

How artificial intelligence can improve real estate valuation through better data and communication

Feyza Yagli*

Irmak Teker**

Harun Rashid***

Abstract

Real estate valuation is becoming increasingly dependent on large and complex data sources. Traditional appraisal practices often rely on fragmented data, subjective judgment, and methods that may not adapt quickly to changing market conditions. Artificial intelligence (AI) can improve valuation accuracy and support more informed decision-making, but it should be used to assist rather than replace professional expertise. At the same time, disconnected data systems and limited interpretability can reduce the usefulness and trustworthiness of AI-driven results. Explainable AI (XAI), integrated real estate data systems, and modern business communication techniques can help address these issues by making data more accessible, transparent, and understandable to investors, appraisers, and policymakers. Together, these developments can improve property valuation and investment decisions while encouraging more transparent and responsible use of AI throughout the real estate industry.

Keywords: Artificial intelligence; real estate valuation; explainable AI; data integration; business communication

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*HSA - Houston, USA, feyzayagli08@gmail.com

**Livingston High School, USA

*** GL Bajaj College of Technology and Management, India



1. Introduction

Real estate valuation affects buying, selling, mortgages, insurance, taxes, and investment, so errors can carry significant financial consequences. Appraisers have traditionally used methods such as the sales comparison, income, and cost approaches, and these methods remain important for individual property assessments. Their limitations become more noticeable when markets change quickly or when valuations have to be produced at a much larger scale. Topraklı notes that traditional approaches can become less effective in volatile markets and in mass-appraisal settings where large numbers of properties must be evaluated consistently (Topraklı, 2024: 2).

In a 2024 review of AI-driven real estate appraisal, Topraklı describes traditional appraisal as a process that often depends on expert judgment and relatively limited datasets. That judgment remains important, but it can also lead to differences between appraisers, especially when a property is unusual or market conditions are changing quickly (Topraklı, 2024: 2). Alsahan and AlZaidan (2024), in a separate review of AI in real estate valuation, describe similar pressure for faster and more consistent appraisal methods supported by larger amounts of market information (Alsahan & AlZaidan, 2024: 2-3). AI becomes useful in this context because modern real estate decisions can involve more information than traditional appraisal workflows can efficiently evaluate.

AI can take a much larger group of variables and look for relationships among them. In real estate, that might mean sale price, square footage, age, location, recent transactions, neighborhood conditions, rent, vacancy, or other market information. Alsahan and AlZaidan discuss Automated Valuation Models (AVMs), predictive analytics, image recognition, and natural language processing as examples of where AI is beginning to affect appraisal (Alsahan & AlZaidan, 2024: 2, 5-6). Topraklı reviews many of the same developments and argues that AI can improve efficiency and risk analysis while lowering some of the time and cost involved in valuation (Topraklı, 2024: 2-3). Those benefits sound straightforward, but they depend on what information the model actually receives.

That makes the data problem just as important as the model. A real estate dataset may include ordinary records such as sale prices, rents, vacancy rates, building size, age, and capitalization rates. It can also include less traditional sources such as satellite images, geospatial information, mobile-use data, or information produced by smart-building sensors. Treleaven, Barnett, Knight, and Serrano describe a real estate sector that is becoming digital across finance, planning, construction, management, regulation, and building operation. Their proposed Real Estate Data Marketplace is meant to connect these separate sources and, importantly, record where the data came from and how it was validated (Treleaven et al., n.d.: 1-3). If those records are wrong or inconsistent, a sophisticated model can still give a bad answer.

There is also the question of whether anyone can explain the answer. Some machine-learning models can produce a very accurate prediction on a test set while giving the appraiser little idea why a particular property received a particular value. In real estate, this is especially concerning because valuation results can affect lending, taxation, investment, and property transactions. Alsahan and AlZaidan call attention to this black-box problem and discuss Explainable Artificial Intelligence (XAI) as one possible response (Alsahan & AlZaidan, 2024: 5-6). Topraklı also treats transparency as a major part of responsible AI valuation (Topraklı, 2024: 2-3). An explanation does not automatically make a model correct, but it gives the person using it something to check.

