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ARTIFICIAL INTELLIGENCE (AI) DRIVEN PREDICTIVE MODEL FOR ENHANCING TENANT RETENTION IN NIGERIA'S RESIDENTIAL REAL ESTATE SECTOR

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ABSTRACT

This study develops an Artificial Intelligence (AI)-driven predictive model aimed at enhancing tenant retention through data- driven insights. Drawing on tenant data from major urban centers—Lagos, Abuja, and Enugu—the study applies supervised machine learning techniques, with a focus on the Random Forest (RF) algorithm, to predict tenant churn. Key variables analyzed include demographic, financial, property, and service quality factors influencing tenant behavior. The findings reveal that the RF model outperforms traditional models such as Linear Regression in accuracy (99.96%), recall (81.63%), and overall predictive performance, demonstrating its suitability for tenant retention prediction. The study highlights the transformative potential of AI in shifting property management practices from reactive to proactive strategies. The research contributes to both academic knowledge and practical applications by integrating machine learning with real estate management in a developing economy context.

1. INTRODUCTION

The residential real estate sector is a vital component of Nigeria's socio-economic framework, serving as the backbone of shelter provision for an estimated population exceeding 220 million (National Bureau of Statistics [NBS], 2023). The residential real estate sector makes imposing positive impacts in the areas of influencing urban development patterns, economic growth, and quality of life. In Nigeria, housing demand far outweighs supply due to rapid urbanization, rural-urban migration, and population growth, consequent to a complex market characterized by challenges such as housing shortages, high rent burdens, and fluctuating tenant retention rates (Fadeyi & Adepoju, 2022). One of the most pressing challenges confronting residential property stakeholders in Nigeria is tenant retention. Tenant retention refers to the ability of landlords and property managers to maintain a continuous leasing relationship with tenants, thus ensuring steady rental income, reduced vacancy rates, and minimized transactional costs associated with tenant turnover (Musa & Oladipo, 2025). High tenant turnover rates lead to significant financial and operational challenges, including loss of rent during vacancy periods, costs of repainting and repairs, marketing expenses to attract new tenants, and administrative burdens related to leasing contracts and tenant screening (Duru & Ojo, 2023). Despite the importance of sustained tenant relationships, many Nigerian residential landlords struggle with maintaining long-term tenants. Several socio-economic factors contribute to tenant churn in Nigeria, including income instability, unreliable utility services, ineffective property management practices, and disparities in housing quality (Adebayo & Smith, 2022). Additionally, traditional rental management practices frequently lack sophisticated tools for data collection and tenant analysis, resulting in reactive rather than proactive retention strategies. The recent expansion of digital technologies in Nigeria, alongside improvements in data accessibility, presents new opportunities for transforming residential real estate management. In particular, artificial intelligence (AI) technologies have shown remarkable potential in many sectors by leveraging large data volumes to generate predictive insights, automate decision-making, and optimize operational efficiency (Russell & Norvig, 2021). In real estate, AI-driven predictive modeling involves the use of algorithms and machine learning techniques to analyze tenant behavior, identify patterns predictive of turnover risks, and recommend targeted actions to retain tenants before they decide to vacate (Johnson et al., 2024). Global trends indicate increasing adoption of AI- powered property management systems that can significantly reduce tenant turnover through personalized engagement, predictive maintenance, and dynamic rent strategies (Zhang et al., 2023). However, most of these innovations have been developed in high- income countries with mature real estate markets and well-established data ecosystems, limiting their immediate applicability in the Nigerian context. Nigeria’s real estate market is distinguished by unique challenges that constrain AI adoption and require customized solutions. Key structural issues include fragmented housing data, infrastructural deficiencies, informal rental agreements, and socio-cultural factors influencing tenant-landlord relations (Okoro & Eze, 2023). Furthermore, the technological infrastructure constraints such as inconsistent internet connectivity and limited digital literacy among some property managers and tenants hinder seamless integration of advanced AI tools. Prior studies focused on tenant retention in Nigeria have predominantly employed qualitative or traditional survey methods, emphasizing socio-economic determinants without leveraging technology-enabled predictive analytics (Musa & Oladipo, 2025). Up until now, there has been limited research exploring AI's capabilities to improve residential tenant retention in Nigeria, leaving a significant knowledge and technology gap. This gap is critical because without predictive insights, landlords may miss early warning signs of tenant dissatisfaction, leading to avoidable vacancies and revenue loss. Leveraging AI predictive modeling tailored to Nigeria's housing sector is thus an urgent need to enhance decision-making capabilities for stakeholders and improve the overall housing market sustainability. Therefore, this study aims to bridge this gap by developing an AI- driven predictive model that integrates real tenant data, contextual factors specific to Nigeria, and advanced machine learning techniques to forecast tenant turnover risks accurately. The model will provide actionable insights and support proactive tenant retention strategies customized for Nigeria's residential real estate market.

