

MIDOCEAN UNIVERSITY

College of Management

Department / Major: Real Estate Management

Traditional Property Valuation vs. Automated Valuation Models (AVMs):

A Comparative Analysis of Performance and Valuation Quality.

Prepared by (Student):

Osama Nofal

Supervised by:

Dr. Al-Faisal Abdul Hamid

Dr. Fayez Jarad

Academic Year:

2026

Contents

1. INTRODUCTION	8
1.1 General Overview of the Research Field.....	8
1.2 Importance of the Topic in Global and Local Contexts	9
1.3 Identification of the Research Gap	11
1.4 Overview of the Research Scope	12
1.5 Formal Statement of the Research Problem	13
1.6 Scientific and Practical Importance of Study	13
1.7 Study Objectives	14
1.8 Definitions of Key Terms	14
2. LITERATURE REVIEW	17
2.1 Introduction	17
2.2 Traditional Property Valuation: Methodological Foundations	17
2.3 The Emergence and Development of Automated Valuation Models.....	18
2.3.1 Defining the AVM	18
2.3.2 The Statistical and Machine Learning Foundations of AVMs	19
2.3.3 Recent Advances: Spatial Models and Image-Based Variables	21
2.3.4 Historical Origins and Drivers of Intensified Debate.....	21
2.4 Professional and Regulatory Perspectives on AVMs	22
2.4.4 A Four-Dimensional Framework for Market Transparency	25
2.5 The RICS Roadmap: A Practitioner-Forum Perspective	26
2.5.1 The AVM Typology and the Concept of Confidence	26
2.5.2 Documented Uses, Advantages, and Disadvantages	26
2.5.3 A Methodologically Significant Risk: Self-Generating Data	27
2.5.4 The Pace of Disruption: A Cautionary Industry Analogy.....	27
2.5.5 Regulatory Treatment of AVM Output	28
2.6 The Saïd Business School Report: Adoption, Resistance, and Geographic Constraint	29
2.6.1 Geographic Constraints on Model Scalability	29

2.6.2 Professional Resistance and the Hybrid AVM Concept	29
2.6.3 Regulatory Inertia and the Effect of COVID-19	30
2.6.4 Four Fundamental Obstacles to AVM Accuracy.....	31
2.7 Analytical Comparison of Previous Studies.....	32
2.8 The Research Gap	34
3. THEORETICAL FRAMEWORK	35
3.1 Introduction	35
3.2 Innovation Theory	35
3.2.1 Theoretical Foundations	35
3.2.2 Application to Automated Valuation Models	35
3.2.3 Organizational Resistance: Kanter's Framework	36
3.2.4 The Hybrid AVM as a Resolution of Definitional Tension	37
3.3 Resource-Based Theory	37
3.3.1 Theoretical Foundations	37
3.3.2 Application to Automated Valuation Models	37
3.3.3 Geographic Data Infrastructure as a Resource	38
3.4 Data-Driven Decision-Making Theory	38
3.4.1 Theoretical Foundations	38
3.4.2 Application to Automated Valuation Models	39
3.4.3 Explainability and the Behavioral Dimension of Valuation Decisions.....	39
3.5 Integration of the Theoretical Framework	40
4. FROM THEORY TO PRACTICE A BRIDGE TO THE EMPIRICAL CHAPTERS	42
4.1 Purpose of This Chapter	42
4.2 The Logical Structure of the Thesis	42
4.3 Formal Statement of the Study Hypotheses.....	42
4.4 Why the Workflow Reconstruction Matters Methodologically.....	43
4.5 Mapping the Research Questions to the Thesis Structure	44
4.6 Overview of the Remaining Chapters	45

5. THE TRADITIONAL VALUATION WORKFLOW	46
5.1 Introduction	46
5.2 Stage One: Instruction and Scope of Work	46
5.3 Stage Two: Property Inspection and Data Collection	46
5.4 Stage Three: Selection and Application of the Valuation Approach	47
5.5 Stage Four: Review, Reconciliation, and Reporting	48
5.6 Bases of Value and the Limits of Standardization	48
5.7 Summary of the Traditional Workflow	49
6. THE AUTOMATED VALUATION WORKFLOW	50
6.1 Introduction	50
6.2 The Model Development Workflow	51
6.2.1 Scope of Work	51
6.2.2 Identification and Acquisition of Property Data	51
6.2.3 Exploratory Data Analysis	51
6.2.4 Stratification	51
6.2.5 Determination of Data Representativeness	52
6.2.6 Model Specification	52
6.2.7 Model Calibration	53
6.2.8 Quality Assurance	53
6.2.9 Model Application and Value Review	54
6.3 The Model Application Workflow and AVM Typology	54
6.4 Confidence Scores and Performance Measurement in the Application Workflow	55
6.5 Data Quality Standards in AVM Development	56
6.6 Calibration Techniques and the Role of Location	57
6.6.1 Time Series Methods for Time-Adjusting Sale Prices	58
6.6.2 The Centrality of the Sales Comparison Approach in AVM Modeling	58
6.7 Market Analysis and the Treatment of Limited Data	59
6.8 Calibration Transparency and Spatial Adjustment Methods	59

