Malgorzata RENIGIER-BILOZOR • Peter ACHE •
Thomas DIMOPOULOS • Artur JANOWSKI

THE FUTURE OF PROPERTY VALUATION: AVMs AND CAMAs IN THE ERA OF AI

Malgorzata RENIGIER-BILOZOR (ORCID: 0000-0002-4630-7564) – Faculty of Geoengineering, University of Warmia and Mazury in Olsztyn

Peter ACHE (ORCID: 0009-0008-6978-3409) – International Federation of Surveyors, Chair of the Commission 9 „Valuation and the Management of Real Estate"

Thomas DIMOPOULOS (ORCID: 0000-0001-9553-4774) – Neapolis University Pafos

Artur JANOWSKI (ORCID: 0000-0002-5535-408X) – Faculty of Geoengineering, University of Warmia and Mazury in Olsztyn

Correspondence address:
Prawocheńskiego Street 15, 10-720 Olsztyn, Poland
e-mail: malgorzata.renigier@uwm.edu.pl

ABSTRACT: The authors analyse Automated Valuation Models (AVMs) integrated with artificial intelligence (AI), positioning them as pivotal in creating a fair, sustainable, and interconnected urban real estate sector. As urbanisation advances, AVMs powered by AI are increasingly central to property valuation, offering data-driven insights that transform traditional appraisal methods. Unlike conventional inspections, AI-enabled AVMs process large datasets for property value estimation, aligning them with urban planning needs. This study highlights AVMs' potential to advance urban real estate practices while addressing challenges in ethics, transparency, and governance. By focusing on the synergy between technology and valuation, AVMs emerge as key in developing adaptive urban planning. Additionally, the paper proposes an ethical framework for AI use in urban contexts, ensuring alignment with professional standards and public trust, serving as a roadmap for practitioners and policymakers in integrating AI responsibly into urban property valuation.

KEYWORDS: AVM and AI integration, transparency frameworks, behavioural factors and limitations, urban property valuation, mass appraisals

Introduction

Automation in real estate valuation has origins that trace back to the 1950s (Dimopoulos & Bakas, 2019b; Glumac & Rosiers, 2021), while it started to become more popular in the 1980s (Gwartney, 1970; Carbone & Longini, 1977). The most common forms of automated solutions are Automated Valuation Models (AVMs) and Computer Assisted Mass Appraisals (CAMAs). AVMs are primarily employed to provide quick and efficient estimations of individual property values, often utilised by financial institutions for mortgage approvals and refinancing purposes. These models rely heavily on statistical analysis and often utilise a large database of property transactions to generate property value estimates. On the other hand, CAMAs are used by local government agencies for property tax assessment, focusing on a broad range of properties at once. CAMAs integrate property-specific data, owner information, and usage statistics to assist in the systematic appraisal of property values across a region, ensuring consistency and fairness in tax assessment.

Despite AVMs (and CAMAs) existing in harmony with traditional valuation methods throughout the years, recently there has been an increased discussion surrounding them that can be attributed to several key factors (Dimopoulos, 2020; Dimopoulos et al, 2014; Dimopoulos et al., 2019a; Lee et al., 2024; Ecker et al., 2020), as shown in Figure 1.

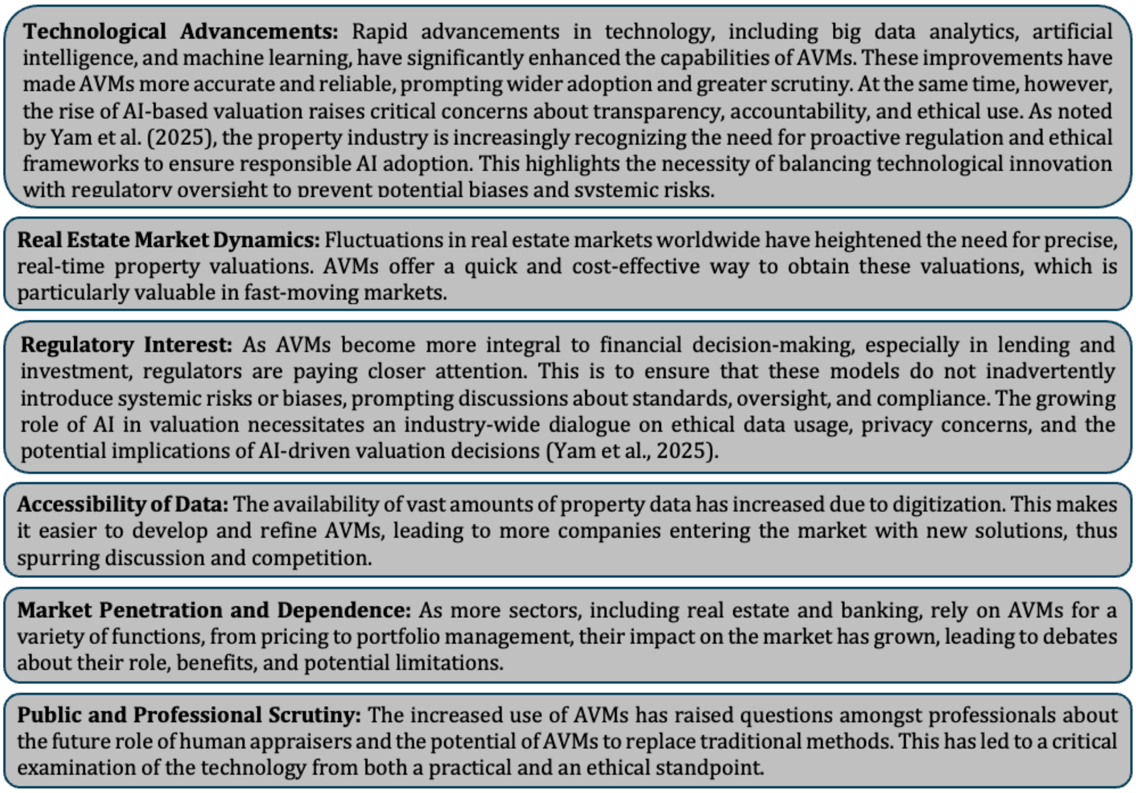

Figure 1. Key factors shaping the AVM and CAMA discourse

Above all, however, it can be noted that there are extensive concerns that seem to be less rational and more emotional, as the successful utilisation of AVM technologies has enhanced land markets and land administration in many advanced economies. Possibly the fear of too great and disruptive changes has priority here. On the other hand, the vast expansion and development of new technologies sometimes brutally displaces conventional solutions and approaches. Due to this fact, the principal undertaking is not to allow the brutal takeover of the real estate market by, for example, "AI commercial business" through understanding, developing, and controlling new approaches/ solutions tailored to the new realities in the real estate markets. Ensuring that AI applications in valuation remain transparent and subject to professional oversight is crucial to mitigating ethical dilemmas and maintaining public trust (Yam et al., 2025).

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Nowadays, the question is not if, but when and how the AVM (probably combined with AI) will be a common tool that will enable increasing real estate market analysis efficiency. The presence of significant resistance and reluctance to adopt AVMs (Automated Valuation Models) for more widespread use may result in real estate valuation and the real estate industry continuing to rely on “conventional” numerical methods. In an age where society seems to “know everything” and many believe they fully understand modern solutions in real estate valuation and market analysis, nearly everyone has an opinion on the topic. Broadly speaking, some valuation clients, in extreme cases, assume that the outcome of a valuation is the product of manipulation by valuers, casting doubt on their opinions. Even appraisers themselves do not always have a clear view of the situation. While many would appreciate tools to assist them in the valuation process, they also fear that these innovations could lead to reduced earnings or even a loss of jobs, as machines and automation could replace human roles. Some appraisers worry that they won’t be able to keep up with the change of pace in the industry.

The primary objective of this paper is to explore the application of Automated Valuation Models (AVMs) and Artificial Intelligence (AI) in real estate valuation, emphasising their potential to become integral components of the property appraisal landscape in the near future. In particular, this study considers not only the technical aspects of AI adoption but also the ethical and regulatory challenges that come with its implementation. As highlighted by Yam et al. (2025), AI-driven valuation must operate within a structured governance framework to ensure transparency, fairness, and accountability. Addressing these ethical concerns is essential to fostering industry-wide acceptance and trust in AI-powered valuation models.

This study aims to present a broad overview of the gradual replacement of traditional valuation methods with automated solutions, highlighting the collaboration with new technologies while simultaneously addressing the needs, dilemmas, and ethical-technological considerations inherent in this transition. The motivation for this research arises not only from the need to explore the opportunities provided by AI in valuation but also from the imperative to challenge entrenched assumptions within the field. Real estate valuation often relies on rigid frameworks, such as a unilateral focus on market value or inflexible comparative criteria grounded in the ceteris paribus assumption – that all other factors remain constant. Such simplifications frequently overlook the dynamic nature of contemporary markets, where key variables, such as demographic shifts, behavioural consumer patterns, or unique locational attributes, can significantly influence property value. This paper proposes an approach that integrates the analytical precision of technology with the human dimension of judgment, enabling the incorporation of complex behavioural, emotional, and cultural factors. For instance, AI can not only calculate a property’s value based on transaction data but also account for non-standard attributes, such as cultural significance or the social context of a given location. This ensures valuations that are more adaptive, equitable, and aligned with the realities of modern markets. This paper fills a critical gap in the understanding of AI-based approaches, positing them as a catalyst for a new era in property market analysis. These approaches promise to better reflect the complexities of the real estate market, where human and behavioural factors play a crucial role. By integrating AI ethics into valuation models, this research contributes to a more responsible and transparent framework for the digital transformation of property valuation.

The work is structured as follows: Section 1 describes the definition of AVM from the perspectives of international real estate associations. Section 2 discusses harnessing AI in AVMs, focusing on behavioural insights shaping real estate market trends. Section 3 presents the transparency and ethics of AI-supported AVMs. Finally, discussions and conclusions are provided.

Definition of AVM from the international real estate associations’ perspectives

The global real estate industry is witnessing a significant shift as major organisations increasingly focus on the development and implementation of Automated Valuation Models (AVMs). Esteemed bodies such as the Royal Institution of Chartered Surveyors (RICS), the European Group of Valuers’ Associations (TEGoVA), the International Association of Assessing Officers (IAAO), and the International Valuation Standards Council (IVSC) are at the forefront of this transformation. These organisations emphasise the importance of AVMs in enhancing valuation accuracy, efficiency, and objectivity. By integrating advanced statistical, economic, and mathematical modelling techniques, AVMs offer robust, data-driven insights into property values, minimising human bias and error. However, these bodies also stress the critical role of professional judgment to complement AVM outputs, ensuring compliance with rigorous international standards. The concerted focus on AVMs by these leading organisations underscores their pivotal role in modernising property valuation practices worldwide, aiming for a future where technology and human expertise synergistically deliver precise and reliable valuations.

An Automated Valuation Model (AVM) is defined by the Royal Institution of Chartered Surveyors (RICS, 2021) as: "A mathematically based computer software program that market analysts use to produce an estimate of market value based on market analysis of location, market conditions, and real estate characteristics from information that was previously and separately collected. The distinguishing feature of an AVM is that it is a market appraisal produced through mathematical modelling. Credibility of an AVM is dependent on the data used and the skills of the modeller producing the AVM". This definition emphasises the key aspects of AVMs, as illustrated in Figure 2.

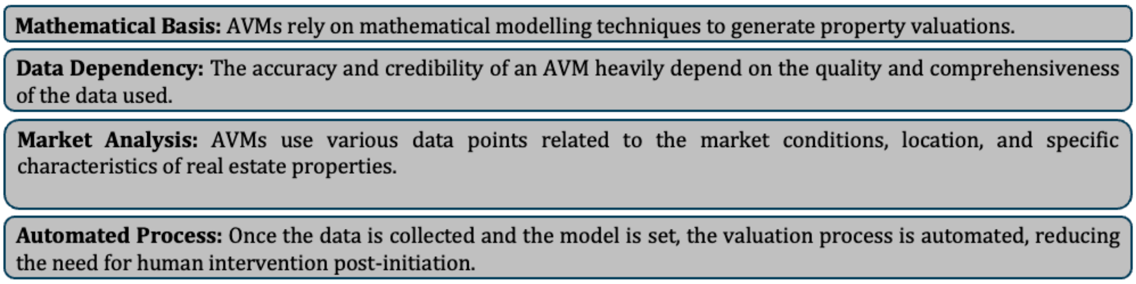

Figure 2. Key characteristics of AVMs according to RICS

RICS also notes that while AVMs can provide useful estimates of market value, they do not include the valuer's judgment and, therefore, may not meet all professional standards required for compliance with International Valuation Standards (IVS) on their own. Human oversight and judgment remain critical components for ensuring the overall reliability and compliance of property valuations.

