



WHITE PAPER

The Impact of Condition and Quality on Appraisal Accuracy

The Hidden \$27B Lending Risk

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Restb.ai White Paper

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The Hidden \$27 billion lending risk

According to a [recent study by Reggora](#), the average mortgage loan repurchase rate is 0.49% and results in an average cost of \$32,288 to the lender. However, what if the repurchase risk was much higher? According to Restb.ai's recent white paper analyzing the reliability of appraisal condition and quality adjustments, a staggering 33.6% of appraisals were identified as either having an unwarranted condition or quality adjustment or including an adjustment that was not justified by AI's analysis of the property's photos. Assuming a [conservative estimate of 2.5M appraisals](#) completed each year, lenders are collectively opening themselves up to a **risk of more than \$27 billion in repurchase costs**.

Executive Summary

This white paper examines the critical role of condition and quality in real estate appraisals, highlighting notable discrepancies between appraiser assessments and AI-driven evaluations. By analyzing 1,271 appraisals and 6,495 comparable properties, we uncover varying types of inconsistencies that can lead to valuation inaccuracies. Our findings emphasize the importance of more robust quality control in appraisal practices, particularly related to adjustments, or lack thereof, of property condition and quality.

The accuracy of appraisals is paramount in real estate transactions, influencing lending decisions, market valuations, and investment strategies. This report highlights the challenges appraisers face in consistently and accurately assessing property condition and quality, and the subsequent impact on appraisal outcomes.

Leveraging advanced AI and computer vision technology, Restb.ai provides an objective analysis of appraisal data, revealing patterns and insights that have previously been overlooked due to technological limitations (i.e. the ability to audit condition and quality at scale).

Key Takeaways

- **Limitations of Appraiser Assessments of Condition and Quality**
 - The limited granularity of the UAD 6-point scale results in clustering of the properties on the middle two values and a lack of transparency on adjustments.
 - Appraisers rated **86.1%** of the subject and comparable properties a C3 or C4 for condition and **97.0%** a Q3 or a Q4 for quality.
 - When both subject and comparables were rated the same, appraisers still utilized adjustments for condition on **11.8%** and quality on **5.3%** of comparable properties.

- **Reliability of AI-Generated Condition and Quality Scores**

- AI analyzes each property independently according to a standardized set of criteria that is not influenced by region, the other selected comparables, or other possible subconscious biases.
- AI's use of decimal-level scoring enables more granular distinctions, helping to clarify subtle differences between properties with similar UAD scores.
- Alongside an overall property score, AI generates scores for the different components of a home (kitchen, bathrooms, interior, and exterior), enabling a more detailed understanding of properties with varying levels of renovations and updates.

- **Impact on Valuation**

- AI-generated scores identified numerous cases where an unwarranted adjustment was made or there was an **adjustment made without meaningful condition or quality differences**.
- **33.6% of appraisals had a high risk** and **73.9%** had a medium risk of inadequate or missing adjustments, **resulting in a repurchase risk of between \$27.1B and \$59.7B**.
- **Inaccurate condition and quality adjustments can lead to overvaluation or undervaluation** of properties, affecting repurchase risk, the cost of borrowing, and ultimately market stability.
- **Introducing automated AI analysis to instantly flag possible condition and quality issues** can make quality control processes more efficient while minimizing risk.

Introduction

Accurate property appraisals are essential for informed decision-making and an efficient lending environment. Condition and quality adjustments play a pivotal role in determining a property's fair market value. However, inconsistencies in these assessments can undermine the reliability of appraisals.

This report presents an in-depth analysis of condition and quality assessments and adjustments, utilizing AI-driven evaluations to provide an objective perspective. By examining a dataset of 1,271 appraisals, we identify trends and discrepancies that highlight the challenges in achieving consistent appraisal accuracy.

Overview of Analyzed Appraisal Features

This study focuses on two critical appraisal components: property condition and quality. The Uniform Appraisal Dataset (UAD) provides a framework detailing how each property can be scored along each dimension.

- **Condition:** Refers to the physical state of a property, including maintenance, wear, and tear.
- **Quality:** Refers to the level of craftsmanship, materials, and finishes used in a property.

Appraisers are required to utilize the UAD framework to assess a condition rating (C1 to C6) and a quality of construction rating (Q1 to Q6) for the subject property and each comparable property. In the event there are differences between a subject property's condition and/or quality and a referenced comparable property, the appraiser may provide a valuation adjustment to account for the impact on the valuation.

Challenges of Condition and Quality Assessment

Consistently and reliably scoring properties based on their condition and quality is a challenge. While the UAD provides clear criteria for assessing these aspects, they are not quantifiable and objective in the same way as other features, such as square footage or the number of bathrooms. They must be interpreted by each appraiser, which can introduce subjectivity.

Appraisers are instructed to adopt a "holistic view" of each property. However, many homeowners implement renovations over time and the extent of those improvements can vary. A property may have a bathroom renovated to a C2 level, but if the rest of the property is in a C4 condition, what is the correct way to account for that? When renovating a kitchen, what's the correct way to differentiate between repainting cabinets vs. replacing them?

Even experienced appraisers often face challenges consistently answering these questions. A paper by Michael D. Eriksen, Chun Kuang, and Wenyu Zhu, analyzing appraisal attributes, highlighted appraisers that had completed an appraisal for a particular property and then reused it as a comparable property on a future appraisal recorded a different condition score 12.6% of the time and a different quality score 9.5% of the time.

Complicating matters further, Figure 1 shows 81.1% of properties from the Appraisal-Level Public Use File (PUF) are classified as either a C3 or C4 and 97.5% are classified as a Q3 or Q4, making it challenging to determine when an adjustment may be necessary. Given the clustering of properties on similar scores, it is a challenge to know when an adjustment may be necessary. Two properties may both “correctly” be considered C4s, but there still may be a material difference in the properties’ condition and a value adjustment may be warranted.

Distribution of Appraisals by Condition and Quality Scores

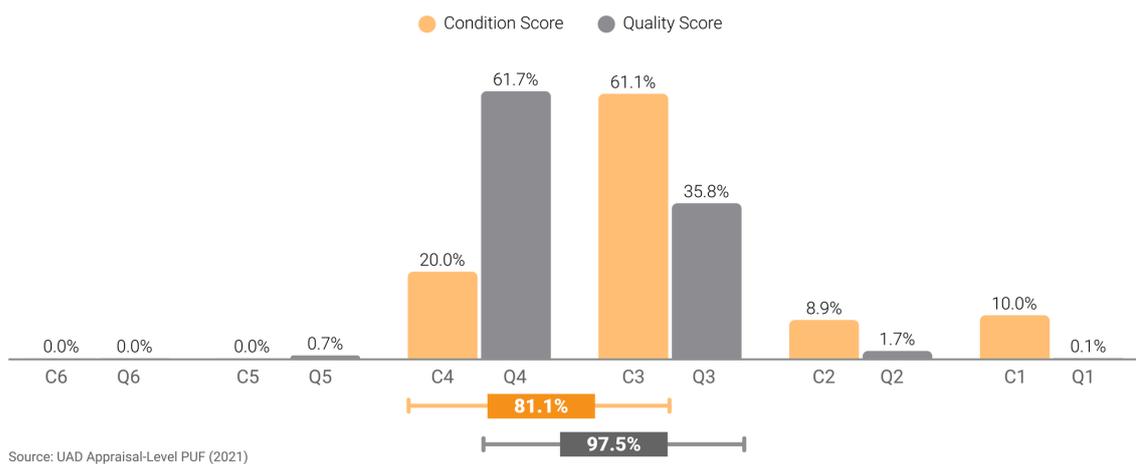


Figure 1: Condition and Quality Distribution from the Appraisal-Level PUF

The reality is that each property exists on a spectrum. Every property that is now a C4, was once a C3, C2, and even a C1. The lines between these categories are blurry, and the perceived condition and quality can vary among appraisers, or even the same appraiser at different times, contributing to the difficulty of achieving objective and consistent assessments.