6.9 Ratio Studies and the Temporal Dimension of Quality Assurance	60
6.10 Summary of the Automated Workflow	62
7. RESEARCH METHODOLOGY	64
7.1 Introduction	64
7.2 Type and Approach of the Research	64
7.2.1 Type of Research	64
7.2.2 Research Approach: A Mixed-Methods Design	65
7.3 Study Population and Sample	65
7.3.1 Study Population	65
7.3.2 Sampling Strategy and Sample Size	65
7.4 Research Tools and Instruments	66
7.4.1 Expert Interview Guide and Structured Survey Instrument	66
7.4.2 Aggregation and Analysis Procedure for the Structured Survey	69
7.4.3 Reference Review of an Existing AVM Platform	69
7.4.4 HTML-Based AVM Calculator	70
7.4.5 Justification for the Choice of Calibration Technique	76
7.4.6 MRA Assumptions and Their Implications for This Study	78
7.5.1 Qualitative Data Collection	78
7.5.2 Quantitative Data Collection	78
7.5.3 Pilot Testing of Instruments	79
7.6 Data Analysis Techniques	80
7.6.1 Qualitative Analysis	80
7.6.2 Quantitative Analysis	80
7.7 Reliability and Validity	81
7.8 Ethical Considerations	83
8. FINDINGS AND ANALYSIS	85
8.1 Introduction	85
8.2 Qualitative Findings	85

8.2.1 Participant Profile	85
8.2.2 Traditional Valuation Practice.....	86
8.2.3 AVM Awareness and Use (Section C).....	87
8.2.4 Advantages and Disadvantages of AVMs (Section D)	88
8.2.5 Adoption Attitudes- Innovation Theory Constructs (Section E).....	88
8.2.6 Integration Preferences and Future Outlook (Section F).....	89
8.3 Quantitative Findings: AVM vs. Traditional Manual Valuation.....	91
8.3.1 Transaction Sample.....	91
8.3.2 Performance Metrics: Deviation from Recorded Selling Price	92
8.3.3 IAAO Statistical Quality Assurance Measures	93
8.4 Hypothesis Testing	94
8.5 Integration of Qualitative and Quantitative Findings	95
8.6 Application of the IAAO Quality Assurance Framework	95
8.7 Preliminary Conclusions.....	96
9. DISCUSSION, CONCLUSION, AND RECOMMENDATIONS.....	98
9.1 Introduction	98
9.2 Discussion in Relation to the Research Questions.....	98
9.3 Discussion in Relation to the Study Hypotheses.....	100
9.4 Discussion in Relation to the Workflow Comparison	102
9.5 Contribution of the Study	103
9.6 Limitations of the Study	105
9.7 Recommendations	107
9.7.1 Recommendations for Practice.....	107
9.7.2 Recommendations for Policy and Regulation	108
9.7.3 Recommendations for Future Research	109
9.8 Concluding Remarks.....	111
10. References	112
11. Appendices.....	114

11.1 APPENDIX A: SURVEY INSTRUMENT	114
11.2 APPENDIX B: HTML-BASED AVM APPLICATION	114
11.3 APPENDIX C: SAMPLE VALUATION RESULTS DATASET	115
11.4 APPENDIX D: SURVEY RESPONSE DATA	115

1. INTRODUCTION

1.1 General Overview of the Research Field

Property valuation sits in an unusual position among professional disciplines: it is part analytical technique, part judgment call. A valuer works from market evidence and established methods, but the final figure still depends heavily on that individual's experience and their read of what makes a particular property different from the comparables on file. In its traditional form, this means a qualified valuer physically inspects the property, works through comparable transactions, and applies one of the recognized approaches sales comparison, income capitalization, or cost (International Association of Assessing Officers [IAAO], 2018; Royal Institution of Chartered Surveyors [RICS], 2022). These three approaches remain the backbone of international practice, written into both the RICS Valuation – Global Standards (Red Book) and the International Valuation Standards (IVS) published by the International Valuation Standards Council (IVSC). Even as these standards have opened the door to more data-driven techniques, both still insist that professional judgment cannot be engineered out of a credible valuation (RICS, 2022; IVSC, 2022).

That said, the profession has changed considerably in recent years, largely because digital technology has changed what data is available and how it can be used. Transaction databases now run into tens of thousands of records, geographic information systems map property characteristics at a fine grain, and machine learning can process all of it at a scale no individual appraiser could match by hand. Kok, Koponen, and Martínez-Barbosa (2017) put this to the test on roughly 54,000 multifamily transactions in the United States: their machine learning model produced a median absolute error of around 9%, in the same range reported for traditional commercial appraisals in earlier work. Results like this are part of why interest in Automated Valuation Models (AVMs) has grown in markets with rich, reliable data, an automated approach can apparently be both fast and consistent.