The European Group of Valuers' Associations (TEGoVA, 2020; 2022) defines an Automated Valuation Model (AVM) as follows: "An AVM is a system that provides an estimate of the value of a specified property at a specified date, using mathematical modelling techniques in an automated manner. This definition implies the use of computer software that queries property and market data, analyses comparable property and market information to assign a value or range of values to a particular property, or generates metrics applicable to assessing the credibility of valuation-related statements or conclusions". Key characteristics of AVMs according to TEGoVA are shown in Figure 3.

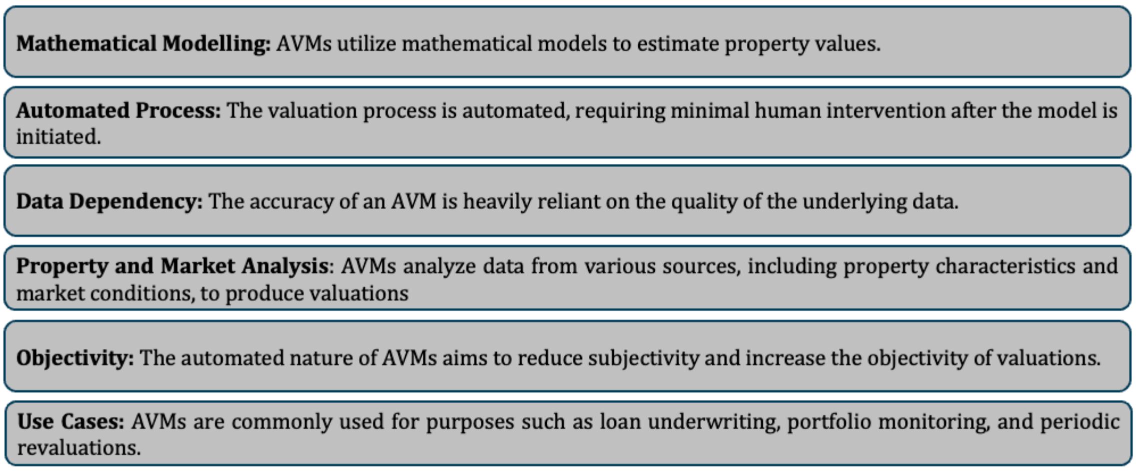

Figure 3. Key characteristics of AVMs according to TEGoVA

The International Association of Assessing Officers (IAAO, 2018; 2022) defines an Automated Valuation Model (AVM) as follows: "An AVM is a mathematically based computer program that produces an estimate of market value based on analysis of location, market conditions, and real estate characteristics from information that was previously collected separately. The distinguishing feature of an AVM is that it is a market appraisal produced through mathematical modelling. The credibility of an AVM is dependent on the data used and the skills of the modeller producing the AVM". Key characteristics of AVMs according to IAAO are shown in Figure 4.

Mathematical Basis: AVMs use mathematical models to estimate property values.

Automated Process: The valuation process is automated, requiring minimal human intervention after data input.

Data Dependency: The accuracy of an AVM is heavily reliant on the quality and comprehensiveness of the data used.

Property and Market Analysis: AVMs analyze data related to property characteristics and market conditions to produce valuations.

Credibility Factors: The reliability of the valuation produced by an AVM depends on the data quality and the expertise of the modeler

Figure 4. Key characteristics of AVMs according to IAAO

The International Valuation Standards Council (IVSC) defines a Valuation Model (IVS, 2025) as follows: " A quantitative implementation of a method in whole or in part that converts *inputs* into outputs used in the development of a *value"*. In addition, IVS (effective 31 January 2025) defines an AVM as: A type of model that provides an automated calculation for a specified asset at a specified date, using an algorithm or other calculation techniques without the valuer applying professional judgement over the model, including assessing and selecting inputs or reviewing outputs. Key characteristics of AVMs according to IVSC are shown in Figure 5.

Mathematical Modelling: AVMs utilize various calculation techniques, often incorporating complex statistical and mathematical methods, to estimate property values.

Automated Process: The process is automated, meaning it requires minimal human intervention once the model is set up and data is inputted.

Data-Driven: Quantitative and qualitative information available to the valuer. Data, assumptions, and adjustments determined to be relevant and assessed or selected by the valuer to be used in the valuation, based upon professional judgement.

Role of Professional Judgement: The use of accumulated knowledge and experience, as well as critical reasoning, to make an informed decision.

Figure 5. Key characteristics of AVMs according to IVSC

IVS 105 Valuation Models further states that: "No model without the *valuer* applying *professional judgement,* for example, an *automated valuation model (AVM),* can produce an IVS-compliant *valuation*." Further to these requirements, the following may apply to compliance with the International Valuation Standards (IVS):

1. **Human Input Required**: A purely automated AVM without valuer input cannot produce an IVS-compliant valuation. Valuers must ensure that all requirements of IVS are met, which includes understanding the model, verifying its assumptions, and applying professional judgment throughout the valuation process.
2. **Documentation and Transparency**: Valuers must keep appropriate records supporting the selection or creation of the AVM, understand and verify the outputs, and ensure the model's assumptions are consistent with the basis and scope of the valuation.

However, it should be noted that though an AVM cannot in itself provide an IVS-compliant valuation, this does not mean that an AVM cannot be used as a tool to assist the valuer in providing an IVS-compliant valuation. Furthermore, standard setting is a continual process, and standards are developed to meet market needs. With the current rapid development of artificial intelligence, this situation may change in the next edition of IVS, which is due to be published in January 2028.

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Mass appraisal involves a broad spectrum of issues pertaining to large-scale property value determination. Automated Valuation Models (AVMs) allow for effective handling of the intricate factors that affect property values, resulting in greater accuracy and reliability – especially in the face of rapidly evolving real estate markets. Despite their utility, AVMs have sparked considerable controversy and remain at the centre of much debate. Discussions revolve around their application, quality benchmarks, and a variety of both specific and overarching topics linked to property valuation and market analysis. These conversations range from detailed examinations of key issues to broader overviews, underscoring the complex and multifaceted aspects of the ongoing discourse.

The concept of an automatic valuation model (AVM) is described as "computer programs based on statistics that utilise property information to produce property-related values or suggested values" (RICS, 2019, 2021; TEGoVA, 2020, 2022). Appraisers can decide how much weight to give to Automated Valuation Model (AVM) results relative to other types of evidence. According to the RICS (2013), Automated Valuation Models (AVMs) are required to meet rigorous quality standards, which reflect an additional objective of using AVMs as a risk analysis tool in investment consulting (IC) and in the assessment of the real estate market (EOED, 2017). A first group of automated valuation models of DCF, dubbed "Regressed DCF", has been proposed by d'Amato and Kauko (2012), subsequently also developed for the purpose of applying the DCFA in the valuation of cyclical assets and exit value (d'Amato et al., 2024).

To address the challenges associated with Automated Valuation Models (AVMs), the current trend is moving towards a **hybrid approach**. This strategy aims to resolve criticisms by combining elements of both traditional and modern techniques, using an agile development process. In this context, the hybrid approach promotes flexible use of manual and automated processes, blending human expertise with computational tools, and integrating classical statistical methods with advanced analyses. This leads to the concept of Hybrid Automated Valuation (HAV), which comprises a collection of methods and procedures in the form of tailored algorithms designed to address specific issues in real estate market analysis and valuation processes (Renigier-Biłozor et al., 2022a).

Research methods

The methodology applied in this paper is based on a critical and comprehensive review of existing literature, international standards, and industry practices related to Automated Valuation Models (AVMs) and Artificial Intelligence (AI) in real estate valuation. The authors analysed definitions and perspectives from major international real estate associations such as RICS, TEGoVA, IAAO, and IVSC to establish a foundational understanding of AVMs. Additionally, the study examined recent advancements in AI technologies and their integration into AVMs, focusing on the potential benefits, challenges, and ethical considerations. By synthesising insights from scholarly articles, industry reports, regulatory documents, and previous publications by the authors, the paper aims to present a holistic view of the current state and future prospects of AI integration in property valuation. This approach allows for an in-depth understanding of the subject matter while identifying gaps in the existing knowledge and proposing directions for future research.

Complementing this literature-based approach, the study also integrates insights gathered through consultations with a broad range of industry stakeholders. Input was obtained from representatives of leading organisations, including the International Association of Assessing Officers (IAAO), the European Group of Valuers' Associations (TEGoVA), the Royal Institution of Chartered Surveyors (RICS), the International Valuation Standards Council (IVSC), as well as developers, AVM providers, and other key players in the property valuation sector. Direct interviews were conducted with over 50 experts from these organisations and related industries, providing a diverse and in-depth understanding of current challenges and opportunities. Furthermore, preliminary findings and ideas from this research were presented at multiple international conferences, where feedback from participants – comprising practitioners, policymakers, and researchers – was systematically collected and incorporated.

By combining a rigorous review of the existing literature with empirical insights from industry experts and conference feedback, this methodology ensures that the proposed framework and recommendations are firmly grounded in both theoretical and practical considerations. This integrated

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approach allows the study to bridge the gap between conceptual analysis and real-world applicability, ensuring that its findings align with the practical realities and priorities of industry professionals.

Results of the research

Harnessing AI in AVMs: behavioural insights shaping real estate market trends.

Unlike traditional valuations that rely solely on physical inspections, Automated Valuation Models (AVMs) employ advanced computational technology, such as artificial intelligence (AI), to process extensive datasets and apply machine learning algorithms to estimate property values. The introduction of Artificial Neural Networks (ANNs) by Borst (1991) in property valuation has garnered attention due to their effectiveness and ease of use, despite facing computational challenges. There remains uncertainty regarding the ideal number of data samples required for effective real estate valuation using ANNs, and the criteria for this remain unclear. While ANNs typically require significant computational power compared to traditional methods, they excel in incorporating uncertainty into predictive models, thereby enhancing correctness. In specific applications, this can lead to a reduction in overall computation time due to more efficient processing of complex data. However, variations in ANN architecture can impact results (Renigier-Biłozor et al., 2022a), and their "black box" nature makes them challenging to interpret, particularly in legal contexts like property taxation disputes. The term "black box" has traditionally been associated with the idea of results that are difficult or impossible to interpret. However, **in reality, it's more about the challenge of interpreting a large volume of model parameters contained within the model rather than any mysterious or hidden modelling approach.** Its true meaning lies in the complexity of models, which often involve numerous parameters, functional relationships between these parameters, and dynamic model selection processes. Rather than indicating an inherent opacity, the term "**black box"** highlights the intricate and multifaceted nature of these models, encouraging a more nuanced understanding of their workings and outputs.

In contemporary modelling, there is a growing emphasis on transparency and interpretability, contrasting with the traditional notion of the "black box." Modern methodologies, such as **explainable artificial intelligence (XAI), aim to demystify complex models** by providing insights into their inner workings and decision-making processes. Through techniques like feature importance analysis, model-agnostic explanations, and interpretable machine learning algorithms, practitioners can better understand how inputs influence outputs and identify potential biases or errors. By adopting these approaches, contemporary modelling endeavours to bridge the gap between complexity and comprehension, facilitating trust and fostering collaboration between model developers, domain experts, and end-users. Thus, the narrative of modelling as a "black box" is evolving towards a more transparent and accountable paradigm, where insights gleaned from data are accessible and actionable, contributing to informed decision-making and societal progress.

One of the critical accusations against the use of AVMs **is the lack of inclusion of the human component**. The refusal to use this tool results in consequences such as limiting or slowing down its development. This accusation likely stems primarily from the fear of job loss among appraisers and real estate market analysts. However, this is somewhat **paradoxical** because the **primary goal of its creation was precisely to support humans**, helping to minimise their shortcomings and increase work efficiency. By combining the computational power of AVMs with the nuanced understanding and expertise of human professionals, one can create a hybrid model that leverages the strengths of both. **This symbiotic relationship (human & machine) could drive innovation, reduce errors, and provide more reliable data for decision-making**. Adapting to technological advancements is crucial for progress, and resisting change due to fear of the unknown can hinder potential growth. Embracing AVMs as a complementary tool rather than a replacement for human expertise can pave the way for a more efficient, effective, and dynamic real estate market. Contrary to commonly repeated statements, **encouraging collaboration between technology and human insight will not only preserve jobs but also create new opportunities** for professionals to enhance their skills and to adapt to the evolving landscape. In the long run, **this approach can lead to a more resilient and forward-thinking industry**.

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It's clear that the real estate market is shaped by human decisions, driven by motives, emotions, and reactions, which adds complexity due to the range of properties and the market itself, along with the perceived homogeneity in common market analysis methods (Renigier-Biłozor et al., 2024). To understand these decision-making processes, it's crucial to explore the human mind's capabilities and constraints within the context where decisions occur. This exploration forms the basis of **cognitive science** and **soft computing**. Integrating advanced technologies into the real estate industry not only enhances human capabilities but also opens new avenues for growth and advancement. The application of new technologies in real estate analysis provides opportunities to increase efficiency and expand the interpretation of results. For example, it enables the use of cognitive science in combination with affective computing. According to Renigier-Biłozor and Janowski (2024), a **major challenge** in current methodological solutions **is the behavioural factor**, which is often neglected. This approach not only better captures relationships in the real estate market but is also primarily focused on designing systems that align with human cognitive abilities, making them easier to interpret and more efficient to improve and modify.

