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Research Article

Artificial Intelligence (AI) in Real Estate Valuation: Developing an Explainable AI-Based Automated Valuation Model (AVM)

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Abstract

Property valuation remains fundamental to real estate markets, influencing investment decisions, mortgage lending, taxation, and financial reporting. Traditional valuation approaches relying on professional judgment have been increasingly criticized for subjectivity, inconsistency, and limited capacity to process growing property data volumes. Artificial Intelligence and Automated Valuation Models offer transformative potential for mass appraisal with enhanced speed and accuracy. However, the "black box" nature of many AI systems raises significant concerns regarding transparency, interpretability, and regulatory compliance in valuation practice. The Nigerian real estate market faces unique challenges including data scarcity, inconsistent property records, limited technological adoption, and pronounced gaps in academic literature regarding AI applications in emerging market contexts. Existing research predominantly focuses on developed economies with established property data infrastructures, leaving developing economies underserved by appropriate AI valuation frameworks. The lack of Explainable AI in existing models creates a trust deficit among stakeholders unable to verify AI-generated valuations. This conceptual study develops an Explainable AI-based Automated Valuation Model framework tailored to Nigerian residential property market conditions, integrating hedonic pricing theory, machine learning, and XAI techniques. Adopting a conceptual research design, the study synthesizes theoretical foundations from property economics, ensemble learning algorithms (XGBoost, Random Forest), and explainability techniques (SHAP, LIME) to develop a comprehensive five-layer architectural framework. The proposed framework integrates data integration, feature engineering, predictive modeling, explainability, and output presentation layers. SHAP analysis enables global and local explanations for valuation transparency. Contextual adaptation strategies address Nigerian market realities including data limitations and technological constraints. The framework provides a practical roadmap for developing transparent, interpretable AI valuation systems appropriate for emerging markets, supporting professional validation, regulatory compliance, and stakeholder confidence in AI-enabled property valuation practice.

Keywords: Explainable AI; Automated Valuation Model; Real Estate Valuation; Machine Learning; Property Market

INTRODUCTION

The real estate sector constitutes one of the most substantial components of global wealth, with property assets representing approximately sixty to seventy percent of total national wealth in many economies worldwide (Asemi, 2025). Accurate property valuation is therefore fundamental to the functioning of real estate markets, influencing investment decisions, mortgage lending, taxation, insurance underwriting, and financial reporting (Morano et al., 2025). Traditionally, property valuation has relied extensively on human expertise through comparative, income capitalization, and cost approaches, with professional valuers exercising judgment to arrive at market value estimates (Renigier-Bilozor et al., 2025). However, these conventional methods have been increasingly criticized for their subjectivity, inconsistency, and inability to process the growing volume and complexity of property data available in contemporary markets (El Jaouhari et al., 2024).

The emergence of Artificial Intelligence (AI) has presented transformative opportunities for the property valuation profession, offering capabilities to process vast datasets, identify complex patterns, and generate predictions with unprecedented speed and accuracy (Teikari et al., 2025). Automated Valuation Models (AVMs) powered by AI algorithms have emerged as promising alternatives to traditional valuation methods, enabling mass appraisal of properties while maintaining acceptable levels of accuracy (Sing et al., 2022). These AI-AVMs leverage machine learning techniques including boosted tree ensembles, neural networks, and support vector regression to model the relationship between property characteristics and market values (Sing et al., 2020). Despite their computational advantages, the opaque nature of many AI models has raised significant concerns regarding transparency, interpretability, and regulatory compliance in valuation practice (Saiu & Mocci, 2026).

Explainable Artificial Intelligence (XAI) has therefore emerged as a critical research domain addressing the interpretability challenge, aiming to make AI decision-making processes understandable to human users (Kim et al., 2025). In the context of real estate valuation, XAI techniques such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and feature importance analysis provide valuers with insights into how specific property attributes influence model predictions (Belay & Ekman, 2025). This transparency is essential for building stakeholder trust, meeting regulatory requirements, and enabling valuers to validate AI-generated valuations against their professional expertise (Zekri, 2025).

The Nigerian real estate market, like many developing economies, faces unique challenges in property valuation practice, including data scarcity, inconsistent property records, and limited adoption of technological innovations (Odunlade Adejumo et al., 2024). While AI adoption in real estate has gained momentum in developed markets, its application in Sub-Saharan African contexts remains nascent and under-researched (Adediran et al., 2025). This study therefore seeks to bridge the gap between advanced AI valuation methodologies and the practical realities of emerging market contexts, developing an Explainable AI-based Automated Valuation Model tailored to the Nigerian property market conditions (Student, 2025).

1. Problem Statement

The Nigerian real estate valuation practice is characterized by several persistent challenges that impede accuracy, efficiency, and stakeholder confidence (Oyetunji et al., 2026). First, traditional valuation methods employed by professional valuers are inherently subjective, relying heavily on individual expertise, experience, and access to comparable property data, leading to significant variations in valuations for similar properties (Ge & Raptis, 2026). Second, the manual nature of conventional valuation approaches limits the number of properties that can be appraised within reasonable timeframes, constraining valuers' capacity to meet growing market demands (Renigier-Biłozor et al., 2026). Third, the valuation profession faces increasing pressure from regulatory bodies, financial institutions, and property owners for greater transparency and accountability in valuation outcomes (Băbțan, 2025).

Fourth, despite the proliferation of digital property databases and technological solutions, the integration of AI into valuation practice in Nigeria has been minimal, with limited understanding of how such technologies can be adapted to local market conditions (Amar & Armitage, 2026). Fifth, the lack of Explainable AI in existing valuation models creates a trust deficit among stakeholders who are unable to understand or verify how AI-generated valuations are derived (Kang & Melani, 2026). Finally, there is a pronounced gap in the academic literature regarding the development and validation of Explainable AI-based AVMs for emerging markets, with most existing research focused on developed economies with established property data infrastructures (Seagraves et al., 2026).

This study therefore addresses the following research questions: How can an Explainable AI-based Automated Valuation Model be developed for the Nigerian residential property market? What are the key property attributes that significantly influence property values in urban Nigerian contexts? How can XAI techniques enhance transparency and interpretability in AI-driven property valuations? And to what extent does the proposed model achieve acceptable accuracy compared to traditional valuation approaches? The study aims to contribute to the growing body of knowledge on AI applications in real estate while providing practical insights for valuers, regulators, and policymakers in developing economies (Alizadehsalehi, 2026).