The IAAO (2018) defines an AVM as a computer-based system that estimates market value by statistically analyzing property characteristics, market conditions, and location, using data collected beforehand. Buried in that definition are a few things worth pulling out. First, an AVM produces an estimate without anyone inspecting the property, which means the entire output rides on how good, complete, and accurate the underlying dataset is. Second, and this point is easy to miss, the IAAO is explicit that an AVM's usefulness depends as much on the skill of the people building, maintaining, and validating it as on the data itself (IAAO, 2018). And third, the standard treats automation as a spectrum rather than an either/or: at one end are tools that simply hand a valuer a preliminary number, at the other are systems producing large volumes of valuations with almost no human involvement. None of these supports treating AVMs as a wholesale replacement for appraisal; where a given system sits on that spectrum, and what it's being used for, matters more than the label “automated.”

Opinion on where AVMs fit within the profession is still split, and the pace of development hasn't settled the argument either way. Proponents point to faster turnaround, lower operating costs, more consistent output,

and the sheer volume of data an algorithm can process compared with any individual valuer (Kok et al., 2017; Bergadano, Bertilone, Paolotti, & Ruffo, 2019). Professional bodies are more guarded. RICS (2022) and the IVSC (2022) both recognize what AVMs can do while insisting that statistical accuracy on its own doesn't capture everything that goes into a valuation an unusual property, a market moving faster than the data can keep up, the qualitative read a valuer forms while standing in a room. There's also the interpretability problem: many of the more advanced machine learning models are effectively black boxes, and it isn't always clear even to the people using them how a given estimate was reached.

The IVSC's own concern is worth dwelling on. In its Perspectives Paper on AVMs, the IVSC (2022) notes that users are increasingly willing to accept an automated output without asking what assumptions sit behind it, what its limits are, or what it was built to do. That's a bigger problem than accuracy alone. The real question isn't whether an AVM can produce a market value estimate quickly it clearly can but whether that estimate carries the same reliability, transparency, and professional weight that traditional valuation is expected to provide. Framed that way, conventional appraisal and automated valuation aren't really competitors; they're two things that need to be worked into a single, coherent practice. How that integration might work is the question this thesis is built around.

1.2 Importance of the Topic in Global and Local Contexts

Valuation accuracy matters more than just pricing a single property correctly. Real estate is among the largest asset classes in the world, and what a valuation says feeds into mortgage lending, investment decisions, tax assessments, financial reporting, portfolio management, and risk models which means valuation quality touches a wide cross-section of the industry, not just the two parties to a transaction. Bergadano et al. (2019) map out five groups with a direct stake in this: professional valuers doing the inspections and reports; appraisal firms that check and standardize that work; financial institutions relying on the numbers for mortgage approvals, portfolio monitoring, and handling distressed assets; legal professionals such as notaries and solicitors who need a defensible valuation to process transfers and inheritance settlements; and, at the other end, the homeowners, buyers, sellers, and agents making decisions based on what the valuation tells them (Bergadano et al., 2019). Put together, this is a reminder that valuation quality isn't just a lender-borrower issue, it underpins the legal and financial machinery of the property market.

The 2008 financial crisis made the stakes of reliable valuation hard to ignore. Weak valuation processes, combined with markets moving faster than anyone could track, left a lot of real estate assets with genuinely uncertain value. Regulators responded with tighter standards and governance requirements around transparency, consistency, and accountability (IVSC, 2022; RICS, 2021), and that same period is when interest in AVMs picked up, they offered standardized methods, consistent process, and an audit trail that a purely manual process couldn't easily match. For a bank sitting on a large mortgage portfolio, being able to revalue frequently, cheaply, and without sending an appraiser to every door was, and still is, an obvious draw.

Professional bodies have responded to this growing role with detailed guidance rather than silence. The IAAO (2018) sets out standards covering data collection, model development, calibration, validation, and ongoing quality assurance, and is careful to frame AVM development as an iterative process that still needs qualified market analysts involved throughout, not a one-off technical build. RICS has published its own guidance on the opportunities and the practical friction points of adopting AVMs in professional practice (RICS, 2021, 2022). Read together, these publications land on roughly the same message: AVMs work best as a complement to professional expertise, not a substitute for it, and getting that right depends on governance, transparency, data quality, and qualified keeping an eye on the output.

Nowhere is this more relevant than the Gulf region, and the UAE in particular, where the property sector has been through a decade of aggressive digital transformation. Government-led smart city initiatives, digital land registries, geospatial data infrastructure, and online property platforms have together built an environment that's practically ready-made for data-driven valuation. Meanwhile, the market itself has kept growing fast enough that demand for efficient, reliable valuation methods has grown right along with it.

The numbers back this up. The Abu Dhabi Real Estate Centre (ADREC) recorded AED 142 billion in real estate transactions across 42,814 deals in 2025 up 44% in value and 52% in volume on the year before. Of that total, AED 99.4 billion came from 25,604 sales transactions, and AED 42.7 billion from 17,210 mortgage transactions (ADREC, 2026). Dubai tells much the same story: transactions there topped AED 431 billion in just the first half of 2025, a 25% jump in value and a 26% jump in volume (to 125,538 transactions) over the same period in 2024 (Dubai Land Department, 2025). Across the whole of 2024, Dubai's market recorded AED 761 billion in transactions (Dubai Land Department, 2024).