Cognitive science explores the human mind, senses, and brain functions to comprehend the nature and operation of the mind (Miller, 2003). Conversely, soft computing, a branch of computer science, embraces the human mind's ability to reason and learn, tolerating imprecision and uncertainty (Ning et al., 2013). By integrating insights from cognitive science and advanced computational techniques, one can create valuation systems that are not only efficient but also context-aware. This integration deepens the understanding of market dynamics, enabling more informed and strategic choices, ultimately transforming the real estate industry to be more resilient and adaptive. Moreover, according to Navin (2024), AI holds significant potential to revolutionise the field of surveying. It acts as a transformative tool for projects that rely on location intelligence and insights. However, human involvement remains essential for navigating complex and emotionally charged scenarios. The evolving role of surveyors, supported by AI tools, highlights the importance of balancing technological precision with human judgment, particularly in nuanced real estate contexts. As AI technology continues to evolve, it is imperative for surveyors to adapt by integrating new technological advancements and establishing themselves as leaders in the realm of intelligent surveying.

Numerous studies have explored the application of AI and machine learning in property valuation, highlighting their potential to enhance accuracy, scalability, and efficiency in valuation processes (Baldaminos et al., 2018; Choy & Ho, 2023; Pai & Wang, 2020; Renigier-Bilozor & Janowski, 2024, etc.). For instance, Soltani and Lee (2024) provide a comprehensive analysis of AI-driven valuation methodologies, demonstrating how big data and advanced machine learning techniques can model complex real estate markets with high precision. Such research underscores the foundational advancements in integrating AI into property valuation practices, which serve as a critical basis for the exploration of Automated Valuation Models (AVMs).

Similarly, other studies have delved into specific AI technologies and their applications in real estate valuation. For example, Yazdani and Raissi (2023) propose a method utilising self-supervised vision transformers, combining machine learning and computer vision to estimate property values with notable accuracy. This approach leverages advanced image processing techniques to account for property characteristics that are challenging to quantify using traditional methods. Further expanding on innovative AI methodologies, Riveros et al. (2024) develop graph-based deep learning models designed to capture intricate spatial relationships between properties. By integrating spatial dependencies, these models improve the accuracy of house price predictions, offering a sophisticated means of handling complex market dynamics.

Addressing challenges in data scarcity, Du et al. (2023) introduce the DoRA framework, which employs domain-based self-supervised learning to enable real estate appraisal in low-resource settings. This approach demonstrates the potential for AI to adapt and provide reliable valuation insights even in markets with limited transaction data or incomplete datasets. In addition to enhancing prediction accuracy, efforts have been made to improve transparency and interpretability in AI-driven valuation models. Angrick et al. (2021) apply evolutionary algorithms to case-based reasoning predictors, achieving high accuracy while maintaining explainability. This balance between precision and interpretability is critical for fostering trust in AI-driven valuation systems among stakeholders. Moreover, the Application of Artificial Intelligence in Real Estate Valuation (Zhang et al., 2023) provides an overarching perspective on how AI technologies, such as artificial neural networks and

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machine vision, have been employed to enhance prediction accuracy and address the limitations of traditional valuation methods.

Together, these studies not only illustrate the advancements in AI-driven valuation methodologies but also highlight the diversity of approaches being adopted to tackle different challenges within the real estate sector. **Building on this body of research, our study seeks to address an important gap: the need for integrating behavioural and contextual factors alongside computational precision.** This approach bridges the gap between technical innovations and real-world applications, offering practical insights for property valuation professionals and industry stakeholders. Extending AI-based methods and procedures to AVM and/or CAMA processes not only increases the efficiency of analysis but also provides an effective alternative to traditional methods by addressing persistent limitations in valuation frameworks. Importantly, our approach complements the largely qualitative perspectives offered by Lee et al. (2024), who explore workforce dynamics and industry transitions within the property sector. While their study provides valuable insights into broader qualitative challenges, our research focuses on the structured application of computational methods, including Artificial Neural Networks (ANNs), Random Forests (RF), and Extreme Gradient Boosting (XGBoost), specifically in the context of mass valuation systems. This duality of perspectives enriches the understanding of how AI can reshape valuation processes by addressing both technical and human dimensions.

To build upon this foundation, Table 1 highlights the specific domains and challenges that can be effectively addressed through the integration of AI-driven technology within Automated Valuation Models (AVMs), offering actionable insights for both practitioners and policymakers. Additionally, it delineates the distinct stages of AVM procedures and steps within the Computer-Assisted Mass Appraisal (CAMA) system where these methodologies can be effectively implemented. The table serves to elucidate the breadth of issues tackled by AI technology in mass appraisal, categorising the applications of Artificial Neural Networks (ANNs) according to their respective types and underscoring the problem-solving potential of both AI and mixed methods. The structure of the table is designed to present the primary advantages and obstacles of using it in the AVM/CAMA stages, specifically focusing on the most troublesome problems encountered. Additionally, the table presents an analysis of the usefulness of the solution from a behavioural perspective, considering human limitations and fallibility, in particular, technologies. It focuses on understanding how the solution can support users in using technology more effectively and safely, minimising the risk of errors. These insights are gleaned from an exhaustive literature review and the authors ' own elaboration – see sources of Table 1(1a…1h).

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Table 1. Advantages and obstacles of AI-based technology in automated valuation models

Table 1a. Advantages and obstacles of NN technology in the AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Artificial Neural Networks (ANN)	**Value assessment**	**8**	**V**
Advantages	**High accuracy**: ANNs can model complex, non-linear relationships in data, leading to precise property valuations. **Able to manage different types of data** and relationships, making them suitable for diverse property datasets and valuation purposes. **Ability to process missing data**: ANN can handle missing input data without imputation. **Learning from large datasets**: Well-suited for large-scale data, which is common in mass property valuation. **Incorporating uncertainty**: Can effectively integrate uncertainty in predictive models, improving robustness. **Reduction in computation time**: Once trained, ANNs can make predictions quickly, which is beneficial for mass valuative tasks. **Adaptation to market volatility**: They can be trained on both historical and continuously updated data, allowing them to adapt to changing market conditions and better predict future property values. **Identifying hidden patterns**: Uncovering 'hidden' patterns and relationships that may be unnoticeable or difficult to spot with traditional property valuation models.			
Obstacles	**Computationally intensive training**: Training ANNs requires significant computational resources and time, especially with large datasets. **Black box nature**: Lack of transparency in how ANNs derive their predictions, making it difficult to interpret and explain the results. – lack of understanding and therefore trust on the part of beneficiaries. **Need for large datasets**: ANNs often require large amounts of data for effective training. **Overfitting risk**: Prone to overfitting, especially if not properly regularized or if the model is too complex relative to the data. **Hyperparameter tuning**: Requires careful tuning of numerous hyperparameters (e.g., number of layers, learning rate), which can be challenging and time-consuming. The lack of training data for specific, unique cases can lead to **problems in accurately predicting values**. **Dependency on data quality**: Highly sensitive to the quality of the training data; noisy or biased data can significantly impact performance.			
ANN provides opportunities to gain additional benefits or eliminate certain drawbacks inherent in the classical NN approach upon integration with:				
Technology within ANN	***Random Forest (RF)***			
Advantages	**Effectiveness** for data with many features (square footage, number of rooms, location, etc.), which is typical in AVM tasks. **Resistance to overfitting:** Random selections of features and observations during tree construction reduce the risk of model overfitting. **Feature importance assessment**: Allows to assess which property features are most relevant to valuation, making it easier to interpret the model. RF does not require scaling or transformation of independent variables, which **simplifies data preparation**. **Ability to process missing data**: RF can handle missing input data without imputation. **Parallel processing**: The construction of individual trees in the forest can be performed in parallel, speeding up the learning process. **Scalability**: Efficiently processes large data sets, which is common in real estate applications.			
Obstacles	**Difficulty of interpretation:** Although RF allows the importance of individual features to be assessed, understanding the interactions between hundreds of decision trees in a forest can be difficult and less transparent than with single models. **Computational requirements**: Building and storing many decision trees in memory requires significant computational resources. **Processing time**: Many trees in the RF can slow down the valuation process, (parallel computing is the solution). **Need for large training data sets**: RF often require large amounts of data for effective training.			

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Technology within ANN	***Extreme Gradient Boosting (XGBoost)***
Advantages	**High accuracy of prediction**: XGBOOST combines predictions of many weak models of decision trees, which often leads to better accuracy of real estate valuation than in the case of individual models. **Effectiveness** for data with many features (square footage, number of rooms, location, etc.). **Feature importance assessment**: Allows to assess which property features are most relevant to valuation, making it easier to interpret the model. **Parallel processing**: The construction of individual trees in the forest can be performed in parallel, speeding up the learning process. **Scalability**: Efficiently processes large data sets, which is common in real estate applications. **Model adjustment**: It offers adjustment mechanisms, such as limiting the number of parameters. **Flexibility**: It can be used with different cost functions and others - adapting the model to the specific needs of real estate valuation. **Handling Missing Data**: Can internally manage missing data. **Regularization techniques** to prevent overfitting.
Obstacles	**Resource-intensive**: Can be computationally intensive, requiring significant memory and processing power, especially for very large datasets. **Sensitivity to noisy data**: Although robust, XGBoost can still be affected by noisy or irrelevant features if not properly managed. **Training time**: While efficient, the training time can still be substantial for very large datasets or complex models. **The complexity of configuring the model** and tuning numerous hyperparameters. The need to understand and tune many model hyperparameters such as tree depth, number of estimators, regularization coefficients, etc. **Debugging complexity**: Difficulties in identifying and repairing problems in the model.
Technology within ANN	***Deep Learning Neural Network (DLNN)***
Advantages	**High Predictive Power:** DLNNs can model complex non-linear relationships between features and the target variable, leading to high prediction accuracy. **Transfer learning**: Deep Learning can easily adapt to new data. **Ease of updating**: Capability to analyse unstructured data and support multimodal inputs. **The ability to learn complex patterns** and **non-linear relationships** in real estate data, which can lead to **higher prediction accuracy** than linear models or decision trees. **Automatically learns feature representations from raw input data** (e.g. image, text), eliminating the need to preprocess it **Scalability**: Efficiently processes large data sets, which is common in real estate applications.
Obstacles	**Increased complexity**: DLNNs are more complex than traditional ANNs, requiring specialized knowledge and computational resources for training and deployment. **Large data requirements**: DLNNs typically require large amounts of labelled data for effective training, which may not always be available in property valuation contexts. **Computational Requirements**: DLNNs are resource intensive, requiring significant computational power, often involving the GPU, TPU, ASIC, clouds or Edge Computing for effective training and inferences. **Interpretability challenges**: DLNNs are often viewed as "black box" models, making it difficult to interpret and explain their decisions, which can be problematic in property valuation where transparency is important. **Risk of overfitting**: DLNNs are susceptible to overfitting, especially when trained on small datasets or when the model architecture is overly complex relative to the data.
Technology within ANN	***Spatial Neural Network (SNN)***
Advantages	**Localized predictions**: SNNs can provide localized predictions by considering the spatial context of each property, enabling more accurate valuations tailored to specific regions or neighbourhoods (precise micro-localization analysis). **Robustness to spatial autocorrelation**: SNNs are robust to spatial autocorrelation, meaning they can capture and account for spatial patterns and trends in property values. **Ability to learn and combine complex spatial patterns** and relationships in property data such as location, neighbourhood, infrastructure availability, etc. **Automatic extraction** of relevant **spatial features** from raw data such images or maps. Potentially **higher accuracy of property value** prediction due to dedicated consideration of spatial context. Often incorporate concepts from Graph Neural Networks (**GNNs**) and Convolutional Neural Networks (**CNNs**).
Obstacles	**Complexity of spatial data**: Handling spatial data requires specialized techniques and preprocessing steps, adding complexity to the model development process. **Data availability and quality**: Spatial datasets may be limited or varying quality, which can impact the effectiveness of SNNs and require careful data preprocessing and validation. **Interpretability challenges**: Like other neural network models, SNNs may lack interpretability, making it difficult to explain how spatial features contribute to property valuations. **Computationally intensive**: Processing spatial data and training SNNs can be computationally intensive, requiring adequate computational resources and time for model training and optimization. **Risk of overfitting** on training data if the model is not properly regularized.