Importance of Condition and Quality Adjustments

Despite these challenges, reliable analysis of condition and quality remain critical due to their impact on valuations and risk. As can be seen in Figure 2, Fannie Mae’s most recent findings highlight inadequate selection of comparables, inadequate adjustments on comparables, and inaccurate reporting of subject condition and quality as their top three findings.

Findings trends (random sample):

Below are Fannie Mae's top 10 findings identified in a random sampling of loans acquired by Fannie Mae in Q2 and Q3 of 2024 (April 2024 – September 2024).



Finding: A loan manufacturing error that does not impact the eligibility of the loan. However, the same error could result in a significant defect in different loan scenarios.

Figure 2: Fannie Mae's Top 10 Findings in 2024 Q2/Q3

Unfortunately, it is difficult and time consuming for Appraisal Management Companies (AMCs) and lenders to easily identify these issues. While the subject property can be validated based on the included imagery within an appraisal, each comparable only features a single photo of its exterior. Quality control teams frequently don't have the bandwidth to pull up each comparable property's images to ensure all adjustments make sense. As such, many condition and quality risks can slip through the cracks.

The lack of transparency on these attributes can even be taken advantage of by appraisers to reach an unjustified value. Notably, in one recently settled appraiser bias case, it was stated in the complaint that,

"The majority of improper adjustments made by "the appraiser" are concealed through her use of "C" and "Q" rates": 1) "She applied Q3 rating to the Plaintiffs' home, a 10% downward adjustment, but such ratings are intended for stock homes located on above-average residential development tracks, rather than the Q2 rating appropriate for semi-custom homes with "detailed, high quality exterior ornamentation, high quality interior refinements, and detail" per the Fannie Mae and Freddie Mac Uniform Mortgage Data Program. 2) She applied a C3 rating to the Plaintiffs' home, a 10% downward adjustment, but such ratings are reserved for homes still in their first cycle "of replacing short-lived building components (appliances, floor coverings, HVAC, etc.)" even though the Plaintiffs had replaced all of those components with high end components, and there was little or no deferred maintenance."

As can be seen through these examples, inaccurate assessment of condition and quality not only leads to greater risk for lenders and the GSEs, but also detrimental outcomes for borrowers as well.

Determining Condition and Quality via Photo-Based AI

Recognizing the critical importance of reliable and consistent condition and quality assessments, AMCs, lenders, and Government-Sponsored Enterprises (GSEs) are turning to technology to aid in quality control processes.

Computer vision and artificial intelligence (AI) are increasingly being utilized to objectively analyze property photos and evaluate properties on their condition and quality.

In a recent [Appraiser Update from Fannie Mae](#), Fannie Mae states computer vision's impact on appraisers will be the following: "Appraisers who are diligent in factually and objectively determining C and Q ratings (and adjustments) will have a competitive advantage, while those who are not rigorous may experience higher rates of defects and all the associated impacts such as lender requests for reconsideration of value, or Appraiser Quality Monitoring letters." They also highlight the reliability of AI with the following comment about their analysis of over a million appraisals, "Appraisal experts in our Loan Quality Center reviewed those reports and found the model prediction was 98% accurate."

An advantage of AI compared to human analysis is that AI can consistently analyze properties in a repeatable fashion. The subjective nature of condition and quality means that subconscious biases related to the location of a home, personal preferences, or something as innocent as an appraiser's mood that day, can unduly influence an assessment. Meanwhile, AI is trained over property imagery independently of that property's price, region, owners, or any other aspect that is more difficult for a human to abstract.

Another key benefit of using photo-based AI is that it can provide more granular assessments of a property. Rather than having 6 ratings to categorize properties, it can consistently provide nuanced analysis that makes it easier to identify when properties are truly comparable and when adjustments may be necessary. For example, Figure 3 provides a case where the subject property is a C3.4 (i.e. a C3) with comparable property A that is a C3.5 (i.e. a C4) and comparable property B that is a C2.6 (i.e. a C3). Which is more deserving of an adjustment?

When does a difference in condition warrant an adjustment?

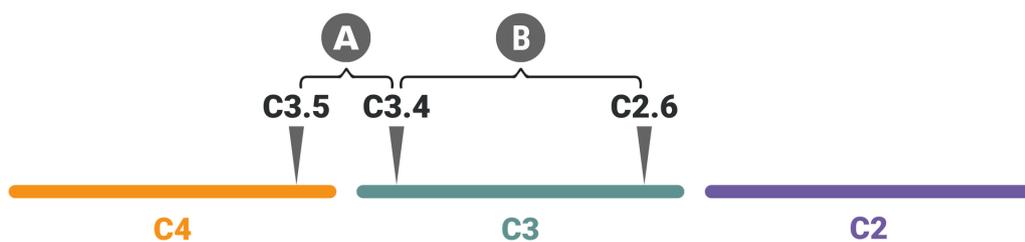
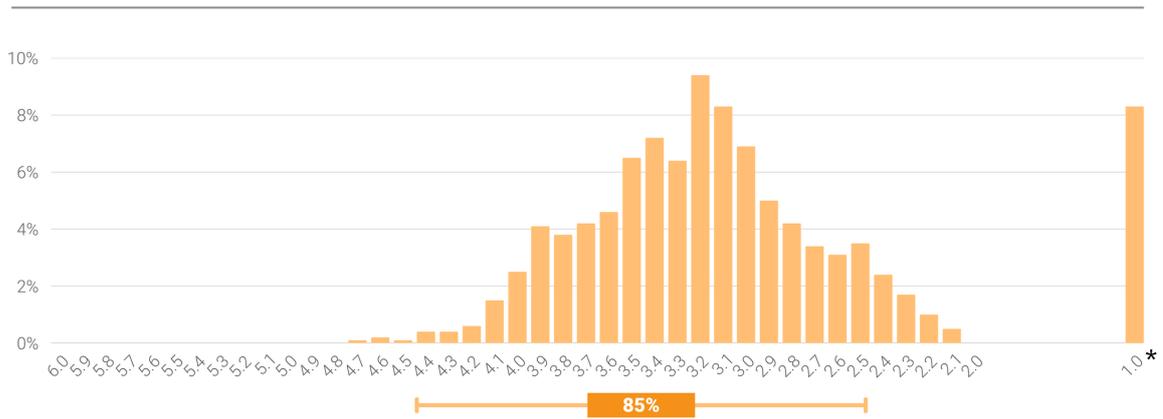


Figure 3: Importance of Granular Scores for Understanding Adjustments

As the Figure 4 below details, a considerable percentage of properties exist in these grey zones between a C3/C4 and a C2/C3. Detailed scores provided by AI can help determine when there are meaningful differences between two properties, regardless of where they fall on the spectrum.