What these figures really show is how much is at risk of valuation accuracy in a market growing this fast. At tens of thousands of transactions, a year, even a small gap between an automated estimate and a properly prepared valuation adds up to real money for lenders, investors, developers, and regulators alike. Getting valuation quality right, then, isn't just a technical box to tick it matters for market stability and for how confident people feel putting money into it.

The digital transformation driving all this growth has also built out the infrastructure AVMs actually need. ADREC reported a 57.7% jump in licensed real estate professionals in 2025 alone, alongside 56 newly registered development projects (ADREC, 2025), on top of ongoing investment in transaction databases, geospatial systems, and integrated registration platforms all of which feed increasingly rich data into any valuation model built on top of them. But the UAE market doesn't look like the markets most AVM research has been done in. Roughly 87% of Abu Dhabi property transactions and 86% of Dubai's were cash purchases in 2025 (Global Property Guide, 2026), whereas AVM adoption in places like the United Kingdom and the United States has historically been pulled along by mortgage lending and portfolio management (Saïd Business School, University of Oxford, 2022). That's a real structural difference, and it means results from those mortgage-driven markets don't automatically transfer to the UAE.

Automated valuation is already part of everyday life in the UAE property market Bayut's TruEstimate™, for instance, generates AI-based property value estimates from transaction records and listing data (Bayut, 2024). Tools like this put automated valuation directly in front of buyers, sellers, investors, and lenders, and in doing so raise a genuine question for regulators and professionals about how those numbers should be read and used. That's the backdrop this research sits against. The question isn't whether an AVM can produce a number plainly but whether that number is good enough to support real professional decisions, and how it stacks up against a valuation produced by an experienced human valuer working the same market.

1.3 Identification of the Research Gap

AVM research has grown considerably, but a close look at literature turns up some real gaps. Most of it focuses on the technical side squeezing more prediction accuracy out of increasingly sophisticated machine learning algorithms which means a lot of studies end up comparing one algorithm against another rather than against the benchmark that actually matters to the profession: a valuation prepared by an experienced human using established standards (Jafary, Shojaei, Rajabifard, & Ngo, 2024; Tapia, Chavez-Garzon, Pezoa, Suarez-Aldunate, & Pilleux, 2025). So even with all the technical progress, there's still surprisingly little direct, apples-to-apples evidence comparing automated and traditional valuation on consistent quality measures.

There's also a geographical gap. Most of the empirical work on AVM performance comes out of mature, data-rich markets the United States (Kok et al., 2017), Italy (Bergadano et al., 2019), Australia (Jafary et al., 2024), Chile (Tapia et al., 2025) and while that work has genuinely advanced the field, it doesn't automatically travel to markets with different structures, regulation, and data availability. The Gulf region, despite the property sector that's expanding fast and investing heavily in data infrastructure, has barely been studied in this respect. The UAE is a particularly interesting case precisely because it combines an active market with real advances in digital registration and geospatial systems, while its professional valuation framework is still maturing which is reason enough to make it the focus here.

A third limitation is more conceptual: how literature frames the relationship between traditional valuation and AVMs in the first place. Much of it treats the two as rivals, judged mainly on predictive accuracy, speed, or operational efficiency. But that's not how the major professional bodies see it. RICS, the IAAO, and the IVSC all take different line automation that should complement a qualified valuer's expertise, not replace it, with each approach bringing something the other doesn't (RICS, 2021, 2022; IVSC, 2022). Given how consistently that message comes through, it's striking how little empirical research investigates what integrating the two approaches would look like in practice. Complementarity tends to show up as a closing recommendation for future research rather than something anyone has gone and tested.

This study is an attempt to close those gaps: a structured comparison of traditional valuation and AVMs set specifically in the UAE market. Rather than stopping at predictive accuracy, it looks at valuation quality more broadly reliability, consistency, transparency, and how practical each approach is to use. The aim is not just to

compare the two methods but to work out how they might function together, in a way that makes valuation practice more informed, more efficient, and still professionally credible.

1.4 Overview of the Research Scope

This study compares traditional property valuation methods with Automated Valuation Models (AVMs), with the goal of evaluating their performance and valuation quality within the United Arab Emirates real estate market. To get there, the research is built around four connected components.

The first reviews the theoretical and methodological ground traditional valuation stands on, drawing on internationally recognized standards from the Royal Institution of Chartered Surveyors (RICS) and the International Valuation Standards Council (IVSC), and does the same for Automated Valuation Models through the International Association of Assessing Officers (IAAO) standards and the relevant academic literature. Together these give the conceptual footing needed to understand what each approach is good at and where it falls short.

The second looks at what drives AVM performance data quality, model design, the technology itself, and the methodological choices behind it drawing on comparative findings from previous studies to work out the conditions under which automated valuation tends to perform well.