Dorgbefe looks at a different part of the process: what happens after the analysis is done. Housing information can involve affordability, zoning, demographic change, infrastructure, supply, demand, prices, and several kinds of risk. The paper argues that investors may still ignore useful analysis when it is buried inside technical language or scattered across different reports (Dorgbefe, 2018: 485-487). To solve that problem, Dorgbefe discusses dashboards, maps, short investor reports, data cards, and AI-assisted summaries (Dorgbefe, 2018: 488-492). This makes communication more than a presentation issue. If the user cannot understand the result, the analysis is not doing much work for the decision.

The four selected papers focus on different parts of the same process. Alsahan and AlZaidan and Topraklı examine AI and appraisal, Treleaven et al. focus on how real estate data can be organized and governed, and Dorgbefe examines how complex housing information is communicated to investors. Reading them together highlights a connection that is easy to miss when each area is considered separately: data quality affects what an AI model can learn, explainability affects whether its output can be questioned, and communication affects whether that explanation can actually be used in a decision. The sources are therefore compared thematically around data quality, valuation, explainability, communication, and professional judgment rather than treated as if they used one shared method or dataset.

2. Literature review

2.1 Artificial intelligence in real estate valuation

Machine learning is probably the clearest example of how AI enters valuation. Instead of programming a computer with one fixed pricing rule, researchers can train a model on past examples and let it learn relationships between property features and value. For a house, those features could include size, age, location, transaction history, neighborhood information, and market conditions. Some of those relationships are fairly simple, but others are not. Alsahan and AlZaidan point out that modern machine-learning methods can capture nonlinear effects and combinations of variables that are harder to represent with traditional models (Alsahan & AlZaidan, 2024: 5). That is one reason these methods have attracted attention as real estate datasets have grown.

AVMs apply this idea directly. They take property and market information and return an estimated value without requiring an appraiser to work through every comparable by hand. This can be helpful for a lender or public agency that is dealing with a large number of properties. Topraklı's review describes AI-based valuation as especially useful for mass appraisal and other settings where speed and consistency matter, and the paper reports advantages in accuracy, efficiency, cost, and risk management across the literature it reviews (Topraklı, 2024: 2). Still, an AVM is not a property inspection. It only knows what is represented in the data.

Predictive analytics moves the question a little further. Instead of asking only what a property is worth now, the model can look at past data and market indicators to estimate where prices or risks may be moving. Alsahan and AlZaidan describe this as useful for forecasting property values and market dynamics (Alsahan & AlZaidan, 2024: 6-7). For an investor, that could mean looking for areas where demand is rising or where a change in vacancy or financing conditions may create more risk. The prediction is still a forecast, though. A model trained on yesterday's pattern cannot know that tomorrow's market will follow it.

The papers also show how the definition of 'real estate data' is expanding. Alsahan and AlZaidan discuss combining structured information, such as property attributes and transaction histories, with unstructured sources such as satellite imagery and social-media sentiment (Alsahan & AlZaidan, 2024: 6). Topraklı's review includes work using property descriptions, images, spatial information, machine learning, and deep learning for valuation (Topraklı, 2024: 2-4). That can give the model a richer picture of the property, but it also adds more chances for noise or irrelevant information. More variables are only useful if they actually describe something related to value.

The black-box issue becomes more obvious as the models become more complicated. With a simpler model, an appraiser can usually see the direction and approximate size of each effect. A deep model may produce a better prediction but make that reasoning much harder to follow. Alsahan and AlZaidan explain that this lack of interpretability has slowed the use of modern machine-learning methods in regulated appraisal, even when the models perform well (Alsahan & AlZaidan, 2024: 5). Topraklı makes the same concern part of the larger question of accountability: if a valuation affects a high-stakes decision, someone should be able to explain what happened (Topraklı, 2024: 2-3).

XAI is supposed to make that process less opaque. Instead of returning only a value, an explainable system can show which inputs mattered most or how the prediction changed when an input changed. For example, an appraiser may find that a model assigns unusually high importance to one location feature while giving relatively little weight to recent comparable sales. That would not prove the model is wrong, but it would give the appraiser a reason to investigate. Alsahan and AlZaidan connect this kind of explanation with transparency and regulatory acceptance, while Topraklı connects it with trust and accountability (Alsahan & AlZaidan, 2024: 5-6; Topraklı, 2024: 3).