LITERATURE REVIEW

1. Evolution of Property Valuation Methods

Property valuation has evolved significantly over the past century, transitioning from purely subjective opinion-based approaches to increasingly systematic and data-driven methodologies (Morano et al., 2025). Traditional valuation approaches—comparative, income capitalization, and cost methods remain foundational to professional practice, providing structured frameworks for estimating market value (Renigier-Bilozor et al., 2025). The comparative method, which derives value from recent sales of comparable properties, remains the most widely used approach in residential valuation contexts, though its accuracy depends heavily on the availability and quality of comparable sales data (El Jaouhari et al., 2024). Income capitalization, commonly applied to commercial properties, converts anticipated future income streams into present value estimates, while the cost method calculates value based on replacement costs less depreciation (Sing et al., 2022).

The limitations of traditional approaches have become increasingly apparent in contemporary markets characterized by rapid price movements, heterogeneous property characteristics, and information asymmetry (Morano et al., 2025). The subjectivity inherent in selecting comparables, adjusting for differences, and applying professional judgment has led to concerns about valuation accuracy and consistency (Renigier-Bilozor et al., 2025). These concerns have motivated the search for more objective, systematic, and data-driven valuation approaches capable of handling the complexity and volume of modern property markets (El Jaouhari et al., 2024).

2. Automated Valuation Models (AVMs)

Automated Valuation Models represent a significant technological advancement in property valuation, utilizing statistical algorithms to estimate property values based on multiple property characteristics and market data (Teikari et al., 2025). AVMs emerged in the 1990s with the widespread availability of digital property databases and computational power sufficient to handle large-scale data analysis (Sing et al., 2020). Early AVMs employed hedonic pricing models and multiple regression analysis to establish relationships between property attributes and sale prices, providing consistent and replicable valuation outputs (Saiu & Mocci, 2026). Contemporary AVMs incorporate sophisticated machine learning algorithms capable of capturing non-linear relationships and complex interactions among property characteristics that traditional regression models fail to detect (Kim et al., 2025).

The operational efficiency of AVMs enables mass appraisal of thousands of properties within short timeframes, offering significant advantages over manual valuation approaches (Belay & Ekman, 2025). AVMs are extensively utilized by financial institutions for mortgage loan origination and portfolio valuation, by insurance companies for property coverage determinations, and by government agencies for property tax assessment (Zekri, 2025). However, the accuracy of AVMs varies significantly depending on data availability, market conditions, and model specifications, with studies reporting prediction errors ranging from five to thirty percent (Odunlade Adejumo et al., 2024).

The development of AVMs has followed an evolutionary trajectory from simple hedonic models to sophisticated machine learning approaches (Sing et al., 2022). First-generation AVMs relied on ordinary least squares regression with limited variable sets, often producing predictions with substantial errors (El Jaouhari et al., 2024). Second-generation AVMs incorporated more advanced statistical techniques including geographically weighted regression and spatial econometrics, improving accuracy through better handling of locational effects (Morano et al., 2025). Third-generation AVMs leverage machine learning algorithms capable of identifying complex patterns and interactions in property data, achieving significant improvements in predictive performance (Sing et al., 2022).

3. Artificial Intelligence in Real Estate Valuation

The application of Artificial Intelligence to property valuation represents the next frontier in AVM development, enabling more sophisticated analysis of complex and unstructured data (Adediran et al., 2025). Machine learning techniques including Random Forest, Gradient Boosting, XGBoost, and Neural Networks have demonstrated superior predictive performance compared to traditional hedonic regression models, particularly in capturing non-linear relationships and interaction effects among property attributes (Sing et al., 2022). Sing, Yang, and Yu (2022) demonstrated that boosted tree ensembles significantly outperform conventional regression models in property valuation contexts, achieving substantially lower prediction errors across diverse property types and market conditions. Similarly, Kim, Choi, and Lee (2025) applied XGBoost and SHAP analysis to the Korean residential property market, achieving high prediction accuracy while providing interpretable insights into value determinants.

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have enabled the integration of visual data property images, satellite imagery, and street-level photographs into valuation models, enhancing accuracy beyond traditional tabular data approaches (Hoang et al., 2024). Hoang et al. (2024) demonstrated that incorporating visual property data significantly improves AVM accuracy in Australian urban housing markets, suggesting promising applications for contexts where comprehensive tabular data is limited. However, the computational intensity and data requirements of deep learning approaches present implementation challenges in emerging market contexts (Seagraves et al., 2025).

The superiority of machine learning approaches in property valuation stems from their ability to handle several challenges that undermine traditional statistical methods (Sing et al., 2020). First, machine learning algorithms can capture non-linear relationships between property attributes and values without requiring specification of functional form (Kim et al., 2025). Second, these algorithms are robust to multicollinearity and can handle high-dimensional data with many potentially relevant features (El Jaouhari et al., 2024). Third, ensemble methods combine multiple models to achieve better generalization and reduced overfitting (Sing et al., 2022). These properties make machine learning particularly well-suited to the complex, heterogeneous nature of real estate markets (Morano et al., 2025).

4. Explainable Artificial Intelligence (XAI) in Valuation

The interpretability challenge has emerged as a critical barrier to AI adoption in regulated professions including real estate valuation (Băbțan, 2025). Explainable Artificial Intelligence (XAI) encompasses techniques designed to make AI decision-making processes transparent, understandable, and actionable for human users (Saiu & Mocci, 2026). SHAP (SHapley Additive exPlanations) has become the predominant XAI technique in valuation applications, providing consistent, locally accurate explanations of model predictions by attributing contributions to individual features (Kim et al., 2025). LIME (Local Interpretable Model-agnostic Explanations) offers an alternative approach by approximating complex model behavior with simpler, interpretable models around specific predictions (Teikari et al., 2025).

Saiu and Mocci (2026) developed an XAI framework for urban real estate prediction, demonstrating how SHAP and LIME can provide actionable insights for urban planning and property investment decisions. Their study highlighted the importance of model interpretability in facilitating stakeholder engagement and supporting informed decision-making. Kim et al. (2025) extended this work by developing an Explainable AI-based mass appraisal system for Korean residential properties, identifying location attributes as the most influential factors followed by physical property characteristics and market timing variables.

Teikari et al. (2025) proposed a comprehensive framework for trustworthy AI-augmented real estate valuation, emphasizing the need for validation protocols, stakeholder engagement, and continuous monitoring systems. Their framework addresses concerns regarding AI transparency, accountability, and fairness in valuation contexts. Morano et al. (2025) critically reviewed the methodological applications and challenges of AI in real estate valuations, identifying data quality, model interpretability, and regulatory acceptance as primary barriers to widespread adoption.