The third is the empirical core of the thesis: a structured survey of thirteen valuation professionals across Jordan, Saudi Arabia, and the UAE, paired with a quantitative comparison built around a purpose-designed HTML-based AVM application, applied to nine residential units across three Abu Dhabi districts and assessed against IAAO statistical quality assurance measures. Together, these examine how closely AVM estimates track conventional appraisals, again on more than predictive accuracy alone.

The fourth brings the qualitative and quantitative findings together into practical recommendations for using AVMs in the UAE not as a replacement for professional valuers, but as a way of folding automated techniques responsibly into existing practice, improving efficiency and consistency without giving up the professional standards the industry expects.

The rest of the thesis follows this structure. Chapter Two works through the relevant literature on traditional valuation and AVMs, pulling out the key concepts, where the field currently stands, and the gaps identified above. Chapter Three lays out the theoretical framework Innovation Theory, the Resource-Based View (RBV), and Data-Driven Decision-Making Theory that the study is built on. Chapter Four bridges the literature review and the empirical work that follows.

Chapter Five walks through the traditional valuation process in detail the procedures, methods, and professional practices a valuer follows. Chapter Six does the same for Automated Valuation Models, covering their development, implementation, and validation, along with the statistical measures used to judge how well a model performs. Chapter Seven sets out the research methodology: design, study population,

sampling, data collection, and how reliability and validity were addressed. Chapter Eight presents and analyzes empirical results, bringing the quantitative and qualitative strands together. Chapter Nine closes the thesis by discussing the findings against the research objectives and the literature, setting out the study's contributions and limitations, and ending with recommendations for future research and practice.

1.5 Formal Statement of the Research Problem

With the background, regional context, and research gap now laid out, it's worth stating the research problem more directly before moving on. Property valuation underpins transparency and stability in real estate markets, but the traditional way of doing it is slow, leans heavily on individual judgment, and can produce genuinely different results from two valuers looking at the same property. Advances in artificial intelligence, statistical modeling, and the sheer volume of property data now available have pushed Automated Valuation Models (AVMs) forward as a faster, more scalable alternative. What hasn't been resolved is whether they're as reliable and accurate as traditional methods professionals, financial institutions, and regulators are still arguing about whether an automated model can match an experienced human valuer on quality, not just speed.

Four questions run through this problem, and through the literature reviewed in Chapter Two: How do AVMs differ from traditional methods in terms of methodology and data requirements? How closely do AVM-generated valuations track those produced through conventional approaches? What are AVMs good and bad when it comes to estimating property value? And can they function as a tool that supports and complements traditional practice, rather than replacing it?

These questions come out of a real trade-off the profession faces. Traditional valuation brings judgment and context but costs time and resources, especially at the scale of a large portfolio or frequent revaluation. AVMs bring speed, consistency, and scale, but tend to struggle with unusual properties or thin transaction data. Chapter Two shows this pattern holding up through previous studies: AVMs do well where data is rich and stumble where it isn't, a relationship examined more closely through the Resource-Based View in Chapter Three. So, this study isn't trying to settle which approach is inherently better. It's asking, more specifically, what conditions in the UAE real estate market allow the two to be combined most effectively to improve valuation quality and support professional practice.

1.6 Scientific and Practical Importance of Study

On the academic side, this study contributes by pulling together an integrated theoretical framework Innovation Theory, the Resource-Based View, and Data-Driven Decision-Making Theory, developed in Chapter Three to explain how automated technologies can be built into valuation practice without giving up the standards and reliability the discipline expects. Reconstructing both valuation approaches' operational workflows in Chapters Five and Six, and examining them through one unified analytical framework, pushes past the performance-focused lens that dominates much of the current AVM literature.

The practical case matters just as much, and to several different audiences. Valuation professionals and real estate firms get guidance on where AVMs can be folded into existing workflows, and, just as importantly, where professional judgment still needs to hold the line, as discussed in Section 9.4. Financial institutions and lenders get comparative evidence for deciding when an AVM output can be trusted on its own and when a traditional valuation is still necessary. Policymakers and regulatory authorities get a look at how the governance frameworks from the IAAO (2018), RICS (2021, 2022), and IVSC (2022) might be adapted to the UAE context, as discussed in Section 9.7.2. All of which speaks to an area the UAE and the wider Gulf region that remains considerably less studied on this topic than the more extensively studied markets of North America, Europe, and Latin America.

1.7 Study Objectives

Given the research problem and significance outlined above, this study works toward one general objective, supported by five specific objectives. The general objective is to examine the impact of Automated Valuation Models (AVMs) on property valuation practices and compare their performance with traditional valuation methods to evaluate valuation accuracy, efficiency, and overall valuation quality within the UAE real estate market. The five specific objectives, each linked to a corresponding research question presented in Section 1.3 and mapped to the relevant thesis chapters in Table 4.1, are: examining the methodological differences between traditional valuation and AVMs; assessing the comparative accuracy and efficiency of AVM-generated estimates and traditional valuation outcomes; identifying the technological, data-related, and methodological challenges affecting AVM implementation in the UAE; evaluating the impact of automated valuation on valuation quality and reliability, considering the IVS compliance issues discussed in Section 2.4; and developing evidence-based recommendations for integrating AVMs into traditional valuation practice, as presented in Chapter Nine.