Neither paper presents AI as a reason to remove the appraiser. Alsahan and AlZaidan actually suggest hybrid systems that combine machine learning with expert knowledge, particularly in complicated or specialized markets (Alsahan & AlZaidan, 2024: 6-7). Topraklı also identifies human-AI collaboration as an area that still needs research (Topraklı, 2024: 3). This seems important for the cases that do not look like the training data. A model can compare thousands of records, but a person may know that the building has recent damage, an unusual easement, a unique design, or a local change that has not shown up in past transactions yet.

Alsahan and AlZaidan also place their discussion inside the Saudi Arabian valuation system, where the Saudi Authority for Accredited Valuers (TAQEEM) regulates and certifies valuation professionals and maintains market information (Alsahan & AlZaidan, 2024: 4-5). That example is useful because it shows why AI adoption is not only a technical decision. Valuation already operates inside professional standards, accreditation, and regulatory expectations. If an AI tool is added to that process, somebody still has to decide whether the data and the result meet those standards. In that sense, the appraiser is not competing with the model; the appraiser is the person expected to decide whether the model can be trusted in the specific case.

2.2 Real estate data and digital infrastructure

AI valuation sounds like a modeling problem, but a large part of it is really a data problem. Real estate information comes from many places and is collected for different purposes. A sales database records transactions. A city may hold tax, zoning, permit, and cadastral records. Property managers track occupancy and maintenance. Smart buildings can produce

sensor data continuously. Treleaven et al. describe the larger data environment as including financial, business, economic, geospatial, building, infrastructure, mobile-use, and Internet of Things information (Treleaven et al., n.d.: 2-4). Dorgbefe's housing-data discussion adds supply, demand, pricing, affordability, demographic change, and risk (Dorgbefe, 2018: 486-487).

These sources do not automatically fit together. Treleaven et al. point out that much real estate data is unstructured and that there is no single agreed method for organizing all of it. The price or usefulness of a dataset can also depend on its age, accuracy, coverage, and commercial sensitivity (Treleaven et al., n.d.: 2). Real estate has another problem too: some of the best information is private. A landlord or investor may know the actual rent achieved in a transaction while another market participant does not. That information asymmetry can affect both pricing and valuation.

The Real Estate Data Marketplace proposed by Treleaven et al. is an attempt to deal with this fragmented setup. Their model is more than one giant database. It includes data providers, data users, licenses, validation, verification, security, and a record of how information moves through the system. The authors also propose blockchain and distributed-ledger technology for recording transactions and changes (Treleaven et al., n.d.: 14-17). One of the most useful ideas is provenance. If an appraiser uses a rent figure, for example, the system should make it possible to tell where that figure came from, when it was collected, and whether somebody verified it.

Standardization is another part of the proposal. Treleaven et al. discuss real estate data standards that cover property and land attributes, valuation, legal and cadastral information, geospatial data, measurements, tenure, leases, and lifecycle costs (Treleaven et al., n.d.: 8). This sounds technical, but the problem is simple. Two datasets can use the same label for slightly different things, or different labels for the same thing. If those records are merged without noticing the difference, the model can learn from a dataset that is internally inconsistent.

The marketplace paper gives a useful example of what integrated data can look like in practice. It describes AI companies combining traditional measures such as rent, vacancy, and capitalization rates with geospatial information, mobile usage, and satellite images to identify market trends and areas with stronger value potential (Treleaven et al., n.d.: 2). That is a much wider evidence base than a conventional spreadsheet of comparable sales. But before the AI can do anything with it, the information still has to be collected, cleaned, matched to the correct property, and stored in a usable format.

IoT makes the data even more detailed. Treleaven et al. discuss connected buildings and sensors that can track energy use, occupancy, maintenance, safety, and other parts of building performance (Treleaven et al., n.d.: 4, 8-9). A future valuation system could use that information to estimate operating costs or building condition more directly. At the same time, a building full of sensors is not only measuring the building. Some of those systems may also reveal how people move through or use the space, so privacy becomes part of the valuation-data problem.

