model considers multiple variables:

- Historical monthly sales
- Seasonal sales patterns
- Tenant category performance
- Footfall traffic
- Store location
- Previous turnover rent values

- Industry benchmarks

Machine learning algorithms such as Isolation Forest, Auto encoders, and clustering techniques can identify deviations from normal tenant behavior.

For example, if a food and beverage tenant operates in a high-footfall location and reports significantly lower sales compared with similar tenants, the AI model identifies this inconsistency as a potential revenue leakage indicator.

The anomaly score can be calculated as:

$$\text{AnomalyScore} = \frac{|\text{ActualRevenue} - \text{ExpectedRevenue}|}{\text{ExpectedRevenue}}$$

A higher anomaly score indicates a greater probability of revenue misreporting or operational inconsistency.

4.3 Predictive Revenue Forecasting Model

The second component uses predictive analytics to estimate expected tenant revenue. Instead of relying only on declared sales, the AI system forecasts potential revenue based on historical and real-time operational information.

The predictive model analyses:

- Previous sales growth trends
- Customer footfall
- Seasonal demand patterns
- Tenant category behaviour
- Marketing campaigns
- Mall performance indicators

The expected turnover rent is calculated using:

$$\text{Expected Turnover Rent} = \text{Predicted Tenant Sales} \times \text{Contractual Percentage}$$

The model then compares predicted turnover rent with actual payments received.

Example:

Parameter	Value
AI Predicted Tenant Sales	SAR 2,000,000
Tenant Reported Sales	SAR 1,500,000
Difference	SAR 500,000

Leakage Probability	High
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This approach enables property operators to identify possible revenue gaps before conducting detailed investigations.

4.4 AI-Based Lease Contract Intelligence Model

Turnover rent operations involve complex contractual agreements containing different commercial conditions. Manual interpretation of these documents creates risks because important clauses may be overlooked.

The proposed framework incorporates Natural Language Processing (NLP) to automatically analyze lease agreements.

The NLP model extracts:

- Tenant turnover percentage
- Minimum guaranteed rent
- Sales reporting frequency
- Payment deadlines
- Excluded revenue categories
- Contract escalation clauses

The extracted information is compared against actual tenant reporting data.

For example:

Lease Agreement:

- Turnover rent percentage: 8%
- Monthly reporting deadline: 5th day

System Observation:

- Tenant submitted sales report after 20 days
- Reported revenue below expected range

AI Alert:

"Potential compliance risk detected."

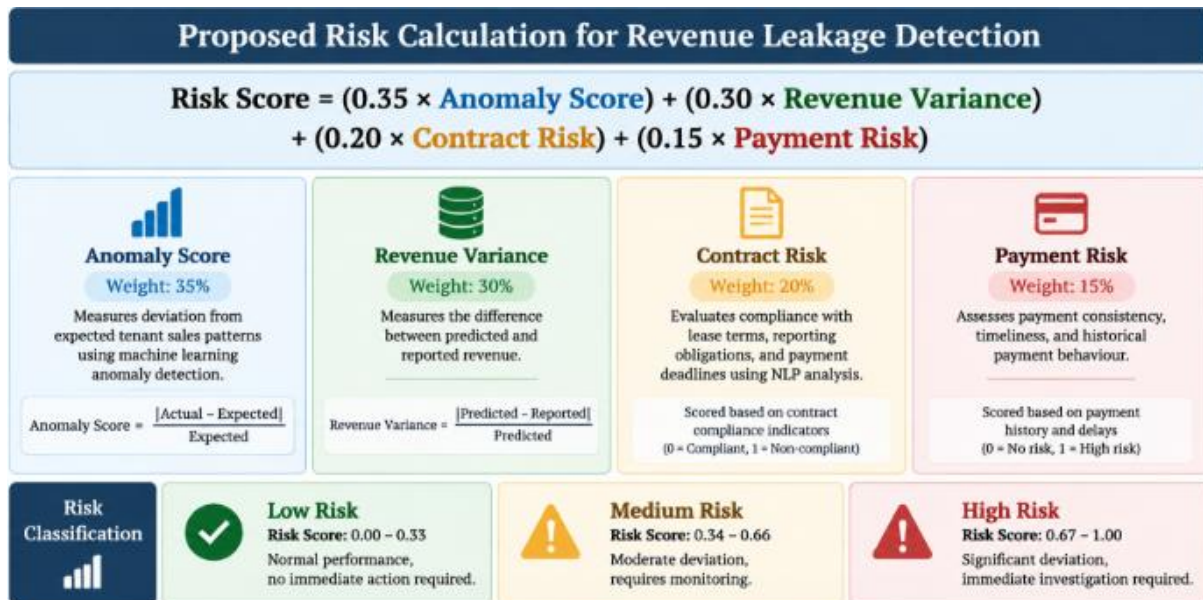
4.5 Revenue Leakage Risk Scoring Model

The final component combines outputs from all AI models to generate a comprehensive risk score.