	Inclusion of spatial data additionally introduces further elements of **uncertainty**, quality, effectiveness of results due to the difficulty of integrating spatial data with other numerical data - assessing their accuracy in relation to these other data.
Technology within ANN	***Support Vector Machines (SVM)***
Advantages	**Effective in high-dimensional spaces**: SVMs perform well in high-dimensional feature spaces, making them suitable for property valuation tasks with many input variables. **Memory efficiency**: SVMs only use a subset of training data points (support vectors) to define the decision boundary, resulting in memory efficiency, particularly with large datasets. **Robustness to overfitting**: SVMs have effective regularization techniques (e.g., kernel tricks, soft margin) that help prevent overfitting, ensuring good generalization performance. **Explicit control over trade-offs**: SVMs allow explicit control over the trade-off between margin maximization and classification error, providing flexibility in model tuning. **Global optimization**: SVMs solve a convex optimization problem, guaranteeing convergence to the global optimum, which ensures reliable and consistent results. **Interpretability**: SVMs provide relatively simple decision functions, making them more interpretable compared to complex neural network models. **Stability of results**: important with frequent updates of property valuations. **Transparency**: simple, linearly defined decision boundaries. **Efficiency** in detecting market anomalies and outliers.
Obstacles	**Limited scalability**: SVMs may become computationally intensive and memory-demanding with very large datasets, especially when using non-linear kernels. SVMs are effective when working with small and medium sized datasets, poor performance with very large datasets. **Difficulty handling noisy data**: SVMs are sensitive to noisy data and outliers, which can affect the positioning of the decision boundary and degrade performance. **Complexity in kernel selection**: Choosing an appropriate kernel function and its parameters can be challenging and may require expert knowledge or extensive experimentation. **Inefficient with unbalanced datasets**: SVMs may produce biased results when dealing with highly imbalanced datasets, where one class dominates the other. **Less effective with non-linear relationships**: While SVMs can model non-linear relationships using kernel tricks, they may not perform as well as neural networks in capturing complex non-linear patterns. **Limited probabilistic outputs**: SVMs originally provide binary classification; obtaining probabilistic outputs requires additional calibration, which can be less straightforward compared to neural networks. **Need** for careful **normalisation** of data. **Sensitivity to data scaling**: Input data should be scaled appropriately to avoid dominance of certain features. **Non-resilience to sequential data,** such as time-dependence, cannot be considered.
Technology within ANN	***General Regression Neural Networks (GRNN)***
Advantages	**Fast training and prediction**: GRNNs have a simple structure and require minimal tuning, leading to faster training and prediction times compared to more complex neural networks. Rapid learning in a single pass-through training data. **Non-parametric regression**: GRNNs perform non-parametric regression, meaning they can capture complex relationships between input and output variables without assuming a specific functional form, which is advantageous in property valuation tasks with nonlinear relationships. **Adaptability to new data**: GRNNs can quickly adapt to new data by updating the kernel bandwidth, enabling continuous learning and adaptation to change property market conditions. **Variance reduction**: GRNN may reduce the variance of results, leading to more stable valuations.
Obstacles	**Limited interpretability**: Like other neural network models, GRNNs may lack interpretability, making it difficult to understand how input features contribute to property valuations. **Memory inefficiency**: GRNNs store training data in memory and perform fast inference using a radial basis function (RBF) kernel, making them memory-efficient, especially with large datasets. **Dependency on kernel bandwidth**: The performance of GRNNs is sensitive to the choice of kernel bandwidth, which requires careful tuning and may impact prediction accuracy. **Scalability**: While GRNNs are efficient with small to medium-sized datasets, they may become computationally intensive and memory-demanding with very large datasets. **Requires data normalisation**: GRNNs, like other neural network methods, require appropriate normalisation of the input data. **Difficulty with high-dimensional data**: GRNNs may struggle to handle high-dimensional data efficiently, as the number of required training data points increases exponentially with the number of dimensions. **Risk of overfitting**: GRNNs can be prone to overfitting, especially if the training dataset is small or noisy, necessitating appropriate regularization techniques and validation strategies. This risk is especially true with small data sets. **Less flexible** than DLNN. **High calculation costs** for large datasets.

	Sensitivity to initiating parameters: Results can be strongly dependent on the choice of parameters, such as population size, mutation rate etc. **Need for calibration**: Often require calibration and adjustment to specific problems, which can be time-consuming and non-automatic.

Behavioral Perspective on Solution Utility

Genetic algorithms stand out due to their construction method based on principles of natural selection, which introduces a new quality to real estate market analysis. Traditional human analytical approaches often exhibit a susceptibility to errors and limitations stemming from personal preferences or biases. In the case of genetic algorithms, the process of solution selection and refinement follows the principles of evolution, thereby eliminating subjective factors and potentially leading to the discovery of optimal solutions in a manner challenging to achieve for the human mind. By leveraging this methodology, genetic algorithms can detect nonlinear dependencies and account for various factors influencing property value in a more objective and comprehensive manner. Additionally, their ability to iteratively refine solutions allows for adaptation to changing market conditions and the detection of patterns that may be overlooked in traditional analyses. Thus, genetic algorithms introduce a novel perspective to real estate market analysis by mitigating human errors and biases and facilitating a more objective approach to valuation and analysis.

Table 1b. Advantages and obstacles of Virtual Reality & EYE Tracking & Computer Vision Technology in AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Virtual Reality (VR) & EYE Tracking (ET) & Computer Vision Technology (CVT)	**Collection the information**	**1** **2**	**II**
Advantages	**Inclusion of behavioral factors**: human perception analyses. **Property features fusion measurement** in an environment close to reality. **The multisensory human perception.** **Objective** lab **analyses.** **Pattern extraction** based on complex dataset. **Time and cost savings** - VR: Eliminates the need for physical visits to properties, CV in conjunction with CNNs and GNNs: Automatic analysis of images and video reduces the need for manual review of material.			
Obstacles	High **cost of technology and equipment** purchase. **Health state-based limitations** for VR use. **Limiting access to infrastructure** (e.g. VR, eye tracking) and their standardization. **Divergent interpretations** of the determinants of people's emotional responses, e.g. based on pupil diameter. **Need for expertise knowledge**: Implementing and operating these technologies requires expertise in machine learning and image processing, psychology in addition to knowledge of property valuation and IT.			

Behavioral Perspective on Solution Utility

The integration of Virtual Reality (VR) with emotions tracking (e.g. pupil tracking) and Computer Vision (CV) technologies significantly enhances the collection and analysis of information in the real estate market, minimizing human limitations. VR with pupil tracking enables immersive property inspections, providing a realistic spatial experience. By tracking pupil movements, this technology reveals user preferences and areas of interest that may not be visible in traditional surveys. CV technologies automatically assess visual aspects of properties, precisely measuring spaces and evaluating their conditions. CV can also detect potential issues that may escape human attention, leading to more accurate and reliable assessments. This technology reduces human errors and biases, ensuring that the gathered data is comprehensive, precise, and useful. As a result, the property valuation process becomes more efficient and reliable, better adapting to dynamic market conditions.

Table 1c. Advantages and obstacles of the Genetic algorithm in the AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Genetic algorithm	**Collection the information**	**1** **2**	**II**
Advantages	**Ability to find the "best overall solution"** - global extreme: Global multi-criteria optimization. **Big data processing.** **Diverse size and form** of coding the data. **Synergistic features** analysis results. **No need to define an objective function.** **Numerical solutions** can be performed **in a parallel manner.** **Resistance to data noise.** **Adaptability**: can adapt to changing market conditions. A **simplified approach to non-linear** problems that are difficult to model with traditional methods. Can be **applied to various stages of AVM**, from defining information to data collection and model calibration.			
Obstacles	**Finding quasi-optimal solutions** - often find solutions that are good enough, i.e. quasi-optimal. **Risk of overtraining.** **Problems with convergence** of analysis results: for very complex optimisation problems. The results **may differ significantly from those obtained by classical AVM** methods, which may require additional analysis and verification. **Time-consuming**: Especially with large datasets and complex problems. May require considerable computing power **Implementation can be complex** and require specialist knowledge.			

Behavioral Perspective on Solution Utility

Artificial Neural Networks (ANNs) - Humans have a limited capacity to analyse vast datasets. ANNs can quickly and accurately process this data, identifying patterns and trends that may elude human analysts. Human minds often struggle with the analysis of complex, nonlinear relationships. ANNs are designed to effectively handle nonlinearity, leading to more precise property valuations. Moreover, humans learn slowly and on a smaller scale. ANNs can rapidly learn from large sets of historical data, continuously improving their forecasts and adapting to changing market conditions. Additionally, humans are susceptible to cognitive biases and fatigue. ANNs operate impartially and without fatigue, reducing the risk of errors, resulting in more reliable valuations. These capabilities underscore the importance of integrating ANNs into mass property valuation processes, providing accuracy, speed, and adaptability that are difficult to achieve with traditional methods and human analysts alone.

Table 1d. Advantages and obstacles of Rough Set Theory & Self-Organising Maps in AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Rough set theory (RST) & Kohonen NN (SOM)	Data selection/ preference indication	2	II
Advantages	**Synergistic features** analysis possibility. RST **Effectively identifies and reduces irrelevant features**, improving the quality of input data. The combination of RST & SOM **enables the detection of complex, non-linear patterns** in real estate data. **Highly interpretable**: RST identifies features, and SOM spatially visualises the results of the analysis (identification of patterns and anomalies). **Increased transparency** of the analyses.			
Obstacles	**Require larger datasets** for comprehensive analysis. **Results may be unpredictable**: dependent on initiating assumptions. **Need for careful tuning of parameters**. **Scalability** issues. High operating **memory requirements.** **Risk of overtraining** especially in relation to SOM. RST is **sensitive to noise** in the data, so requires pre-processing.			
Behavioral Perspective on Solution Utility This approach effectively handles the imprecision and subjectivity inherent in data selection and preference indication. Rough Set Theory helps manage vague and uncertain data without requiring additional information, while Self-Organizing Maps facilitate the visualization and clustering of complex data, mirroring human cognitive processes. Together, they provide a robust framework that accommodates human fallibility, offering a more intuitive and flexible method for analyzing and interpreting data.				

Table 1e. Advantages and obstacles of Emotion recognition technology & Neural Networks in AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Emotion recognition technology (ERT) & NN	**Attributes significance indication**	**2** **5**	**IV**
Advantages	**Objectivity** of the obtained results (low probability of manipulation). **Higher flexibility** in response to changes in trends and market preferences. **Speed of data acquisition** with indirect (remote) contact with the respondent. **Precision** in understanding customer preferences. **Adaptability** - rapid adaptation of the prioritization of features in relation to the changing preferences of real estate market participants. **Faster identification of relevant features** in real estate market analysis.			
Obstacles	**Cost-effectiveness** and technical accessibility. **Big data processing**: Calculation requirements. **Legal and ethical constraints**: Safeguarding requirements for sensitive data. **Difficulty of interpreting** the results and their accuracy.			
Behavioral Perspective on Solution Utility Humans are susceptible to subjective judgments and cognitive biases that can affect data interpretation. Emotion recognition technology eliminates these subjective elements by providing an objective analysis of the emotional responses of potential buyers. This allows for the identification of hidden preferences, used to gauge market sentiment and consumer preferences, thereby increasing the accuracy of property valuations through the analysis of emotional reactions to various property attributes. Furthermore, this technology enables faster adaptation to changing market trends and reduces the time and costs associated with market research. As a result, emotion recognition technology not only enhances the precision and objectivity of assessments but also provides deeper and more valuable insights.				

Table 1f. Advantages and obstacles of Rough set technology & Robust geo-estimation in AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Rough set technology (RST) & Robust geo-estimation (RG)	**Homogeneity market indicating**	**6** **7**	**III** **IV**
Advantages	**No need to define precise boundary** markets a priori. **No need to define weights** (significance) of features a priori. **The area is interpreted as an adjacency and mutual phenomenon** described by the features developed in the buffer mode. **Indicated homogeneous areas** are understood as the indiscernibility areas that consider specificity of the properties and markets related to their fundamental differentiation. **High flexibility and scalability** of the algorithm related to the boundary conditions of the model (k coefficient and entropy weight). **Automated** selection of comparable properties. **Reducing human subjectivity** in market area indication.			
Obstacles	**Adjustable comparability** coefficient and minimum significance weight **based on analytics.** **Probability of obtaining large groups** of non-characters with a small number of objects. **Manual supervision** strongly required for optimal results obtained in an iterative procedure. **Objectivity** of the obtained results **depends on the amount of information contained** in the database. **High computational requirements.** Implementation **complexity.**			
Behavioral Perspective on Solution Utility Humans often struggle with interpreting large, intricate datasets that may contain ambiguities and uncertainties. Rough set technology enables the analysis of such data more precisely, eliminating subjective errors and cognitive biases. This allows for a more accurate determination of market homogeneity by identifying patterns and relationships that may be challenging for human analysts to detect. Robust geo-estimation further supports this process by providing tools for accurately assessing spatial parameters of properties. This enables more reliable and precise estimations that consider both locational and spatial market characteristics. This technology minimizes errors stemming from human interpretation and allows for better adaptation to dynamic changes in the real estate market. As a result, the application of rough set technology and robust geo-estimation not only enhances the precision and objectivity of assessments but also provides deeper and more valuable insights.				

