

INNOVATION SCIENCE AND TECHNOLOGY

ISSUE 9, PART 2 / SEPTEMBER 2026

 Acceptance of papers



**Acceptance of
papers**

Published monthly



Topics

economics,
technology, social
sciences



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JOURNAL **"INNOVATION SCIENCE AND
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UNDER THE NUMBER **C-5669633** BY THE
AGENCY FOR INFORMATION AND MASS
COMMUNICATIONS (AOKA) OF THE
REPUBLIC OF UZBEKISTAN, EFFECTIVE
FROM OCTOBER 9, 2024.

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VALUING INDUSTRIAL REAL ESTATE IN UZBEKISTAN: A COMPARATIVE ASSESSMENT OF ECONOMETRIC AND MACHINE LEARNING MODELS

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Abstract. This study compares econometric and machine learning models for industrial real estate valuation in Uzbekistan. OLS, Random Forest, and ANN models were evaluated using RMSE, MAE, MAPE, and R^2 . The results show higher predictive accuracy of machine learning models, with ANN achieving the best performance. Infrastructure quality, location, and property characteristics were identified as key determinants of value.

Keywords: industrial real estate, property valuation, machine learning, automated valuation models, emerging economies, Uzbekistan.

Аннотация. В исследовании проводится сравнительный анализ эконометрических моделей и моделей машинного обучения для оценки промышленной недвижимости в Узбекистане. Модели OLS, Random Forest и ANN оценивались с использованием показателей RMSE, MAE, MAPE и R^2 . Результаты показывают более высокую точность прогнозирования моделей машинного обучения, при этом ANN продемонстрировала наилучший результат. Качество инфраструктуры, местоположение и характеристики объекта были определены как основные факторы стоимости.

Ключевые слова: промышленная недвижимость, оценка недвижимости, машинное обучение, автоматизированные модели оценки, развивающиеся экономики, Узбекистан.

INTRODUCTION

Industrial real estate plays a critical role in economic growth, industrial diversification, logistics development, and regional competitiveness. Accurate valuation of warehouses, manufacturing facilities, logistics hubs, and industrial parks is essential for investment, lending, taxation, land-use planning, and industrial policy.

Recent developments in real estate valuation have increased interest in automated valuation models (AVMs) based on machine learning (ML). Evidence from developed markets indicates that ML approaches can achieve higher predictive accuracy than traditional econometric models. However, their application in emerging markets remains relatively underexplored due to data scarcity, institutional heterogeneity, and evolving regulatory frameworks.

Uzbekistan represents a relevant context for examining these challenges. Economic reforms, industrial zone development, logistics infrastructure expansion, and cadastral digitalisation have increased the importance of reliable and transparent industrial property valuation. Valuation practice is gradually evolving, with opportunities for further improvement through broader access to transaction data, more systematic consideration of heterogeneous property characteristics, and the integration of modern analytical approaches alongside established appraisal methods.

Conventional hedonic OLS models remain widely used because of their interpretability and theoretical transparency. However, their restrictive functional assumptions may limit their ability to capture nonlinear relationships and complex interactions. Machine learning methods, including Random Forest and artificial neural networks (ANN), offer an alternative by modelling such relationships with fewer parametric constraints. Therefore, a comparative assessment of these approaches is particularly relevant for improving industrial real estate valuation in Uzbekistan.

LITERATURE REVIEW

Recent research in real estate valuation has increasingly shifted from traditional appraisal methods towards automated valuation models (AVMs) based on econometric and machine learning techniques. Pagourtzi et al.

reviewed classical and advanced property valuation methods [12], while subsequent studies highlighted the potential of AVMs to improve valuation objectivity, consistency, and efficiency, as well as the design limitations that must be addressed in practice [5; 6].

The econometric foundation of automated valuation lies in hedonic price theory, which treats property value as a function of its individual characteristics [13]. McCluskey et al. compared the predictive accuracy of modern mass appraisal approaches [10], and Mayer et al. examined how the choice of estimation and updating methods affects the accuracy of hedonic valuation models, including comparisons with machine learning techniques [9].