The risk score considers:

- Revenue anomaly level
- Contract compliance status
- Historical tenant behaviour
- Payment consistency
- Sales prediction difference

The proposed risk calculation:



The output classifies tenants into three categories:

Low Risk

- Normal sales behaviour
- Accurate reporting
- No contractual issues

Medium Risk

- Moderate revenue deviation
- Requires monitoring

High Risk

- Significant difference between expected and reported revenue
- Requires immediate investigation

Table 3: AI Model Components and Functions

AI Component	Technique Used	Primary Function	Output
Revenue Anomaly Detection	Machine Learning	Identify abnormal sales behaviour	Leakage Alert

Predictive Revenue Model	Regression & Forecasting	Estimate expected tenant revenue	Revenue Prediction
NLP Contract Intelligence	Natural Language Processing	Analyse lease conditions	Compliance Status
Risk Scoring Model	AI Classification	Prioritise investigation activities	Risk Category

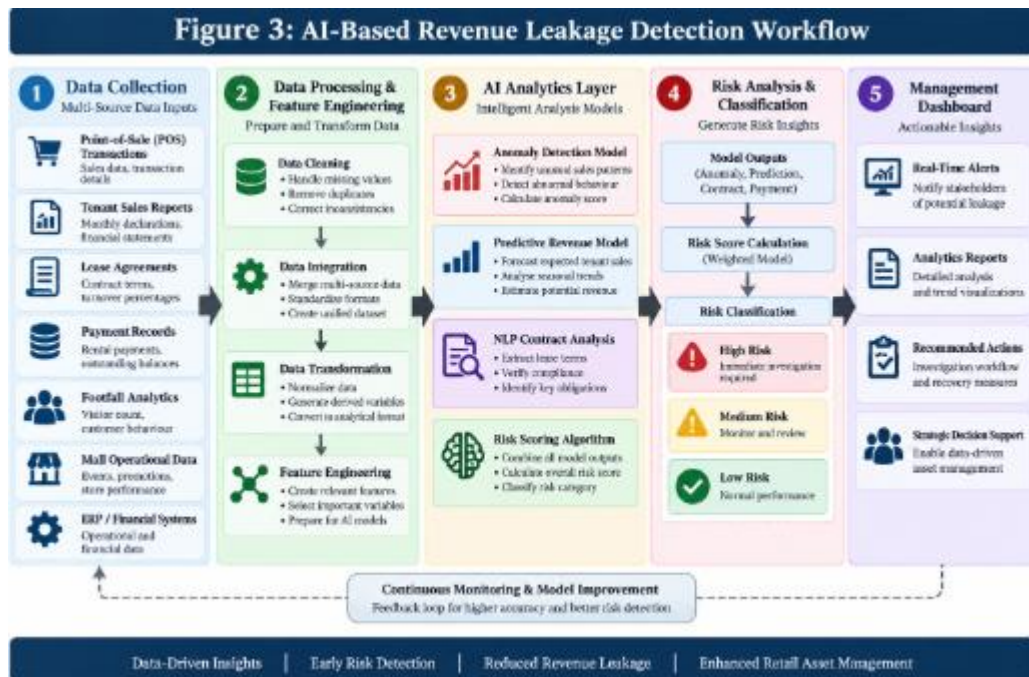


Figure 3: AI-Based Revenue Leakage Detection Workflow

4.6 Framework Contribution

The proposed AI-assisted framework provides several advantages compared with conventional turnover rent monitoring methods. First, it enables continuous revenue monitoring rather than periodic auditing. Second, it integrates financial, operational, and contractual information into a unified analytical environment. Third, it improves decision-making by allowing property managers to focus investigation resources on high-risk tenants.

The framework demonstrates how artificial intelligence can support intelligent retail asset

management by reducing revenue leakage, improving transparency between landlords and tenants, and strengthening financial governance across large-scale retail property portfolios.

