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IDENTIFYING THE CURRENT STATUS OF REAL ESTATE APPRAISAL METHODS

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ABSTRACT

Real estate appraisal, also known as property valuation, plays a crucial role in numerous economic activities and financial decisions, such as taxation assessment, bank lending, and insurance, among others. However, the current methods used in real estate appraisal face several challenges related to fundamental aspects such as accuracy, interpretation, data availability, and evaluation metrics. Therefore, the purpose of this research is to identify the current status of real estate appraisal methods, highlighting challenges and providing guidance for scholars to undertake further research in addressing them. The methodology retrieves the most recent papers published in the Scopus database over the past five years, covering the period from 2019 to the end of 2023, with an emphasis on empirical studies. These retrieved papers serve as references to capture the current status of real estate appraisal methods. The research findings confirm a clear trend towards increased utilization of artificial intelligence techniques, especially machine learning, but with unfinished work regarding related challenges. Artificial intelligence techniques enhance the accuracy of real estate appraisal, paving the way for improved decision support systems in business, financial, and economic sectors.

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1. Introduction

This research intends to identify the current status of the real estate appraisal methods along with their fundamental aspects such as performance, interpretability, data availability, and evaluation metrics. Consequently, this paper contributes to providing guidance for scholars undertaking further research to address challenges within the real estate appraisal industry. The importance of real estate appraisal stems from its pivotal role in numerous critical financial decisions, including taxes, transactions, loans, mortgages, insurance, renting, construction, expropriation, settlement, renovation, division of assets, accounting, bank guarantees, auctions, property transfers, and the dissolution of partnerships (Parmar et al., 2018). Moreover, when real estate appraisal pertains to land valuation, it becomes a crucial component of the land administration system, alongside land tenure, land use, and land development (Tomić et al., 2021).

The term real estate appraisal refers to the process of determining a value to a property at a specific time for specific purposes, considering a complete understanding of the market in terms of demand and supply, legal impact, planning regime, physical constraints, economy, and all other influencing factors (also called variables, features, or attributes) (Shetty et al., 2020). The value itself is determined by the selling price it can bring (Parmar et al., 2018), taking into account that the value of a property can differ depending on the reason for the valuation, such as for selling and buying, taxation, mortgages, and similar purposes (Mankad, 2022). It can be challenging to distinguish between pricing and valuation as they both aim to determine the value of a property and establish its worth based on various factors that influence it (Alsawan & Alshurideh, 2023). Generally speaking, real estate appraisal methods range from

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traditional to model-based (Guliker et al., 2022). The traditional methods, often referred to as non-model methods, include comparative, cost, income, profit, and development (Gabrielli & French, 2021). In contrast, model-based methods are categorized based on their functional form.

This research is planned to be conducted by reviewing all the published papers in the field of real estate appraisal methods, particularly those published in the last five years within the Scopus database. The reviewed papers also need to include empirical studies for the proposed methods, where observation size, variables and metrics are incorporated. The target research papers are intended to be initially identified by running a code string with multiple combinations of keywords, enabling the retrieval of the most relevant ones. Subsequently, these identified papers undergo further screening to ensure they meet all the required specifications. Finally, the papers are summarized in a table that includes information such as the author, year, country of origin, method(s) used, sample size, and evaluation metrics. This facilitates the analysis of results and the derivation of conclusions.

As for the structure of the paper, it includes six sections: Section 1 contains what this research is all about, why this research is important and how it is conducted, in addition to its contribution and significance, along with the inclusion of important definitions. Section 2 explores all similarly published papers that aim to profile the real estate appraisal industry. Section 3 includes the methodology of the research. Section 4 summarizes all the retrieved papers that meet the specifications. Section 5 includes the analysis and discussion. Finally, Section 6 contains the conclusion.

2. Literature review

The literature includes several papers that aimed to explore trends, directions, and patterns in the real estate appraisal industry. Ja'afar et al. (2021) followed the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) techniques, as pointed out by Page et al. (2021), to conduct a systematic literature review on the usage of machine learning as a method for real estate appraisal. This approach includes four steps: identification, screening, eligibility and inclusion. The identification includes building a search code that can be performed in Scopus and Web of Science databases to retrieve all relevant research articles and conferences proceedings using appropriate keywords, published from 1999 to 2021 in English. The paper concluded that, among other machine learning methods, the random forest is the most successful method due to its compatibility with the data situation.

Similarly, Wang and Li (2019) conducted a systematic literature review to examine the papers published on mass appraisal models between 2000 and 2018. They specifically searched for English-language journal articles indexed in the Web of Science database. The findings revealed that there was an increasing interest in mass appraisal, as evidenced by the rise in related articles and citations. The authors categorized the models used in mass appraisal into three groups, namely the AI-Based Model, GIS-Based model, and MIX-Based Model, and referred to it as the 3I-trend classification. The AI-Based Model comprised several techniques such as Expert System and Decision Support System (ES), Artificial Neural Networks (ANN), tree-based Model, Hierarchical Model, Cluster Analysis, Rough Set Theory and Fuzzy Set Theory, Reasoning-Based Model, Genetic Algorithm, Support Vector Machine, Data Envelopment Analysis and Conformal Predictors. On the other hand, the GIS-Based Model involved methods such as Geographically Weighted Regression (GWR), Geographically Weighted Principal Component Analysis, the Spatial Error Model (SEM) and the Spatial Lag Model (SLM), and Location Value Response Surface. Finally, the MIX-Based Model combined both AI and GIS models.

In addition, Jayantha and Oladinrin (2019) carried out a bibliometric analysis of papers on hedonic price modeling (HPM) in real estate journals that were published in the Scopus database in English. They only included peer-reviewed articles in their search, using a specific set of keywords related to HPM, and looked at papers published between 1970 and 2019. The results of their study identified important authors, productive countries, and significant references in the HPM research field. They found that the application of HPM is widespread in advanced nations, suggesting a need for more research on this topic in developing nations.

In another literature review, Xu and Zhang (2021) examined studies that utilized machine learning methods for real estate appraisal across one hundred major cities during the period spanning 2010 to 2019. The authors categorized the studies based on themes, such as country of origin, purpose, focus, and accuracy. Several countries, including China, Singapore, the United States, the United Kingdom, Australia, Spain, Tanzania, Uganda, Iran, New Zealand,

Malawi, Turkey, Italy, Nigeria, Malaysia, Russia, and South Korea, have utilized machine learning techniques for house pricing. The purposes of these studies included property valuation and technical forecasting. The focus varied among the studies, including using a single machine learning method, combining methods, comparing with other machine learning techniques, or comparing with traditional methods. The authors grouped the studies based on their achieved accuracy, measured by mean absolute percentage error (MAPE). They found that the majority of studies came from China, with the purpose of technical valuation, focusing on a single machine learning technique, and with a MAPE accuracy ranging from 10% to 20%.