1.1 ***Overview:*** The residential real estate sector in Nigeria is inundated with immense pressure due to the country's rapid urbanization and demographic growth. According to the United Nations Human Settlements Programme (UN-Habitat, 2023), Nigeria's urban population is growing at approximately 4% annually, leading to increased demand for affordable, quality housing. The National Bureau of Statistics (NBS, 2023) estimates that Nigeria's urban population currently exceeds 50%, and is projected to surpass 60% by 2030, intensifying the demand-supply imbalance in residential properties. Nigeria's housing shortage is estimated at over 17 million units, a shortfall that has persisted despite government interventions and private sector efforts (Fadeyi & Adepoju, 2022). The majority of this shortage exists within the affordable housing segment—the segment primarily inhabited by tenants rather than property owners. This disparity compels landlords to manage increasingly diverse tenant populations with varying expectations and economic capabilities, complicating tenant retention efforts. Furthermore, excessive rent costs and poor housing conditions have been identified as primary causes of tenant dissatisfaction in Nigerian cities. Many landlords pay less attention in investing in maintenance, consequent to declining property quality, which further increases turnover (Duru & Ojo, 2023). Utilities such as electricity, water, and waste management are often unreliable, affecting tenants' quality of life and inclination to remain in their current residences. These infrastructural limitations coupled with socio- economic pressures contribute to tenant instability. The consequences of tenant turnover are many sided. Apart from imminent loss of rental income during vacancy periods, landlords encounter tremendous costs related to property repairs required after tenant move- outs, administrative overheads in tenant screening and lease processing, and marketing expenses for attracting potential tenants (Musa & Oladipo, 2025). Research estimates that high tenant turnover can reduce landlords' net rental income by up to 10-15% annually in Nigeria (Okoro & Eze, 2023). These costs ultimately translate into higher rents for new tenants, further fueling the cycle of turnover. More importantly, high tenant turnover undermines the stability and sustainability of residential real estate markets. Frequent vacancies frustrate tenants seeking long-term housing security, disrupt community cohesion, and discourage investments into property upgrades by landlords wary of low returns (Adebayo & Smith, 2022). The need for strategic and informed approaches to tenant retention is therefore critical for the sector's health. The Nigerian real estate sector is a big part of the country's economy by contributing majorly to the country's GDP and plays an important role in providing housing, ironically, despite being a huge industry worth billions of Naira, it still uses old-fashioned industrial age ways of working or operations. While sectors like banking and telecommunications have undergone digital revolutions, property management practices in Nigeria remain deeply entrenched in traditional, manual, and reactive methodologies. This section extensively reviews the current state of property management, highlighting the structural inefficiencies, the reliance on intuition, and the lack of data-driven decision-making that plagues the industry.

1.2 Research Problem Statement

Tenant turnover remains a persistent and costly challenge within Nigeria's residential real estate market, significantly affecting the profitability and sustainability of rental housing investments (Musa & Oladipo, 2025). Frequent tenant exits result in prolonged vacancy periods, loss of rental income, increased marketing and administrative expenses, and additional costs associated with property maintenance, refurbishment, and tenant onboarding. Over time, high turnover rates can also negatively influence neighborhood stability and diminish the perceived value and attractiveness of residential properties, thereby weakening investor confidence in the sector. Despite the growing severity of this problem, tenant retention strategies employed by many landlords and property management firms in Nigeria remain largely reactive and unsophisticated. Common approaches—such as rent discounts, flexible payment arrangements, or routine lease renewals—are often applied uniformly, without evidence- based assessment of tenant behavior or individualized risk profiling. These conventional methods fail to account for the diverse socioeconomic, behavioral, and service-related factors that influence tenants' decisions to remain in or vacate residential properties. Consequently, property managers are often unable to anticipate tenant exits early enough to implement timely and effective retention measures. This disconnects highlights a critical research and practical gap: the absence of an AI-driven predictive model specifically tailored to Nigeria's residential real estate environment that can accurately identify tenants at risk of vacating. Addressing this gap through the development of a context- specific AI-based predictive model has the potential to transform tenant retention practices by enabling proactive, data-driven decision-making and more targeted, cost- effective retention interventions within Nigeria's residential real estate sector.