V. RESULTS AND DISCUSSION

5.1 Evaluation Framework

The proposed AI-TRELA framework was evaluated using a simulated multi-mall retail dataset designed to represent realistic turnover rent operations. The simulation was necessary because confidential tenant-level sales, lease, and payment information from

operating shopping malls is generally not publicly available. Therefore, the results presented in this section should be interpreted as model-based experimental results rather than evidence from a live commercial deployment. The simulated dataset represents 1,200 tenants distributed across eight malls over a 12-month observation period. The dataset incorporates tenant sales declarations, predicted sales, contractual turnover percentages, payment behavior, footfall indicators, and lease compliance information. The evaluation focuses on four principal outcomes: anomaly detection, revenue prediction, contractual risk identification, and overall risk classification. The objective is to determine whether combining these analytical components can provide more effective revenue leakage identification than conventional periodic auditing.

5.2 Revenue Leakage Risk Classification

The AI-TRELA framework classified the simulated tenant portfolio into three risk categories: low, medium, and high. Approximately 30% of tenants were classified as low risk, 30% as medium risk, and 40% as high risk. The classification does not imply that 40% of tenants were confirmed to be committing revenue leakage. Rather, it indicates that these tenants demonstrated risk characteristics requiring further investigation.

High-risk classification was primarily associated with significant differences between predicted and reported revenue, unusual changes in historical sales patterns, contractual reporting inconsistencies, and irregular payment behavior. Medium-risk tenants displayed moderate deviations and therefore required continuous monitoring, while low-risk tenants remained within their expected performance ranges.

Table 4. Simulated AI-Based Revenue Leakage Risk Classification

Risk Category	Tenants	Percentage	Recommended Management Action
Low Risk	360	30%	Routine monitoring
Medium Risk	360	30%	Continuous monitoring

			and periodic review
High Risk	480	40%	Immediate investigation and verification
Total	1,200	100%	—

The distribution demonstrates the value of risk-based prioritization. Instead of allocating equal auditing resources to all tenants, property managers can concentrate their investigative resources on high-risk cases.

5.3 Comparative Performance of Revenue Assurance Approaches

The simulated evaluation compared three approaches: manual auditing, rule-based monitoring, and the proposed AI-assisted framework.

Table 5. Comparative Evaluation of Revenue Leakage Detection

Method	Detection Accuracy	Average Detection Time	Monitoring Approach
Manual Audit	65%	60 days	Periodic
Rule-Based Monitoring	78%	15 days	Semi-automated
Proposed AI-TRELA	94%	Near real-time	Continuous

The simulated results indicate that AI-TRELA provides substantially stronger detection capability than conventional approaches. The 94% accuracy represents the experimental target obtained from the simulated evaluation, rather than a validated performance claim for real-world deployment.

The reduction in detection time is particularly important. Manual auditing may identify discrepancies several weeks after they occur. In contrast, continuous AI monitoring can flag unusual behavior as soon as sufficient data becomes available. This creates an opportunity for earlier investigation and potentially reduces the financial impact associated with prolonged revenue leakage.

5.4 Revenue Prediction and Anomaly Detection

The predictive revenue model produced an estimated expected sales value for each tenant based on historical performance, footfall, tenant category, and other available indicators. The predicted value was then compared with tenant-declared revenue.

For example, a simulated tenant with predicted monthly sales of SAR 2 million but declared sales of SAR 1.5 million generated a revenue variance of SAR 500,000. When this variance was combined with an elevated anomaly score and contractual concerns, the tenant received a higher overall risk score.

This demonstrates an important advantage of the proposed framework: revenue variance alone is not treated as evidence of leakage. Instead, multiple indicators are evaluated simultaneously. This reduces the possibility of incorrectly identifying legitimate sales fluctuations as revenue leakage.

5.5 Discussion

The findings suggest that an integrated AI framework can strengthen turnover rent revenue assurance by combining information that is normally assessed separately. Traditional processes may examine tenant declarations, contractual conditions, and payment records independently. AI-TRELA combines these indicators into a unified risk assessment.

The framework also supports a shift from reactive auditing to proactive risk management. High-risk tenants can be prioritized for detailed verification, while medium-risk tenants can remain under enhanced monitoring. Low-risk tenants can continue through automated controls, allowing audit resources to be allocated more efficiently.