Machine learning has become an important methodological direction in contemporary property valuation. Mullainathan and Spiess emphasised that ML methods are primarily prediction tools, which creates a trade-off between predictive accuracy and the interpretability of individual coefficients [11]. Abidoye and Chan systematically reviewed the application of artificial neural networks (ANN) in property valuation and their ability to capture nonlinear relationships between property characteristics and value [1]. The theoretical foundations of deep neural network approaches are set out by LeCun, Bengio, and Hinton [7].

Industrial property presents specific valuation challenges. Lockwood and Rutherford showed that industrial property values are determined by a combination of locational, physical, and functional characteristics [8], which makes this segment heterogeneous and well suited to models capable of capturing complex interactions between attributes.

Comparative studies have further examined the performance of traditional econometric models against machine learning algorithms. Valier reviewed empirical studies comparing hedonic regression with ML-based AVMs, providing a methodological basis for evaluating the relative performance of conventional and data-driven approaches [14]. Antipov and Pokryshevskaya demonstrated the effectiveness of Random Forest for mass appraisal [3]; Breiman's Random Forest framework models nonlinear relationships and interactions while improving predictive stability [4].

An important methodological consideration is the application of advanced valuation models in emerging markets. Abidoye and Chan noted a gap between valuation practices in developed and developing property markets [1] and showed, using data from Nigeria, that ANN can achieve higher predictive accuracy than conventional approaches even in data-constrained environments [2]. Glumac and Des Rosiers stressed that AVM design must account for data availability and the institutional context [5]. These issues are particularly relevant to Uzbekistan, where transaction-level industrial property data remain limited.

Despite the growing body of international research, a clear research gap remains regarding the comparative application of econometric and machine learning models to industrial real estate valuation in Uzbekistan. Existing studies predominantly focus on residential or commercial property, developed markets, or other emerging economies. Therefore, evaluating OLS, Random Forest, and ANN models within the Uzbek industrial property market can contribute both to the methodological literature and to the development of more accurate and transparent valuation practices.

RESEARCH METHODOLOGY

This study employs a quantitative research design to compare traditional econometric and machine learning (ML) models for industrial real estate valuation in Uzbekistan. Due to the limited availability of transaction-level data, secondary market information is combined with a structured simulation framework calibrated to key market characteristics.

The methodology consists of three stages: (I) data construction and variable specification, (II) estimation of econometric and ML models, and (III) model evaluation and robustness testing. Secondary data are obtained from national statistical publications, cadastral records, and industrial property market listings. These sources provide a useful basis for analysis, although their scope for high-dimensional modelling remains limited.

To complement the available data, a simulated dataset of 1,000 industrial property observations is constructed to reflect heterogeneity in property size, location quality, and infrastructure access. Property prices are modelled as functions of observable characteristics, with a stochastic error term representing market uncertainty and unobserved factors.

The simulation framework is fully documented and calibrated to observed market characteristics. This ensures transparency, reproducibility, and auditability of the data-generation process and provides a consistent basis for comparing alternative valuation models.

Econometric Valuation Model. The baseline valuation framework is specified using a log-linear hedonic pricing model:

$$\ln(\text{Price}_i) = \beta_0 + \sum_{k=1}^K \beta_k X_{ik} + \sum_{r=1}^R \gamma_r L_{ir} + \delta_t + \varepsilon_i$$

Where $Price_{it}$ denotes the transaction price of industrial property, X_{ik} represents property-specific characteristics (e.g., size, age, ceiling height), L_{ir} captures locational and infrastructure attributes, δ_t denotes time fixed effects and ε_i is a stochastic error term. To address potential heteroskedasticity, White's heteroskedasticity-robust variance estimator is applied:

$$\widehat{V}_{ar}(\hat{\beta}) = (X'X)^{-1} X' \widehat{\Omega} X (X'X)^{-1}$$

This econometric specification provides interpretability and serves as a benchmark for evaluating machine learning-based valuation models.