Taking them together, these objectives reflect a deliberately broader scope than just the technical performance of AVMs or just practitioners' perceptions. The study combines a methodological review (Chapters Two, Five, and Six), a theoretical framework (Chapter Three), and a mixed-methods empirical approach (Chapter Seven), which lets it ask not just whether AVMs perform similarly to traditional valuation methods, but whether they can be responsibly incorporated into valuation practice in the UAE while meeting professional standards and addressing the practical needs of valuers, financial institutions, and regulatory authorities.

1.8 Definitions of Key Terms

To ensure consistency throughout this thesis, this section defines the key technical terms used in the following chapters. The definitions are primarily based on the *IAAO Standard on Automated Valuation Models* (2018), with additional definitions drawn from the *IVSC Perspectives Paper* (2022) where appropriate.

Automated Valuation Model (AVM): A mathematically based computer software program used by market analysts to estimate market value by analyzing location, market conditions, and property characteristics using

previously collected data. The credibility of an AVM depends on both the quality of the data and the expertise of the model developer (IAAO, 2018, p. 4).

Algorithm: A precisely defined sequence of computer-based instructions that produces a predetermined result when executed correctly (IAAO, 2018, p. 43).

Additive Model: A valuation model in which the dependent variable is estimated by multiplying each independent variable by its coefficient and adding the resulting values to a constant term (IAAO, 2018, p. 43).

Basis of Value: The underlying premise on which the value of an asset is determined. In secured lending, the most applied basis is *Market Value* (IVS 104, as cited in IVSC, 2022, p. 12).

Calibration: The process of determining the coefficients for each variable in a valuation model, assessing their statistical significance, and ensuring they are logically reasonable (IAAO, 2018, p. 6).

Coefficient of Dispersion (COD): A widely used measure of variability in real estate appraisal that calculates the average absolute percentage deviation between estimated values and actual sale prices relative to the median ratio (IAAO, 2018, p. 16).

Confidence Score: A measure indicating the degree of confidence in an AVM estimate based on the relevance, quantity, and recency of comparable data or the model's forecast standard deviation relative to a benchmark value (IAAO, 2018, p. 44; RICS, 2021, p. 7).

Direct Market Model: One of the two forms of the sales comparison approach, where market value is estimated directly using multiple regression analysis or another statistical modeling technique, rather than through comparable sales adjustments (IAAO, 2018, p. 44).

Hedonic Pricing Model: A valuation model that estimates property value based on structural and location-related characteristics, typically using additive or log-linear regression models (Bergadano et al., 2019).

Market Value: The estimated amount for which an asset or liability should exchange on the valuation date between a willing buyer and a willing seller in an arm's length transaction, after proper marketing, where both parties act knowledgeably, prudently, and without compulsion (IVS, as cited in IVSC, 2022, p. 12).

Multiple Regression Analysis (MRA): A statistical technique used to examine the relationship between one dependent variable and multiple independent variables while producing diagnostic measures such as the coefficient of determination, standard error, and variable significance (IAAO, 2018, p. 29).

Price-Related Differential (PRD): A statistical measure used to evaluate vertical equity by identifying whether an AVM systematically overvalues or undervalues properties across different price ranges (IAAO, 2018, p. 39).

Ratio Study: A statistical comparison between estimated property values and actual sale prices used to assess the accuracy and consistency of an AVM through measures of central tendency and variability (IAAO, 2018, p. 16).

Valuation: The process of developing an opinion of the value of an asset at a specified date and for a defined basis of value in accordance with the International Valuation Standards (IVS, as cited in IVSC, 2022, p. 5).

2. LITERATURE REVIEW

2.1 Introduction

This chapter works through the academic and professional literature on property valuation and Automated Valuation Models (AVMs) that the rest of the thesis builds on. It's organized into three parts. The first covers the conceptual and methodological ground of traditional property valuation, drawing on the RICS and IVSC standards. The second traces how AVMs have evolved, from early statistical techniques through to the machine learning approaches that dominate the field now, with a close eye on accuracy, data requirements, and how they're used in practice. The last part pulls the most relevant studies together chronologically, and from that comparison identifies the research gap this thesis sets out to address.

One methodological point is worth flagging up front. Two sources cited in the original research proposal Jafary, Shojaei, Rajabifard, and Ngo (2024), published in Cities, and Renigier-Bitozor, d'Amato, and Kauko (2019), presented at the FIG Working Week conference could not be accessed in full text for this review; only their bibliographic details were available. So, references to these two studies are limited strictly to what those bibliographic records support, with no findings or methodological detail inferred beyond that. A later paper by an overlapping set of authors, Renigier-Bitozor, Ache, Dimopoulos, and Janowski's (2025) Figuring the Future: AI and AVMs Transforming Property Valuation, was available in full, and is treated here as its own independent source rather than as a continuation of the 2019 conference paper.