Table 1g. Advantages and obstacles of Rough Sets Theory & Kohonen NN in AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Rough Sets Theory (RST) & Kohonen NN (SOM)	**Representative indication**	**7** **8** **10**	**IV** **V**
Advantages	Particularly **useful for limited transaction** markets. **Tolerant** of attribute variability and missing of data. **Supports any functional correlation** between attributes and price. **Does not require preliminary analysis**. **No limits** related to the number of transactions and their attributes. **Identification of hidden correlations** in high-dimensional data sets. **Precise selection of comparable properties** (RST identifies key features, SOM clusters properties based on these features). **Automatic** data analysis and segmentation. **Effective model calibration**: RST eliminates unobserved variables. SOM allows continuous learning from new data. **High transparency** of the mathematical apparatus of the model. **Scalability**: RST effectively processes large sets of information.			
Obstacles	There are **multiple possible alternative choices** for the representative decisional rule, posing the challenge of having to select one. **Conditional attributes of properties can be repeatedly duplicated** by multiple decisional rules. **High calculation requirements** for both RST and SOM. **Risk of overtraining**, especially the SOM component. **Difficult to adapt to different markets** (RST for different markets requires separate models). **Sensitive** to parameter tuning.			
	Rough Set theory (RST) & Fuzzy logic (FL)	**Insufficient number of comparable properties**	**7** **8**	**V**
Advantages	**Effective** in the **absence** of comprehensive information on the property market. **Effective** in **inaccurate and "fuzzy"** character of real estate data.			

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	Effective in **complex methods** of **data description** (differences in the scale of attribute description). **Absence of the restrictive assumption** of linearity in data relation. **Absence of homogenous functional dependencies** between real estate attributes.
Obstacles	High **design requirements**: of both RST and FL. **Implementation complexity** - RST as well as FL require specialist knowledge. **Risk of overtraining -** FL models can be susceptible to overtraining.
Behavioral Perspective on Solution Utility This approach accommodates the inherent imprecision and subjectivity in real estate valuations. It allows for the modelling of complex decision-making processes where crisp boundaries between valuation criteria are unsuitable from a rational and realistic perspective. By handling degrees of truth rather than binary true/false values, Fuzzy Logic provides a more nuanced and flexible approach to property valuation, reflecting the real-world complexities and subjective judgments that often influence market values.	

Table 1h. Advantages and obstacles of Cognitive systems & Machine Learning Technologies in AVM and CAMA stages

Advantages/ Obstacles	Technology used	Challenges in automated valuation and market analyses	AVM stages*	CAMA steps**
	Cognitive systems (CS & Machine Learning Technologies (MLT)	Preserve the original data structure/avoid decreasing the information capacity	*1* *2* *3*	*II*
Advantages	**Automation**: The system automatically identifies similar properties, significantly speeding up the valuation process and reducing manual effort. **Scalability**: Most ML algorithms are scalable, allowing the system to handle increasing amounts of data without a significant rise in computational power demands. **Relationship Detection**: ML is adept at identifying complex relationships that are difficult to define a priori. **Handling Incomplete Data**: The solution can manage incomplete or inconsistently recorded data, ensuring robust analysis even with imperfect datasets. **Multi-Threaded Search**: ML performs multi-threaded and multi-epoch searches to find optimal solutions efficiently. **Accuracy Control**: A well-trained ML model ensures precise valuations, leading to more accurate property comparisons. **Automatic Parameter Adjustment**: The solution adjusts model parameters automatically based on data and the specific analysis purpose. **Model Analysis**: The solution evaluates multiple models and their parameters to find the optimal solution. **Continuous Retraining**: Models are continuously updated with new data, allowing adaptation to new requirements, emerging data, and changing trends.			
Obstacles	**Complex Development**: Building, training, and fine-tuning machine learning models requires specialized knowledge and expertise. **Data Requirements**: Constructing a flexible and precise model necessitates a large, semantically diverse dataset, which can be difficult to obtain. **Overfitting Risk**: Models may become overly fitted to training data, reducing their ability to generalize and predict outcomes accurately, making them sensitive to noise and nuances. **Interpretability**: Complex models can be difficult to interpret, complicating the explanation of decisions made by the ML. **Resource Intensive**: Training and maintaining effective models demand significant computational resources and time.			
Behavioral Perspective on Solution Utility The utility of this technology lies in its ability to preserve the original data structure and avoid diminishing information capacity, particularly due to human limitations or inadequacies. Cognitive systems and machine learning (ML) technologies excel in processing vast amounts of data with minimal human intervention, ensuring that the integrity and richness of the dataset are maintained. By leveraging these technologies, we can mitigate the risk of data loss or distortion caused by human error or insufficient analysis. Additionally, cognitive systems and ML can uncover patterns and insights within the data that may elude human perception, enhancing the overall quality and depth of analysis.				

** The main stages of AVM procedures are:*

1. Information definition 2. Data collection 3. Database creation 4. Data verification and selection 5. Feature significance indication 6. Homogeneity market definition 7. Comparable properties set definition 8. Initial value determination 9. Model calibration 10. Model testing 11. Quality control 12. Indication of representative sets of assessed properties 13. Value determination of assessed properties

***. According to the IPTI Workshop 2024, the main steps of the CAMA system are:*

I. Definition of appraisal assignment II. Data collection III. Data review and validation IV. Exploratory data review and analysis V. Model development and calibration VI. Model testing and quality control VII. Model application and value review

Source: Abidoye et al., 2021; Aydinoglu et al., 2020; Baldominos et al., 2018; Baum, 2020; Bovkir & Aydinoglu, 2018; Chmielewska et al., 2022; Choy & Ho, 2023; Dimopoulos, 2020; Dimopoulos et al., 2014; Dimopoulos & Bakas, 2019b; Ecker et al., 2020; Hjort et al., 2023; Hoang et al., 2022; Horvath et al., 2021; Janowski et al., 2024a; Kok et al., 2017; Krämer et al., 2023; Pai & Wang, 2020; Peter et al., 2020; Renigier-Biłozor & Janowski, 2024; Renigier-Biłozor et al., 2019; Renigier-Biłozor et al., 2021; Riveros et al., 2024; Sisman & Aydinoglu, 2022; Soltani & Lee, 2024; Yacim & Boshoff, 2020; Yazdani & Raissi, 2023; Zaki et al., 2022; Zhan et al., 2023.

The use of Automated Valuation Models (AVM) and Computer-Assisted Mass Appraisal (CAMA), powered by Artificial Intelligence (AI), in real estate valuation holds significant potential to enhance the efficiency and accuracy of market analyses, while also providing new insights and perspectives. An increasing number of companies offer AVMs that utilise advanced AI algorithms to estimate property values, as shown in Figure 6. And of course, many other solutions that are being published online on a regular basis.

In the USA: Zillow – Zestimate; Redfin - Redfin Estimate; HouseCanary - HouseCanary Value Report; CoreLogic - Automated Valuation Solutions

In Europe: SonarHome - SonarHome Estimator (Poland); Urban.one - Urban.one Valuation (Poland); Hometrack - Hometrack AVM (United Kingdom and Australia); PriceHubble - PriceHubble Valuation (Switzerland & Germany); Proportunity - Proportunity Valuation (United Kingdom); Homeday - Homeday Price Estimation (Germany); Immo Scout24 (Germany); Tinsa Digital – (Spain); Ubimet – (Austria); VALUATE - VALUATE AVM (PwC Cyprus).

Figure 6. Notable AI-powered AVMs in the USA and Europe

In summary, harnessing AI in AVMs provides valuable behavioural insights that are shaping real estate market trends and driving innovation in valuation methodologies. As illustrated in Figure 7, the integration of artificial intelligence (AI) into Automated Valuation Models (AVMs) and Computer-Assisted Mass Appraisal (CAMA) systems offers numerous capabilities and benefits that enhance real estate market analysis.

Integration of the Human Component: One of the primary criticisms against AVMs is their perceived lack of inclusion of the human element. By combining the computational power of AI with the nuanced understanding and expertise of human professionals, a hybrid model can be created that leverages the strengths of both. This symbiotic relationship can drive innovation, reduce errors, and provide more reliable data for decision-making, thus enhancing the overall effectiveness of real estate market analyses.

Enhanced Market Analysis: Traditional market analysis methods often overlook the complexity of human decisions, which are influenced by motives, emotions, and reactions. Integrating advanced technologies such as cognitive science and soft computing allows for a more comprehensive understanding of these decision-making processes. For instance, technologies like emotion recognition and neural networks can increase the objectivity and flexibility of market analyses by incorporating behavioural factors.

Advanced Analytical Techniques: AI enables the processing and analysis of large datasets through techniques. These methods can identify complex patterns and relationships that may be missed by human analysts.

Cognitive Science and Soft Computing: These fields delve into the human mind's capabilities and constraints, which are crucial for understanding market dynamics. By integrating cognitive science with AI, systems can be designed to align with human cognitive abilities, making them easier to interpret and more efficient to improve and modify. Soft computing techniques, which tolerate imprecision and uncertainty, can further enhance the robustness and adaptability of market models.

Figure 7. AI-driven advancements in AVMs and CAMA

Despite these significant benefits, challenges remain in implementing AI within AVMs and CAMA systems, as outlined in Figure 8

Complexity and Cost of Implementation: Implementing advanced technologies such as Virtual Reality (VR) with pupil tracking, computer vision technologies (CVT), and neural networks can be costly and time-consuming. Additionally, certain technologies may have health-related limitations or diverse interpretations of results, requiring careful consideration in their application.

Data Quality Issues: The effectiveness of AI is heavily dependent on the quality of data it is trained on. Inaccurate or incomplete datasets can lead to erroneous valuations and analyses. Ensuring rigorous data verification and selection processes is essential to maintain the reliability of AVM outputs.

Change Management: Adapting to new technologies necessitates changes in both technological infrastructure and human practices. Resistance to change can hinder the development and implementation of AI in AVMs. It is crucial to foster an environment that encourages collaboration between technology and human expertise to fully realize the potential benefits.

Figure 8. Challenges in AI implementation within AVMs and CAMA systems

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The integration of AI in AVMs and real estate market analyses offers substantial potential to enhance the efficiency, accuracy, and depth of market analyses. By utilising advanced technologies alongside human expertise, it is possible to achieve more precise and perceptive evaluations.

Role of AVMs in Different Real Estate Markets

With their data-driven insights that improve appraisal accuracy and efficiency, Automated Valuation Models (AVMs) have become revolutionary instruments in the field of property valuation. Their use, however, differs greatly between various real estate markets, including the residential and commercial sectors. These differences are examined in this section, along with the opportunities and difficulties that AVMs encounter in each situation.

Residential Real Estate Market

Data Abundance and Simplicity: The residential real estate market benefits from a high volume of transactions and relatively standardised property characteristics. These factors contribute to the abundance of data available for analysis, enabling AVMs to generate reliable and accurate valuations. Key variables such as property size, location, and condition are more uniform, simplifying the modelling process. *Common Use Cases*: AVMs are extensively used in residential markets for:

- Mortgage underwriting and refinancing.
- Property tax assessments.
- Market trend analysis and forecasting.

Advantages:

- Speed and Efficiency: The automation provided by AVMs significantly reduces the time required for property appraisals.
- Cost-Effectiveness: AVMs offer a more affordable alternative to traditional valuation methods.

Challenges: Despite their strengths, AVMs in residential markets must address challenges such as:

- Behavioural Factors: Emotional considerations, such as a buyer's attachment to a neighbourhood, are difficult to quantify.
- Unique Property Features: Characteristics like architectural style or historical value may not be adequately captured by AVMs.

Commercial Real Estate Market

Complexity of Variables: Commercial real estate valuation is inherently more complex due to diverse property types, income potential, lease structures, and capitalisation rates. These factors require sophisticated modelling techniques and data inputs that may not be as readily available as those in residential markets.

Limited Transaction Data: Unlike residential markets, commercial real estate experiences fewer transactions, and detailed financial data – such as lease agreements and operating expenses – is often proprietary. This scarcity of data poses significant challenges for AVMs in delivering accurate valuations.

Common Use Cases: In commercial markets, AVMs are primarily employed for:

- Portfolio assessments and investment analyses.
- Risk evaluations for lenders and institutional investors.
- Periodic revaluations for financial reporting.

Advantages:

- Scalability: AVMs can process large datasets, making them suitable for portfolio-level analyses.
- Consistency: Automated processes help ensure uniformity in valuations across multiple properties.