Distribution of property listings per C1-C6 Scores

% of listings (2022/2023, n = 4M listings)



* No values between 1.0 and 2.0 as 1.0 is new construction but once inhabited, it is at least a 2.0.
Source: Restb.ai Market Intelligence insights

Figure 4: AI’s Condition Distribution Analyzing Property Images

Beyond just providing an overall score, Figure 5 demonstrates computer vision’s ability to break out and score the different components of a property. While humans may struggle at consistently providing scores of homes with varying levels of updates, AI is able to effectively and consistently aggregate how different areas of a home impact its overall score.



Figure 5: Example of AI-Generated Scores for Property and Sub-Components

With the GSE’s appraisal modernization efforts and the new UAD requiring condition and quality scores to be broken out into interior and exterior scores, it is essential to incorporate more robust ways to ensure appropriate assessments of condition and quality.

Analysis of Condition and Quality Adjustments

To understand the prevalence of condition and quality issues, we analyzed 1,271 appraisals. AI was leveraged to generate scores for the subject properties based on their appraisal imagery while the most recent listing photos were utilized to score each comparable property.

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In the following section we will examine:

- **Analysis of adjustment frequency:** How frequently appraisers make condition and quality adjustments
- **Analysis of the subject properties:** How appraiser and AI-generated condition and quality scores vary for subject properties
- **Analysis of the comparable properties:** How appraiser and AI-generated condition and quality scores vary for comparable properties
- **Analysis of missing and unwarranted adjustments:** How frequently are needed adjustments missing or adjustments made when unwarranted

More details on the scope and distribution of analyzed appraisals can be found in Exhibit A at the end of the report.

Analysis of Adjustments Frequency

To begin our analysis, Table 1 highlights the various cases that can occur when examining an appraisal for potential condition and quality issues. For clarity, these observations are based purely on the appraiser provided scores and are not considering any AI analysis.

Score properties on Condition & Quality on a granular basis from 1.0-6.0

Scores provided for the property as a whole and at the kitchen, bathroom, interior and exterior sub-levels

Comparables with:	Condition	Quality
An adjustment	34.4%	11.6%
A different rating than subject	25.3%	6.6%
An adjustment and a different rating than subject	22.6%	6.3%
An adjustment and the same rating as subject	11.7%	5.3%
A different rating than subject and no adjustment	2.6%	0.4%

Source: Restb.ai Market Intelligence insights

Table 1: Condition and Quality Considerations in Appraisals

Notably, over one in three comparable properties (34.4%) feature a condition adjustment while more than one in ten comparable properties (11.6%) feature a quality adjustment. Furthermore, the data indicates appraisers are almost 3x more likely to make an adjustment for condition than quality. Potentially this could be because appraisers are more comfortable with scoring condition than quality or they assume that the quality of homes in similar areas varies less frequently than condition. We will revisit this assumption later in the report by comparing these appraiser adjustment frequencies with what AI recommends.

It is also important to highlight that many appraisers are willing to make adjustments when a comparable property is rated the same as the subject property. For every two adjustments made for properties with different condition scores, there is one adjustment made for properties with the same score (22.6% vs. 11.7%). When examining quality, it is only marginally more common to make an adjustment when the scores vary (6.3% vs. 5.3%). On one hand, adjusting properties with the same score makes sense, as a property that is barely a C4 (e.g. an AI-scored C3.5) should be valued differently than a property that is almost a C5 (e.g. an AI-scored C4.4). On the other hand, this lack of transparency makes it difficult for quality control teams to validate these adjustments are needed.

Most alarming, 2.6% of comparables have different condition scores and 0.4% have different quality scores with no recorded adjustment.

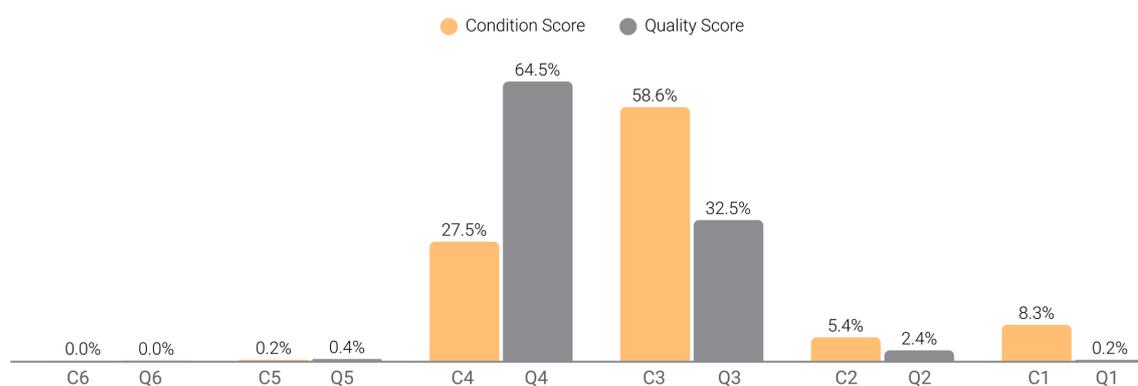
Analysis of Subject Properties

Next we examine how condition and quality scores vary for the subject property. The subject property is intentionally differentiated from the assessments of comparable properties due to differences in how the scores were determined for both cases.

For the subject property, the appraiser has either visited it in person or received a complete set of data from a data collector, while for the comparable properties, the appraiser may have done as little as drive by the front of the property and at most, analyzed the photos from a recent listing. Similarly, the AI-generated scores are based off of the appraisal imagery for the subject property, while the comparable property scores are generated from listing imagery. While extensive work has been put into our AI models to normalize differences in image quality and property presentation, we decided it was more appropriate to evaluate both independently.

Analyzing the scores provided in each report, Figure 6 shows 86.1% of appraisals were scored as C3 or C4 and 97.0% of appraisals were scored as a Q3 or a Q4. This is consistent with the numbers previously highlighted above based on appraisals in the Appraisal-Level PUF.

Subject Property: Appraiser Condition and Quality Distribution



Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Figure 6: Appraiser Condition and Quality Scores for Subject Property

When similarly looking at the rounded AI-generated scores for the subject property, Figure 7 reveals 85.8% of appraisals fall between a C2.5 and a C4.4 (i.e. rounding values to either a C3 or a C4) and 97.0% of appraisals fall between Q2.5 and Q4.4. While there are some small differences between the appraiser generated scores and the AI-generated scores, they largely mirror each other.