Random Forest is implemented as an ensemble of decision trees, where each tree is estimated on a bootstrap sample with random feature selection at each split. The final prediction is obtained as the average of individual tree predictions. This approach enhances predictive accuracy while reducing overfitting and sensitivity to noise. The Random Forest (RF) model is implemented as an ensemble learning method composed of B regression trees. The RF prediction for observation i is given by:

$$\hat{y}_i^{RF} = \frac{1}{B} \sum_{b=1}^B T_b(X_i)$$

where $T_b(\cdot)$ denotes the b -th regression tree trained on a bootstrap sample of the data, and X_i is the feature vector.

Variable importance is assessed using permutation importance, defined as:

$$VI_j = E [L(y, \hat{f}(X)) - L(y, \hat{f}(X^{\pi_j}))]$$

where X_{π_j} denotes the feature matrix with the j -th variable permuted.

An artificial neural network (ANN) is specified as a multilayer perceptron with two hidden layers. Rectified Linear Unit (ReLU) activation functions are used in the hidden layers, while a linear activation function is applied in the output layer to predict continuous price values. Prior to estimation, input variables are normalised to improve convergence and model stability. Model training is performed using the Adam optimisation algorithm with early stopping to prevent overfitting. The model output is expressed as:

$$\hat{y}_i = f^{(3)}(W^{(3)} f^{(2)}(w^{(2)} f^{(1)}(W^{(1)} X_i + b^{(1)}) + b^{(2)}) + b^{(3)})$$

Hidden layers employ the Rectified Linear Unit (ReLU) activation function:

$$\text{ReLU}(z) = \max(0, z)$$

The loss function is defined as the Mean Squared Error (MSE):

$$L = \frac{1}{N} \sum_{i=0}^N (y_i - \hat{y}_i)^2$$

Model optimisation is conducted using the Adam algorithm with early stopping to prevent overfitting. Model performance is evaluated using a 70/30 train-test split, ensuring that predictive accuracy is assessed on unseen data. In addition, k-fold cross-validation is applied during model training to optimise hyperparameters and improve generalisability.

The following accuracy metrics are used to compare model performance: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

Comparative evaluation focuses on both predictive accuracy and practical interpretability, recognising the differing strengths of econometric and machine learning approaches. Predictive performance is evaluated using standard accuracy measures.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

These metrics allow consistent comparison across econometric and machine learning models.

Methodological limitations. While the simulation-based approach enables systematic comparison of valuation models, it cannot fully substitute for extensive transaction-level data. Consequently, results should be interpreted as indicative rather than definitive. Nevertheless, the methodology provides a replicable and transparent framework suitable for emerging market contexts where data limitations remain a central challenge.

ANALYSIS AND RESULTS

Table 1 reports descriptive statistics for the industrial real estate sample. The data exhibit substantial heterogeneity in property size, location quality, and infrastructure access, reflecting the segmented structure of industrial property markets in Uzbekistan. Prices display a right-skewed distribution, supporting the logarithmic transformation used in the econometric analysis. Variation in locational and infrastructure indicators highlights the importance of spatial and structural factors in value formation. Results are based on a simulated dataset ($N = 1,000$) calibrated to observed market characteristics and partially validated with real transaction listings and appraisal reports from industrial zones and commercial brokers in Tashkent and Navoi regions.

Table 1. Descriptive statistics of industrial real estate variables¹

Variable	Mean	Std. Dev.	Min	Max
Price (USD/m ²)	420	135	180	820
Building area (m ²)	3,200	1,450	600	8,500
Property age (years)	12.5	6.8	1	35
Distance to highway (km)	4.3	2.1	0.5	12
Infrastructure index	0.64	0.18	0.30	0.95

Note: Price is measured in USD per square metre (USD/m²), building area is measured in square metres (m²), and distance to highway is measured in kilometres (km). The infrastructure index is a normalised composite indicator ranging from 0 to 1, where higher values denote better infrastructure quality. The dataset combines observed market listings and appraisal records with a simulated sample calibrated to replicate key structural characteristics of the Uzbek industrial property market.