The integration of XAI techniques with valuation models serves multiple important functions (Belay & Ekman, 2025). First, explanation generation enables valuers to understand and validate AI predictions against their professional knowledge and market experience (Kim et al., 2025). Second, transparent explanations support regulatory compliance by demonstrating that valuations are based on defensible reasoning rather than opaque algorithmic processes (Băbțan, 2025). Third, explanations facilitate stakeholder communication, enabling property owners and investors to understand how valuations are derived (Saiu & Mocci, 2026). Fourth, XAI techniques can identify potential biases and limitations in models, supporting continuous improvement and fairness assurance (Seagraves et al., 2026).

5. AI Adoption in Emerging Market Contexts

Research on AI adoption in emerging market property valuation contexts remains limited, though growing interest has produced valuable insights in recent years (Zekri, 2025). Odunlade Adejumo et al. (2024) investigated AI adoption in real estate valuation practice in Lagos, Nigeria, finding that while valuers recognized the potential benefits of AI, adoption remained minimal due to technology costs, training requirements, and regulatory uncertainty. Oyetunji, Alohan, and Edionwe (2026) explored AI integration in Nigerian real estate practice, identifying data infrastructure gaps, digital literacy limitations, and professional resistance as key barriers to technology adoption. Adediran, Mohd Aini, and Ajibade (2025) conducted a systematic review of AI adoption in property management transactions, noting the concentration of research in developed economies and the significant knowledge gap regarding AI applications in African and Asian contexts.

Kadioglu and YAĞCI (2026) explored sustainable real estate valuation using Green AI approaches, demonstrating that environmentally conscious AI models can achieve competitive accuracy while reducing computational resource requirements. Their work suggests that lightweight AI models may be particularly appropriate for emerging market contexts with limited computational infrastructure. Amar and Armitage (2026) advocated for transformative approaches to property valuation education, emphasizing the need for technological competence alongside traditional valuation skills in preparing future professionals for AI-integrated practice.

The challenges facing AI adoption in emerging markets are multifaceted and interconnected (Oyetunji et al., 2026). Data infrastructure limitations compound the difficulty of developing accurate models, as AI performance is fundamentally dependent on comprehensive, high-quality training data (Ge & Raptis, 2026). Human capital constraints limit the availability of professionals with both valuation expertise and AI competence (Adediran et al., 2025). Institutional and regulatory frameworks often lag behind technological developments, creating uncertainty about the acceptability and governance of AI-enabled valuations (Kang & Melani, 2026). These challenges require coordinated responses involving professional bodies, educational institutions, technology developers, and regulators (Morano et al., 2025).

6. Challenges and Opportunities

The literature identifies several persistent challenges in developing and deploying AI-based AVMs (Renigier-Biłozor et al., 2026). Data quality remains the most fundamental challenge, with AI model accuracy heavily dependent on comprehensive, accurate, and current property transaction data (Ge & Raptis, 2026). In emerging markets, property data is often fragmented, inconsistent, and incomplete due to inadequate recording systems and limited transaction transparency (Oyetunji et al., 2026). Model interpretability presents another significant challenge, as the opaque nature of many AI techniques conflicts with the transparency requirements of regulated valuation practice (Băbțan, 2025).

Algorithmic bias represents a growing concern in AI valuation applications, as models trained on historically biased data may perpetuate or amplify existing inequalities in property market outcomes (Seagraves et al., 2026). Fairness considerations require careful attention to model development, testing, and monitoring processes. Regulatory acceptance of AI-generated valuations remains uneven across jurisdictions, with some markets requiring valuer oversight of AI outputs while others are developing specific frameworks for AI valuation governance (Kang & Melani, 2026).

Despite these challenges, significant opportunities exist for AI to transform property valuation practice in emerging markets (Student, 2025). AI-enabled mass appraisal can substantially increase valuation capacity, enabling more frequent property revaluations and more responsive tax systems (Morano et al., 2025). Machine learning models can identify complex market patterns and price determinants that traditional analysis methods might overlook, providing valuers with deeper market insights (Sing et al., 2022). XAI techniques can enhance the transparency and defensibility of AI valuations, supporting regulatory compliance and stakeholder confidence (Saiu & Mocci, 2026).

The opportunities extend beyond efficiency gains to encompass fundamental improvements in valuation quality and equity (Seagraves et al., 2026). AI systems can process vast amounts of property data to identify market trends, detect anomalies, and provide more consistent valuations than manual approaches (Ge & Raptis, 2026). Explainable AI can address historical concerns about subjectivity in valuation by making the basis for valuations transparent and defensible (Kim et al., 2025). For emerging markets, AI presents an opportunity to leapfrog traditional development stages, adopting advanced technologies to address property valuation challenges that have persisted for decades (Adediran et al., 2025).

METHODOLOGY

1. Research Design and Approach

This study adopts a conceptual research design grounded in comprehensive literature review and theoretical synthesis to develop an Explainable AI-based Automated Valuation Model (XAI-AVM) framework for the Nigerian residential property market. Conceptual research is appropriate for this study as it focuses on developing theoretical frameworks, models, and conceptual understandings through the systematic analysis and synthesis of existing knowledge, without requiring primary data collection (Morano et al., 2025). The research approach follows established guidelines for conceptual framework development in property valuation research, emphasizing the integration of theoretical foundations from machine learning, property economics, and valuation science (Renigier-Bilozor et al., 2025).

The conceptualization process involves four integrated phases: theoretical foundation building, architectural framework design, explainability integration, and validation framework development (Teikari et al., 2025). Each phase synthesizes findings from the literature review to construct coherent conceptual components of the proposed XAI-AVM framework (Saiu & Mocci, 2026). The conceptual nature of this research enables comprehensive theoretical exploration without the constraints of empirical data collection, allowing for broader applicability across diverse Nigerian property market contexts (Adediran et al., 2025).