Challenges:

- Hybrid Models: The complexity of commercial properties often necessitates a hybrid approach, combining AVM outputs with human expertise.
- Market Dynamics: Factors such as tenant demand, zoning changes, and macroeconomic conditions are difficult to model accurately.

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Comparative Analysis: Residential vs. Commercial

Table 2. Comparative analysis of residential and commercial markets

	Residential Market	Commercial Market
Data Availability	Abundant transaction data	Limited and often proprietary
Complexity of Variables	Standardized property characteristics	Diverse and complex valuation factors
Use of AVMs	Mortgage approvals, tax assessments	Portfolio analysis, risk evaluations
Challenges	Capturing emotional/unique features	Modeling financial data and market dynamics
Reliance on Hybrid Models	Low to moderate	High

The regulatory frameworks governing AVM use vary between residential and commercial markets. Residential markets often have stricter oversight due to the direct impact on individual homeowners. In contrast, commercial markets, while less regulated, require robust compliance measures to ensure transparency and fairness in large-scale investments.

Additionally, AVM developers must address ethical concerns, such as ensuring data accuracy and mitigating biases, particularly in markets with sparse or incomplete data.

To fully realise their potential, AVMs must evolve to address the specific needs of residential and commercial markets:

- *Enhanced Data Integration:*

  Incorporating alternative data sources, such as environmental and demographic information, can improve accuracy.
- *Behavioural Insights:*

  Developing models that account for human preferences and emotional factors will make AVMs more versatile.
- *Hybrid Solutions:*

  Combining AVMs with professional judgment ensures reliability and compliance, especially in complex commercial markets.
- *Regulatory Alignment:*

  Collaborating with industry bodies to develop standards that foster trust and accountability.

By tailoring their approaches to the unique characteristics of each market segment, AVMs can drive innovation and efficiency across the real estate industry.

Transparency and ethics in AVMs supported by AI

When researching "land market and ownership transparency," the first step is to identify methodological definitions of these terms. Recently, both international and national levels have increasingly examined this topic. Findings come from classical and behavioural economics, large data handling, database networking, and legal sciences, especially regarding tax evasion, terrorist financing, money laundering, and transparency registers. *The term "transparency" often serves different interests for companies, institutions, or the state, lacking a universal definition in the property market context.* Still, it is frequently used without specific content, making constructive discourse challenging. Society, politics, and the economy seem to "avoid" debating this term directly.

The property market significantly impacts financial well-being and market stability. Despite its importance, irrational behaviours and undesirable trends persist, often termed "Misbehaving of the property market." Behavioural economics, notably work by Daniel Kahneman and Amos Tversky, shows people don't always act rationally, especially under uncertain conditions (Tversky & Kahneman, 1974). Their "Prospect Theory" challenged economic views, suggesting market decisions depend on psychological, non-rational factors (Kahneman & Tversky, 1979). This is relevant in real estate, where considerable uncertainty and long-term investments prevail, and property ownership often involves strong emotions tied to personal identity. Richard H. Thaler expanded on these ideas in his book "Misbehaving. The Making of Behavioral Economics" (Thaler, 2015), a fitting title for the article, as it aptly describes real estate market behaviors. Consequently, the property market doesn't

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always align with economists' expectations and reflects individual actions, often irrationally. *It's uncertain if theoretical models can accurately value properties or determine trend impacts, especially when the underlying data quality is poor.* Does an expert's judgment suffice to estimate a value near a property's anticipated price? It's relevant to question whether intrinsic and extrinsic biases may lead to inaccuracies.

To analyse a market, assess property values, and make informed decisions on investments, taxes, or disputes, thorough market data analysis is essential. This data is crucial in contexts where property values guide decisions. Exclusive reliance on economic models, assuming all individuals have equal economic understanding, is increasingly outdated. Therefore, greater transparency in the property market is essential.

It's no secret that these days we generate huge amounts of data about every aspect of our lives. It is also no secret that this data is analysed and used for commercial purposes by companies such as Google, Amazon, Facebook, etc. It is also widely accepted that valuations are generally based less on concrete data and more on theoretical, economic approaches. A decidedly conservative and often rather helpless approach, which is then balanced by the so-called expertise of the experts. This overlooks the fact that experts, like judges, teachers, police officers and bosses, are subject to psychological bias. The data is not used, or is used far too little, for the state's pension obligations, for the fair valuation of property for tax purposes or – on a larger scale – for improving the foundations of democracies through greater transparency. Combined with the knowledge that markets in general, and property markets in particular, function not only on the basis of economics but also on the basis of psychological aspects, it becomes clear that the theoretical models based on economics explain the property market inadequately. Given the ability to analyse data today, this no longer makes sense and is no longer responsible. **The possibilities of using artificial intelligence and automated valuation models are immense and can help to produce good valuations that truly reflect the market.**

Shifting to evidence-based valuations (EBV), grounded in empirical data such as actual sale prices and buyer-seller profiles, allows for valuations minimally dependent on theoretical models. This approach meets the demands of a rapidly changing market, and it calls for a revised understanding of "Transparency in the Real Estate Market," explored further in the next section.

Transparency in Real Estate Markets, an approach to a definition

The Financial Action Task Force (FATF) is an international body that sets standards to combat money laundering, terrorist financing, and the financing of weapons of mass destruction. FATF emphasises the importance of transparency in ownership and access to information by authorities as essential for preventing real estate misuse (Financial Action Task Force, 2014). Real estate plays a critical role in national, social, and security policy, spanning residential, commercial, and agricultural sectors. In today's data-driven world, enhanced computational power allows for the swift processing of vast data sets, enabling deeper insights and more accurate predictions across industries, including real estate. As technology advances, data analysis becomes ever more crucial for informed decision-making and growth.

Despite available data, policy and investment decisions often rely on outdated theoretical models disconnected from everyday realities. Data-driven analysis, rooted in observable realities, highlights the need to define and classify data specifically for the property market. A clear definition of "transparency in the property market" serves this purpose effectively.

The following broad definition applies: *A transparent real estate market enables the free flow of information, allowing all market participants – including the state in its legislative, judicial, and executive roles – to make informed, long-term decisions.* Additional perspectives include access to quality real estate information for all parties, including the public.

This definition reflects insights from international literature, current expert discussions, and political requirements, evolving as research and industry standards progress (e.g., Ache & Krägenbring, 2023).

The following concrete approach to defining transparency in the property market is put forth for consideration, as outlined in Figure 9.

The careful discussion of the term "Transparency in the Real Estate Market" is a fundamental prerequisite for the advancement of investor decisions, political actions, and the actions of authorities. This also applies in the context of the ethical handling of data that concerns individuals. Only

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when these fundamental issues are well clarified can technical developments, such as the use of artificial intelligence for property valuation, be successful and be used for meaningful policies, such as tax policy.

Real estate or property is all undeveloped and developed land, including undesignated/unregistered land/communally owned land and land used for all sorts of purposes be it e.g., agriculture, forestry, and natural habitats and more broadly also land that relates to water. It therefore includes public land, governmental land und unregistered land.

Real estate market transparency can be categorised according to:
- The type of access to real estate market information for all involved parties.
- The availability and
- The quality of real estate market information.

Real estate market information is data on the components of the real estate market and related markets as well as the whole economy and includes
- Individual data for each property (e.g. purchase price, location, size, etc.) as a direct comparable evidence,
- Categorized individual data as statistical information on property classes in regional and functional submarkets as indirect comparable evidence or general market data,
- Appraisals, valuations and other expert opinions on individual properties, e.g. on market value, tax value, mortgage lending value, etc., and
- Other sources, e.g. assessed data based on professional judgement (IVSC, 2024)

Components of the real estate market are:
- Properties (real identifiable assets relating to land) and their spatial and material characteristics,
- Owners, buyers, and holders of rights to real estate, including but not limited to inheritable building rights, letting, leasing, mortgaging, rights at the expense of others, encumbrances,
- Type, origin, and intention of buyer of/with property and
- Transaction prices and income from properties.

The quality of real estate market information depends on its:
- timeliness,
- granularity in spatial and substantive submarkets,
- reliability and
- consistency.

Figure 9. Key components for real estate market transparency

Ethical implications of transparency and the utilisation of AVMs

Enhancing transparency in the property market necessitates broad data exposure, which also risks personal data misuse or flawed analyses from complex but misleading methods. Effective safeguards are essential to prevent such misuse.

First, data collection should minimise bias by design, with controlled access to prevent exploitation. Ensuring data accuracy and establishing quality metrics for AVM results is also crucial. The European Commission's High-Level Expert Group on AI (2018) highlights the risk of biases, especially when training data lacks diversity, leading to racially or gender-biased outcomes. Additionally, the opaque, "black box" nature of AI-based AVMs can hinder transparency, making results incomprehensible and therefore unacceptable for critical decisions. Professional associations must champion ethical standards, ensuring AVM transparency is not abused. A rigorous, scientifically grounded discourse is essential to develop and refine solutions that align transparency with accountability. These concerns correspond with the European Union's broader policy framework for trustworthy artificial intelligence, which emphasises transparency, accountability, and human oversight as key principles for the development and deployment of AI systems (European Commission, 2020).

In this context, the European Union's Artificial Intelligence Act (AI Act) plays a pivotal role by establishing a comprehensive regulatory framework for artificial intelligence systems based on a risk-classification approach and introducing requirements for transparency, accountability, and human oversight (European Commission, 2021). The European Union Artificial Intelligence Act (AI Act) was formally signed on March 13, 2024, and published in the Official Journal of the EU on July 12, 2024 (The EU Artificial Intelligence Act,2024). It came into force on August 2, 2024, with regulations

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implemented in stages, achieving full application by August 2026. All 27 member states unanimously approved the AI Act. The main implementation stages of this act are as follows (Reed Smith, 2024), (MIT Technology Review,2024) as categorised in Figure 10.

The AI Act classifies AI systems according to risk levels:
• **Low risk:** Light transparency obligations.
• **High risk:** Strict requirements for risk management, technical documentation, oversight, and compliance.
• **Unacceptable risk:** Total ban, e.g., manipulative behavioural techniques, scoring systems, crime prediction based on profiling.

Figure 10. Risk levels and implementation of the AI Act

Exceptions apply to systems used exclusively for military and defence purposes and for research purposes. The AI Act also provides special provisions for the use of AI by law enforcement agencies in extraordinary situations (Reed Smith, 2024). These regulatory initiatives are poised to significantly impact various sectors, including real estate valuation, by providing clarity regarding legal responsibilities and fostering a safer and more accountable environment for AI deployment in the EU market.

In their study, Yam et al. (2025) emphasise the importance of industry certification as a regulatory measure to ensure the ethical and secure implementation of technology in the real estate sector. Recommendation 3 suggests promoting certifications, such as the "Certified Property Data Analyst" offered by the Australian Property Institute (API), as a tool to address ethical concerns. The authors note that implementing such certifications could be supported by continuous professional development programs, including workshops and seminars, fostering a culture of innovation and ethical practices. Additionally, the recommendation highlights the need for regulatory oversight of big data activities by appropriate bodies to ensure privacy protection and advocates for the integration of business analytics into university curricula, preparing graduates for roles in the rapidly evolving real estate sector.

In the context of our research, implementing a certification standard may be crucial in developing a technically proficient and ethically responsible workforce capable of effectively operating at the intersection of technology and real estate. Such an approach would ensure that professionals are not only technically adept but also aware of and committed to upholding the highest ethical standards, which is essential given the increasing role of AI and big data in property valuation.

To address the ethical implications of transparency and the utilisation of AVMs, an effective implementation strategy must align technological advancements with ethical principles, as outlined in Figure 11.

Transparency: The methods, algorithms, and outcomes generated by AVMs must be disclosed in a comprehensible manner. Emphasizing the use of Explainable AI (XAI) can help reduce the "black box" nature of many models, making their processes more accessible and trustworthy for stakeholders.

Bias Mitigation: The development of AVMs should prioritize diverse and representative training datasets. This reduces the risk of biased outcomes and ensures that the models produce equitable results, avoiding potential discrimination based on race, gender, or other factors.

Accountability: Clear guidelines for reviewing and validating AVM results must be established. These guidelines should define the responsibilities of developers, users, and organizations, fostering trust in the technology and ensuring ethical use.

Data Protection and Security: The sensitive nature of property-related data necessitates robust data protection measures. Ensuring compliance with regulations such as the European Union's General Data Protection Regulation (GDPR) can safeguard user trust and prevent misuse of personal data. Implementing industry-recognized certifications, like the "Certified Property Data Analyst" offered by the Australian Property Institute (API), can further enhance data protection standards. These certifications provide professionals with frameworks to adhere to best practices in data handling, ensuring alignment with current legal and ethical standards.

Integration of the Human Factor: Human expertise should complement AI-driven models by validating results and contextualizing them within market dynamics and local conditions. This collaboration ensures that the unique nuances of real estate markets are accurately reflected.