Subject Property: AI Condition and Quality Distribution (Rounded)

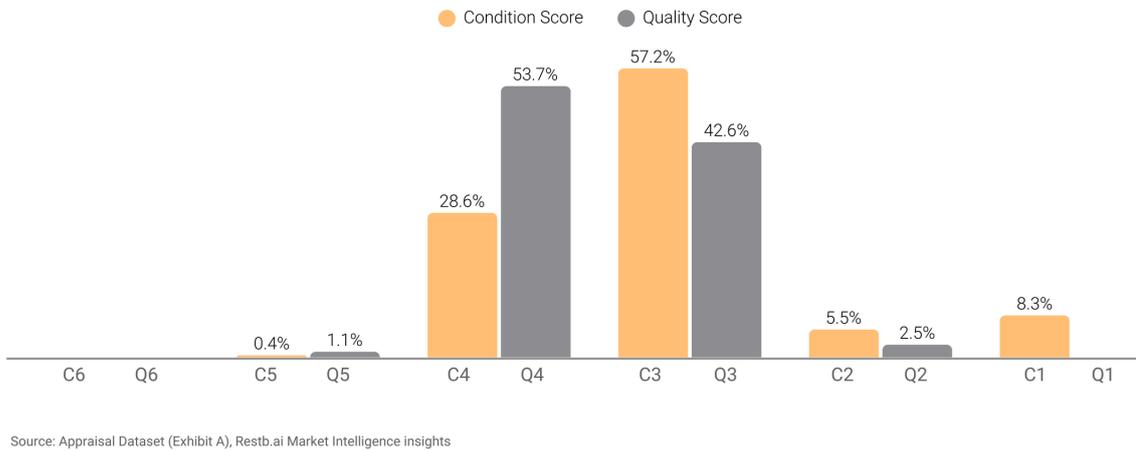


Figure 7: AI-Generated Condition and Quality Scores for Subject Properties

However, when looking at the raw, more granular AI-generated scores for the subject property in Figure 8, there are some notable insights. 18.3% of properties fall between C3.4 - C3.6, while 20.4% of properties are rated between a Q3.4 and Q3.6. The clustering of properties near the boundaries highlights the fine margins that may lead to a miscategorization of a property’s condition or quality, and potentially an inaccurate valuation.

Subject Property: AI Condition and Quality Distribution (Granular)

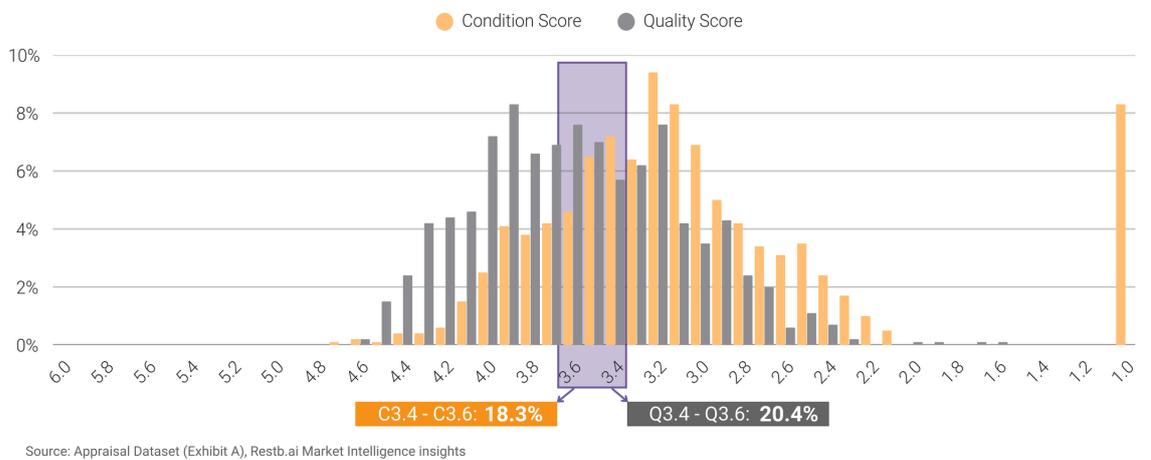


Figure 8: AI-Generated Condition and Quality Scores for Subject Properties

Furthermore, despite the high-level distribution of the appraiser scores and the AI-generated scores closely aligning, that doesn't mean the appraiser and AI always agree. Table 2 below shows the difference between the appraiser score (treated as a whole number 1.0, 2.0, 3.0, etc.) and the AI-generated condition and quality scores.



	Absolute Condition Difference (>=)	% of Properties	Absolute Quality Difference (>=)	% of Properties
	0.6	22.2%	0.6	25.7%
	0.7	14.4%	0.7	19.5%
	0.8	10.0%	0.8	13.7%
	0.9	6.1%	0.9	9.7%
	1.0	3.2%	1.0	5.9%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 2: Appraiser vs. AI Subject Property Condition and Quality Differences

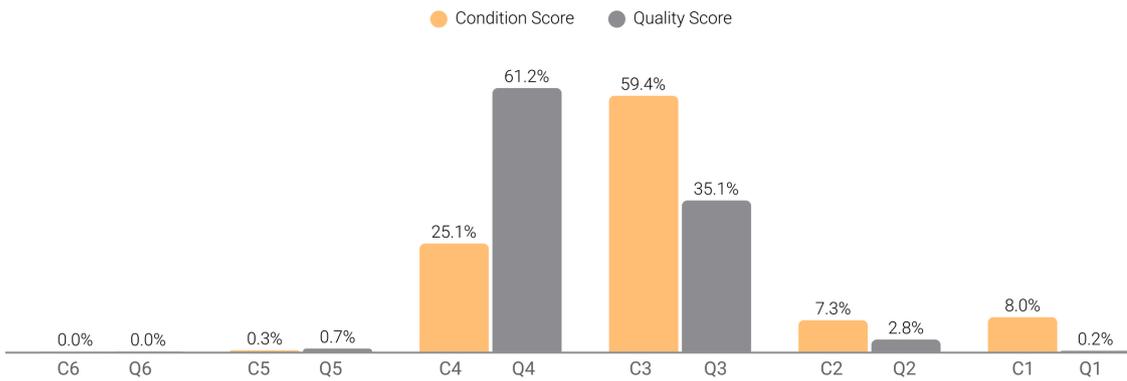
Due to the appraiser scores always being considered as whole numbers, the magnitude of these differences may be overstated. For example, an appraiser rated property that was barely a C3 may not really be 0.6 off from a C3.6. As such, we consider the cases where a property is off by 0.6 a medium risk and a difference by 1.0 or greater as a high risk. In a review process, an AMC or lender could specify which reports to flag for review based on their risk appetite.

It is also interesting to note that the errors on quality scores are consistently more frequent than the errors on condition. This could be related to appraisers being more reluctant to make adjustments on quality and therefore often not distinguishing between a subject and its comparables. On the other hand, it may simply be reflective of quality being more difficult to consistently evaluate.

Analysis of Comparable Properties

When examining the differences between appraiser scores on the comparable properties they selected, Figure 9 shows a roughly similar distribution to the subject property analysis with 84.5% of properties being scored as C3 or C4 (vs. 86.1 for subject) and 96.3% of properties being scored as Q3 or Q4 (vs. 97.0% for subject).

Comparable Property: Appraiser Condition and Quality Distribution

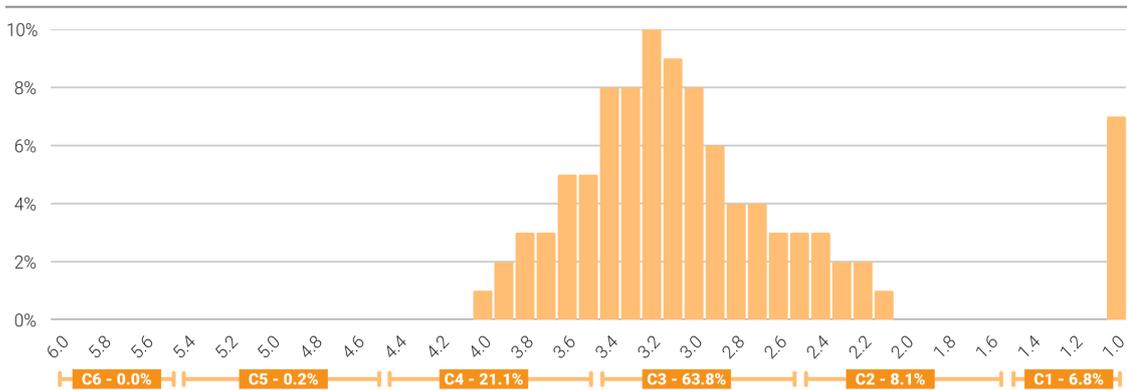


Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Figure 9: Appraiser Condition and Quality Scores for Comparable Properties

Meanwhile, there are more noticeable differences between the subject and comparables when analyzing the AI-generated scores. According to Figure 10, the comparable condition scores are generally lower compared to the subject. Where 28.6% of subject properties had C4 ratings, 21.1% of comparable properties were C4. Conversely, 57.2% of subject properties were C3, while 63.8% of comparable properties were C3, revealing appraisers used comparables in better condition more frequently. There are various possible explanations, but it could be related to a subconscious bias to compare a property with better condition comparables in order to achieve a higher valuation. This would be consistent with a recent [CSS study](#) highlighting that appraisals in H1 2024 came in higher than the sale price 51.1% of the time, at the sale price 40.5% of the time, and below the sale price in 8.4% of cases.