For that reason, Treleaven et al. spend a surprising amount of their paper on governance and ethics, not only technology. Their marketplace includes rules for access, licensing, validation, verification, anonymization, and user control. They argue that AI and data systems should be lawful, fair, transparent, and understandable (Treleaven et al., n.d.: 12-18). The point is

important: a large dataset is not automatically a good dataset. If the information cannot be trusted or should not have been used in the first place, adding AI on top of it does not fix the problem.

Treleaven et al. also describe a case study connected to UCL Estates and the PEARL construction project. In that pilot, project participants worked through stage-gateway meetings and tried to agree on which documents should be attached to each stage and how approvals and changes should be recorded (Treleaven et al., n.d.: 19). It is a small example compared with the marketplace they propose, but it shows what data governance looks like in practice. The problem is not only storing a document. The system also needs to preserve who approved it, whether it changed, and which version should later be treated as reliable. Those details become important if the same information is later used for compliance, risk assessment, or valuation.

2.3 Investment and decision-making

A valuation is often only one piece of a larger investment decision. An investor may also care about rent, vacancy, financing cost, development time, maintenance, neighborhood change, and how easily the property could later be sold. AI can help compare these variables across many properties at once. Treleaven et al. describe AI being used to identify market trends and direct investors toward locations where values may be stronger (Treleaven et al., n.d.: 2). Alsahan and AlZaidan connect predictive analytics with market forecasting, risk reduction, and investment planning (Alsahan & AlZaidan, 2024: 6-7).

Topraklı also treats investors and lenders as major users of AI valuation. A lender comparing a large portfolio of loans may value a consistent automated estimate because every property can be processed with the same basic method (Topraklı, 2024: 2). But even then, the predicted price is not the whole investment decision. Two buildings worth the same amount can have very different rents, repair needs, financing terms, or exposure to market changes. AI is useful when it helps organize those differences, not when the predicted value is treated like a final instruction to buy or sell.

Dorgbefe makes the investment side more specific by separating investors into different groups. Pension funds may care most about long-term cash flow and stable reporting. Development finance institutions may need both financial performance and development impact. Impact-oriented venture investors may be more interested in scalability, while philanthropic investors may focus on equity or community outcomes (Dorgbefe, 2018: 487). That means the exact same housing project can look different depending on who is reading the report. The data has not changed; the question being asked has.

This is where many technical reports lose people. Dorgbefe argues that housing reports often contain zoning, demographic, construction, and social information without connecting those measures to the financial questions investors actually use, such as risk, return, and timing (Dorgbefe, 2018: 487-490). An analyst may think the report is complete because all the data is there. An investor may still need to know what the result means for the decision at hand. Better analysis does not answer that question automatically.

Dorgbefe gives several concrete examples of translating raw measures into something closer to investment language. A vacancy rate can be discussed in terms of market absorption. A construction schedule can be explained in relation to financing expectations. Energy-efficiency scores can be connected to green-bond criteria (Dorgbefe, 2018: 490-491).

The value of that translation is not that it makes the project sound better. It is that the number is placed next to the reason an investor cares about it.

Interactive dashboards can push this further. Dorgbefe describes tools where users can filter by region, risk, or development stage and test what-if questions rather than reading one fixed report (Dorgbefe, 2018: 488-490). For example, an investor might want to see what happens if vacancy rises or if a construction timeline slips. A predictive model can help generate those scenarios. The screen should still make it clear that they are scenarios, though, because changing one assumption can change the result a lot.

2.4 Communicating complex real estate information

Dorgbefe's paper is useful partly because it focuses on something technical papers sometimes leave until the end: what the user actually sees. Housing datasets can be completely accurate and still be difficult to use. A long PDF with dozens of indicators, abbreviations, and separate charts may contain everything an investor needs, but the important result can still be hard to find. Dorgbefe argues that this communication gap can reduce engagement even when the underlying analysis is strong (Dorgbefe, 2018: 485-487).

One solution is to use visual tools. Dorgbefe discusses infographics, dashboards, interactive maps, and data cards (Dorgbefe, 2018: 488-489). The paper's dashboard examples are designed so an investor can move between regions, risk levels, development stages, affordability measures, and expected returns. Data cards are even simpler: one measure, its source, a short explanation, and some indication of direction or change. That kind of design reduces the amount a person has to process at once, which matters when the original dataset is very large.