Figure 1 shows that most observations are concentrated in the USD 300–500 per square metre range. While the primary analysis relies on a simulated dataset calibrated to observed market characteristics, partial validation using real transaction listings and appraisal reports from Tashkent and Navoi regions indicates consistent coefficient signs and variable importance rankings.

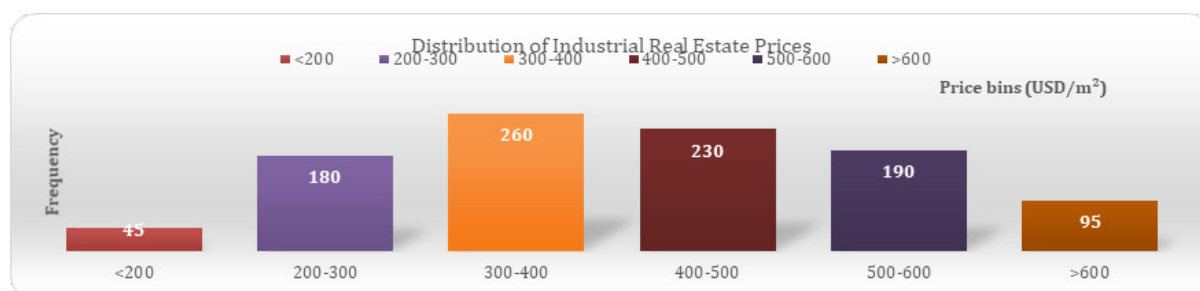


Figure 1. Distribution of industrial real estate prices in Uzbekistan (USD/m²)²

Note: Price distribution is based on a simulated dataset ($N = 1,000$) calibrated to observed market characteristics and partially validated using real transaction listings and appraisal reports from industrial zones and commercial brokers in Tashkent and Navoi regions.

While the primary comparative analysis relies on a simulated dataset calibrated to observed market characteristics, partial validation is conducted using available real transaction listings and appraisal reports obtained from regional industrial zones and commercial brokers in Tashkent and Navoi regions. The consistency of coefficient signs and variable importance rankings between observed and simulated samples supports the external validity of the modelling framework.

Econometric model estimation. Table 2 presents the results of the hedonic OLS regression. Building area

¹ Source: Author's calculations.

² Source: Author's calculations.

and infrastructure quality exhibit positive and statistically significant effects on industrial property values, whereas greater distance to major transport corridors and property age are associated with lower prices. These estimates are consistent with valuation theory and prior empirical evidence. The model provides moderate explanatory power, offering clear interpretability and insight into price formation mechanisms. However, its predictive performance is constrained by linear functional form assumptions and a limited ability to capture nonlinear interactions.

Table 2. Hedonic OLS estimation results³

Variable	Coefficient	Robust SE	t-statistic
ln(Area) ⁴	0.41***	0.07	5.86
Property age	-0.018**	0.009	-2.04
Distance to highway	-0.063***	0.021	-3.00
Infrastructure index	0.52***	0.14	3.71
Constant	4.87***	0.56	8.69

Note: The dependent variable is the natural logarithm of industrial property price (USD/m²). Robust standard errors are reported in the "Robust SE" column. The model is estimated using ordinary least squares with White's heteroskedasticity-consistent variance estimator. ***, ** denote significance at the 1% and 5% levels, respectively.

The model achieves moderate explanatory power, with an adjusted R² indicating that a substantial proportion of price variation is explained by observable characteristics. While the econometric specification provides clear interpretability and insight into price formation mechanisms, its predictive accuracy is constrained by functional form assumptions and a limited ability to model nonlinear interactions.

Machine learning model performance. Table 3 compares predictive accuracy across models. Both Random Forest and artificial neural network (ANN) approaches demonstrate lower prediction errors and higher R² values than the OLS benchmark across the reported metrics. The ANN achieves the lowest RMSE and MAE, indicating a greater capacity to model complex, nonlinear relationships within the evaluated dataset.