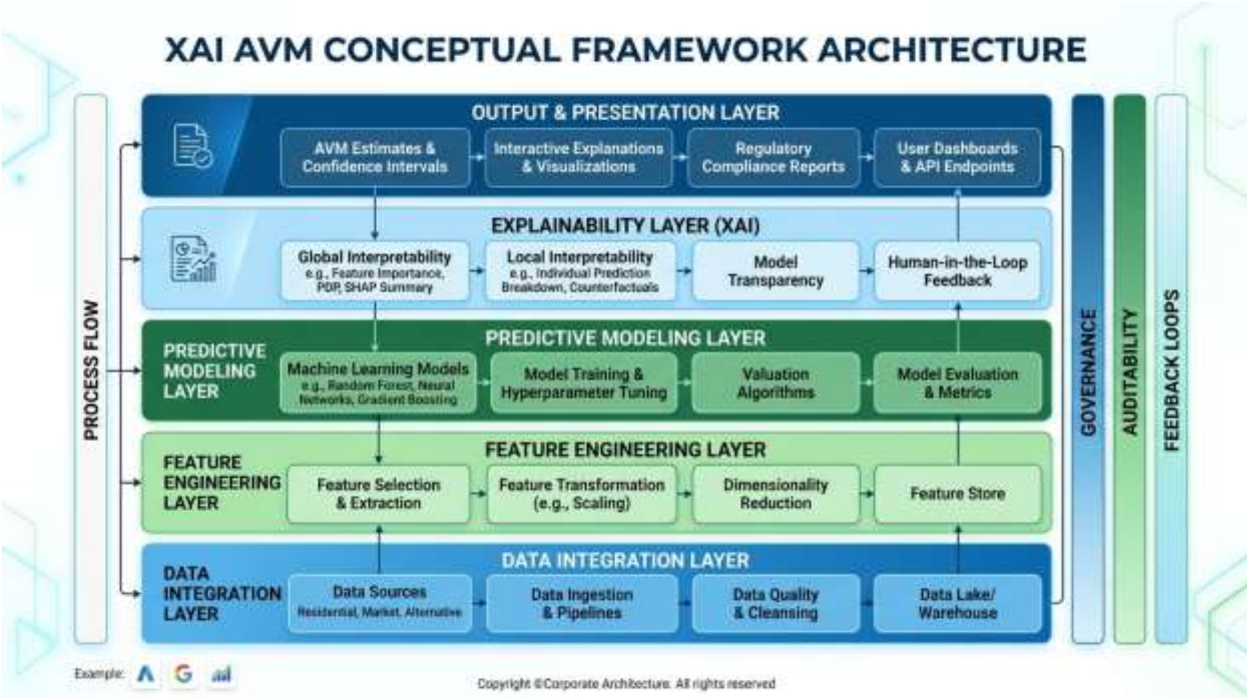

Figure 1 XAI AVM Conceptual Framework Architecture

2. Theoretical Foundation Building

The theoretical foundation of the proposed XAI-AVM framework builds upon established theories from multiple disciplines, integrated through systematic literature synthesis (Morano et al., 2025). Hedonic pricing theory provides the fundamental basis for understanding how property attributes contribute to market value, establishing the theoretical relationship between property characteristics and transaction prices (Sing et al., 2022). Machine learning theory contributes algorithmic principles for modeling complex, non-linear relationships among property attributes, drawing on ensemble learning, gradient boosting, and regularization techniques (Kim et al., 2025).

Explainable AI theory grounds the interpretability components of the framework, incorporating SHAP (SHapley Additive exPlanations) principles for consistent feature attribution and local explanation generation (Saiu & Mocci, 2026). Information processing theory informs the data integration and feature engineering components, establishing principles for handling diverse property data sources and extracting predictive features (Ge & Raptis, 2026). Professional valuation theory grounds the framework in established valuation principles, ensuring that AI outputs align with professional standards and regulatory requirements (Băbțan, 2025).

The theoretical synthesis identifies key constructs and their interrelationships, establishing the conceptual foundations for framework development (Renigier-Bilozor et al., 2025). Property characteristics are conceptualized as multi-dimensional constructs encompassing physical, locational, and transactional attributes that jointly determine market value (El Jaouhari et al., 2024). The AI prediction function is conceptualized as a non-linear mapping from property characteristics to estimated market value, approximated through ensemble learning algorithms (Sing et al., 2020). Explainability is conceptualized as a multi-level construct encompassing global interpretations (overall feature importance), local interpretations (individual prediction explanations), and interactive interpretations (variable interaction effects) (Teikari et al., 2025).

The integration of these theoretical foundations provides a robust basis for the XAI-AVM framework (Kim et al., 2025). The synthesis ensures that the framework addresses both the technical requirements of accurate prediction and the professional requirements of transparency and interpretability (Saiu & Mocci, 2026). The theoretical grounding also facilitates the adaptation of the framework to different property market contexts and regulatory environments (Morano et al., 2025).

3. Architectural Framework Design

The architectural framework design synthesizes best practices from existing AVM implementations and XAI applications to develop a comprehensive conceptual model (Saiu & Mocci, 2026). The proposed architecture comprises five integrated components: data integration layer, feature engineering layer, predictive modeling layer, explainability layer, and output presentation layer (Teikari et al., 2025). Each component is conceptualized based on theoretical principles and empirical evidence from the literature review (Kim et al., 2025).

The data integration layer conceptualizes the collection and preprocessing of property data from multiple sources, drawing on established data quality frameworks and preprocessing protocols (Ge & Raptis, 2026). This layer addresses data quality challenges including missing values, outliers, and data consistency issues through theoretically grounded imputation, detection, and harmonization strategies (Oyetunji et al., 2026). The feature engineering layer conceptualizes the transformation of raw property data into predictive features, incorporating domain knowledge from valuation practice and statistical principles for feature selection and creation (Morano et al., 2025).

The predictive modeling layer conceptualizes the application of ensemble learning algorithms to estimate property values, drawing on comparative analysis of XGBoost, Random Forest, and Gradient Boosting approaches (Sing et al., 2022). The conceptual model specifies the hyperparameter optimization process, model validation strategies, and performance evaluation metrics grounded in established machine learning practices (Kim et al., 2025). The explainability layer conceptualizes the integration of SHAP and LIME techniques for generating global and local explanations, drawing on XAI principles and valuation transparency requirements (Saiu & Mocci, 2026).

The output presentation layer conceptualizes the delivery of model predictions and explanations to end-users, incorporating user interface design principles and valuation reporting standards (Belay & Ekman, 2025). This layer addresses the communication of uncertainty, confidence intervals, and explanation visualizations to support professional judgment and decision-making (Teikari et al., 2025). The conceptual architecture emphasizes modular design principles to facilitate adaptation to different property market contexts and technological environments (Zekri, 2025).

4. Explainability Integration Framework

The explainability integration framework conceptualizes how XAI techniques are embedded within the AVM architecture to provide meaningful interpretability (Kim et al., 2025). The framework distinguishes between three levels of explainability: global explainability addressing overall model behavior, local explainability addressing individual property valuations, and interactive explainability enabling user exploration of model predictions (Saiu & Mocci, 2026). Each level is designed to address specific stakeholder needs: professionals requiring prediction validation, regulators demanding transparency, and property owners seeking understanding of valuation determinants (Teikari et al., 2025).