The same idea could be used for AI valuation output. A screen does not have to show either one unexplained price or every variable in the model. It could show the predicted value, a few comparable properties, the strongest factors behind the estimate, recent market movement, where the data came from, and some measure of uncertainty. If the user needs more detail, the system can let them open it. This is a small design choice, but it changes whether the AI result feels like evidence or just a number produced by a machine.

Dorgbefe also discusses framing, anchoring, and storyboarding (Dorgbefe, 2018: 489). These ideas sound more like communication theory than real estate, but they show up in ordinary investment decisions. A 6% vacancy rate means more when the reader knows whether the local market is usually at 3% or 10%. A projected return means more when it is compared with a relevant benchmark. The danger is obvious too: the wrong benchmark can make a weak result look strong. Clear communication has to make the context easier to understand without turning the analysis into advertising.

AI can also be used to write the summary itself. Dorgbefe describes AI-assisted tools that take long feasibility or investment reports and turn them into shorter briefs (Dorgbefe, 2018: 491-492). That could save time, especially when the original file is dozens of pages. It also creates another point where information can be lost or overstated. A summary that drops an important warning or changes the level of certainty may lead the reader to a different conclusion than the source material would. For that reason, automated summaries used in major real estate decisions should remain traceable to the underlying report and subject to human review.

The case studies in Dorgbefe's paper make the communication idea more concrete. One case describes affordable-housing bonds where the revised investor material used income-distribution overlays, maps, and ESG-related measures instead of relying only on bond documentation. Another case on urban regeneration presents risk through dashboards that pair categories of uncertainty with possible mitigation. A third case describes tech-integrated housing marketed to different investor personas using mobile dashboards and performance forecasts (Dorgbefe, 2018: 492-493). The examples are different, but the pattern is similar: the underlying data is reorganized around the decision the audience is trying to make. That is a useful lesson for AI valuation too, because an accurate output can still be ignored if the user has to decode the entire model before understanding why the result matters.

This is where XAI and communication start to overlap. XAI is supposed to explain why the model reached a result. Communication determines whether that explanation is understandable to anyone besides the person who built the model. A technically correct explanation full of model-specific terms may not help an appraiser or investor. On the other hand, a very simple graphic may hide too much. Different users can need different levels of detail, but they should still be able to reach the evidence underneath the summary.

2.5 Challenges, ethics, and human oversight

The four papers do not treat AI as a simple improvement with no tradeoffs. The first problem is still the data. Missing records, outdated values, and inconsistent definitions can all affect the model. Treleaven et al. therefore place validation, verification, provenance, and standardization at the center of their marketplace proposal (Treleaven et al., n.d.: 14-18). This is easy to overlook when the model itself is impressive. A complicated algorithm cannot repair a sale price that was entered incorrectly or a property attribute that means something different in two databases.

Bias is harder because the data can be accurate and still preserve patterns from earlier market decisions. Topraklı warns that AI models can inherit and perpetuate biases present in historical data, potentially leading to discriminatory valuations (Topraklı, 2024: 3). A model trained to reproduce those patterns may carry them into future estimates even when nobody intentionally programs discrimination into the system. This makes bias testing important not only during model development but also when a model is applied to different locations or groups of properties.

Bias also becomes harder to notice when the model is a black box. Alsahan and AlZaidan explain that lack of interpretability has been a major obstacle to the regulatory use of newer machine-learning methods (Alsahan & AlZaidan, 2024: 5). XAI helps by exposing more of the reasoning, but an explanation is not proof that the model is fair. A model can explain a biased result very clearly. The explanation has to be considered together with the training data, performance tests, and the particular property being valued.

Privacy becomes a larger issue when real estate analysis includes sources beyond traditional public property records. Treleaven et al. discuss IoT information, building-use data, and other detailed digital records in the marketplace (Treleaven et al., n.d.: 12-18). They also argue that users should have control over private or generated data. This matters because combining datasets can reveal things that were not obvious in either dataset alone. Location, building-use patterns, and other records may become sensitive once they are connected.

Communication has its own ethical problem: simplification. Dorgbefu warns that investor-friendly messaging can become misleading when it compresses a complicated housing situation into a simple signal (Dorgbefu, 2018: 495-497). A dashboard may label a project low risk, for example, while hiding assumptions about rent growth or future subsidies. The better approach is layered information. The user sees the main result first, but can still reach the assumptions, uncertainty, and source data behind it.