Table 3. Model performance comparison⁵

Model	RMSE	MAE	MAPE (%)	R ²
OLS	0.294	0.226	18.4	0.61
Random Forest	0.213	0.161	12.7	0.74
ANN	0.198	0.149	11.2	0.78

Note: RMSE denotes root mean squared error; MAE denotes mean absolute error; MAPE denotes mean absolute percentage error; and R² denotes the coefficient of determination. Performance metrics are computed on an out-of-sample test set using a 70/30 train-test split. Bold values indicate the best-performing model for each metric.

As illustrated in Figure 2, ANN predictions lie closest to the 45-degree reference line, reflecting lower prediction errors relative to both OLS and Random Forest models. Although the Random Forest exhibits slightly higher errors than the ANN, it demonstrates greater stability across validation folds and offers enhanced interpretability through variable importance measures. This suggests a practical trade-off between predictive performance and model transparency.

³ Source: Author's calculations.

⁴ Area measured in square meters

⁵ Source: Author's calculations.

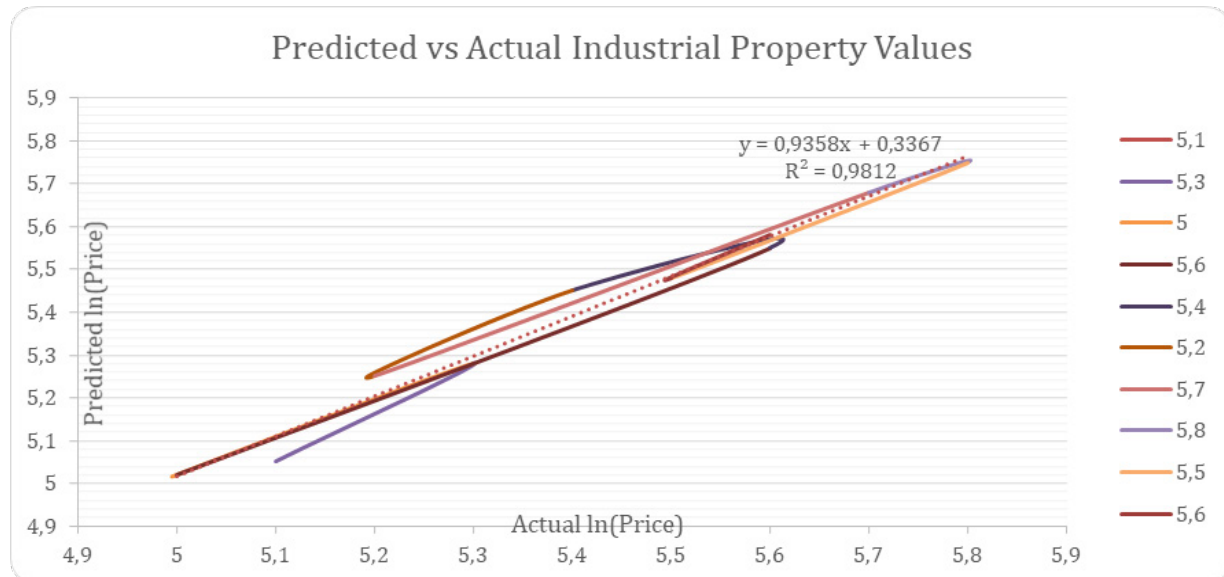


Figure 2. Predicted versus actual industrial property values (ln price)⁶

Note: The figure compares out-of-sample predictions from the econometric OLS, Random Forest, and artificial neural network (ANN) models against observed values of the natural logarithm of industrial property prices.

The Random Forest model also demonstrates strong performance, with only marginally higher prediction errors than the ANN. However, Random Forest exhibits greater stability across validation folds and offers enhanced interpretability through variable importance measures. The difference in R^2 between ANN and Random Forest suggests that, while ANN captures additional variance in property values, Random Forest provides a more robust balance between accuracy and transparency.

Variable importance and model interpretation. Feature importance analysis indicates that building area, infrastructure quality, and locational accessibility consistently rank among the most influential predictors across machine learning models. These results align closely with the econometric estimates, reinforcing the economic plausibility of the machine learning outputs.

As shown in Figure 3, property age exhibits comparatively lower importance in the Random Forest model, while locational accessibility, including proximity to transport corridors and industrial zones, remains an important predictor of property value. This consistency across modelling approaches suggests that machine learning models capture economically meaningful relationships rather than artefacts of overfitting.