1.3 Aim and Objectives

Aim: The aim of this study is to develop an AI-driven predictive model to enhance tenant retention in Nigeria's residential real estate sector.

Objectives: The specific objectives are: To generate tenant retention dataset from Nigeria setting. To design and implement an artificial intelligence-based model (RF) that predicts tenant turnover using real estate data. To analyze and compare RF model with other machine learning model.

1.4 ***Significance of the Study:*** This study is significant due to its theoretical, practical, and policy-oriented contributions to knowledge and practice within the fields of real estate management, artificial intelligence, and housing studies. It contributes to the refinement of tenant turnover and churn theories by incorporating behavioral, socioeconomic, and service-related variables that are unique to Nigeria's housing environment. Furthermore, the study integrates machine learning theory with established housing and consumer behavior frameworks, thereby offering a multidisciplinary approach to understanding tenant decision-making. Additionally, improved tenant retention can lead to stronger landlord–tenant relationships, higher tenant satisfaction, and improved property reputation, all of which contribute to long- term asset value appreciation. The findings will highlight the role of AI and digital technologies in improving residential property management and housing sustainability. Policymakers can leverage the study's outcomes to design policies and incentives that encourage technology adoption among property owners and management firms, particularly small and medium-scale operators who dominate Nigeria's housing sector. Moreover, the study's emphasis on predictive analytics and proactive management aligns with broader national objectives related to smart cities, digital transformation, and sustainable urban development. Consequently, the study will contribute to the formulation of informed regulatory frameworks and strategic initiatives aimed at fostering a more resilient, transparent, and sustainable housing sector in Nigeria.

1.6 Scope and Limitation

Scope: This study is geographically scoped to Nigeria's residential real estate sector with specific focus on Abuja, Lagos, and Enugu, selected due to their high levels of urbanisation, population growth, and dynamic rental housing markets. These cities represent diverse urban characteristics: Lagos as Nigeria's commercial and population hub, Abuja as the federal capital with a structured housing market and high rental demand, and Enugu as a fast-growing urban center in southeastern Nigeria. Focusing on these cities will enable the study to capture varying tenant behaviors, housing supply conditions, and management practices associated with rapid urban expansion. The study will concentrate exclusively on residential rental properties, utilizing tenant-level data derived from property management records within the selected cities, data can also be collected using surveys and simulation. The data will cover key variables relevant to tenant retention analysis, including tenant demographics, rent payment histories, lease durations, maintenance and complaint records, and basic property location attributes. The timeframe for data collection and model development will be limited to the most recent years for which reliable data are available, ensuring that the predictive model reflects current market conditions and contemporary tenant behavior patterns. The study will focus on the development and validation of an AI- driven predictive model designed to identify tenants at risk of vacating residential properties in Abuja, Lagos, and Enugu. The model is primarily intended for use by landlords and property management firms seeking data-driven tenant retention strategies. While broader macroeconomic, regulatory, and policy-related factors may influence tenant mobility, the study will deliberately limit its analysis to variables that are directly measurable from property management datasets and suitable for machine learning applications. This focused approach enhances the practicality, reliability, and replicability of the model within Nigeria's rapidly urbanizing residential real estate context.

Limitations**:** Limited application of machine learning models to residential tenant retention. Lack of housing-specific datasets and feature engineering approaches. Minimal use of explainable AI (XAI) in tenant churn prediction. Poor integration of predictive analytics into property management systems. Scarcity of studies focusing on developing- country housing markets.

2. Literature Review

2.1 *Overview:* The literature review is a critical component of this study, serving as the bridge between the established body of knowledge and the specific problem being investigated. This chapter presents a comprehensive review of scholarly works, theoretical frameworks, and empirical studies related to tenant retention, artificial intelligence (AI), and predictive modeling in real estate. The objective is to synthesize existing information to identify trends, validate the relevance of the research topic, and highlight gaps that current literature has failed to address, particularly within the Nigerian context. Given the rapid pace of technological advancement, this review places significant emphasis on recent studies published between 2023 and 2025. This temporal focus ensures that the insights drawn are contemporaneous and reflect the latest developments in machine learning algorithms and PropTech (Property Technology). The chapter is structured to progress from general concepts—defining tenant retention and AI— to specific theoretical frameworks and empirical evidence, culminating in a clear identification of the research gap that this study intends to fill.