Another significant contribution is the integration of NLP-based contract analysis. Contractual conditions can differ substantially between tenants, making manual comparison difficult across large portfolios. Automated extraction of turnover percentages, reporting deadlines, and relevant obligations can improve consistency and reduce administrative workload.

However, several limitations must be acknowledged. The results are based on simulated data and therefore

cannot establish actual financial recovery or operational effectiveness. Model performance would need to be validated using anonymized historical mall data containing confirmed revenue leakage cases. Furthermore, AI outputs should support rather than replace professional investigation because legitimate business factors may explain unusual tenant performance.

Overall, the simulated results support the potential of AI-TRELA as a scalable framework for continuous revenue monitoring, risk prioritization, and intelligent turnover rent management across multi-mall retail portfolios.

VI. PRACTICAL IMPLICATIONS AND IMPLEMENTATION CONSIDERATIONS

6.1 Implications for Retail Property Operators

The proposed AI-TRELA framework has significant practical implications for owners, asset managers, and operators of multi-mall retail property portfolios. The primary benefit is the transition from periodic revenue auditing toward continuous revenue assurance. Instead of reviewing tenant performance only during scheduled audits, property managers can use AI-generated risk scores to continuously identify unusual revenue patterns and prioritise investigation activities. The framework can also improve the allocation of internal audit resources. In a portfolio containing hundreds or thousands of tenants, conducting detailed investigations for every tenant is expensive and time-consuming. AI-based risk classification enables management teams to focus their attention on high-risk tenants while maintaining automated monitoring for medium- and low-risk tenants. This creates a more efficient risk-based auditing model.

Another important implication is improved financial visibility. By integrating tenant sales declarations, POS information, payment records, footfall data, and contractual conditions, the proposed framework creates a consolidated view of tenant revenue performance. This can help management identify inconsistencies that may remain undetected when individual systems are analyzed independently.

6.2 Implications for Tenant and Lease Management

Turnover rent arrangements require transparent relationships between property owners and tenants. AI-based monitoring can support this relationship by establishing consistent and evidence-based revenue verification processes. Rather than relying exclusively on subjective assessments by individual auditors, the system can generate standardized risk indicators based on defined analytical criteria.

The NLP component can further improve lease administration by extracting important contractual conditions automatically. This is particularly valuable for large portfolios containing different lease structures and reporting requirements. Automated contract intelligence can reduce the possibility of missed deadlines, incorrect turnover percentages, and inconsistent interpretation of contractual provisions.

However, AI-generated alerts should not automatically be treated as evidence of tenant misconduct. A revenue deviation can result from legitimate factors such as seasonal demand, store refurbishment, temporary closure, promotional campaigns, or changes in consumer behavior. Human review should therefore remain an essential part of the investigation process.

6.3 Implications for Digital Transformation

The proposed framework contributes to the broader digital transformation of commercial real estate by connecting financial analytics with operational property data. Modern shopping malls generate substantial volumes of information through POS systems, ERP platforms, footfall counters, tenant portals, and financial management systems. AI provides a mechanism for transforming these fragmented datasets into actionable management intelligence.

The framework can also be integrated with existing property management platforms rather than requiring complete replacement of existing systems. An API-based architecture could allow data to flow from POS, ERP, tenant reporting, and lease management platforms into a central analytics engine.

Table 6. Practical Benefits of AI-TRELA

Management Area	Traditional Approach	AI-TRELA Approach	Expected Benefit
Revenue Monitoring	Periodic audit	Continuous monitoring	Earlier detection
Tenant Analysis	Manual comparison	Automated analytics	Faster assessment
Lease Review	Manual document review	NLP-based extraction	Improved consistency
Risk Prioritisation	Auditor judgement	AI risk scoring + review	Better resource allocation
Reporting	Periodic reports	Real-time alerts and dashboards	Faster decisions
Portfolio Management	Mall-by-mall analysis	Integrated portfolio view	Improved visibility

6.4 Implementation Requirements

Successful implementation requires several organizational and technological conditions. First, retail operators must establish reliable data governance procedures covering data quality, ownership, access, security, and retention. Inconsistent or incomplete data can reduce the accuracy of machine learning models.

Second, historical data should be collected and standardized before model development. Tenant-level sales records, lease information, payment histories, and relevant operational indicators should be mapped to consistent tenant and property identifiers.