In the same context, Binoy et al. (2022) employed a comprehensive method for conducting bibliometric analysis in the field of real estate appraisal. They initiated the process by identifying relevant search keywords from existing literature on real estate appraisal. The search syntax was developed to exclusively target journal articles published in English before 2020 and was implemented using the user-friendly and comprehensive Scopus database. The retrieved articles were then screened and relevant ones were downloaded into BibTeX format and imported into the bibliometrix package in R for further analysis. The analysis covered various aspects such as publication trends, scientific production, journals, affiliations, citations, co-occurrence and co-citation networks. The detailed summary statistics revealed the top countries, authors, affiliations, and journals in terms of the number of articles, citations, and h-index. The study also identified the authors with the highest number of articles and citations and the top affiliations for collaboration. According to the study, the trend in publishing articles on property valuation has significantly increased since 2000 with more focus on modern techniques due to advancements in computational power and data availability (Rampini & Re Cecconi, 2022). The research primarily focused on property valuation for houses and apartments, with the majority of the studies being conducted in developed countries.

Finally, Dimopoulos and Bakas (2019) conducted a bibliometric study to examine the literature on mass valuation. They aimed to identify the main computational methods used, the connections between technical concepts in different papers, the leading authors and academic journals in the field, and how the field has developed over time. They analyzed 30 years' worth of research on mass valuation from the Scopus database, and found that the number of relevant research papers in scientific journals has not only increased, but has grown exponentially in recent years.

The Table 1 summarizes the abovementioned comprehensive literature review conducted in the field of real estate appraisal.

Table 1

The summery of the research papers that includes comprehensive literature review or bibliometric in the field of real estate appraisal

	Author and Date	Field	Database	Period
1.	Ja'afar et al. (2021)	Machine learning techniques in the field of real estate appraisal	Scopus and Web of Science	1999 - 2021
2.	Wang and Li (2019)	Mass appraisal models	Web of Science	2000 - 2018
3.	Jayantha and Oladinrin (2019)	Bibliometric analysis of papers on hedonic price modeling (HPM) in real estate journals	Scopus	1970 - 2019
4.	Xu and Zhang (2021)	Machine learning methods for property valuation	---	2010-2019
5.	Binoy et al. (2022b)	Property valuation	Scopus	before 2020
6.	Dimopoulos and Bakas (2019)	Mass valuation	Scopus	30 years

Source: own study.

3. Methodology

This paper intends to review research papers that aid in identifying the current status of real estate appraisal methods, with a focus on specific aspects such as performance, interpretability, data availability, and evaluation metrics. The process to retrieve the target papers consisted of three key stages: identification, screening, and analysis. In the identification stage, search queries were developed using relevant keywords and criteria, including time frame, language, and document type, to retrieve articles from a reliable database. In the screening stage, the title, abstract, conclusion, or full text of the retrieved articles were examined to ensure their relevancy to the topic of the research. During the analysis stage, the pertinent

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findings from the articles were synthesized and summarized to draw conclusions regarding the current status of real estate appraisal methods and their various aspects. In terms of the criteria set to retrieve target papers, the search is limited to the Scopus database, known for its comprehensiveness, ease of use and frequent use in locating relevant literature (Lazar & Chithra, 2021). Scopus also offers more extensive coverage of scientific publications compared to other research databases such as Google Scholar and Web of Science (Zhao et al., 2019). To avoid any difficulties or confusion arising from translation, the review is limited to English-language publications. The review focuses on publications from the past five years to emphasize the current status of real estate appraisal methods and their aspects. Recent research is more likely to be relevant to the present situation and can offer valuable insights (Xiao & Watson, 2019). This timeframe is likely sufficient to assess the current status and offer guidance for future studies. The review includes only peer-reviewed publications to ensure a high level of quality for the retrieved references. Moreover, the retrieved papers incorporate empirical experiments to enhance the likelihood of capturing significant information about the employed methods, including their fundamental aspects such as performance, interpretability, dataset size, and evaluation metrics. There is no geographic limitation on the area in which the empirical experiment was conducted. The criteria are demonstrated in Table 2.

Table 2
The criteria of the target papers published in the area of real estate appraisal methods

Criteria	Eligibility
Research type	Peer reviewed
Language	English
Timeline	Starting from 2019 till March 2023
Database	Scopus
Content	Empirical studies

Source: own study.

Practically, to retrieve all articles related to real estate appraisal methods in accordance with the set criteria, the search syntax needs to encompass synonyms, abbreviations, alternative spellings, and related terms (Rowley & Slack, 2004). In addition, different terminology for the topic needs to be incorporated in the search (Xiao & Watson, 2019). Therefore, for the current research, "real estate appraisal", "property valuation", and "house price prediction" are included in the searched keywords as they are the most commonly used terms that refer to the process of estimating the value of a property, whether it be land or improvements such as buildings or other structures. The search string also incorporates synonyms for appraisal, valuation, and prediction, such as forecasting and estimation, along with their combinations. Thus, the Boolean search syntax can be formulated as follows:

(TITLE-ABS-KEY ("property valuation" OR "property price appraisal" OR "property price estimation" OR "property price prediction" OR "property price forecasting" OR "property value prediction" OR "real estate appraisal" OR "real estate valuation" OR "real estate prediction" OR "real estate forecasting" OR "real estate estimation" OR "real estate value" OR "real estate price" OR "real estate pricing" OR "house price estimation" OR "house price appraisal" OR "house price valuation" OR "house price forecasting" OR "house price prediction" OR "house price assessment" OR "Housing price" OR "house pricing" OR "Housing prices" OR "property mass valuation" OR "mass property valuation" OR "mass appraisal" OR "automated valuation method")) AND (TITLE-ABS-KEY("Artificial Intelligence" OR "machine learning" OR "Deep learning" OR "linear regression" OR "Hedonic price method")) AND (LIMIT-TO (SRCTYPE,"j") OR LIMIT-TO (SRCTYPE,"p")) AND (LIMIT-TO (DOCTYPE,"ar") OR LIMIT-TO (DOCTYPE,"cp")) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO (PUBYEAR,2019) OR LIMIT-TO (PUBYEAR,2020) OR LIMIT-TO (PUBYEAR,2021) OR LIMIT-TO (PUBYEAR,2022) OR LIMIT-TO (PUBYEAR,2023) OR LIMIT-TO (PUBYEAR,2024))

Figure 1 illustrates the process of identifying research papers on real estate appraisal methods. The method involves establishing criteria, such as publication within the last five years, being in English, indexed in Scopus, and having been peer-reviewed. A code syntax aligned with Scopus requirements is created to identify papers meeting these criteria. The code is then executed in the Scopus database, where the retrieved papers are reviewed and analyzed.