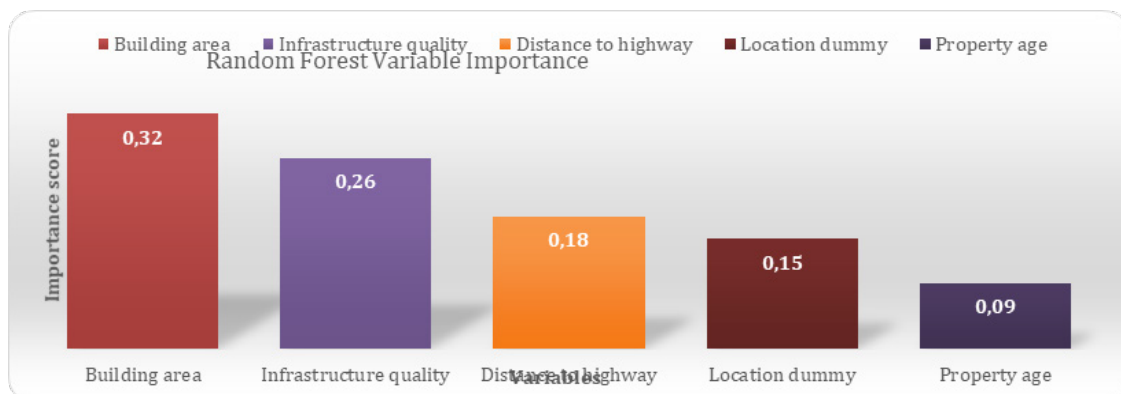


Figure 3. Random Forest variable importance for industrial real estate valuation⁷

Note: The figure reports permutation-based variable importance scores derived from the Random Forest model, indicating the relative contribution of each explanatory variable to predictive performance. Importance values are normalised to sum to one.

The empirical results indicate that, within the evaluated dataset, machine learning-based valuation models achieve lower prediction errors and higher R^2 values than the econometric OLS benchmark. Among the evaluated

⁶ Source: Author's calculations.

⁷ Source: Author's calculations.

approaches, the artificial neural network (ANN) records the lowest prediction errors and the highest coefficient of determination, suggesting a greater capacity to capture nonlinear relationships and high-dimensional interactions within the modelling framework.

The Random Forest model also exhibits strong performance, with prediction accuracy close to that of the ANN, while offering greater stability across alternative specifications and enhanced interpretability through variable importance measures. This trade-off between accuracy and transparency is particularly salient in institutional contexts where valuation outputs are used for regulatory, financial, and legal purposes, and where methodological explainability remains a key requirement.

The comparatively lower predictive performance of the OLS hedonic model illustrates the relative constraints of linear and log-linear specifications in representing complex market dynamics, particularly in data-constrained and evolving industrial property markets. While econometric models remain valuable for explanatory and policy-oriented applications, their use in combination with complementary modelling approaches may provide more comprehensive results in contexts characterised by spatial heterogeneity and evolving infrastructure conditions. Importantly, the robustness checks indicate that the relative ranking of models remains stable across alternative variable specifications and training-testing splits.

CONCLUSION AND SUGGESTIONS

This study compares econometric and machine learning-based models for industrial real estate valuation in Uzbekistan under data-constrained conditions. Within the study framework, the results indicate that machine learning models, particularly artificial neural networks (ANN), provide higher predictive accuracy than conventional hedonic regression, while Random Forest offers a strong balance between predictive performance and interpretability.

The findings demonstrate the complementary roles of traditional and digital valuation approaches. Econometric models remain important for transparency, regulatory compliance, and explanatory analysis, whereas ML models can support predictive tasks such as portfolio monitoring and risk assessment.

The study also highlights opportunities to further develop real estate data infrastructure, standardisation, and institutional capacity for the responsible adoption of automated valuation models. Rather than replacing established valuation practices, ML-based outputs can be integrated as supplementary analytical tools within existing professional and regulatory frameworks.