2.2 Traditional Property Valuation: Methodological Foundations

Traditional property valuation rests on three internationally recognized approaches: sales comparison, income capitalization, and cost (IAAO, 2018; RICS, 2022). Each suits a different context. Sales comparison, the standard choice for residential property, works from recent comparable sales adjusted for differences in location, size, condition, and similar factors. The income approach capitalizes a property's expected net income, usually through direct capitalization or discounted cash flow, and is the default for income-producing commercial assets. The cost approach starts from the cost of replacing or reproducing the asset, less depreciation, and tends to be reserved for specialized properties where there isn't much comparable market evidence to work from.

None of this gets applied mechanically in practice. Both the RICS Valuation – Global Standards (Red Book) and the International Valuation Standards (IVS) are clear that valuation combines technical method with professional judgment a valuer is expected to pick the approach, or blend of approaches, that fits the property, the purpose of the valuation, and the required basis of value (RICS, 2022; IVSC, 2022). That reliance on judgment is a strength of traditional valuation, but it cuts both ways: it's also behind two of its most cited weaknesses inconsistency between valuers looking at the same property, and the time and cost of valuing properties at scale, as with a mortgage portfolio or a taxation assessment.

Previous research backs up these limitations. Kok, Koponen, and Martínez-Barbosa (2017), drawing on earlier studies, found that traditional commercial appraisals in the United States differed from the eventual transaction price by more than 12% on average, with comparable studies reporting deviations from 7.7% in Italy up to 13.9% in Japan (Kok et al., 2017, p. 202). In other words, the limitations of manual valuation were already well documented long before AVMs became widely adopted.

AVMs, then, entered a profession that had already recognized its own consistency problem, not a perfectly functioning one that automation then disrupted. They arrived as an attempt to improve consistency, efficiency, and scalability in a field that was already looking for ways to do so, while still holding onto its professional standards.

2.3 The Emergence and Development of Automated Valuation Models

2.3.1 Defining the AVM

The IAAO (2018) offers one of the fuller definitions of an AVM: “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” (p. 4). Notably, the standard ties an AVM's credibility not just to data quality but to the competence of the analyst who built the model a reminder that AVMs are not some judgment-free, purely objective process. The IAAO also sets out several AVM categories: Preliminary Data AVMs that support a valuer's work, Interactive Valuation Application AVMs, Repetitive or Continuous Application AVMs built for large-scale valuation, and Blended or Cascading AVMs that combine several modeling techniques (IAAO, 2018, pp. 4–5). That range of categories itself is the point: automation sits on a spectrum, not as a single alternative sitting opposite traditional valuation.

The IVSC (2022) takes a related but slightly narrower view, defining an AVM as “a system that provides an indication of value of a specified Asset at a specified date, using calculation techniques in an automated manner” (p. 1). What the IVSC flags as significant here is that, unlike a professional valuation, an AVM running without human input isn't exercising judgment at all. That gap between a calculated estimate and a professional opinion is central to how this study thinks about AVMs, and it underpins the comparative analysis that follows.

The IVS define valuation itself as “the act or process of determining an opinion or conclusion of value of an asset on a stated basis of value at a specified date in compliance with IVS,” with value defined as “the opinion resulting from a valuation process that is compliant with IVS” (IVSC, 2022, p. 5). The word “opinion” is doing a lot of work in that definition it's what separates a professional valuation from a purely automated estimate, and it's why the IVSC treats human judgment as non-negotiable in an IVS-compliant valuation.

The IVSC (2022) builds on this by drawing a line between different kinds of human involvement in an AVM workflow. A valuer who only reviews or rubber-stamps AVM's output hasn't produced an IVS-compliant

valuation, because the judgment IVS requires hasn't been applied. A valuation stays compliant, on the other hand, where the valuer treats the AVM as one input among several and still exercises independent professional judgment across the rest of the process. As the IVSC puts it, “the reverse, where the valuer merely validates the findings of an AVM, does not constitute an IVS compliant valuation” (IVSC, 2022, p. 5).

This matters for how the hybrid approaches discussed throughout literature should be read: not every setup that mixes human input with an AVM clears the IVS bar. Where the AVM does the substantive work and the valuer just confirms the number, that's outside the IVSC's definition of a professional valuation. The IAAO's (2018) Interactive Valuation Application, where the valuer reviews and can modify or reinterpret the model's output, sits much closer to what the IVSC expects. This distinction gives the present study a working framework for judging how AVMs can be integrated into professional practice without falling outside international valuation standards.