Comparable Property: AI Condition Distribution

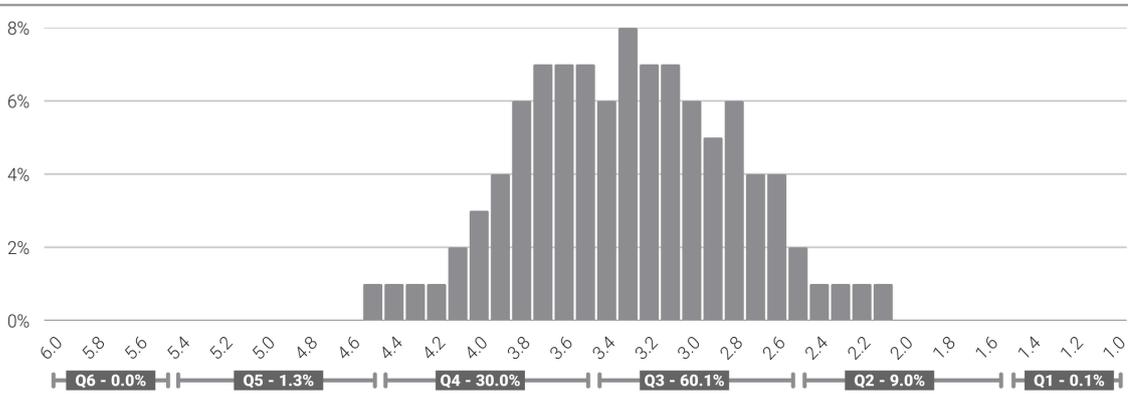


Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Figure 10: AI-Generated Condition Scores for Comparable Properties

Figure 11 reveals an even more dramatic shift with comparable properties being higher quality on average. 59.4% of subject properties were Q4 compared to 37.4% of comparable properties and 37.6% of subject properties were Q3 compared to 53.8% of comparable properties. Similar to the condition scores, this could be evidence of a tendency to utilize higher quality comparable properties that, if not adjusted for, could lead to overvaluations.

Comparable Property: AI Quality Distribution



Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Figure 11: AI-Generated Quality Scores for Comparable Properties

When comparing each comparables' appraisal score with the corresponding AI-generated score in Table 3, we see a notably greater percentage of inconsistencies than when analyzing the subject properties. This higher percentage could be linked to the shifts seen in the condition and quality scores, or indicate that appraisers are more inconsistent when evaluating comparable properties they have not analyzed to the same extent as the subject properties, as could be reasonably expected.

	Absolute Condition Difference (\geq)	% of Properties	Absolute Quality Difference (\geq)	% of Properties
Medium Risk	0.6	27.5%	0.6	42.3%
	0.7	19.6%	0.7	34.4%
	0.8	14.2%	0.8	26.1%
	0.9	8.8%	0.9	19.8%
High Risk	1.0	5.9%	1.0	14.4%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 3: Appraiser vs. AI Comparable Property Condition and Quality Differences

Analysis of Missing and Unwarranted Adjustments

While identifying when an AI-generated score differs from an appraiser rating may help identify problematic appraisals (see Exhibit B at end of report), it is more relevant to determine when adjustments were improperly made or omitted based on the AI's standardized analysis of the subject and comparable property.

For example, an appraiser may score the subject and all comparable properties incorrectly, but if their scores are all over/under assessed like in the example appraisal in Exhibit C, then there isn't necessarily a risk of over or undervaluation.

Let's start by analyzing all of the cases where the AI-generated scores indicate an adjustment may be needed. Table 4 below details the cases when there is a medium risk of an adjustment being warranted up to a high risk. If you recall earlier when looking at the appraiser scores, condition adjustments were made on more than a third of comparables (34.4%) and quality adjustments were made on more than one in every ten (11.6%). At the medium risk threshold that indicates more adjustments should be made, while at the higher risk threshold, fewer adjustments are warranted. Additionally, the AI-generated scores similarly show a more consistent need for condition adjustments than quality adjustments, though the exact magnitude varies depending on the specified tolerance.

	Absolute Condition Difference (\geq)	% of Properties	Absolute Quality Difference (\geq)	% of Properties
Medium Risk	0.6	47.1%	0.6	26.5%
	0.7	25.2%	0.7	25.1%
	0.8	21.1%	0.8	11.9%
	0.9	17.5%	0.9	7.0%
High Risk	1.0	15.2%	1.0	4.4%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 4: AI Subject vs. AI Comparable Property Condition and Quality Differences

However, in many of these cases, the appraiser made an adjustment to account for the differences in condition or quality. More relevant to our study is when the comparables' AI-generated values were meaningfully different from the AI-generated subject score and no adjustments were made by the appraiser. An example of an appraisal where adjustments were expected based on the AI assessment, but none were included can be seen in Exhibit D.

As can be seen in Table 5 below, just under a quarter of comparables are a medium risk of needing an adjustment for either condition (23.4%) or quality (24.5%), while 11.7% of comparables are at a high risk of warranting a condition adjustment and 4.1% of needing a quality adjustment.

	Absolute Condition Difference (\geq)	% of Properties	Absolute Quality Difference (\geq)	% of Properties
Medium Risk	0.6	23.4%	0.6	24.5%
	0.7	18.2%	0.7	16.8%
	0.8	15.3%	0.8	10.4%
	0.9	13.1%	0.9	6.4%
High Risk	1.0	11.7%	1.0	4.1%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 5: AI Subject vs. AI Comparable Property Condition and Quality Differences for Comparables without Adjustments

Notably, there are more cases with comparable properties being utilized without proper condition adjustments than quality adjustments. Furthermore, despite appraisers already making condition adjustments at a 3x rate of quality adjustments, there are still more cases where condition differences are not properly being accounted for than quality issues.

The last case we investigated was the rate when an adjustment was made but the differences in AI-scores indicate it may not have been needed. For this scenario, we identify a medium risk case as when an adjustment exists for a difference of less than or equal to 0.5 and a high risk when an adjustment exists for a difference of less than equal to 0.1 (i.e. essentially considered the same by the AI). An example of an appraisal with unwarranted adjustments can be found in Exhibit E.

Surprisingly, Table 6 indicates appraisers are making adjustments incorrectly more frequently than they are failing to provide adjustments, which could be indicative of appraisers using condition and quality adjustments to justify inaccurate valuations.