4. Data

During October 2023, a search was performed in the Scopus database using a syntax that fulfilled the entire set of criteria. The search yielded a total of 436 articles. These articles were further screened by reading their titles, abstracts, and body content to establish their pertinence to the research topic and the set of criteria. The screening resulted in 62 papers that were deemed relevant and have been listed in

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Table 3. The table includes the author's name and the date of publication (Column 1), the country of origin (Column 2), the applied method (Column 3), the sample size used (Column 4), and the evaluation metrics employed (Column 5).

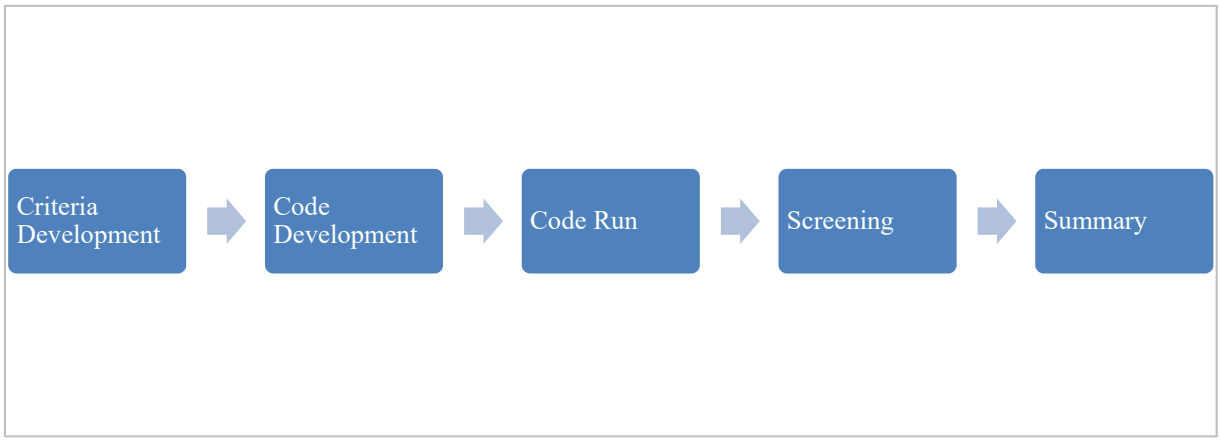

Fig. 1. The approach implemented to identify research papers related to real estate appraisal methods. *Source:* own study.

Table 3

The list of papers that meet the systematic literature review as per the identified criteria

	1 Author and Date	2 Country	3 Method	4 Dataset size	5 Evaluation Metrics
1.	Teoh et al. (2023)	United States Australia	LR, RF	Two datasets from different countries: 2,930 (United States) 34,857 (Australia)	RMSE, R^2
2.	Hjort et al. (2023)	Norway	GAM, GBM, LitBoost	14,382	---
3.	Krämer et al. (2023)	Germany	LR, GAM, XGBoost, ANN	1,200,000	MAPE, MdAPE, PE
4.	Zhan et al. (2023)	Hong Kong	HBO, HBOS, HBOB, HBOT	1,898,175	MSE, RMSE, MAE, R^2, MAD, MAPE, R^2 adj, RMSLE, EVS, ME, MPD, MGD, PL
5.	Lee et al. (2023)	Australia	CNN	42,335	R^2, MAPE, PPE, COD, PRD
6.	Shi et al. (2023)	China	LR, FR, DT, ARMA, LSTM, GRU, Transformer	20,843	MAE, MAPE, RMSE
7.	Zhang et al. (2023)	Canada	GBM, SVM, RF, ANN	10,418	RMSE, R^2
8.	Zaki et al. (2022)	United States	HPM, XGBoost	506	MAE, MSE
9.	Gao et al. (2022)	Australia	GWR, LR, Lasso, Ridge, ElasticNet, DT, RF, GBM, XGBoost, ANN	Two datasets of different types: 44,128 (Houses) 19,298 (Apartment)	R^2, MAPE, MdAPE
10.	Alzain et al. (2022)	Saudi Arabia	ANN	Multiple datasets from different cities: 959 (Riyadh) 430 (Jeddah) 656 (Dammam) 1,673 (Al-Khobar)	MSE, RMSE, NRMSE, R^2
11.	Soltani et al. (2022)	Australia	LR, DT, FT, GBM	428,000 residential	R^2, MAE, RMSE
12.	Louati et al. (2022)	Saudi Arabia	DT, RT, LR	21,591	MAE, MSE, MdSE
13.	Iban (2022)	Turkey	RF, GBM, XGBoost, LightGBM, LR	1,002	R^2, MAE, RMSE, COD, PRD
14.	Wang et al. (2022)	China	GNNWR, GWR, LR	2,871	R^2, MAPE, MAE, RMSE