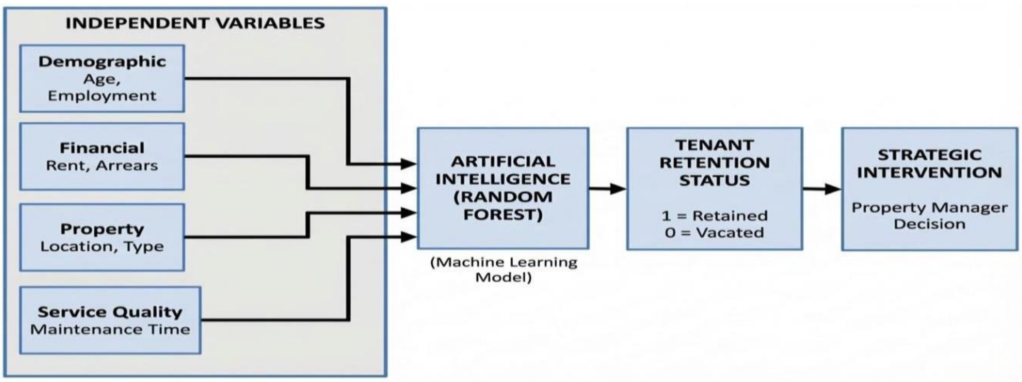

Figure 1: Conceptual Framework.

Figure 1 represents the logical flow of the AI- driven tenant retention model. It shows the transformation of data into actionable intelligence. The framework is divided into four distinct phases: Inputs, Processing, Output, and Application.

2.1.1 Concept of Tenant Retention: Tenant retention is fundamentally a measure of a rental property's ability to keep its occupants over time. In academic and industry literature, it is often viewed through the lens of "relationship marketing," where the tenant is not merely a payer of rent but a customer whose loyalty must be cultivated. High retention rates are synonymous with tenant satisfaction, property stability, and financial health. Conversely, tenant turnover—or churn—is the rate at which tenants vacate properties, necessitating replacement. The concept of retention in real estate differs from other industries due to the "stickiness" of the product; moving house is a high-effort, high- cost activity for the tenant. Therefore, when a tenant chooses to leave, it is often the result of accumulated dissatisfaction or a significant life event rather than an impulsive decision. Understanding the drivers of this decision is the core of the conceptual review.

2.1.2 Economic and Operational Dimensions: From an operational perspective, tenant retention is a primary driver of Net Operating Income (NOI). The cost of turnover is not limited to the loss of rent during the vacancy period. As noted by Adekunle et al. (2023), the "total cost of churn" includes tangible expenses such as repainting, repairs, marketing fees, and agent commissions, as well as intangible costs like the stress of management and the potential for property damage during the move-out process. In the conceptual framework of property management, retention is often linked to the concept of "switching barriers." High switching barriers (such as high moving costs, scarcity of housing, or favorable lease terms) naturally increase retention. However, in a competitive market where these barriers are lowered, the quality of service becomes the dominant retention factor.

2.1.3 The Nigerian Context: Unique Determinants: In the specific context of Nigeria, the conceptualization of tenant retention must be adapted to local realities. Unlike in developed markets where monthly leases are common, the Nigerian market is dominated by annual or bi-annual advance payments. This structure theoretically creates high switching barriers. However, retention is threatened by unique socio-economic factors. Infrastructural deficit is a major conceptual variable in Nigeria. The reliability of power supply, water availability, and security are not merely amenities but core components of the housing product. When these fail, the "contractual" obligation of the tenant is tested against their "quality of life" needs. Furthermore, the inflationary pressure in the Nigerian economy often forces landlords to impose rent increases that outpace wage growth, creating a financial push factor that drives turnover. Traditional management in Nigeria relies heavily on "gut feeling" or rigid enforcement of lease terms. This conceptual approach is reactive. It fails to account for the psychological contract between landlord and tenant—the unwritten set of expectations regarding responsiveness and respect. Therefore, modernizing the concept of retention in Nigeria requires shifting from a "lease enforcement" mindset to a "customer relationship management" mindset.