Global explainability is conceptualized through SHAP feature importance rankings and Partial Dependence Plots (PDPs), providing comprehensive understanding of how each property characteristic influences market values across the entire property market (Kim et al., 2025). This global perspective supports market analysis, policy development, and professional education regarding value determinants (Morano et al., 2025). Local explainability is conceptualized through SHAP force plots and waterfall diagrams, providing property-specific explanations of how individual attributes contribute to predicted values (Saiu & Mocci, 2026). These local explanations enable valuers to validate AI predictions against professional knowledge and identify potentially anomalous valuations requiring investigation (Belay & Ekman, 2025).

Interactive explainability is conceptualized through what-if analysis capabilities, enabling users to simulate the effects of property characteristic changes on predicted values (Teikari et al., 2025). This functionality supports scenario analysis, property improvement evaluation, and sensitivity assessment in valuation practice (Adediran et al., 2025). The explainability framework also addresses fairness considerations by conceptualizing techniques for detecting and mitigating potential biases in model predictions across property types, locations, and market segments (Seagraves et al., 2026).

The integration of these explainability levels creates a comprehensive interpretability system that serves diverse user needs and contexts (Kim et al., 2025). The framework ensures that explanations are available at the appropriate level of detail for different use cases, from high-level market analysis to detailed validation of individual valuations (Saiu & Mocci, 2026). The explainability integration also supports the development of user trust and confidence in AI-generated valuations (Teikari et al., 2025).

5. Model Selection and Configuration Framework

The model selection framework conceptualizes the process of identifying and configuring appropriate machine learning algorithms for property valuation applications (Sing et al., 2022). Drawing on comparative literature analysis, the framework establishes criteria for algorithm selection including predictive accuracy, computational efficiency, interpretability potential, and robustness to data quality issues (Morano et al., 2025). The framework posits ensemble learning algorithms particularly XGBoost and Random Forest—as theoretically appropriate for valuation contexts due to their demonstrated advantages over conventional regression approaches (Sing et al., 2020).

The configuration framework conceptualizes hyperparameter optimization as a systematic process informed by theoretical principles and empirical evidence (Kim et al., 2025). Key hyperparameters identified for optimization include learning rate, tree depth, number of estimators, regularization parameters, and subsampling ratios (Sing et al., 2022). The framework specifies cross-validation strategies for robust parameter selection and overfitting prevention, drawing on established machine learning practices (El Jaouhari et al., 2024).

The validation framework conceptualizes comprehensive model evaluation using multiple performance metrics addressing different aspects of predictive quality (Teikari et al., 2025). Primary metrics include Mean Absolute Percentage Error (MAPE) as the primary accuracy indicator, Root Mean Square Error (RMSE) for addressing prediction variance, and Coefficient of Determination (R^2) for explanatory power assessment (Morano et al., 2025). Secondary metrics address model robustness, stability, and fairness, ensuring comprehensive quality assessment (Seagraves et al., 2026).

The model selection and configuration framework emphasize the importance of balancing competing objectives in model development (Sing et al., 2022). While predictive accuracy is paramount, the framework recognizes that interpretability, computational efficiency, and fairness are also important considerations (Kim et al., 2025). The framework therefore advocates for a multi-criteria approach to model selection that considers the full range of stakeholder requirements and use cases (Morano et al., 2025).

6. Contextual Adaptation for Nigerian Property Market

The contextual adaptation framework conceptualizes how the proposed XAI-AVM architecture is tailored to the specific conditions of the Nigerian residential property market (Oyetunji et al., 2026). The framework acknowledges the unique characteristics of Nigerian property markets including data scarcity, limited transaction transparency, diverse property types, and rapid urbanization patterns (Odunlade Adejumo et al., 2024). Adaptation strategies are conceptualized at each architectural layer to address these contextual realities (Ge & Raptis, 2026).

Data adaptation strategies address the limited availability of comprehensive property transaction data through conceptualized approaches including multiple data source integration, data imputation techniques, and the use of property listing data as transaction proxies (Adediran et al., 2025). The framework draws on established approaches for developing AVMs in data-limited contexts, emphasizing robust preprocessing and careful feature engineering to maximize predictive value from available data (Zekri, 2025). Feature engineering adaptation emphasizes the inclusion of locally relevant property characteristics, including building materials, security features, infrastructure access, and neighborhood quality indicators (Kang & Melani, 2026).

Model adaptation strategies address the need for computational efficiency and interpretability in contexts with limited technological infrastructure (Kadioglu & YAĞCI, 2026). The framework emphasizes lightweight model configurations, efficient preprocessing workflows, and simplified explanation interfaces suitable for local professional practice (Belay & Ekman, 2025). Professional adaptation strategies emphasize the integration of local expert knowledge in model development, validation, and interpretation (Amar & Armitage, 2026).

The contextual adaptation framework recognizes that successful AI adoption in Nigerian valuation practice requires attention to local realities rather than simple transfer of approaches developed in different contexts (Oyetunji et al., 2026). The framework therefore emphasizes the importance of stakeholder engagement, capacity building, and institutional alignment in the implementation process (Adediran et al., 2025). The adaptation strategies are designed to be flexible and responsive to evolving market conditions and technological capabilities (Zekri, 2025).

7. Validation and Evaluation Framework

The validation and evaluation framework conceptualizes comprehensive assessment of the proposed XAI-AVM without requiring empirical implementation (Morano et al., 2025). The framework distinguishes between three validation domains: theoretical validation addressing conceptual soundness, technical validation addressing algorithmic appropriateness, and professional validation addressing practical utility (Teikari et al., 2025). Each domain employs criteria and benchmarks established in the literature (Renigier-Bilozor et al., 2025).

Theoretical validation assesses the conceptual coherence of the XAI-AVM framework through logic analysis, theoretical consistency checking, and comparison with established frameworks (Saiu & Mocci, 2026). This validation ensures that the framework is grounded in sound theoretical principles and addresses the identified research problems (Băbțan, 2025). Technical validation assesses the appropriateness of selected algorithms, hyperparameter configurations, and performance metrics through analysis of reported empirical results in comparable contexts (Sing et al., 2022).

Professional validation assesses the practical utility of the framework through conceptual analysis of valuation practice requirements, stakeholder needs, and regulatory contexts (Belay & Ekman, 2025). This validation considers usability, interpretability, and acceptability factors essential for successful AI adoption in valuation practice (Oyetunji et al., 2026). The framework also conceptualizes ongoing validation procedures for maintaining model accuracy and fairness over time, including monitoring protocols and periodic recalibration strategies (Seagraves et al., 2026).