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15.	Mayer et al. (2022)	United States Switzerland	LR, XGBoost, XGBoost STAR, LR XGBoot, ANN STAR, mboost STAR, LightGBM, LightGBM STAR, QR with LightGBM	Two datasets from different countries: 13,932 (United States) 67,000 (Switzerland)	MAE, RMSE
16.	Lee (2022a)	South Korea	ANN	Two datasets of different types: 29,032 (land) 22,227 (houses)	RMSE
17.	Lee (2022b)	South Korea	ANN	Two datasets from different cities: 22,213 (Seoul) 22,106 (Jeollanam)	RMSE, MAPE
18.	Guliker et al. (2022)	Netherlands	LR, GWR, MGWR, XGBoost	Multiple datasets from different cities: 1,494 (Amersfoort) 5,084 (Amsterdam) 1,845 (Eindhoven) 1,160 (Groningen) 3,011 (Rotterdam)	R^2, MAE, RMSE
19.	Foryś (2022)	Poland	LR, ANN	299	R^2
20.	Binoy et al. (2022)	India	HPM, GWR	837	R^2, MAE, RMSE, AIC, SE
21.	Museleku (2022)	Kenya	HPM	264	R^2, MAPE, PRD
22.	Fu (2022)	China	ANN	10	R^2, MAE, RMSE
23.	Chongwilaikasaem & Chalermyanont (2022)	Thailand	HPM	380	---
24.	Lee (2022a)	South Korea	ANN	Two datasets of different types: 29,032 (Land) 22,227 (Houses)	RMSE
25.	Przekop (2022)	Poland	LR, SDM, SDEM, SAC, GNS, ANN	18,166	RMSE, MAPE
26.	Hurley & Sweeney (2022)	Ireland	GAM	5,208	R^2, RMSE
27.	Deaconu et al. (2022)	Romania	GLM, ANN	900	R^2, RMSE, RMSPE, MSE
28.	Mankad (2022)	India	LR, ANN	360	RMSE, MAPE
29.	Hjort et al. (2022)	Norway	LR, KNN, RF, XGBoost	126,719	R^2, RMSE, MdE, 10% measure, 20% measure
30.	Rampini & Re Cecconi (2022)	Italy	ElasticNet, XGBoost, ANN	1,203	MAE
31.	Steurer et al. (2021)	Austria	LR, RF, MARS, LASSO, ANN	10,797	48 metrics *Refer to the paper
32.	Luo et al. (2021)	China	HPM, LR	51,395	----
33.	Hernández & Rosales (2021)	Chile	Ensemble Algorithms	228	MAE, RMSE
34.	Xu & Zhang (2021)	China	ANN	---	rRMSE
35.	Rico-Juan & Taltavull de La Paz (2021)	Spain	RF, HPM	56,000	R^2, RMSE, %RMSE, MAE, %MAE, P
36.	Terregrossa & Ibadi (2021)	Turkey	LR, ANN, Combined	100	MAE
37.	Stanišić et al. (2021)	Serbia	BHPM, LR, GBM, RF, XGBoost	12,904	R^2, RMSE, MAE, MAPE
38.	Horvath et al. (2021)	China	HPM, SVM, ANN, SNN	Multiple datasets from different cities: 1,119 (Beijing) 3,430 (Shanghai) 2,604 (Guangzhou)	R^2, RMSE

				2,67 (Shenzhen) 4,796 (Changsha)	
39.	Sa'at et al. (2021)	Malaysia	HPM, ANN	3,732	MAE, RMSE
40.	Marzagão et al. (2021)	Brazil	LR, SVM, ANN, BT, RF	15,627	MdAE
41.	Yasnitsky et al. (2021)	Russia	ANN	---	---
42.	Ho et al. (2021)	Hong Kong	SVM, RF, GBM	40,000	MSE, RMSE, MAPE
43.	Gnat (2021)	Poland	KNN, XGBoost, LR	1,000	rRMSE
44.	Kalliola et al. (2021)	Finland	ANN	4,041	R^2, MAE, RMSE, MSE,
45.	Lin et al. (2021)	China	LR, KNN, GBM,	120,403	R^2, RMPSE,
46.	Pai & Wang (2020)	Taiwan	LSSVR, CART, GRNN, BPNN	32,215	MAPE, NMAE
47.	Bogin & Shui (2020)	USA	LR, RF	420,3709	R^2, RMSE
48.	Shetty et al. (2020)	India	LR, CM, IM, SCM, DEM	20	Variation
49.	Štubňová et al. (2020)	Slovak Republic	HPM, ANN	256	R^2, MAPE, MAE, RMSE
50.	Hong et al. (2020)	South Korea	HPM, RF	16,061	R^2, MAPE, COD
51.	Kang et al. (2020)	South Korea	LR, ANN, GA	*Refer to the paper	MAPE, RMSE
52.	Gnat & Doszyn (2020)	Poland	LR, RR, RF, KNN	318	R^2, MAPE, MPE
53.	Yacim & Boshoff (2020)	Turkey	LR, SEM, SLM, GWR, NNSVMs,	3,225	MAE, RMSE, AICE, PRD, COD
54.	Yildirim (2019)	Turkey	LR, KNN, ANN	3,114	R^2, RMSE, MAE
55.	Huang (2019)	USA	LR, DT, GBM, RF, SVM	89,412	MSE
56.	Rahman et al. (2019)	Malaysia	ANN	640	R^2, RMSE, MAD, MAPE
57.	Niu & Niu (2019)	China	RS, GBM, RF, BP NN, FM	44,113	MAPE, RMSE
58.	Y. Zhao et al. (2019)	Australia	XGBoost, KNN, ANN	186	MAE, MAPE
59.	Dimopoulos & Bakas (2019)	Cyprus	RF, GB, LR, NLR	3,561	ρ, MAE, APE, RMSE, MAXAPE, COD
60.	Bidanset et al. (2019)	Australia	Modified GWR	511	R^2
61.	Lisi (2019)	Italy	SCA, LR	546	---
62.	Koktashev et al. (2019)	Russia	RR, RF, LR	1,970	MAE, RMSE, MAPE

CNN: Convolutional Neural Network, GWR: Geographically Weighted Regression, Lasso: Least Absolute Shrinkage and Selection Operator, DT: Decision Tree, RF: Random Forest, GBM: Gradient Boosting Machine, XGBoost: Extreme Gradient Boosting, STAR: Structured Additive Regression, QR: Quantile Regression, GNNWR: Geographically Neural Network Weighted Regression, GWR: Geographically Weighted Regression, MGWR: Multi-Scale Geographically Weighted Regression, HPM Hedonic Pricing Model, SDEM: Spatial Durbin Error Model, GNS: General Nesting Spatial Model, SAR: Spatial Autoregressive Model, SDM: Spatial Durbin Model, SAC: Spatial Autoregressive Model With Autoregressive Disturbances, GAM: General Additive Model, SNN: Spatial Neural Network, SVM: Support Vector Machines, LR: Linear Regression, BT: Boosted Tree, VAE: variational autoencoder, CM: Cost Method, IC: Income Method, SCM: Sale Comparison Method, DE: Detailed Estimation Method, GBDT: Gradient Boosting Decision Tree, BP NN: Back Propagation neural network, FM: Fusion Model, KNN: K-Nearest Neighbor, NLR: Non-Linear Regression, SCA: Sale Comparison Analysis, RR: Ridge Regression model, BHRM: Bayesian hedonic regression model, LSSVR: Least Squares Support Vector Regression, CART: Classification And Regression Tree, GRNN: General Regression Neural Networks, BPNN: Backpropagation Neural Networks, SEM: spatial error model, SLM: spatial lag model, NNSVMs: neural networks support vector machines, ARMA: Autoregressive Moving Average, LSTM: Long short-term memory, MARS: Multivariate Adaptive Regression Splines, GRU: Gated Recurrent Unit, HBO: Hybrid Bayesian Optimization, HBOS: models combined with Stacking, HBOB: Hybrid Bayesian Optimization combined with Bagging, and HBOT: Hybrid Bayesian Optimization combined with Transformer.