2.3 Artificial Intelligence and Machine Learning: Artificial Intelligence (AI) is a broad branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. As defined by Suh (2023), AI encompasses a wide range of capabilities, including reasoning, knowledge representation, planning, learning, natural language processing, and perception. Machine Learning (ML) is a specialized subset of AI that focuses on the development of algorithms that can learn from and make predictions or decisions based on data. Unlike traditional rule-based programming, where a human explicitly codes the logic (e.g., "if rent is late, send warning"), ML systems ingest historical data to discover patterns and create their own rules for prediction. In the context of this study, ML serves as the engine that processes tenant data to identify those likely to churn.

2.3.1 Key Machine Learning Algorithms for Prediction: Predictive analytics, the specific branch of ML used in this study, employs several algorithms, each with distinct strengths: Logistic Regression: A fundamental algorithm used for binary classification problems (predicting one of two outcomes, such as "Renew" or "Exit"). It provides a probability score between 0 and 1, making it highly interpretable for determining risk levels. Decision Trees: These models break down data into smaller subsets while developing an associated decision tree. The tree is visualized as a flowchart-like structure, making it easy for property managers to understand the logic (e.g., "If maintenance delay > 7 days AND rent increase > 20%, THEN probability of exit = High"). Random Forest: An ensemble learning method that operates by constructing a multitude of decision trees at training time. It outputs the class selected by the majority of the trees (mode). According to Chang et al. (2024), ensemble methods like Random Forest generally outperform single models because they reduce the risk of overfitting. Gradient Boosting: Another ensemble technique that builds models sequentially, with each new model correcting the errors of the previous one. It is known for high predictive accuracy on structured data. Neural Networks: Complex algorithms modeled after the human brain, capable of capturing highly non-linear relationships in data. While powerful, they are often criticized for being "black boxes."

2.4 AI Applications in Real Estate: The integration of AI into real estate is broadly categorized under PropTech (Property Technology). Globally, AI has disrupted several verticals of the industry: 1. Automated Valuation Models (AVMs): Algorithms that estimate property values by analyzing comparable sales, market trends, and property features. 2. Rental Price Optimization: Dynamic pricing algorithms used by landlords and platforms (like Airbnb) to adjust prices in real-time based on demand, seasonality, and local events. 3. Predictive Maintenance: Using IoT (Internet of Things) sensor data to predict when building systems (elevators, HVAC) will fail before they actually do, allowing for scheduled repairs.

2.4.1 Predictive Analytics for Tenant Churn: A specific and growing application of AI is in predicting tenant behavior. Similar to how telecommunications companies predict "subscriber churn," real estate firms are beginning to use ML to analyze tenant "digital footprints." This includes analyzing rent payment timestamps, the frequency and sentiment of maintenance requests, engagement with community apps, and even demographic shifts. Chang et al. (2024) note that predictive analytics enables a shift from "one-size-fits-all" retention strategies to "hyper-personalized" interventions. For example, the model might identify that a tenant living in a specific neighborhood who pays rent exactly on the due date (rather than early) and has recently logged a complaint about noise is at high risk. The manager can then send a personalized message addressing the noise issue, potentially averting the churn.

3. Research Gap

Despite these advancements, the literature indicates that AI adoption in the African real estate sector remains nascent. The primary barriers identified include the fragmentation of data (data is held in isolated silos rather than central databases), low levels of digitization in smaller firms, and a lack of technical expertise. Okafor & Bello (2024) observe that while Nigerian property managers are increasingly using software for accounting (bookkeeping), they are not yet utilizing these platforms for predictive intelligence. This represents a significant

System Architecture Flow Diagram

Missed opportunity, as the high cost of tenant turnover in developing economies makes the ROI (Return on Investment) of AI implementation potentially even higher than in developed markets.

4. Methodology

The research study adopted a quantitative research design underpinned by predictive analytics. This design is necessitated by the study's aim to forecast a specific binary data.

4.1 Framework: The study utilizes a predictive modeling design, a subtype of the quantitative research paradigm. Unlike descriptive research, which seeks to explain what is happening, or correlational research, which seeks to explain relationships between variables, predictive modeling is concerned with using known values to predict unknown future events.
The justification for this design lies in the problem statement. Property managers in Nigeria currently operate in a reactive mode; they only know a tenant is leaving when they leave. A predictive design allows the study to shift the timeline from reactive to proactive. The study will utilize Supervised Machine Learning, where the system is trained on a labeled dataset. The "supervision" comes from the historical outcomes (whether a tenant renewed or left), which serve as the "ground truth" for the algorithm to learn from. The design also incorporates a comparative technical analysis. While the study proposes the Random Forest algorithm as the primary model, the design allows for the testing of this model against baseline algorithms (such as Logistic Regression) to empirically demonstrate its superiority.