	Absolute Condition Difference (\geq)	% of Properties	Absolute Quality Difference (\geq)	% of Properties
Medium Risk	0.5	51.8%	0.5	57.7%
	0.4	43.3%	0.4	48.0%
	0.3	34.5%	0.3	37.6%
	0.2	22.6%	0.2	29.5%
High Risk	0.1	14.3%	0.1	17.2%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 6: AI Subject vs. AI Comparable Property Condition and Quality Differences for Comparables with Adjustments

Given the above calculated rates, the final step is to determine how many appraisals feature at least one problematic comparable property. As can be seen below in Table 7, a remarkable 73.9% of appraisals have a medium risk and 33.6% have a high risk of an improper condition or quality adjustment.

	Medium Risk	High Risk
Missing Condition Adjustment	29.7%	12.2%
Missing Quality Adjustment	40.8%	8.3%
Unwarranted Condition Adjustment	35.9%	12.5%
Unwarranted Quality Adjustment	13.3%	5.0%
Any problematic Condition Adjustment	58.7%	24.5%
Any problematic Quality Adjustment	50.0%	13.3%
Any problematic Condition/Quality Adjustment	73.9%	33.6%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 7: Appraisals with a Condition or Quality Adjustment Risk

Opportunity for AI in Quality Control Processes

As this study has detailed, condition and quality assessments and price adjustments are frequently inaccurate, inevitably leading to imprecise valuations and increased risk. These errors are understandable given the difficulty of manually condensing complex property details into two high-level scores.

While multiple quality reviews exist through the lifetime of an appraisal, consistently identifying and correcting these issues has remained a challenge. It is simply too difficult to know when a problematic condition or quality adjustment, or lack thereof, may exist, and too time consuming to pull up photos of comparable properties to ensure all properties have been evaluated consistently.

Fannie Mae has identified these inaccuracies as frequent risks, and legal cases have highlighted how they can lead to flawed valuations.

These risks translate to significant financial costs for lenders. According to a recent study by Reggora, the average mortgage loan repurchase rate is 0.49% and results in an average cost of \$32,288 to the lender. Assuming a conservative estimate of 2.5M appraisals completed each year, the 33.6% of high risk appraisals would equate to a collective **lender risk of more than \$27 billion in repurchase costs**.

Fortunately, this study highlights the opportunity of computer vision to automatically identify these issues. While some appraisers remain skeptical of AI, its value is in its ability to immediately flag potential issues for closer review rather than waiting for discrepancies to be found later in the appraisal process. The detailed nature of the computer vision scores enables each appraiser, lender, AMC or GSE to determine their own risk tolerance by setting the thresholds for when they would like to be notified of a possible issue.

By leveraging AI-driven evaluations and adhering to best practices, appraisers can improve accuracy and lenders can minimize risk. Furthermore, this data driven approach can lead to greater transparency and trust in the appraisal process for all stakeholders.

For those interested in more studies like this, please let us know at insights@restb.ai what topic you would like analyzed next!

Exhibits

Exhibit A: Study Overview

Count unique appraisals	1,271
Average appraiser subject condition	3.06
Average AI subject condition	3.04
Average appraiser subject quality	3.63
Average AI subject quality	3.58
Count of comparables	6,495
Average number of comparables	4.98
Average number of comparables - Subject C1	5.70
Average number of comparables - Subject C2	5.32
Average number of comparables - Subject C3	4.86
Average number of comparables - Subject C4	5.42
Average number of comparables - Subject C5	6.00
Average number of comparables - Subject C6	n/a
Average number of comparables - Subject Q1	6.50
Average number of comparables - Subject Q2	5.10
Average number of comparables - Subject Q3	5.08
Average number of comparables - Subject Q4	5.12
Average number of comparables - Subject Q5	6.00
Average number of comparables - Subject Q6	n/a
Average appraiser comparable condition	3.02
Average AI comparable condition	2.99
Average appraiser comparable quality	3.59
Average AI comparable quality	3.26

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 8: Breakdown of Appraisals based on Subject and Comparable Properties

Exhibits

Exhibit B: Appraiser and AI Condition and Quality Overview

Percent of subjects with:	Percentage (%)
AI condition score off by 0.6 of appraiser value	26.3%
AI condition score off by 0.7 of appraiser value	18.4%
AI condition score off by 0.8 of appraiser value	13.2%
AI condition score off by 0.9 of appraiser value	8.2%
AI condition score off by 1.0 of appraiser value	5.3%
AI quality score off by 0.6 of appraiser value	25.7%
AI quality score off by 0.7 of appraiser value	19.5%
AI quality score off by 0.8 of appraiser value	13.7%
AI quality score off by 0.9 of appraiser value	9.7%
AI quality score off by 1.0 of appraiser value	5.9%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 9: Appraiser and AI Subject Property Differences

Percent of comparable properties with:	Percentage (%)
AI condition score off by 0.6 of appraiser value	27.5%
AI condition score off by 0.7 of appraiser value	19.6%
AI condition score off by 0.8 of appraiser value	14.2%
AI condition score off by 0.9 of appraiser value	8.8%
AI condition score off by 1.0 of appraiser value	5.9%
AI quality score off by 0.6 of appraiser value	42.3%
AI quality score off by 0.7 of appraiser value	34.4%
AI quality score off by 0.8 of appraiser value	26.1%
AI quality score off by 0.9 of appraiser value	19.8%
AI quality score off by 1.0 of appraiser value	14.4%

Source: Appraisal Dataset (Exhibit A), Restb.ai Market Intelligence insights

Table 10: Appraiser and AI Comparable Property Differences

Exhibits

Exhibit C: Appraisal where no adjustments are needed, but scores are consistently off

Figure 12 details a comparables grid where the appraiser has indicated the quality of the subject and all comparable properties as Q4. No adjustments have been made for quality.