SEE: Standard Error of the Estimate, MAE: Mean Absolute Error, MSE: Mean Square Error, MAPE: Mean Absolute Percentage Error, RMSE: Root Mean Square Error, AIC: Akaike Information Criterion, PRD: Price-Related Differential, COD: Coefficient of Dispersion, MAXAPE: Maximum Absolute Percentage Error, ρ: Pearson Correlation Coefficient, MPE: Mean Percentage Error, RMPSE: Root Mean Square Percentage Error, rRMSE: relative Root Mean Square Error, RMSPE: Root Mean Square Percentage Error, MAD: Mean Absolute Deviation, NMAE: Normalized Mean Absolute Error, P: the degree of model's explanatory accuracy, NRMSE: Normalized Root-Mean-Squared Error, RME: Relative Mean Error, PPE: Percent Predicted Error, MdSE: Median Squared Error, RMSLE Root Mean Square Logarithmic Error, EVS Explained Variance Score, ME: Max Error, MPD: Mean Poisson Deviance, MGD: Mean Gamma Deviance, PL: Pinball loss, PE: Error Bucket.

Source: own study.

5. Analysis

Table 3 serves as a storyteller, offering a clear depiction of the current status of real estate appraisal methods along with their fundamental aspects. The analysis sheds light on the widely used methods and related challenges in the last five years, exploring basic aspects, such as performance, interpretability, data availability and evaluation metrics, as elaborated in the following sections.

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5.1. Methods applied for real estate appraisal

Upon reviewing the content of the papers listed in Table 3, real estate appraisal methods can be categorized into two primary groups: non-model-based and model-based approaches. Non-model-based methods, which are not explored in this research and are often referred to as manual methods, encompass techniques like comparative, cost, income, profit, and development (Gabrielli & French, 2021). Model-based methods are further divided into two subcategories: functional form-based models and non-functional form models.

Functional form-based models primarily include linear regression (LR) and Geographically Weighted Regression (GWR). Non-functional form models are subdivided into machine learning and deep learning techniques. Machine learning comprises tree-based models like decision trees (DT), random forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost), as well as methods like K-nearest neighbor (KNN) and support vector machine (SVM). Deep learning encompasses artificial neural networks (ANN). The organizational structure of real estate appraisal methods is depicted in Fig. ***2*** in the form of an organizational flowchart.

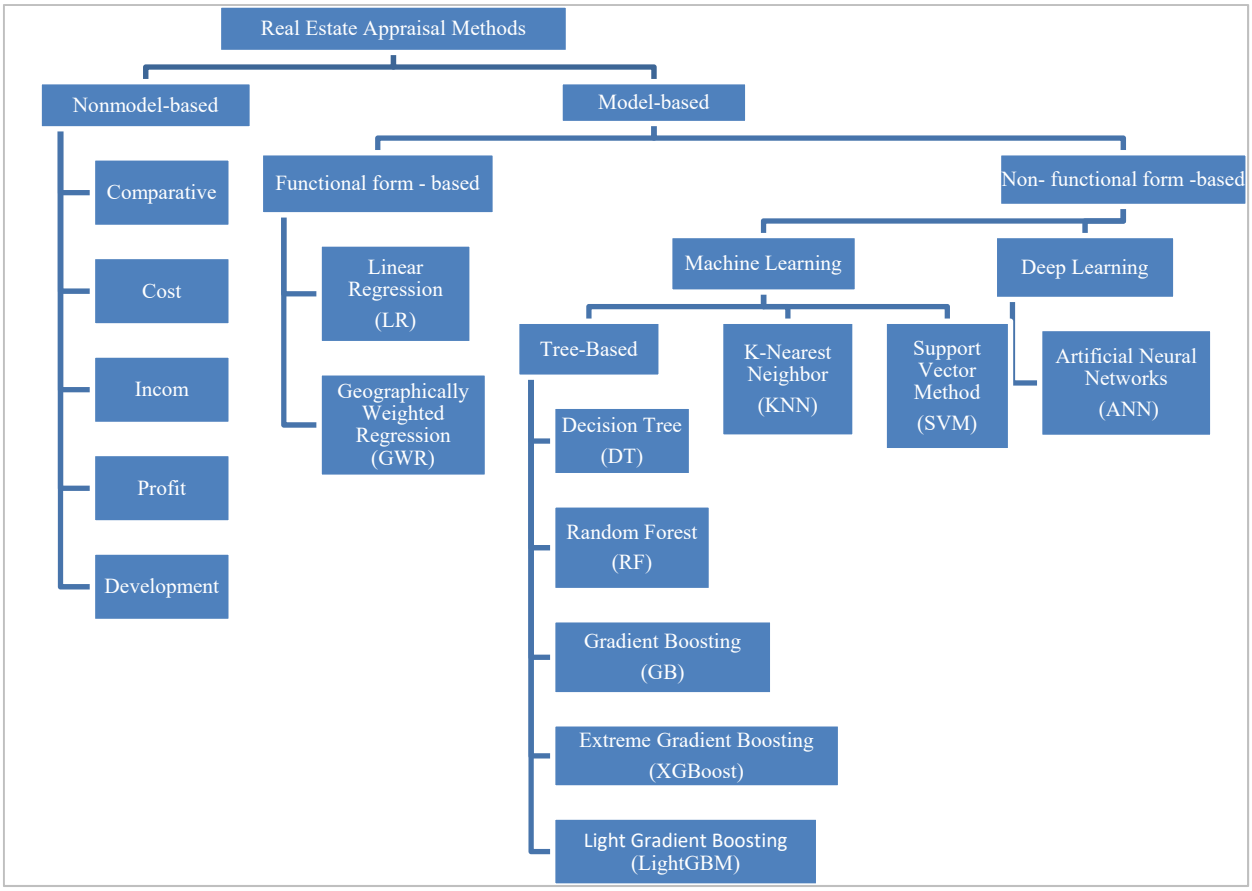

Fig. 2. The organizational flowchart of real estate appraisal methods implemented in the identified papers. *Source*: own study.

In the following sections, a comprehensive discussion is conducted on the most employed methods over the past five years to better understand their current status, along with the related daunting challenges. This sheds light on the necessity for further research and potential improvements whenever possible.