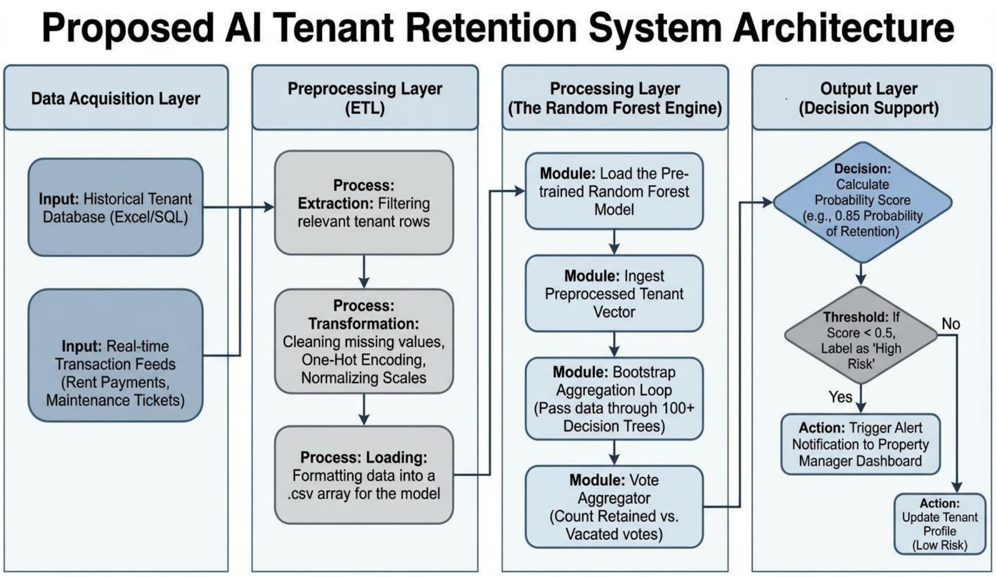

Fig 2. AI Tenant Retention System Architecture.

System requirements

Hardware requirement: Personal computer with Intel Core i5 processor, 8 GB RAM, 500 GB ROM and running Windows 10 operating system.
Software Requirements: The implementation of this methodology will utilize the following

software technology stack: Python (v3.9+), Pandas & NumPy, Scikit-Learn, (Sklearn) and Matplotlib/Seaborn

4.2. Data Collection: The primary data source for this study consists of historical tenant records. The data collection involved partnering with residential property management firms operating in major Nigerian urban centers, specifically Lagos, Abuja, and Enugu. These cities are selected because they represent the three major tiers of the Nigerian property market (Commercial hub, Administrative capital, and fast rising real estate hub), ensuring that the dataset captured a diverse range of economic conditions and tenant behaviors. Inaccessibility of real-time proprietary data was the limitation.

4.4 Dataset Preprocessing: The dataset was structured as a flat table (tabular data) comprising approximately 1,200 to 2,000 rows (records), where each row represents a unique tenancy period. The data will cover a 5-year historical window (e.g., 2019–2024). Raw data from property management systems is rarely suitable for immediate machine learning implementation due to inconsistencies, missing values, and noise. The methodology implements a rigorous six- step preprocessing pipeline.

4.4.1 Data Cleaning: The first step involves identifying and rectifying data quality issues. Missing Values: For numerical variables (e.g., Age), missing values will be imputed using the Mean Imputation method. For categorical variables (e.g., Employment Status), the Mode (most frequent category) will be used. Outlier Detection: Outliers, such as rent values significantly higher than the neighborhood average, will be detected using the Interquartile Range (IQR) method. Values falling below Q1 - 1.5IQR or above Q3 +1.5IQR will be capped or removed to prevent them from skewing the model.

4.4.2 Feature Encoding: Machine learning algorithms require numerical input. Therefore, categorical variables must be converted. One- Hot Encoding: For nominal variables without inherent order (e.g., Property Location, Marital Status), One-Hot Encoding will be used. This creates binary columns for each category (e.g., Location_Lagos: 1/0). Label Encoding: For ordinal variables with a natural order (e.g., Management Interaction: Low=0, Medium=1, High=2), Label Encoding will be used.