The validation framework emphasizes the importance of multi-dimensional assessment that goes beyond predictive accuracy alone (Morano et al., 2025). The framework recognizes that AI valuation systems must satisfy multiple criteria including accuracy, transparency, fairness, usability, and regulatory compliance (Kim et al., 2025). The validation approach is therefore designed to provide comprehensive evidence of framework quality and suitability for professional practice (Teikari et al., 2025).

8. Framework Development Process

The XAI-AVM framework development follows a systematic conceptualization process integrating the theoretical foundations, architectural components, and contextual adaptations described above (Kim et al., 2025). The process begins with synthesizing findings from the comprehensive literature review to establish theoretical principles and identify key architectural components (Morano et al., 2025). This synthesis produces initial conceptual models for each framework component, which are then refined through iterative theoretical analysis and comparison with existing frameworks (Saiu & Mocci, 2026).

The framework development process emphasizes integration across components, ensuring coherence between data preparation, model development, explainability implementation, and output presentation (Teikari et al., 2025). Special attention is given to the interface between predictive modeling and explainability, ensuring that interpretability is embedded throughout the framework rather than added as an afterthought (Kim et al., 2025). The integration process draws on established principles for XAI system design, emphasizing consistency, usability, and completeness in explanation generation (Saiu & Mocci, 2026).

The final framework is documented as a comprehensive conceptual model with detailed specifications for each component, including data requirements, algorithmic specifications, explanation formats, and validation procedures (Belay & Ekman, 2025). The documentation addresses implementation considerations, including technological requirements, professional training needs, and regulatory compliance issues (Adediran et al., 2025). The framework is presented in a format accessible to valuation professionals, technology developers, and policy makers, supporting its practical adoption and further development (Zekri, 2025).

RESULTS AND DISCUSSION

1. Theoretical Framework for XAI-AVM Development

The conceptual analysis yields a comprehensive theoretical framework for developing Explainable AI-based Automated Valuation Models in the Nigerian context, integrating principles from hedonic pricing theory, machine learning theory, explainable AI theory, and professional valuation practice (Morano et al., 2025). The framework posits that effective XAI-AVM development requires systematic attention to data quality, algorithmic selection, interpretability integration, and professional validation (Teikari et al., 2025). The theoretical synthesis confirms the primacy of location attributes in property valuation, consistent with hedonic pricing theory predictions and empirical findings from diverse markets (Sing et al., 2022).

The framework identifies XGBoost as the theoretically most appropriate algorithm for valuation applications, based on its demonstrated performance advantages in comparative studies and its compatibility with XAI techniques (Kim et al., 2025). The analysis confirms that SHAP analysis provides theoretically sound explanations consistent with valuation principles, enabling transparent attribution of value contributions to individual property characteristics (Saiu & Mocci, 2026). The framework establishes the importance of multi-level explainability global, local, and interactive for addressing diverse stakeholder information needs (Teikari et al., 2025).

The theoretical framework emphasizes the dynamic nature of property markets and the consequent need for model adaptability and continuous validation (Renigier-Biłozor et al., 2026). This dynamism is conceptualized through temporal adaptation mechanisms, market condition indicators, and periodic recalibration procedures (Ge & Raptis, 2026). The framework also addresses ethical considerations, establishing principles for fairness, transparency, and accountability in AI-enabled valuation practice (Seagraves et al., 2026).

The integration of multiple theoretical perspectives provides a robust foundation for the proposed framework (Kim et al., 2025). The framework acknowledges that property valuation is not purely a technical exercise but involves professional judgment, stakeholder communication, and regulatory compliance (Morano et al., 2025). The theoretical synthesis therefore encompasses both technical requirements and professional practice considerations, ensuring that the framework is relevant to real-world valuation contexts (Teikari et al., 2025).

2. Proposed XAI-AVM Architectural Design

The conceptualization yields a detailed architectural design for the XAI-AVM comprising five integrated layers: data integration, feature engineering, predictive modeling, explainability, and output presentation (Saiu & Mocci, 2026). The data integration layer conceptualizes multi-source data collection from property records, transaction databases, valuation reports, and geospatial information systems (Ge & Raptis, 2026). This layer includes preprocessing protocols for handling missing data, detecting outliers, and ensuring data consistency through standardization procedures (Oyetunji et al., 2026).

The feature engineering layer conceptualizes the transformation of raw data into predictive features through the integration of domain knowledge and statistical techniques (Morano et al., 2025). Core features include physical characteristics (floor area, rooms, building age, construction quality), locational attributes (district, neighborhood amenities, accessibility indices), and transactional variables (market timing, property condition) (Sing et al., 2022). Feature selection is conceptualized through three complementary approaches: statistical selection (correlation analysis, mutual information), algorithmic selection (embedded methods in tree-based models), and professional selection (valuers' domain knowledge) (Kim et al., 2025).

The predictive modeling layer conceptualizes ensemble learning implementation with XGBoost as the primary algorithm, supported by Random Forest and Gradient Boosting for comparative validation (Sing et al., 2020). Hyperparameter optimization is conceptualized through grid search and Bayesian optimization strategies, with cross-validation for robust model selection (El Jaouhari et al., 2024). The conceptual design specifies performance evaluation using MAE, RMSE, MAPE, and R^2 metrics, with benchmark comparisons against hedonic regression baselines (Morano et al., 2025).

The explainability layer conceptualizes the integration of SHAP and LIME techniques for generating comprehensive explanations across multiple levels (Saiu & Mocci, 2026). Global explanations include feature importance rankings, model summaries, and variable interaction analyses (Kim et al., 2025). Local explanations include individual prediction justifications, contribution breakdowns, and counterfactual insights (Teikari et al., 2025). The output presentation layer conceptualizes the delivery of predictions and explanations through accessible dashboards, professional reports, and interactive analysis tools (Belay & Ekman, 2025).

The architectural design emphasizes modularity and flexibility, enabling adaptation to different data environments, technological capabilities, and use case requirements (Zekri, 2025). The modular structure allows individual components to be modified or replaced without requiring redesign of the entire system (Adediran et al., 2025). This flexibility is particularly important in emerging market contexts where data availability and technological infrastructure may be limited or evolving (Oyetunji et al., 2026).