FEATURE	SUBJECT	COMPARABLE SALE NO. 1		COMPARABLE SALE NO. 2		COMPARABLE SALE NO. 3	
Address							
Proximity to Subject		0.64 miles NW		0.37 miles NW		0.46 miles SW	
Sale Price	\$ 3,812,500	\$ 4,250,000		\$ 3,780,000		\$ 3,740,000	
Sale Price/Gross Liv. Area	\$ 1,229.84 sq. ft.	\$ 1,402.6 sq. ft.		\$ 1,271.4 sq. ft.		\$ 1,380.0 sq. ft.	
Data Source(s)							
Verification Source(s)							
VALUE ADJUSTMENTS	DESCRIPTION	DESCRIPTION	+() \$ Adjustment	DESCRIPTION	+() \$ Adjustment	DESCRIPTION	+() \$ Adjustment
Sale or Financing		ArmLth		ArmLth		ArmLth	
Concessions		Conv:0		Conv:0		Conv:0	
Date of Sale/Time		s12/23;c11/23		s10/23;c09/23		s05/23;c04/23	
Location	N;Res;	N;Res;		N;Res;		N;Res;	
Leasehold/Fee Simple	Fee Simple	Fee Simple		Fee Simple		Fee Simple	
Site	10815 sf	23000 sf	-279,625	7440 sf	59,500	7680 sf	53,500
View	N;Res;	N;Res;		N;Res;		N;Res;	
Design (Style)	DT1;Traditional	DT2;Traditional	0	DT2;Traditional	0	DT1;Traditional	
Quality of Construction	Q4	Q4		Q4		Q4	
Actual Age	76	109	0	89	0	96	0
Condition	C4	C4		C3	-100,000	C4	
Above Grade	Total Bdrms Baths	Total Bdrms Baths	20,000	Total Bdrms Baths	0	Total Bdrms Baths	20,000
Room Count	10 4 2.1	10 3 3.1	-20,000	9 4 3.1	-20,000	9 3 3.0	-10,000
Gross Living Area 350	3,100 sq. ft.	3,030 sq. ft.	0	2,973 sq. ft.	44,450	2,710 sq. ft.	136,500
Basement & Finished Rooms Below Grade	0sf	0sf		0sf		0sf	
Functional Utility	Average	Average		Average		Average	
Heating/Cooling	Fwa/None	Fwa/None		Fwa/None		Fwa/None	
Energy Efficient Items	None	None		None		None	
Garage/Carport	3gd3dw	2gbl2dw	25,000	2gbl2dw	25,000	2gbl2dw	25,000
Porch/Patio/Deck	Patio/Porch/Deck	Patio/Pool/Lans	-100,000	Patio/Porch/Pool	-35,000	Patio/Porch	0
	2 F/P	2 F/P		1 F/P	2,000	1 F/P	2,000
Net Adjustment (Total)		<input type="checkbox"/> + <input checked="" type="checkbox"/> -	\$ 354,625	<input type="checkbox"/> + <input checked="" type="checkbox"/> -	\$ 24,050	<input checked="" type="checkbox"/> + <input type="checkbox"/> -	\$ 227,000
Adjusted Sale Price of Comparables		Net Adj. -8.3%	\$ 3,895,375	Net Adj. -0.6%	\$ 3,755,950	Net Adj. 6.1%	\$ 3,967,000
		Gross Adj. 10.5%		Gross Adj. 7.6%		Gross Adj. 6.6%	

Figure 12: Example Comparables Grid with Quality Errors

Meanwhile, the AI-generated scores in Figure 13 show that each property is closer to a Q2 than a Q4. Given the similar nature of the properties' quality, there likely isn't a risk of over or undervaluation, even if the appraiser has misassessed the quality of each property. However, this can still cause issues as many systems and portals may show appraisers what properties have been scored based on prior appraisals, leading to problematic data being referenced by other appraisers in the future.

Exhibits

Exhibit C: Appraisal where no adjustments are needed, but scores are consistently off

Address	Subject	Q2.8	Comp. #1	Q2.6	Comp. #2	Q2.5	Comp. #3	Q2.7
			No adjustment		No adjustment		No adjustment	
Exterior								
Kitchen								
Bathroom								
Interior								

Figure 13: Property Snapshots and AI-Generated Quality Scores

Exhibits

Exhibit D: Appraisal where adjustments weren't made, but were warranted

Figure 14 details a comparables grid where the appraiser has indicated the condition of the subject and all comparable properties as C4. No adjustments have been made for condition.

FEATURE	SUBJECT	COMPARABLE SALE NO. 4			COMPARABLE SALE NO. 5			COMPARABLE SALE NO. 6		
Address										
Proximity to Subject		0.96 miles SE			0.79 miles NE			0.24 miles NE		
Sale Price	\$	\$ 215,000			\$ 240,000			\$ 199,000		
Sale Price/Gross Liv. Area	\$ 0.00 sq. ft.	\$ 131.26 sq. ft.			\$ 152.38 sq. ft.			\$ 165.83 sq. ft.		
Data Source(s)										
Verification Source(s)										
VALUE ADJUSTMENTS	DESCRIPTION	DESCRIPTION	+() \$ Adjustment	DESCRIPTION	+() \$ Adjustment	DESCRIPTION	+() \$ Adjustment			
Sale or Financing Concessions		ArmLth Conv:0		ArmLth Conv:0		Listing				
Date of Sale/Time		s10/23:c09/23		s07/23:c06/23		Active				
Location	N:Res:	N:Res:		N:Res:		N:Res:				
Leasehold/Fee Simple	Fee Simple	Fee Simple		Fee Simple		Fee Simple				
Site	3000 sf	3049 sf		3920 sf		3049 sf				
View	N:Res:	N:Res:		N:Res:		N:Res:				
Design (Style)	DT2:Colonial	DT2:Bungalow		DT2:Bungalow		DT1.5 Bungalow				
Quality of Construction	Q3	Q3		Q3		Q3				
Actual Age	1	84		104		104				
Condition	C2	C2		C2		C2				
Above Grade	Total Bdrms Bths	Total Bdrms Bths		Total Bdrms Bths		Total Bdrms Bths				
Room Count	5 3 2.1	10 5 3.0		7 4 2.0		3 3 2.0				
Gross Living Area 15	1,383 sq. ft.	1,638 sq. ft.		1,575 sq. ft.		1,200 sq. ft.				
Basement & Finished Rooms Below Grade	692sf173sfin 1rr0br0.0ba1o	1500sf675sfin 1rr0br0.1ba1o		475sf0sfin		900sf0sfin				
Functional Utility	3 Bedrooms	5 Bedrooms		4 Bedrooms		3 Bedrooms				
Heating/Cooling	FWA C/Air	FWA/None		FWA/None		FWA/None				
Energy Efficient Items	None	None		None		None				
Garage/Carport	2qd2dw	1qd1dw		2qd1dw		1qd1dw				
Porch/Patio/Deck	Porch	Porch		Porch		Porch				
Fireplace	None	None		None		None				
Fence, etc.	Fence	Fence		Fence		Fence				
Net Adjustment (Total)		<input checked="" type="checkbox"/> + <input type="checkbox"/> -	\$ 0	<input checked="" type="checkbox"/> + <input type="checkbox"/> -	\$ 0	<input checked="" type="checkbox"/> + <input type="checkbox"/> -	\$ 0			
Adjusted Sale Price of Comparables		Net Adj. 0.0% Gross Adj. 0.0%	\$ 215,000	Net Adj. 0.0% Gross Adj. 0.0%	\$ 240,000	Net Adj. 0.0% Gross Adj. 0.0%	\$ 199,000			

Figure 14: Example Comparables Grid with Condition Errors

Meanwhile, the AI-generated scores in Figure 15 show that while the subject property is a C2, the other properties are comfortably C3s or worse. In this case, there is a high risk the property may be undervalued due to its better condition not being accounted for appropriately.