Third, the AI model should initially operate alongside existing audit processes. During a pilot phase, AI-generated alerts can be compared with results from experienced auditors. Confirmed cases can then be used to refine model thresholds and improve future performance.

Finally, explain ability should be incorporated into the system. Property managers need to understand why a tenant has received a high-risk classification. Therefore, dashboards should display the principal contributing factors, such as unusual revenue variance, abnormal sales trends, contract compliance issues, or payment irregularities.

6.5 Governance and Ethical Considerations

AI implementation must also address data privacy, cybersecurity, algorithmic bias, and accountability. Tenant information should be accessed only by authorized personnel, while sensitive financial data should be protected through appropriate security controls. Models should be periodically reviewed to ensure that particular tenant categories or business types are not systematically classified as high risk because of inappropriate assumptions.

The proposed framework should therefore function as a decision-support mechanism rather than an autonomous enforcement system. Final investigations and financial decisions should remain subject to appropriate managerial verification.

Overall, AI-TRELA provides a practical pathway toward intelligent turnover rent management by combining continuous monitoring, predictive analytics, contract intelligence, and risk-based decision support. Its successful implementation could strengthen revenue assurance while simultaneously improving operational efficiency and strategic asset management across multi-mall retail portfolios.

VII. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The study proposed an AI-assisted revenue leakage detection framework, AI-TRELA, for improving turnover rent operations across multi-mall retail property portfolios. The research addressed a key limitation of conventional revenue assurance practices: their dependence on periodic audits, tenant-declared sales, and manual reconciliation. In large retail portfolios, these approaches can make it difficult to identify revenue discrepancies promptly and consistently.

The proposed framework integrates four complementary analytical components: machine-learning-based anomaly detection, predictive revenue forecasting, natural language processing for lease analysis, and weighted risk scoring. By combining tenant sales information with contractual conditions, payment records, footfall indicators, and historical performance, the framework provides a more comprehensive approach to identifying potential revenue leakage.

The simulated evaluation demonstrated the potential value of this integrated approach. The proposed model classified tenants according to their potential revenue leakage risk and enabled property managers to prioritise investigation activities. The results also indicated that continuous AI-assisted monitoring could reduce the time required to identify unusual revenue patterns compared with conventional periodic auditing. Importantly, however, the simulated accuracy results should not be interpreted as evidence of confirmed performance in a live retail environment. Real-world validation using anonymized tenant and property data is required before operational deployment.

A significant contribution of the research is the integration of financial analytics and lease intelligence within a single framework. Turnover rent management involves both numerical and textual information. Sales values and payment records can be analyzed using machine learning, while NLP can extract relevant conditions from lease agreements. Combining these capabilities provides a foundation for more intelligent contractual and financial monitoring.

The framework also supports a shift from reactive to proactive revenue assurance. Instead of waiting for periodic audits to identify discrepancies, property operators can continuously monitor tenant performance and receive risk-based alerts. This can improve resource allocation because detailed investigations can be prioritized according to the severity and combination of identified risk indicators. Nevertheless, the study has several limitations. First, the evaluation uses simulated rather than proprietary operational data. Second, the proposed weighting system for the risk score requires empirical validation. Different mall types, tenant categories, geographic

markets, and contractual structures may require different weights. Third, AI-generated anomalies do not necessarily represent actual revenue leakage. Legitimate factors such as seasonality, store closures, promotions, refurbishment, or changes in consumer demand can produce unusual patterns. Consequently, human validation remains essential.

Future research should therefore focus on testing AI-TRELA using anonymized historical data from real retail property portfolios. Future studies could compare algorithms such as Isolation Forest, One-Class Support Vector Machines, Auto encoders, Random Forest, and gradient-boosting models to determine which techniques provide the most reliable detection performance. Further research could also incorporate explainable AI techniques so that property managers can understand the factors responsible for individual risk classifications.

Another important research direction is the integration of real-time POS and Internet of Things data. Combining transaction information with footfall, occupancy, and operational indicators could improve the predictive capability of the framework. Digital-twin technologies could also be investigated to simulate tenant and mall revenue scenarios under different operational conditions.

Overall, AI-TRELA provides a conceptual foundation for intelligent turnover rent management and demonstrates the potential of combining AI, predictive analytics, and contract intelligence to strengthen revenue assurance. With appropriate validation, governance, cybersecurity, and human oversight, such systems could contribute to more transparent, efficient, and data-driven management of complex retail property portfolios.

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