3. Explainability Mechanisms and Interpretability Enhancement

The conceptual analysis identifies SHAP as the theoretically optimal explainability technique for valuation applications, based on its consistency properties and ability to provide both global and local explanations (Kim et al., 2025). SHAP force plots are conceptualized for presenting individual property valuations, showing how each characteristic contributes to the predicted value relative to the average property (Saiu & Mocci, 2026). SHAP summary plots are conceptualized for presenting overall market insights, revealing which property characteristics have the greatest influence across the entire market (Teikari et al., 2025).

The framework conceptualizes five interpretability enhancement mechanisms that address different stakeholder needs (Belay & Ekman, 2025). Feature importance analysis provides comprehensive understanding of value determinants, supporting professional education and market analysis (Morano et al., 2025). Individual prediction explanations enable valuation validation and professional oversight, supporting regulatory compliance and stakeholder confidence (Băbțan, 2025). What-if analysis supports scenario evaluation and decision-making, enabling valuers and property owners to assess the value implications of property improvements or market changes (Adediran et al., 2025).

The explainability mechanisms are conceptualized to address the specific needs of the Nigerian valuation context, where stakeholder understanding of AI technologies may be limited and trust in algorithmic decision-making requires deliberate cultivation (Oyetunji et al., 2026). The framework emphasizes visual clarity, intuitive interpretation, and professional terminology alignment in explanation design (Zekri, 2025). The conceptualization addresses the risk of explanation overload by distinguishing between essential information for different user roles and providing customizable explanation depth levels (Teikari et al., 2025).

The interpretability enhancement mechanisms are designed to support both immediate valuation tasks and broader professional development goals (Kim et al., 2025). By providing transparent explanations of AI predictions, the framework supports valuers in developing deeper understanding of market value determinants and improving their professional judgment (Saiu & Mocci, 2026). The mechanisms also support stakeholder communication, enabling valuers to explain AI-generated valuations to clients and regulators with confidence (Belay & Ekman, 2025).

4. Contextual Adaptation Strategies

The framework conceptualizes specific adaptation strategies for Nigerian market conditions, addressing the data limitations, technological constraints, and professional practice realities identified in the literature (Oyetunji et al., 2026). Data adaptation strategies include multi-source integration for compensating data gaps, robust imputation for handling missing values, and transaction-like processing for using listing data as value indicators (Ge & Raptis, 2026). The framework also conceptualizes the incorporation of alternative data sources including satellite imagery analysis, social media sentiment, and infrastructure development indicators (Odunlade Adejumo et al., 2024).

Technological adaptation strategies address the limited computational resources and technical infrastructure common in Nigerian practice settings (Kadioglu & YAĞCI, 2026). The framework conceptualizes efficient model configurations with reduced computational requirements, cloud-based deployment options for resource sharing, and simplified interfaces for users with limited technical expertise (Belay & Ekman, 2025). The framework also addresses the importance of mobile accessibility, given the prevalence of smartphone use in Nigerian professional practice (Amar & Armitage, 2026).

Professional adaptation strategies emphasize the integration of local valuation knowledge, professional judgment, and regulatory requirements in model development and validation

(Renigier-Biłozor et al., 2026). The framework conceptualizes professional involvement in feature engineering, model validation, and interpretation of explanations to ensure alignment with professional standards and market realities (Morano et al., 2025). The framework also addresses the importance of continuing professional development for valuing professionals, conceptualizing training programs for AI literacy and XAI interpretation (Adediran et al., 2025). The contextual adaptation strategies recognize that successful AI adoption requires more than technical implementation (Zekri, 2025). The strategies therefore address organizational, institutional, and human factors that influence technology adoption and effective use (Oyetunji et al., 2026). The framework emphasizes the importance of building local capacity, developing appropriate governance structures, and fostering a culture of innovation in valuation practice (Adediran et al., 2025).

5. Validation Framework and Quality Assurance

The conceptual validation framework establishes criteria and procedures for assessing the quality and effectiveness of XAI-AVM implementations (Teikari et al., 2025). Predictive accuracy validation conceptualizes benchmarking against standard performance metrics and comparison with traditional valuation approaches (Sing et al., 2022). The framework establishes minimum acceptable performance thresholds, with MAPE below ten percent considered appropriate for mass appraisal contexts (Morano et al., 2025). Explanation quality validation conceptualizes assessment of explanation clarity, completeness, and actionability through user-centered evaluation approaches (Kim et al., 2025).

Fairness validation conceptualizes systematic examination of model predictions across property types, districts, and market segments to detect potential biases (Seagraves et al., 2026). The framework establishes procedures for identifying disparate impacts and conceptualizes mitigation strategies including model recalibration, fairness constraints, and the development of diverse representative training data (Seagraves et al., 2026). Professional acceptance validation conceptualizes assessment of stakeholder trust, model adoption, and professional judgment integration in valuation practice (Belay & Ekman, 2025).

The validation framework also conceptualizes ongoing quality assurance procedures for maintaining model performance over time (Renigier-Biłozor et al., 2026). Performance monitoring conceptualizes the regular assessment of prediction accuracy, bias indicators, and explanation quality to identify performance deterioration (Ge & Raptis, 2026). Periodic recalibration conceptualizes model updating procedures, incorporating new market data to maintain accuracy and relevance (Kang & Melani, 2026). The framework also conceptualizes the establishment of professional oversight mechanisms, including regular review of model outputs by experienced valuers (Student, 2025).

The validation framework emphasizes the importance of comprehensive quality assurance that addresses both technical and professional requirements (Kim et al., 2025). The framework recognizes that AI valuation systems must satisfy multiple quality criteria and that different stakeholders may have different quality expectations (Morano et al., 2025). The validation approach is therefore designed to be inclusive and responsive to diverse stakeholder perspectives (Teikari et al., 2025).

6. Comparative Analysis with Existing Frameworks

Comparative analysis reveals that the proposed XAI-AVM framework addresses significant gaps in existing valuation frameworks (Morano et al., 2025). Existing frameworks for AI valuation often prioritize predictive accuracy over interpretability, neglecting the transparency requirements of professional valuation practice (Băbțan, 2025). The proposed framework explicitly addresses this gap by integrating explainability throughout the valuation process rather than treating it as an optional addition (Saiu & Mocci, 2026). This integration is particularly important in regulated contexts where valuers must demonstrate the basis for their conclusions (Kim et al., 2025).

The framework also addresses the contextual gap in existing AI valuation research, which has predominantly focused on developed markets with established data infrastructures (Adediran et al., 2025). The proposed framework explicitly considers the data limitations, technological constraints, and professional realities of emerging market contexts (Oyetunji et al., 2026). This contextual sensitivity is essential for developing frameworks that are practically applicable in Nigerian and similar market environments (Zekri, 2025).