Exhibits

Exhibit D: Appraisal where adjustments weren't made, but were warranted

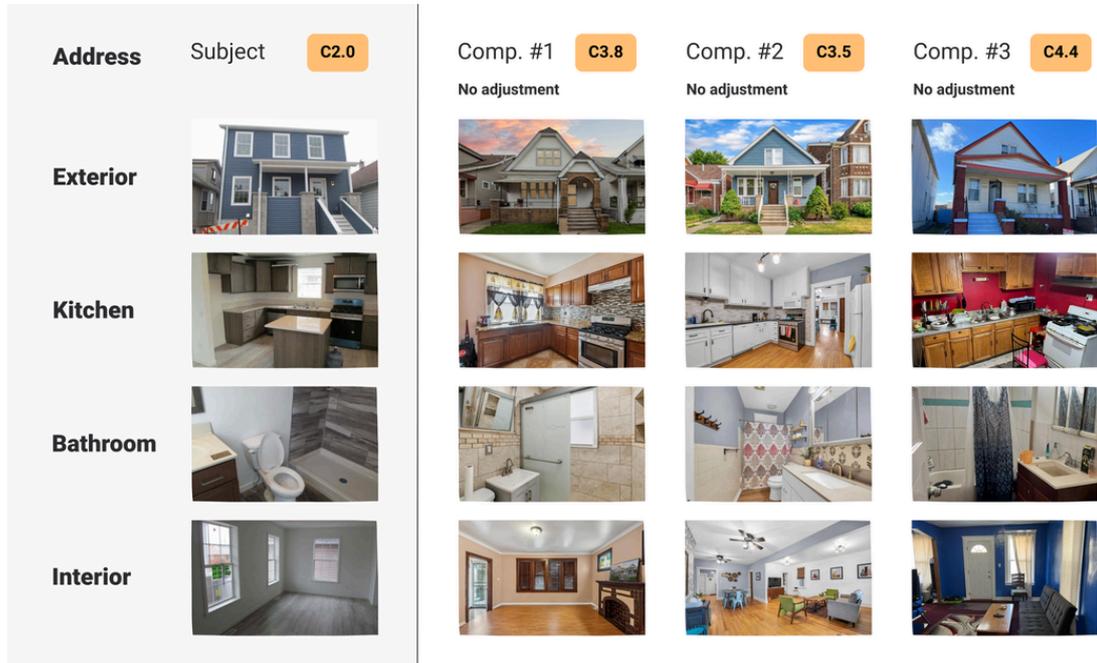


Figure 15: Property Snapshots and AI-Generated Condition Scores

Exhibits

Exhibit E: Appraisal with adjustments made that were not warranted

Figure 16 details a comparables grid where the appraiser has indicated the condition of the subject and all comparable properties as C3. Condition adjustments have been made for Comparables 1 and 2.

FEATURE	SUBJECT			COMPARABLE SALE NO. 1			COMPARABLE SALE NO. 2			COMPARABLE SALE NO. 3		
Address												
Proximity to Subject				0.5 miles SW			1.03 miles SW			0.36 miles NE		
Sale Price	\$ 1,730,000			\$ 2,000,000			\$ 1,778,700			\$ 1,600,000		
Sale Price/Gross Liv. Area	\$ 390.96 sq. ft.			\$ 416.75 sq. ft.			\$ 421.59 sq. ft.			\$ 382.14 sq. ft.		
Data Source(s)												
Verification Source(s)												
VALUE ADJUSTMENTS	DESCRIPTION			DESCRIPTION			DESCRIPTION			DESCRIPTION		
Sale or Financing Concessions				ArmLth Conv:35000			ArmLth Conv:0			ArmLth Conv:7500		
Date of Sale/Time				s11/23:c10/23			s10/23:c09/23			s05/23:c04/23		
Location	N:Res:			N:Res:			N:Res:			N:Res:		
Leasehold/Fee Simple	Fee Simple			Fee Simple			Fee Simple			Fee Simple		
Site	6600 sf			7200 sf			6300 sf			6000 sf		
View	N:Res:			N:Res:			N:Res:			N:Res:		
Design (Style)	DT2:Traditional			DT2:Traditional			DT2:Traditional			DT2:Traditional		
Quality of Construction	Q3			Q3			Q3			Q3		
Actual Age	97			10			19			88		
Condition	C3			C3			C3			C3		
Above Grade Room Count	Total	Bdms	Baths	Total	Bdms	Baths	Total	Bdms	Baths	Total	Bdms	Baths
	13	5	5.1	11	4	4.1	11	4	3.1	11	4	4.2
Gross Living Area	130 4,425 sq. ft.			4,799 sq. ft.			4,219 sq. ft.			4,187 sq. ft.		
Basement & Finished Rooms Below Grade	0sf			0sf			0sf			0sf		
Functional Utility	Average			Average			Average			Average		
Heating/Cooling	FWA			FWA			FWA			FWA		
Energy Efficient Items	Insulation			Insulation			Insulation			Insulation		
Garage/Carport	2qa2dw			2qa2dw			2qa2dw			2qd2dw		
Porch/Patio/Deck	CovPatio/Porch			CovPatio/Porch			CovPat/Balc/Prc			CovPatio/Porch		
	1 FP			1 FP			1 FP			1 FP		
				Pool						Pool		
										-40,000		
										ODK		
										-8,000		
Net Adjustment (Total)				[]+ [X]-			[]+ [X]-			[]+ [X]-		
Adjusted Sale Price of Comparables				Net Adj. -13.2%			Net Adj. -5.2%			Net Adj. -1.2%		
				Gross Adj. 14.2%			Gross Adj. 10.4%			Gross Adj. 5.7%		
				\$ 1,736,380			\$ 1,687,078			\$ 1,580,440		

Figure 16: Example Comparables Grid with Condition Adjustment Errors

Meanwhile, the AI-generated scores in Figure 17 show that all of the properties are in largely similar conditions (C3). In this case, there is a high risk the property may be undervalued due to its comparables being adjusted down unnecessarily.

Exhibits

Exhibit E: Appraisal with adjustments made that were not warranted

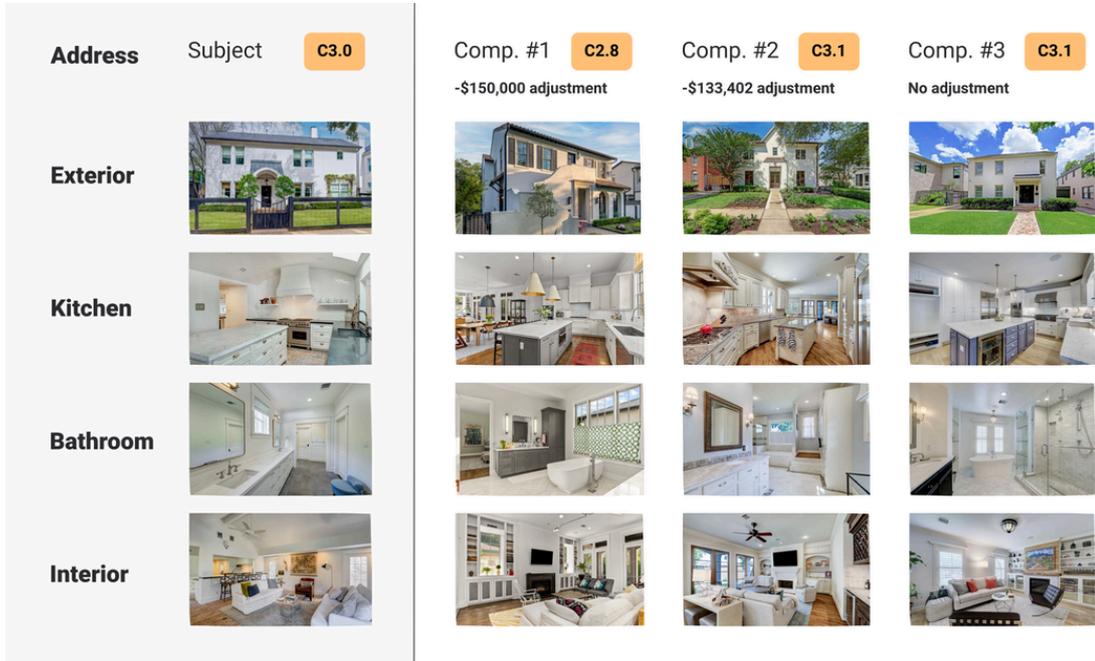


Figure 17: Property Snapshots and AI-Generated Condition Scores