Figure 11. Key pillars for the ethical implementation of AVMs

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Our research emphasises operationalising this framework through actionable strategies. One key proposal is the introduction of **transparent valuation reports** that not only present AVM results but also detail the underlying data, methodologies, and factors influencing the outcomes. Such reports would enhance trust and usability for stakeholders. Additionally, the establishment of **independent commissions** to monitor compliance with ethical and regulatory standards is critical. These commissions would regularly evaluate AVM practices, ensuring adherence to transparency, accountability, and fairness principles. By integrating these strategies, the ethical framework for AVM utilisation can foster a more transparent, accountable, and equitable approach to property valuation, ultimately advancing the adoption of AI in real estate markets while safeguarding public trust.

Discussion

The application of artificial intelligence is already widespread and shows no signs of slowing down. It is therefore evident that criticism of AI should not be regarded as a form of generalisation, but rather as a constructive process that facilitates the safe and beneficial utilisation of AVMs. It is of the utmost importance to prevent material damage, such as financial disadvantages, security breaches, and tax manipulation, as well as immaterial damage, including the loss of privacy and the restriction of freedom of expression (European Commision, 2020).

This is one of the reasons why the General Conference of the United Nations Educational, Scientific and Cultural Organisation (UNESCO) adopted the "Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021) at its meeting in Paris from 9 to 24 November 2021. This resolution acknowledges the profound and dynamic positive and negative impacts of artificial intelligence (AI) on societies, the environment, ecosystems and on human life, including the human mind. This is due to the new ways in which the human mind is influenced, including the ways in which its use affects human thinking, interaction and decision-making, and affects education, human, social and natural sciences, culture, communication and information. The recommendation represents the inaugural globally negotiated text pertinent to international law in the domain of AI ethics. Moreover, the recommendation is not only global in scope but also holistic in its content. The recommendation provides the 193 member states of UNESCO with a framework for action in this crucial future field. In this context, experts are expected to provide constructive contributions based on scientific research in the fields of technology, law, psychology and ethics. Nevertheless, the political decision-makers in the countries are also obliged to validate the expert knowledge and to distinguish between interest-driven approaches and genuine expertise.

This is particularly pertinent in instances where state interests are at odds with the principles of liberalism, equality and freedom. This is the challenge that must be met. The guiding principle in the development of AVMs, their use and review should be transparency in the property market.

Data quality and standard

The accuracy and reliability of Automated Valuation Models (AVMs) are contingent upon the quality of the data employed. The utilisation of high-quality real estate market data is imperative to ensure the precision of valuations, the accurate capture of current market trends and price movements, and the appropriate consideration of local location factors. It is of particular importance that valuations are accurate for lenders, investors and taxation purposes. In the event that the underlying data is incomplete, outdated, or incorrect, this can result in inaccurate valuations, which may subsequently lead to a loss of trust in the AVMs and potentially result in financial losses and even a lack of trust in government action. The quality of the data is of the utmost importance and serves as the fundamental basis for any valuation. The availability of high-quality data allows AVMs to gain a deeper understanding of current market trends and price movements. In volatile markets, where property prices can change rapidly, it is of the utmost importance that these changes are promptly captured and included in the models. The utilisation of high-quality data facilitates the maintenance of valuation accuracy and ensures that the resulting data accurately reflects the prevailing market conditions.

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The location of a property, including its proximity to schools, transportation links, shopping facilities and other amenities, can exert a significant influence on its value. In order to accurately assess these factors, AVMs require detailed and up-to-date geographical data. It is only through the utilisation of precise and comprehensive data that AVMs are able to perform complete and accurate property valuations.

Furthermore, high-quality data is critical for the validation and calibration of models. Comparing AVM-generated valuations with actual sale prices allows for accuracy checks and necessary adjustments. This continuous improvement process is essential and is only possible with high-quality data, contributing to the reliability of the models over time. Finally, good data contributes to transparency and trust in valuations. When market participants know that AVM valuations are based on reliable and current data, they are more likely to trust these valuations and incorporate them into their decision-making processes. Transparent and trustworthy valuations foster confidence in the real estate market and support market stability.

Overall, data quality is the key factor for the performance and reliability of AVMs. Only through the use of precise, current, and comprehensive data can AVMs deliver accurate and reliable valuations that meet the high demands of various market participants.

If data is one of the most crucial aspects of utilising AI in general and AVMs in particular, it is imperative to ascertain how property market data should be collected. It is equally important to ensure that property market data is comparable and adheres to uniform standards so that it can be employed in machine learning processes. However, the problem is often that the cadastre is organised differently in regions, countries, and states. The descriptive characteristics for properties are not uniformly standardised, so that a retail shop in city A may be a different property from a retail shop in city B. The circumstances under which the purchase prices in sales cases arise are also recorded differently, and the characteristics that determine the price are recorded according to different criteria. This leads to imprecision in the data, which, particularly in the case of rare transactions, leads to inaccuracies and distortions in the results of the analyses when data is combined across larger spatial areas. To summarise, it can be stated that the collection of data must begin where it is generated. This is the case when the land is first registered, i.e. the parcel is created at the land registry, as well as during the transaction itself, usually before the notary. In this context, there is still a considerable need for development with regard to the meaningful application of artificial intelligence, including in the context of valuation.

Challenges and best practices in implementing Automated Valuation Models

The evolving field of property valuation has increasingly embraced AVMs, leveraging technology to enhance both efficiency and accuracy. However, implementing AVMs brings significant challenges and ethical considerations that must be addressed to ensure their responsible and fair use. Dimopoulos (2020) highlights that human qualities, like feelings and empathy, can both enrich and distort valuations. While these traits contribute to humanity, they can also introduce biases, limiting neutrality in assessments. In contrast, AI, which lacks emotional influence, can deliver more objective valuations by maintaining consistency across cases. However, there are political and professional barriers, as many licensure bodies are human-centred and resistant to technological change due to concerns over job security and the potential loss of human relevance in valuations.

Beyond these ethical and professional concerns, AI adoption in AVMs also faces significant technical and regulatory challenges. The accuracy and reliability of AVMs are fundamentally tied to the quality and consistency of the data used in their models. Despite advancements in data integration, significant challenges remain in ensuring standardisation across regions, particularly due to disparities in cadastral systems and inconsistencies in data collection practices. For instance, property characteristics recorded in one region may differ significantly from those in another, introducing variability that undermines the robustness of AI models. Additionally, incomplete or low-quality datasets can exacerbate biases, leading to valuations that fail to reflect true market conditions. While these issues are substantial, AI itself can offer solutions. For example, **transfer learning techniques enable pre-trained models to adapt to new datasets with limited additional training, making them particularly useful in regions with sparse or inconsistent data. Additionally, AI systems can auto-**

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mate data preprocessing, detecting and correcting errors, and harmonising datasets to improve reliability.

AI-driven AVMs inherit biases from their training data, making it crucial to examine the sources of potential distortions. Historical sales data, for example, may reflect systemic inequalities, such as neighbourhood-level disparities influenced by socioeconomic factors. These biases can become embedded within AI models, perpetuating inaccurate or unfair valuations. To mitigate such issues, a hybrid approach that combines AI precision with human judgment is essential. Human appraisers can critically evaluate AI outputs and contextualise valuations based on market-specific nuances. Furthermore, blockchain technology can enhance transparency by providing immutable records of data sources and valuation processes, ensuring stakeholders have trust in the system's integrity. Blockchain can also be used to trace and verify the origins of data used for training AI models, reducing the risk of perpetuating systemic biases.

The adoption of AI in AVMs raises significant regulatory challenges, particularly in ensuring accountability and compliance. Unlike traditional valuation processes, where human appraisers can be held liable for errors, the use of AVMs introduces ambiguity about responsibility. This issue is increasingly addressed in European regulatory discussions concerning civil liability for damages caused by artificial intelligence systems, which aim to clarify responsibility between developers, providers, and users of AI technologies (European Commission, 2022). For instance, if an AVM generates an incorrect valuation leading to financial loss, it remains unclear whether liability rests with the developers, users, or organisations deploying the system. **The regulatory frameworks for AVMs differ across countries, reflecting varying levels of technological maturity and legal infrastructure. However, transparency should be a universal standard, with clear guidelines for auditing AI models, ensuring explainability, and defining accountability mechanisms. Such transparency not only fosters trust but also provides a pathway for regulatory bodies to adapt as AI technologies evolve.**

Despite these concerns, there is a broad consensus that human valuers remain crucial in complex valuations, especially for legal accountability. When a human valuer conducts an appraisal, they can be held responsible, but it becomes challenging to assign responsibility in cases where AVMs are used. Questions arise: who is liable when an AVM's valuation results in financial loss, and who should sign off on such automated assessments? These ambiguities are a significant drawback to fully integrating AI in valuation practices.

While accountability issues are not easily resolved, consistent data inputs and model maintenance can minimise errors, potentially reducing the need for costly legal recourse. In cases where routine valuations are required – such as for mortgage assessments or repossessions – AI models can provide cost-effective and swift valuations, helping reduce dependency on human labour. Addressing these regulatory, data, and bias-related challenges is critical to fostering trust and reliability in AI-driven AVMs. With clear regulatory and operational guidelines, AI can support accurate, high-volume valuations.

The impact of AI on employment remains complex. Frey and Osborne (2017) argue that while automation may streamline roles, it doesn't necessarily mean job loss. Instead, human valuers might be empowered to focus on complex, high-value cases, which can elevate the quality and value of human-conducted assessments. This could increase the achieved price per valuation, benefiting valuers and stakeholders alike by improving trust and quality within the financial ecosystem.

Every technological advancement, including Automated Valuation Models (AVMs), comes with its own set of advantages and challenges, requiring a balanced approach to maximise benefits while addressing limitations. AVMs offer notable advantages, including efficiency and cost savings by automating the valuation process, which minimises the need for extensive manual labour. They also enhance objectivity, reducing human errors through the use of standardised algorithms. However, challenges remain, particularly regarding accuracy when dealing with insufficient or low-quality data and valuing unique or non-standard properties. Additionally, over-reliance on technology may lead to the undervaluation of local expertise and human intuition, which are essential for capturing market-specific nuances. Balancing these strengths and limitations is key to optimising the use of AVMs in property valuation.

Ethical Challenges and Guidelines for Ethical Use of AVMs

There are issues with opaque valuation methods and the potential for algorithmic discrimination. It is crucial that AVMs are transparent in their methodologies to ensure fairness and avoid biases. Determining responsibility for misvaluations can be challenging. Clear guidelines are needed to assign accountability in cases of errors. While AVMs automate much of the valuation process, human oversight is essential to validate and interpret the results, ensuring they are reasonable and accurate.

Developing comprehensive guidelines for the ethical use of AVMs is essential, as summarised in Figure 12.

- **Data Access and Quality:** Ensuring access to high-quality data is critical for accurate valuations.
- **Transparency:** AVMs should clearly disclose their methods, the data used, and the models employed.
- **Predictor Impact:** Understanding and communicating the influence of various predictors used in AVMs.
- **Fairness and Non-Discrimination:** Ensuring that AVMs do not perpetuate biases or unfair practices.
- **Accountability:** Establishing clear lines of accountability for the outputs of AVMs.

Figure 12. Guidelines for the ethical use of AVMs

Best Practices and Practical Implications for Implementing AI and ML in AVMs

Ensuring that data inputs are regularly updated and validated is crucial for maintaining the performance of Automated Valuation Models (AVMs) and the accuracy of the results. For example, inconsistent property records or missing transactional data can lead to biased results of valuations. By establishing robust data governance frameworks, standards and taxonomies, as well as periodic audits of input data or integrating cadastral databases with market transaction systems, AVMs can achieve higher reliability. Transparent communication about the capabilities and limitations of AI and machine learning (ML) technologies with customers and stakeholders is essential to fostering trust and setting realistic expectations. Continuous training and updates of AI-based ML models are necessary to adapt to changing market conditions and user behaviour, ensuring that the systems remain robust and effective. Moreover, the developed models must not function as a "black box"; instead, the significance of the features used and their impact on the target variable (e.g., the estimated purchase price) must be made transparent.

In addition to these best practices, the integration of AI into machine learning algorithms and AVMs carries substantial practical implications for professional appraisers and market stakeholders, as illustrated in Figure 13.

By adhering to these fundamental considerations as well as practices and addressing both the ethical challenges and practical implications of AI integration, AVMs can enhance the efficiency, accuracy, and fairness of property valuations. For example, stakeholders in high-growth regions, such as urban hubs experiencing rapid gentrification, can benefit from AI-driven systems that quickly adjust to market dynamics, providing up-to-date valuations critical for both private investors and public administrators. This responsible approach ensures that the benefits of AI technologies are maximised while maintaining trust and accountability across all levels of the real estate industry.