4.4.3 Feature Scaling: To ensure that features with large magnitudes (like Rent Amount) do not dominate features with smaller magnitudes (like Household Size), the methodology proposes Standardization. This uses the formula: $z= x-\mu/\sigma$ Where x is the value, μ is the mean, and σ is the standard deviation. This transforms the features to have a mean of 0 and a standard deviation of 1.

4.4.4 Feature Selection: To improve computational efficiency and model interpretability, Recursive Feature Elimination (RFE) combined with Pearson Correlation will be used. This step removes variables that have little to no predictive power or are highly correlated with each other (multicollinearity).

Table 1: Independent Variables.

CATEGORY	VARIABLE NAME	VARIABLE TYPE/ MEASUREMENT	DESCRIPTION/EXAMPLE
A. Demographic Features	Tenant Age	Continuous	Age of the tenant in years (e.g., 30 years).
	Employment Status	Categorical	Employment state (Employed, Self-Employed, Unemployed, Retired).
	Household Size	Continuous	Number of occupants in the unit.
	Marital Status	Categorical	Civil status (Single, Married, Divorced).
B. Financial Features	Annual Rent Amount	Continuous	Annual payment amount (e.g., ₦450,000).
	Payment Frequency	Categorical	Payment interval (Monthly, Quarterly, Bi-Annual, Annual).
	Arrears Count	Numerical	Count of late payments or defaults.
	Payment Consistency Score	Derived	Standard deviation of payment dates relative to the due date.
C. Property Features	Property Location	Categorical	Geographical area (Lagos Island, Lagos Mainland, Abuja, Enugu).
	Property Type	Categorical	Unitstructure (Flat, Mini-Flat, Duplex, Bungalow
	Amenities Score	Binary	Presence of key amenities (Generator, Borehole, Security) rated as 1/0.
D.ServiceQualityFeatures	Maintenance Response Time	Numerical	Average time (in hours/days) taken to resolve a request.
	Complaint	Numerical	Number of maintenance

	Frequency		complaints logged per year.
	Management Interaction Score	Categorical	Frequency of communication (High, Medium, Low).

4.4.5 Data Splitting: The cleaned dataset will be split into two distinct subsets: Training Set (70%): Used to teach the model the underlying patternsof tenant retention.
Testing Set (30%): Kept entirely separate and unseen by the model during training. This set is used to evaluate how well the model generalizes to new tenants.

4.6 Algorithm: Random Forest Classifier The study adopted Random Forest Classifier as the core algorithm for the tenant retention prediction model.

4.7 Model Training and Hyperparameter Tuning

To achieve optimal performance, the methodology proposes a Hyperparameter Tuning phase using GridSearchCV (Cross- Validation).

4.7.1 Hyperparameters: **n_estimators:** The number of trees in the forest. We will search between 50 and 500 trees. Too few leads to underfitting; too many increases computational load with diminishing returns. max_depth: The maximum depth of each tree. Limiting depth prevents overfitting. min_samples_split: The minimum number of samples required to split an internal node. min_samples_leaf: The minimum number of samples required to be at a leaf node.

4.7.2 Validation Strategy: K-Fold Cross- Validation: To ensure the model is robust, 10- Fold Cross-Validation will be used. The training data is split into 10 parts. The model is trained on 9 parts and validated on the 1st part, and this process is repeated 10 times. The average score across the 10 folds is taken as the model's performance. This eliminates the luck of having a specific "good" or "bad" test split.

4.8 ***Model Evaluation Metrics:*** The model will be evaluated using standard binary classification metrics. We cannot rely solely on Accuracy because the dataset may be imbalanced (more tenants stay than leave). Accuracy indicates total proportion of predictions that were correctly classified. Precision is ratio of true positive predictions to total predicted positives. Recall (Sensitivity) reflects how well the model identifies true positive cases. Specificity is the capability of a model to accurately identify true negative cases. F1-Score is the harmonic mean of precision and recall, offering a balanced amount reflects both false positives then false negatives.

These metrics are mathematically expresses as follows:

1. $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$

2. $Precision = \frac{TP}{TP+FP}$

3. $Recall = \frac{TP+TN}{TP+FN}$

4. $F1 - Score = \frac{2TP}{(2TP + FP + FN)}$

Experimental Analysis

The experimental analysis presents the results of the analysis in comparison with LR which have been considered by the related researchers.