5.1.1. LR

LR follows the Hedonic Pricing Method (HPM), initially proposed by Lancaster (1966) and later applied to property valuation by Rosen (1974). LR constructs the relationship between the dependent variable and independent variables in a linear form, capturing the direction and magnitude of influence of each independent variable. The coefficients of the independent variables are determined based on one of the regression techniques, such as Ordinary Least Squares (OLS), which minimizes the difference between the actual and predicted values of the dependent variable.

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Column 3 in Table 3 clearly demonstrates that LR is still widely used, considered as a baseline for all other methods due to its ability to interpret the results of real estate appraisal. However, this approach is criticized for its linearity and stationarity, which limits its ability to capture nonlinearity and nonstationarity in the relationship between the dependent variable and independent variables.

5.1.2. GWR

The Geographically Weighted Regression (GWR) constructs a linear prediction equation for each observation in the dataset based on neighboring observations within a specified bandwidth. GWR provides a solution to address the stationarity issue.

The third column of Table 3 suggests that several studies consider GWR or one of its versions, such as Geographically and Temporally Weighted Regression (GTWR) and Geographically Neural Network Weighted Regression (GNNWR), to address the stationarity issue. However, the determination of optimal bandwidth, kernel function and its linearity aspect remains a subject of focus.

5.1.3. Tree-based models (Ensemble models)

The tree-based methods, also known as ensemble methods, involve splitting the data into branches based on the values of one of the independent variables, and end up with leaves. This process is optimized by selecting the best data splitting that minimize the variance which is the sum of the squares of the difference between the observed value and the mean in the two branches (Breiman et al., 2017).

Column 3 in Table 3 clearly includes several studies that used tree-based models such as DT, RF, GBM, AdaBoostXGBoost) and LightGBM. While these methods are considered as artificial intelligence based techniques and thus address the nonlinearity issue of the data, they fail to produce interpretable results.

5.1.4. K-Nearest Neighbor (KNN)

The K-Nearest Neighbor (KNN) is a non-parametric supervised learning method that predicts the output value by averaging the values of a specific number of surrounding similar observations (García-Magariño et al., 2020). The key step in the KNN algorithm is the definition of similarity between objects using the Euclidean distance.

The KNN algorithm has several strengths, such as its ability to handle nonlinear relationships and its requirement of minimal assumptions about the data distribution. However, it also has several limitations. One major limitation is that it can be computationally expensive, particularly when working with large datasets. Additionally, KNN is sensitive to outliers and irrelevant observations, and may perform poorly if there is a lack of sufficient data or diversity in the data. The choice of the distance metric, scale of variables, and the presence of categorical variables can also affect the performance of the KNN algorithm in real estate prediction (García-Magariño et al., 2020).

5.1.5. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is found to be used in scenarios where the dataset exhibits a high dimensionality, especially when data transformation to a higher-dimensional space is necessary. It proves to be particularly effective when dealing with semi-structured or unstructured data and when there is an inadequate dataset available for knowledge acquisition. Nonetheless, SVM faces challenges in optimizing its hyperparameters, including the choice of kernel function, regularization, and margins. Furthermore, it is computationally intensive and less suitable for handling highly correlated variables.

5.1.6. The Artificial Neural Network (ANN)

The Artificial Neural Network (ANN), firstly introduced by Borst (1991) in the area of property valuation, is gaining popularity because of its effectiveness and ease of implementation, but with significant computational difficulties (Rampini & Re Cecconi, 2022). There is still uncertainty about the appropriate number of data samples required for an effective real estate valuation using ANNs, and it is unclear if there is a specific criterion for this (Horvath et al., 2021). The main advantage of ANN is their ability to incorporate uncertainty in the variables of the predictive model, while also improving accuracy and reducing computation time. The primary challenge associated with the utilization of ANNs is the impact that differences in the architecture of the ANN model can have on the results (Renigier-Biłozor et al., 2022). ANNs operate as a "black box" system (Yacim & Boshoff, 2020), meaning that they do not provide a clear explanation of how the output values were generated. This lack of transparency makes ANNs challenging to use in certain applications, such as property taxation and expropriation, where the valuations may be questioned and need to be defended in a court of law.

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5.2. Performance

The papers listed in Table 3 tend to measure performance, which, in this context, pertains to accuracy, using two primary methods. The first method involves the utilization of evaluation metrics, while the second entails comparing the outcomes of the implemented method with the results obtained from other methods. This represents the prevailing approach for assessing the performance of a specific method.

There is no consensus regarding which method achieves the highest level of performance, as performance itself is influenced by numerous factors. Factors such as the included variables, sample size, hyperparameter settings, and other considerations all play a significant role in determining the level of performance attained.

5.3. Interpretability

The interpretability remains the main challenge for the use of artificial intelligence (AI) techniques, such as machine learning and deep learning, in the real estate appraisal sector (Lee, 2022b). Several studies have attempted to address the issue of interpretability, as certain industries consider it to be a fundamental component of their business requirements, such as tax assessment. Lee (2022b) conducted research aimed at reducing the black box nature of the ANN model. Interpretability tools consist of both model-specific and model-agnostic tools, with the latter including Permutation Feature Importance (PFI), which encompasses Shapley additive explanations (SHAP) as well as example-based explanations, such as counterfactual explanations and adversarial examples. Feature importance visualization, such as the Partial Dependence Plot (PDP), is also a model-agnostic tool. Likewise, Iban (2022) implemented the PFI method to explain the tree-based ML regressor, namely RF, GB, XGBoost, and LightGBM. The PFI is used to detect the most important factors in determining property valuation. Kucklick and Müller (2023) discussed the issue of the intransparent mechanic of decision making in the property valuation domain, particularly where the justification of the decision is necessary.

The inclusion of the imageries in the prediction process assist in capturing implicit information related to properties that are otherwise hidden. In addition to PFI, PDP, and SHAP, the Grad Regression Activation Maps (Grad-Ram) and Image Principal Component Analysis (Image-PCA) are suggested when working with imageries. Mayer et al. (2022) suggests the Structured Additive Regression (STAR) models, which include the generalized linear model (GLM) and the generalized additive model (GAM) in order to resolve the issue of interpretability of the XGBoost and LightGBM. Figure 3 provides a visual representation of the interpretability techniques utilized in real estate appraisal methods.

5.4. Data availability

The fourth column of Table 3 clearly indicates varying dataset sizes in real estate appraisal methods. This raises questions about measuring the impact of dataset size on result accuracy on one hand and the representativeness of the data on the other.