Addressing the critical challenges of AI adoption in AVMs – data limitations, biases in AI models, and regulatory hurdles – requires both technological advancements and collaborative governance. Approaches such as transfer learning and blockchain can improve data reliability and enhance transparency, while hybrid models that combine human expertise with AI outputs help mitigate biases and build trust in valuations. Although regulatory frameworks vary across regions, they must emphasise transparency and accountability to encourage the wider adoption of AVMs. These efforts are vital to ensuring that AVMs address the needs of diverse stakeholders while maintaining fairness and reliability in rapidly evolving property markets.

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Impact on Professional Appraisers: AI technologies, such as machine learning and neural networks, are designed to complement the expertise of human appraisers, not replace them. These tools automate repetitive tasks like data collection, property classification, and preliminary analyses, allowing appraisers to focus on complex cases that require nuanced professional judgment. For instance, neural network algorithms can process extensive datasets, identifying patterns that human analysts might overlook, such as emerging trends in urban redevelopment areas. This enables appraisers to incorporate localized market changes into their valuations with greater precision. By mitigating human limitations, such as cognitive biases and susceptibility to fatigue, AI enhances the consistency and reliability of valuations, thereby increasing trust in the valuation process. Additionally, by using AI to pre-screen comparable sales or adjust for atypical features (e.g., proximity to industrial zones or green spaces), appraisers can deliver valuations faster without compromising quality. However, it is crucial to ensure that models are not overfitted to training data, as this can limit their applicability to real-world scenarios. Such issues become apparent only through rigorous performance testing using independent test datasets, which helps validate model reliability and generalizability.

Benefits for Market Stakeholders: For financial institutions, policymakers, and other stakeholders, AI-driven valuation systems provide substantial efficiencies, offering real-time insights into market trends and enabling quicker decision-making in areas like taxation, loan underwriting, and urban planning. For example, financial institutions can use AI to pre-approve mortgages by instantly assessing property value, reducing the average time from application to decision from weeks to days. Similarly, municipalities can use AI-enabled CAMA systems to predict revenue from property taxes, aiding in budget planning and identifying areas for reassessment. Moreover, blockchain technology can be integrated into AVMs to enhance transparency and data security, particularly for the critcal step of data collection and data management Blockchainprovides an immutable ledger of transactions that ensures that all parties can verify the accuracy of property data, including sales history, ownership records, and different values of the property. This level of transparency builds trust among stakeholders and minimizes the potential for disputes,data manipulation, and it prevents money loundering ultimately corruption.

Advanced Technologies: Blockchain and Transfer Learning: Blockchain technology is increasingly being recognized as a tool to improve the traceability and integrity of property data. For example, a blockchain-based system could securely store transactional data, such as sales prices and ownership details, while maintaining data privacy. This ensures that AVM models have access to verifiable and high-quality data, ultimately leading to more reliable valuations. Blockchain also provides stakeholders, including appraisers and financial institutions, with confidence in the accuracy and immutability of valuation records. Transfer learning, another advanced AI methodology, enables pre-trained models to be adapted for new tasks with limited additional training data. This technique ensures that AVMs are efficient and adaptable across diverse market conditions, providing reliable outputs even in regions with sparse transaction data.

Ethical and Professional Considerations: The adoption of AI in valuation necessitates professional training to equip appraisers with the skills to interpret AI outputs effectively and apply human judgment where necessary. Training programs offered by institutions like the Royal Institution of Chartered Surveyors (RICS) or the International Association of Assessing Officers (IAAO) increasingly include modules on integrating AI tools into traditional appraisal workflows, ensuring practitioners can use these technologies responsibly. Ethical considerations, such as algorithm- and resultstransparency, accountability of the responsible valuer and compliance with international valuation standards, must also be prioritized to ensure public trust in these systems. For instance, AI models used in taxation assessments should clearly disclose the variables influencing the values to avoid accusations of bias or manipulation. Clear documentation of these processes helps stakeholders understand and trust the outputs.

Figure 13. Practical implications of AI integration in AVMs

Conclusions

As the field of artificial intelligence (AI) continues to evolve at a rapid pace, its integration into fields such as real estate valuation presents both opportunities and challenges. It is of the utmost importance to guarantee the accuracy and transparency of Automated Valuation Models (AVMs), especially as these technologies become more prevalent in decision-making processes. This article examines the potential impact of AI and behavioural insights as drivers of regulatory and enhancement measures for AVMs, with the objective of fostering a more efficient and equitable property valuation system.

One of the most critical aspects of any modelling process is the accuracy and efficiency of its output. The difficulty in interpreting results from AI-based models is key and recurring criticism that often discredits AI technology in the eye of users. This can be attributed to the long-standing principle of evaluating model quality through a binary lens, often relying on a percentage-based metric that measures how well the model fits the input data. The most popular metric for evaluating model quality assesses how well the model fits the historical data on which it was trained. However, the paradox is that these models, designed to predict future outcomes, are evaluated against past data. This inherent contradiction can create cognitive dissonance, leading analysts to sometimes "bend" reality to fit the model, all in the name of achieving high model quality. The regression-based multiple linear regression remains a popular method, yet it may not always align with the true dynamics of future events. Given the rapid advancement of AI technology, it may be worth reconsidering how we measure the quality of a model. Instead of focusing solely on how well a model fits historical data, alternative metrics could provide a more holistic view. Metrics that incorporate the model's adaptability to changing environments, its ability to generalise across diverse datasets, and its robustness in handling uncertainties could offer deeper insights into its true predictive power. Emphasising these aspects could lead to models that not only perform well in hindsight but also excel in anticipating future trends and events, thereby enhancing their practical utility and reliability in decision-making processes.

The following conditions are of paramount importance in ensuring the accuracy, transparency, and utility of automated valuation models (AVMs) in real estate valuation processes, as outlined in Figure 14.

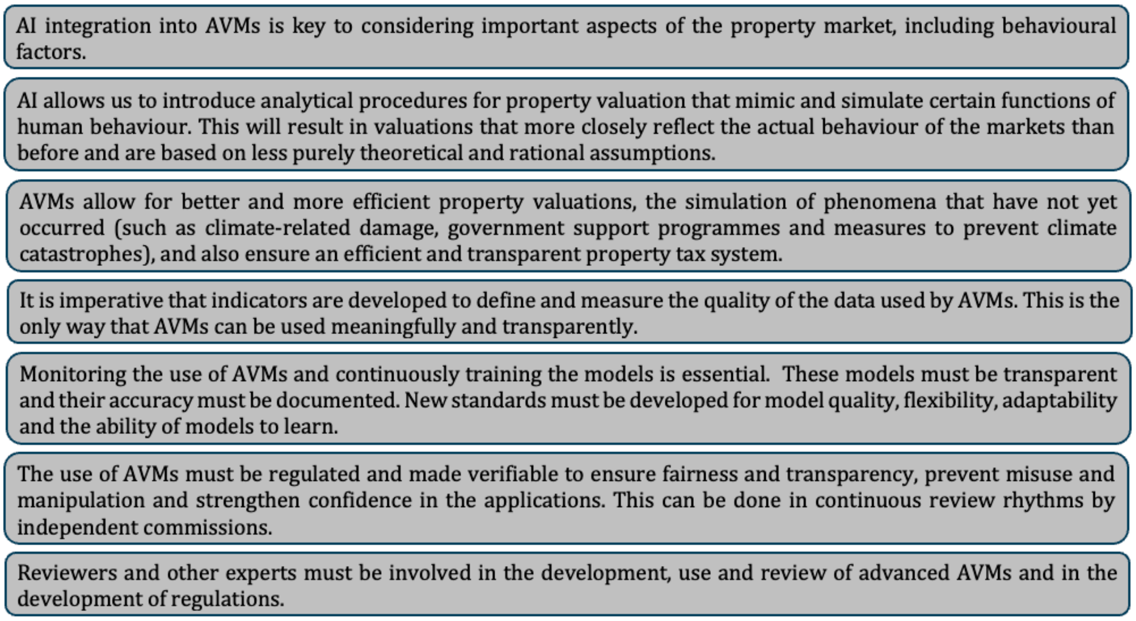

Figure 14. Key requirements for accuracy and transparency in AVMs

In concluding the paper, a vision is presented that holds the potential to become reality in the near future. While this may initially appear as mere speculation, it is essential to recognise that, as history has shown, the development of artificial intelligence has transformed what once seemed improbable and purely conceptual into tangible outcomes. These scenarios can now be considered as genuine possibilities, either as a vision or as a forewarning of upcoming changes.

The future is approached with the understanding that technology, driven by dynamic progress, possesses the capability to profoundly alter various aspects of daily life. Therefore, the scenarios outlined should be viewed not just as speculative but as potential pathways for development that could substantially influence and even revolutionise the real estate industry.

Possible scenarios for transforming the real estate industry through advanced AI-driven AVM models are outlined in Figure 15.

In summary, the successful adoption of AI-driven AVMs depends on addressing critical challenges such as data quality, biases, and regulatory uncertainty. Employing innovative solutions like transfer learning, blockchain technology, and hybrid approaches, combined with transparent and internationally consistent regulatory frameworks, can help ensure the accuracy, fairness, and reliability of AVMs.

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These advancements are essential for ensuring their continued relevance and for fostering a more dynamic, equitable, and efficient property valuation process.

Personalised property valuations based on demographic and infrastructural forecasts and plans: It is conceivable that advanced AVM systems will be capable of delivering valuations that are tailored to the specific requirements of individual users, taking into account their individual preferences and lifestyles. The utilisation of algorithms that learn from behavioural data, such as that observed on social media platforms, would enable these systems to analyse user preferences and sentiments in order to predict market trends with unprecedented accuracy. Such systems would not only be capable of forecasting property values, but would also be able to provide advice on the optimal times to buy or sell.

Ethical and Fair Use of AI: The potential for AI algorithms to eliminate biases rooted in historical data could be harnessed to counteract social and economic unfairness and speculation. The use of AVM systems would facilitate the creation of decentralised databases powered by blockchain technology, thereby ensuring indisputable and transparent histories of real estate transactions. Each record would be publicly accessible, reducing the risk of data manipulation and increasing trust in valuation systems.

Interactive Analyses of Property Values and simulation Potential Investments in Real-Time: The integration of virtual and augmented reality systems (VR/AR) provides the following: Potential purchasers may undertake virtual tours of properties utilising sophisticated VR/AR systems integrated with AVM. This would facilitate not only the visualisation of spaces but also the provision of interactive analyses of property values and potential investments in real time.

Figure 15. Future scenarios for AI-driven AVM transformation in real estate

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The contribution of the authors

Conceptualisation, M.R.B., P.A., T.D., A.J..; literature review, M.R.B., P.A., T.D., A.J.; methodology, M.R.B., P.A., T.D., A.J.; formal analysis, M.R.B., P.A., T.D., A.J.; writing, M.R.B., P.A., T.D., A.J.; conclusions and discussion, M.R.B., P.A., T.D., A.J.

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Malgorzata RENIGIER-BILOZOR • Peter ACHE • Thomas DIMOPOULOS • Artur JANOWSKI

PRZYSZŁOŚĆ WYCENY NIERUCHOMOŚCI: AVM I CAMA W ERZE SZTUCZNEJ INTELIGENCJI

STRESZCZENIE: Autorzy dokonują analizy Zautomatyzowanych Modeli Wyceny (AVM) zintegrowanych ze Sztuczną Inteligencją (SI), przedstawiając je jako kluczowe narzędzia w tworzeniu sprawiedliwego, zrównoważonego i zintegrowanego sektora nieruchomości miejskich. W miarę postępu urbanizacji, AVM wspierane przez SI odgrywają coraz istotniejszą rolę w procesie wyceny nieruchomości, oferując analizy oparte na danych, które rewolucjonizują tradycyjne metody szacowania. W przeciwieństwie do konwencjonalnych inspekcji, AVM zasilane SI przetwarzają obszerne zbiory danych w celu oszacowania wartości nieruchomości, co umożliwia lepsze dostosowanie do potrzeb planowania miejskiego. Badanie podkreśla potencjał AVM w usprawnianiu praktyk na rynku nieruchomości miejskich, jednocześnie zwracając uwagę na wyzwania związane z etyką, przejrzystością i zarządzaniem. Poprzez skupienie na synergii między technologią a procesem wyceny, AVM jawią się jako kluczowe elementy w rozwoju adaptacyjnego planowania miejskiego. Ponadto, artykuł proponuje etyczne rekomendacje wykorzystania SI w kontekstach miejskich, zapewniając zgodność z normami zawodowymi i zaufaniem publicznym, służąc jako przewodnik dla praktyków i decydentów w odpowiedzialnej integracji SI w wycenie nieruchomości miejskich.

SŁOWA KLUCZOWE: integracja AVM i SI, transparentność, czynniki behawioralne i ludzkie ograniczenia, wycena nieruchomości miejskich, masowa wycena