Random Forest (RF)

Table 2: Summary of the Results.

Techniques	Precisio n	Recall	Accurac y	F1-Score
RF	96.38%	81.63%	99.96%	49.00%

The Based on the results presented by Table 4.1, the first four algorithms outperform the proposed two algorithms in this work.

Linear Regression (LR)

Table 3: Summary of Linear Regression (LR) from a related study.

Techniques	Precision	Recall	Accuracy	F1-Score
LR	16.17%	82.65%	99.23%	44.70%

Comparative analysis of RF and the related result of LR

Table 3 compare the LR algorithm against the proposed algorithms RF and the results are clearly shown in table 4.

Table 4: Comparative Analysis of LR against the proposed Algorithms RF.

Techniques	Precision	Recall	Accuracy	F1-Score
RF	X	√	√	√
LR	√	X	X	X

From Table 4, it is very obvious that RF technique outperform the related technique in terms of recall, accuracy and F1-score. However, the precision of the related technique that is, LR outweigh the RF. **Summary of Experimental Analysis**

The experimental analysis compares the performance of Random Forest (RF) and Linear Regression (LR) using evaluation metrics such as precision, recall, accuracy, and F1-score.
The results show that RF achieved high accuracy (99.96%), strong recall (81.63%), and better F1-score (49.00%), indicate superior overall performance. In contrast, LR recorded lower precision (16.17%), slightly higher recall (82.65%), and lower accuracy (99.23%) with an F1-score of 44.70%. The comparative analysis further reveals that RF outperforms LR in recall, accuracy, and F1-score, making it more effective for the task. However, LR demonstrates better precision than RF. The findings indicate that while LR may be more precise in predictions, RF provides a more balanced and reliable performance across most evaluation metrics.

5. Summary, Conclusion and Future Research

***Summary*:** This study examined the role of artificial intelligence in improving tenant retention within Nigeria's residential real estate sector. It began by identifying tenant turnover as a critical issue affecting property profitability, operational efficiency, and housing market stability. Traditional tenant management approaches in Nigeria were found to be largely reactive, lacking predictive capabilities and data-driven decision-making frameworks. The research adopted a quantitative predictive modeling approach using supervised machine learning. A structured dataset comprising tenant demographic, financial, property, and service- related variables was developed and preprocessed through data cleaning, encoding, scaling, and feature selection techniques. The Random Forest (RF) algorithm was selected as the primary predictive model and evaluated against Linear Regression (LR) using standard performance metrics such as accuracy, precision, recall, and F1-score. Findings from the experimental analysis indicated that the Random Forest model significantly outperformed Linear Regression in most evaluation metrics, particularly in accuracy and recall, making it more reliable for predicting tenant churn. The study demonstrated that AI-driven predictive analytics can effectively identify tenants at risk of vacating, enabling proactive and personalized retention strategies.

CONCLUSION**:** This study concludes that the application of AI-driven predictive modeling presents a viable and effective solution to the persistent problem of tenant turnover in Nigeria's residential real estate sector. The findings confirm that traditional methods of tenant management are insufficient in addressing the complexities of modern housing markets characterized by diverse tenant behaviors and socio-economic dynamics. The Random Forest model demonstrated superior predictive capability, making it a robust tool for identifying tenants at risk of churn. Its high accuracy and balanced performance across evaluation metrics indicate that machine learning models can significantly enhance decision-making processes in property management. By leveraging predictive insights, landlords and property managers can transition from reactive approaches to proactive strategies, thereby reducing vacancy rates, minimizing turnover costs, and improving long-term rental income. *Future Research***:** While this study makes significant contributions, several areas warrant further investigation: Expansion of Dataset Scope: Future research should incorporate larger and more diverse datasets across additional Nigerian cities and rural areas to improve model generalizability and robustness. Integration of Real-Time Data: Subsequent studies can explore the use of real-time data streams, including IoT-enabled smart property systems, to enhance predictive accuracy and enable dynamic decision- making. Comparative Analysis of Advanced Algorithms: Future studies can evaluate more advanced algorithms such as Gradient Boosting, Deep Learning, and Hybrid Models to determine optimal performance in tenant retention prediction. Integration with PropTech Platforms: Future work can focus on embedding predictive models into existing property technology (PropTech) platforms to create end-to-end intelligent property management systems.

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