Human oversight is the common response across the papers. Topraklı and Alsahan and AlZaidan both argue for AI that works with professional expertise rather than replacing it (Topraklı, 2024: 3; Alsahan & AlZaidan, 2024: 6-7). Treleaven et al. are even more cautious when they discuss legal decisions involving property rights, payments, and borrowing; they argue that these should not simply be handed over to a machine (Treleaven et al., n.d.: 18). A professional can stop and ask whether an output makes sense in a way that an automated pipeline may not.

That could also change the appraiser's job instead of eliminating it. Repetitive comparison and data processing can be automated, while the appraiser spends more time checking data, interpreting model output, dealing with unusual properties, and explaining results. Topraklı specifically notes that appraisers may need stronger skills in data interpretation and model validation as AI becomes more common (Topraklı, 2024: 2-3). The work becomes more technical, but the responsibility for the decision does not disappear.

2.6 Future directions and limitations

Several questions are still open. One is whether a model that works well in one market will keep working somewhere else. Real estate is local in a way many datasets are not. A model trained on one city, one property type, or one period may learn relationships that do not transfer. Topraklı calls for more empirical validation and more standardized approaches to data collection and model evaluation (Topraklı, 2024: 3-4). Alsahan and AlZaidan also identify future work on AI valuation, XAI, data integration, and hybrid human-AI systems (Alsahan & AlZaidan, 2024: 6-7).

Another question is whether explanations actually improve decisions. An XAI tool may look informative without showing whether appraisers use the explanation correctly. One useful next step would be to compare how professionals respond to the same AI valuation when the explanation is presented in different ways and measure whether some formats help them identify questionable estimates. Communication tools need similar testing. Dorgbefu provides many examples of dashboards, reports, and visual formats, but those examples do not establish which designs consistently improve understanding across different users. Testing that question directly would connect the communication literature more closely to the valuation literature.

The data marketplace also needs to be tested outside a conceptual paper. Treleaven et al. propose standards, validation, distributed ledgers, governance, AI, and a roadmap for implementation (Treleaven et al., n.d.: 14-19). That is ambitious. A real-world version would have to show that many different organizations are willing to share data, follow the same standards, protect confidential information, and pay the cost of maintaining the system. The technical architecture is only one part of whether the marketplace would work.

The review is intentionally focused on four selected papers representing different parts of the AI-supported real estate decision process. Since the sources use different approaches, their findings are synthesized thematically rather than combined statistically. The value of this

scope is the ability to trace one decision process across areas that are often discussed separately: the quality of the data, the performance and interpretability of the model, the way the result is communicated, and the role of professional judgment. Broader systematic reviews and empirical studies would be needed to test these relationships across a larger body of evidence.

3. Conclusions

Artificial intelligence can make parts of real estate valuation faster and more consistent, especially when a large number of properties or variables have to be analyzed. The AI-focused papers show why machine learning, AVMs, predictive analytics, and XAI are receiving so much attention. They can find patterns across large datasets and give appraisers or investors information that would take much longer to assemble manually. But a more complicated model is not automatically a better valuation. It can still be built on weak data, miss an unusual property condition, or produce a result that nobody can explain.

Treleaven et al. show why the process starts before the model. Real estate data is spread across transactions, public records, building systems, geospatial sources, and other platforms. If those sources do not use the same definitions or cannot be verified, the AI result inherits the problem. Standards, provenance, validation, security, and clear access rules are therefore part of valuation quality, even though they happen behind the prediction itself.

Dorgbefe adds what happens at the other end. An investor or appraiser has to understand the result before using it. Dashboards, visualizations, summaries, and audience-specific reports can make complex information easier to work with, but they can also hide assumptions if they are simplified too far. That becomes especially important when AI is producing both the analysis and the explanation of the analysis.

Overall, the four papers point to a fairly practical role for AI. Let the computer process the large dataset, find patterns, and produce forecasts, but keep a person in the loop to check the property, the data, the explanation, and the context. Better real estate valuation is not only a question of building a stronger algorithm. It also depends on whether the information can be trusted, whether the result can be explained, and whether the person making the final decision understands what the model can and cannot do.

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