Overall, the research contributes to the literature by proposing an Uzbekistan-focused, replicable framework for comparing valuation models in emerging markets with limited transaction data.

REFERENCES

1. Abidoye R. B., Chan A. P. C. Artificial neural network in property valuation: application framework and research trend // *Property Management*. – 2017. – Vol. 35, No. 5. – P. 554–571. – URL: <https://doi.org/10.1108/PM-06-2016-0027>.
2. Abidoye R. B., Chan A. P. C. Modelling property values in Nigeria using artificial neural network // *Journal of Property Research*. – 2017. – Vol. 34, No. 1. – P. 36–53. – URL: <https://doi.org/10.1080/09599916.2017.1286366>.
3. Antipov E. A., Pokryshevskaya E. B. Mass appraisal of residential apartments: an application of Random Forest for valuation and a CART-based approach for model diagnostics // *Expert Systems with Applications*. – 2012. – Vol. 39, No. 2. – P. 1772–1778. – URL: <https://doi.org/10.1016/j.eswa.2011.08.077>.
4. Breiman L. Random forests // *Machine Learning*. – 2001. – Vol. 45, No. 1. – P. 5–32. – URL: <https://doi.org/10.1023/A:1010933404324>.
5. Glumac B., Des Rosiers F. Practice briefing – Automated valuation models (AVMs): their role, their advantages and their limitations // *Journal of Property Investment & Finance*. – 2021. – Vol. 39, No. 5. – P. 481–491. – URL: <https://doi.org/10.1108/JPIF-07-2020-0086>.
6. Kok N., Koponen E.-L., Martínez-Barbosa C. A. Big data in real estate? From manual appraisal to automated valuation // *The Journal of Portfolio Management*. – 2017. – Vol. 43, No. 6. – P. 202–211. – URL: <https://doi.org/10.3905/jpm.2017.43.6.202>.
7. LeCun Y., Bengio Y., Hinton G. Deep learning // *Nature*. – 2015. – Vol. 521, No. 7553. – P. 436–444. – URL: <https://doi.org/10.1038/nature14539>.
8. Lockwood L. J., Rutherford R. C. Determinants of industrial property value // *Real Estate Economics*. – 1996. – Vol. 24, No. 2. – P. 257–272. – URL: <https://doi.org/10.1111/1540-6229.00690>.
9. Mayer M., Bourassa S. C., Hoesli M., Scognamiglio D. Estimation and updating methods for hedonic valuation // *Journal of European Real Estate Research*. – 2019. – Vol. 12, No. 1. – P. 134–150. – URL: <https://doi.org/10.1108/JERER-08-2018-0035>.
10. McCluskey W. J., McCord M., Davis P. T., Haran M., McIlhatton D. Prediction accuracy in mass appraisal: a comparison of modern approaches // *Journal of Property Research*. – 2013. – Vol. 30, No. 4. – P. 239–265. – URL: <https://doi.org/10.1080/09599916.2013.781204>.
11. Mullainathan S., Spiess J. Machine learning: an applied econometric approach // *Journal of Economic Perspectives*. – 2017. – Vol. 31, No. 2. – P. 87–106. – URL: <https://doi.org/10.1257/jep.31.2.87>.

12. Pagourtzi E., Assimakopoulos V., Hatzichristos T., French N. Real estate appraisal: a review of valuation methods // *Journal of Property Investment & Finance*. – 2003. – Vol. 21, No. 4. – P. 383–401. – URL: <https://doi.org/10.1108/14635780310483656>.
13. Rosen S. Hedonic prices and implicit markets: product differentiation in pure competition // *Journal of Political Economy*. – 1974. – Vol. 82, No. 1. – P. 34–55. – URL: <https://doi.org/10.1086/260169>.
14. Valier A. Who performs better? AVMs vs hedonic models // *Journal of Property Investment & Finance*. – 2020. – Vol. 38, No. 3. – P. 213–225. – URL: <https://doi.org/10.1108/JPIF-12-2019-0157>.

Proofreader: Zokir ALIBEKOV

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2026. № 9

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