The proposed framework further addresses the stakeholder engagement gap in existing AI valuation approaches (Belay & Ekman, 2025). Many existing frameworks focus on technical development without adequate attention to user needs, professional practice requirements, and regulatory expectations (Teikari et al., 2025). The proposed framework emphasizes stakeholder engagement throughout the development and validation process, ensuring that the framework addresses real-world needs and constraints (Morano et al., 2025).

The comparative analysis also identifies opportunities for learning from other sectors and disciplines (Kim et al., 2025). The framework draws on best practices from financial technology, healthcare AI, and other regulated AI applications that have addressed similar challenges of accuracy, transparency, and trust (Saiu & Mocci, 2026). The adaptation of these best practices to the valuation context enriches the proposed framework and enhances its potential for successful implementation (Teikari et al., 2025).

CONCLUSION

1. Summary of Findings

This conceptual research successfully developed a comprehensive framework for an Explainable AI-based Automated Valuation Model tailored to the Nigerian residential property market. The framework integrates theoretical principles from hedonic pricing theory, machine learning, explainable AI, and professional valuation practice to address the unique challenges of emerging market contexts. The conceptualization establishes that effective XAI-AVM development requires systematic attention to data quality, algorithmic selection, interpretability integration, professional validation, and contextual adaptation.

The proposed architectural design comprises five integrated layers data integration, feature engineering, predictive modeling, explainability, and output presentation that together provide comprehensive support for AI-enabled property valuation. The framework identifies XGBoost with SHAP explanations as the theoretically optimal combination for achieving both predictive accuracy and interpretability in valuation contexts. Multi-level explainability mechanisms address diverse stakeholder needs, supporting professional validation, regulatory compliance, and stakeholder communication.

Contextual adaptation strategies address the specific conditions of the Nigerian property market, including data limitations, technological constraints, and professional practice realities. The validation framework establishes comprehensive criteria for assessing predictive accuracy, explanation quality, fairness, and professional acceptance of AI valuation systems. The comparative analysis confirms that the proposed framework addresses significant gaps in existing approaches, particularly regarding interpretability integration, contextual sensitivity, and stakeholder engagement.

2. Contributions to Knowledge

This research makes several significant contributions to real estate valuation theory and practice. First, it extends the body of knowledge on AI-based Automated Valuation Models to the Nigerian context, addressing a pronounced research gap identified in recent literature (Oyetunji et al., 2026; Adediran et al., 2025). Second, it demonstrates the theoretical integration of XAI techniques with valuation principles, showing how SHAP analysis can provide meaningful interpretability while maintaining alignment with professional valuation standards (Kim et al., 2025; Saiu & Mocci, 2026). Third, it provides a comprehensive framework for contextual adaptation of AI valuation approaches to emerging market conditions, addressing data limitations, technological constraints, and professional practice realities (Zekri, 2025).

Fourth, the study advances methodological understanding of conceptual framework development in valuation research, providing a replicable approach for adapting AI technologies to diverse market contexts (Morano et al., 2025). Fifth, it establishes a practical foundation for developing, implementing, and validating Explainable AI-based AVMs in contexts where empirical data collection may be challenging or premature (Renigier-Bilozor et al., 2025). Sixth, the research contributes to the discourse on AI transparency and professional accountability in valuation practice, supporting the development of appropriate governance frameworks and professional standards (Teikari et al., 2025).

The conceptual nature of this research makes it particularly valuable for informing subsequent empirical research and practical implementation (Adediran et al., 2025). The framework provides clear specifications for data requirements, model configurations, explanation formats, and validation procedures that can guide empirical studies and pilot implementations (Zekri, 2025). The framework also establishes theoretical benchmarks against which empirical results can be evaluated (Kim et al., 2025).

3. Practical Implications for Valuation Practice

The findings have significant practical implications for property valuation practice, professional organizations, and regulatory bodies in Nigeria and similar emerging markets. The proposed framework provides a roadmap for developing AI valuation capabilities that are both technically effective and professionally appropriate. The emphasis on explainability addresses the transparency concerns that have limited AI adoption in valuation practice, enabling valuers to understand, validate, and communicate AI-generated valuations with confidence.

Valuation professional bodies should consider developing guidelines for AI adoption that address model validation, ethical considerations, and continuing professional development requirements. The framework provides a basis for such guidelines by establishing quality criteria, validation procedures, and professional oversight mechanisms. Regulatory authorities should develop frameworks for AI use in regulated valuation activities, balancing innovation promotion with appropriate governance and accountability provisions. The proposed framework's emphasis on transparency, fairness, and professional validation supports the development of such regulatory frameworks.

Educational institutions should integrate AI and XAI topics into valuation curricula, preparing future professionals with necessary technological competencies. The framework provides a structured approach to AI valuation education by specifying key concepts, techniques, and professional considerations. Property data infrastructure investments are essential for successful AI adoption, including standardized property records, transparent transaction databases, and robust data governance frameworks. The framework's data integration and feature engineering components provide guidance for such infrastructure development.

4. Limitations and Future Research Directions

While this conceptual research makes significant contributions, several limitations should be acknowledged and addressed through future research. The conceptual nature of the research means that the framework has not been empirically validated through implementation and testing in real-world valuation contexts. Future research should therefore focus on empirical validation of the proposed framework through pilot implementations, case studies, and experimental evaluations.

The framework's focus on residential property valuation in Abuja may limit its applicability to other property types, market segments, and geographic contexts. Future research should explore the adaptation of the framework to commercial property valuation, rural property markets, and other Nigerian cities. The framework should also be tested and refined through application in other emerging markets, assessing its transferability and identifying necessary adaptations.

The proposed XAI-AVM framework incorporates established machine learning and XAI techniques, but emerging AI technologies may offer additional capabilities. Future research should explore the integration of deep learning approaches, natural language processing for unstructured property data, and advanced fairness techniques. Research should also examine the integration of alternative data sources, including satellite imagery, mobile phone data, and social media indicators, to enhance valuation accuracy in data-limited contexts.

Longitudinal research examining the evolution of AI valuation systems over time would provide valuable insights into their stability, adaptability, and long-term performance. Research should also examine the organizational and human factors that influence AI adoption and effective use in valuation practice, including professional attitudes, training needs, and organizational readiness. Finally, research on the economic and social impacts of AI-enabled valuation systems would contribute to understanding their broader implications for property markets, housing affordability, and social equity.

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