The reviewed papers illustrated that real estate data accessibility is more prevalent in developed countries, whereas limited access is observed in developing countries. The articles also indicated an increased use of unstructured data, which necessitates more advanced techniques to capture information accurately

5.5. Evaluation Metrics

The fifth column in Table 3 clearly shows that the most commonly utilized metrics to assess the performance of property valuation models are Root Mean Square Error (RMSE), Coefficient of Determination (R2), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE). The evaluation metrics are illustrated in Figure 4.

Evidently, comparing real estate appraisal methods across various research papers becomes challenging when different evaluation metrics are employed. It is crucial to establish consensus on a set of minimum evaluation metrics to simplify comparisons and draw meaningful conclusions. The selection of a metric for model evaluation is a pivotal decision. Steurer et al. (2021) conducted a study where they assessed 48 metrics for 5 models, revealing that each model demonstrated superior performance in at least one metric compared to others.

In parallel to this, an ongoing debate revolves around determining the optimal strategy for data split techniques, which directly influences the calculated metrics. Typically, raw data is partitioned into training and testing datasets, with the training set further divided using k-fold cross-validation, as implemented by Wang et al. (2022). This approach entails evaluating the model twice – during training and post-training – necessitating yet another decision on the choice of metric that ultimately guides the final decision-making process. Another aspect related to metrics that is

being discussed in the context of real estate appraisal is estimating the uncertainty when measuring the accuracy of predictions. In this regard, Pollestad et al. (2024) proposed a framework to quantify the uncertainty in model predictions to enhance reliability, ensuring that informed decisions are made.

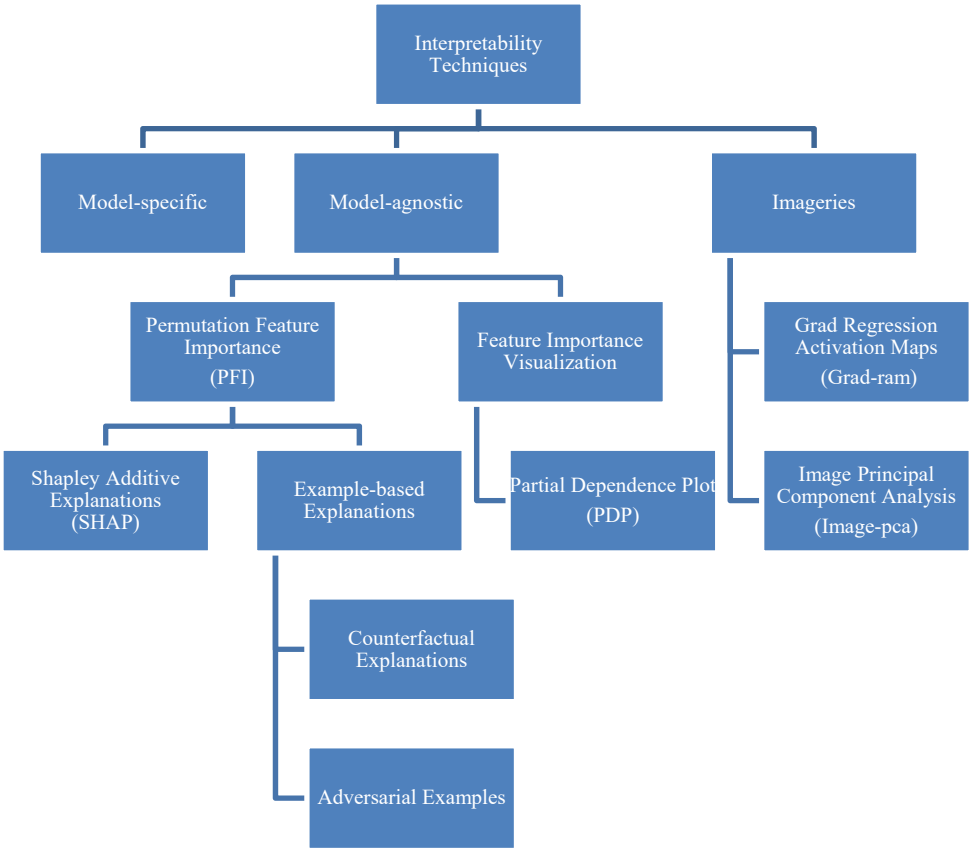

Fig. 3. Interpretability methods for the machine learning models in the field of real estate appraisal. *Source*: own study.

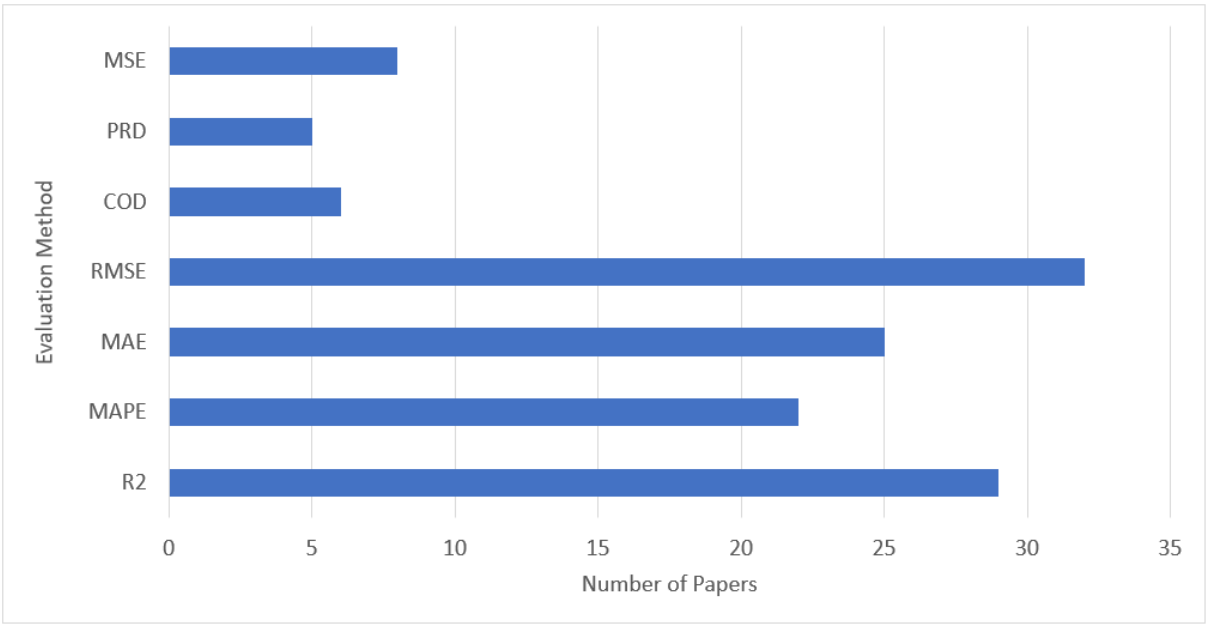

Fig. 4. Most common metrics for evaluating real estate appraisal models. *Source*: own study.

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5.6. Other relevant topics

The research papers listed in Table 3 include insights into automated valuation methods (AVMs), mass valuation techniques, and the application of Building Information Systems (BIM) and Three-Dimensional (3D) data, as elaborated in the following sections.

5.6.1. Automated Valuation Methods (AVMs)

There is an increasing need for Automated Valuation Methods (AVMs) that use AI, driven by the rapid growth of the real estate industry and other related economic activities. A significant distinction between manual property valuations and automated systems is that manual valuations involve physical inspections of the property and its surroundings by human valuers.

Hjort et al. (2022) stated that property valuation plays a critical role in modern economies, particularly in countries where homeownership rates are high and the majority of homeowners rely on mortgages to purchase property. Therefore, the machine learning-based AVMs are expected to become increasingly prevalent in the near future as they are a necessary component for credit institutions to have. Banks typically use dwellings as collateral for mortgages, making it essential for them to regularly evaluate the value of properties for risk management reasons. AVMs are commonly used to update the estimated value of the property on a quarterly basis.

5.6.2. Mass valuation

According to a recent analysis of research on property valuation, a number of studies in the real estate field are prioritizing mass appraisals over advancing current valuation methods (Dimopoulos & Bakas, 2019). Properties can be valuated either individually or through a mass appraisal process. Individual valuation involves assessing one property at a time, which is typically done by a valuer. On the other hand, mass appraisal involves valuing many properties simultaneously, usually through an algorithm. Both methods have their advantages and disadvantages. Individual valuation allows the appraiser to consider all unique features of the property, resulting in a more accurate valuation. However, this approach can be time-consuming and limits the number of properties that can be valued in a given time frame. Mass valuation, on the other hand, enables the valuation of numerous properties in a relatively short amount of time. Nevertheless, it requires a representative set of previously valued properties (which were valued individually) to estimate the value of the properties.

Wang and Li (2019) classified the mass property valuation models into three groups: machine learning-based models, GIS-based models, and mixed models. As a result, they believe that the integration of the existing data resources with GIS software and machine learning is the key to predicting mass valuation trends in the future. Nevertheless, the use of mass valuations has faced significant criticism for its lack of transparency and high levels of critical errors (Rico-Juan & Taltavull de La Paz, 2021).

5.6.3. Building Information System (BIM) and Three-Dimensional (3D) data

Several studies have explored the potential use of Building Information Modeling (BIM) and Three-Dimensional (3D) data in property valuation. With the BIM and 3D, data for the incorporated variables can be captured directly. However, the integration of 3D variables into the property valuation process is still limited.

6. Conclusion

This research serves as a review of the current status of real estate appraisal methods, outlining challenges in various aspects, such as performance, interpretability, data availability and evaluation metrics. Identifying the present status of real estate appraisal methods and their key aspects provides guidance for researchers to consider in future studies.

Initially, 436 research papers within the real estate appraisal field, including empirical studies from the past five years, were identified. Following a meticulous examination of titles, abstracts, keywords, content and conclusions, this number was refined to 61 papers. The reviewed papers confirm that each real estate appraisal method has its strengths and weaknesses, and thus, there is no consensus regarding which method to use. However, the third column in Table 3 clearly shows that AI-based methods are the most commonly used.

In terms of performance, the third column of Table 3 profiles a wide range of real estate appraisal methods, clearly illustrating the extensive efforts made to enhance accuracy in real estate appraisal. While traditional methods such as linear regression remain a baseline for other approaches, artificial intelligence techniques are the most frequently employed methods, achieving a higher level of accuracy.

Regarding interpretability, despite the high accuracy level of AI models, they are still deemed as black boxes due to their failure to explain results, especially in cases where justification for decision-

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making is necessary. The reviewed papers suggest ongoing efforts to address this challenge through the proposal of explainable artificial intelligence (XAI). For instance, tree-based machine learning models employ feature importance techniques to elucidate their output. These papers confirm that the accuracy achieved by AI models necessitates considering the interpretability-accuracy trade-off to leverage their advantages. Nevertheless, there remains a significant need for sophisticated techniques to comprehensively interpret the results of AI techniques, highlighting the requirement for substantial efforts in this area.

With respect to the evaluation metrics for real estate appraisal methods, there is no consensus among the retrieved papers on which specific metrics need to be used for the evaluation. This lack of agreement on standard evaluation metrics minimizes the chance to compare the performance of the methods applied in the studies; however, R^2, MAE, MAPE and RMSE remain the most predominant evaluation metrics conducted. In the same context, most of the retrieved papers compare the suggested method for real estate appraisals with other methods in order to identify the level of superiority of the suggested method compared to others and then judge its relative performance. This might highlight the need to standardize the description of results obtained by the metrics to provide a meaningful assessment of the accuracy level of the appraisal methods.

Pertaining to data availability in the field of real estate appraisal, the reviewed papers highlighted a notable increase in accessible and downloadable datasets, especially in economically developed nations. However, the persistent issue of limited data access in developing countries continues to pose a barrier to the widespread adoption of new techniques in real estate appraisal. Moreover, the papers did not provide guidance on determining the appropriate size of datasets for specific methods, which is crucial for their effective implementation. For example, Mankad (2022) recommends incorporating huge datasets as a viable option to enhance the results. In the same context, there was a significant focus on leveraging unstructured data, such as textual content from websites and imagery, to analyze their content for real estate appraisal purposes. For instance, Zhang et al. (2023) employed textual description data to conduct real estate appraisal, achieving satisfactory accuracy. In return, the review pointed out the lack of research papers that indicate how the dataset size affects the accuracy with the absence of criteria on how to measure the representativeness of the dataset. This is also correct when it comes to determining which mandatory variables are required to be incorporated in the dataset in order to ensure better results.

The identification of the current status of real estate appraisal is based on the papers retrieved from the Scopus database, leaving relevant papers available in other databases unexplored. However, this research provides an integrated study on the current status of real estate appraisal methods with particular attention to their performance, interpretability, data availability, and evaluation metrics. This can be viewed as a roadmap for future research aimed at addressing the challenges related to the methods and their aspects. Resolving challenges in real estate appraisal holds significant implications for decision-making processes, encompassing financial, economic, and business considerations.

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