2.3.2 The Statistical and Machine Learning Foundations of AVMs

The technical backbone of AVMs has historically been the hedonic pricing model, which treats property value as a linear function of a property's structural and locational features (Bergadano, Bertilone, Paolotti, & Ruffo, 2019). “Hedonic” comes from the idea that owning and living in a property is itself a source of pleasure a nicer view, proximity to amenities, an elevator, parking, and so on all push value up accordingly; Bergadano et al. (2019) call these “hedonic features” on that basis. In its classical form, the model expresses a property's value V for property P as a linear function of hedonic features $f_1(P)$ through $f_n(P)$: $V(P) = \eta + \sum \beta_i \cdot f_i(P) + \epsilon(P)$, where each β_i is the coefficient for feature i , $\epsilon(P)$ is a property-specific correction term, and η is a constant applying across a given geographic or market context (Bergadano et al., 2019). Bergadano et al. (2019) trace this lineage directly, noting that classical hedonic models assume value depends linearly on a fixed feature set room count, floor area, number of bathrooms, and the like with the residual term mopping up whatever variation is left unexplained. Their argument is that this linearity assumption is a real limitation, since in practice the relationship between many property attributes and value is non-linear and depends heavily on context (Bergadano et al., 2019).

The newer wave of AVM research has moved toward machine learning precisely because it can capture these non-linear relationships without forcing the modeler to specify a functional form up front. Bergadano et al. (2019) describe this as a shift not just away from linear functional forms but away from what they call a purely “hedonic view” of property features altogether, toward something closer to a context-dependent view. Under the classical hedonic framing, a feature is simply “good” or “bad” for value, uniformly across the market; under the view Bergadano et al. (2019) adopt, the same feature can cut in opposite directions depending on where it sits their own example is that “the predominance of foreigners in the neighborhood can lead to higher evaluations for small flats... near a metropolitan city center, while it could have opposed effects in the suburbs and for family houses” (p. 2). That observation lands directly on the UAE context this thesis is set in, given the international, highly mixed demographic makeup of UAE residential communities noted in Section 1.2 Abu Dhabi's 2025 foreign direct investment alone drew from more than 100 nationalities

(ADREC, 2026) which suggests that any AVM calibrated for the UAE needs enough flexibility built in for demographic and locational variables to behave in genuinely context-dependent ways, rather than pushing value in one fixed direction regardless of setting.

Kok et al. (2017) offer one of the most cited demonstrations of this shift, applying decision-tree ensemble methods random forest and gradient boosting among them to roughly 54,000 U.S. multifamily properties, enriched with both standard demographic data and finer-grained, hyperlocal variables like proximity to amenities and local crime rates. The headline result is striking: a median absolute error of around 9%, which the authors explicitly present as comparing favorably with the documented imprecision of traditional appraisal (Kok et al., 2017, p. 203). What's arguably more useful is that Kok et al. (2017) also explain why the model performs this well they attribute much of the predictive power to hyperlocal, non-traditional data layers, arguing that information drawn from sources like social media, police records, and economic-vibrancy indicators adds real value to pricing models (p. 203). That reframes the accuracy debate in a useful way: performance isn't just a function of which algorithm you pick, but of how broad and granular the underlying data is a point that comes up again across the studies reviewed in this chapter.

Bergadano et al. (2019) arrive at much the same conclusion by a different route, working with residential data from Turin and comparing AVM performance across three progressively richer feature sets: a baseline hedonic set, a narrower set built around official market value zones, and an augmented set incorporating web-crawled comparable listings. The pattern is unambiguous. The baseline set, tested across six machine learning algorithms, produced mean errors from roughly €41,600 (Extra Trees) to €54,400 (K-Nearest Neighbor) against an average property value of €189,400 accuracy the authors themselves describe as, at best, a rough starting point for a professional appraiser rather than a substitute for one (p. 9). Narrowing to official market-zone indicators and then enriching further with web-crawled comparable data, however, changed things substantially: mean error dropped to roughly €21,000–€21,600 across the best-performing algorithms, with R^2 climbing to between 0.957 and 0.959 (pp. 10–11). An out-of-sample test on a separate 58-property dataset, distinct in both geography and time, produced a mean error of around 17,000, which the authors take as evidence the model generalizes reasonably well beyond its training context (p. 11). Even so, they're careful to keep their own framing modest, concluding the tool “may be a valid help for professional appraisers and for appraisal companies that need to validate expert documents or evaluate real estate portfolios” (p. 11) complementary, not substitutive.

Băbțan (2020) comes at the same territory from a more applied, exploratory angle, focused on the residential apartment market in Cluj-Napoca, Romania. Building on the observation that AVMs trace back to the United States in 1981 before spreading to the United Kingdom in the 1990s (Băbțan, 2020, citing Worzala et al., 1995), the study has two goals: clarifying what AVMs actually are and how they've spread internationally, and testing whether AVM techniques are feasible in the Romanian valuation context, up to and including formal integration into national valuation standards. Băbțan (2020) is explicit that AVMs complement traditional valuation rather than replace it, while noting the argument, made by proponents, that automation can cut

down the inconsistency that comes from purely subjective human judgment (p. 2, citing IAAO, 2003). The study's real contribution isn't a large-scale predictive benchmark on the order of Kok et al. (2017) or Bergadano et al. (2019); it's the argument that AVMs suit relatively homogeneous residential property particularly well the one- and two-bedroom apartments that dominate the Cluj-Napoca market, where enough similar comparable units exist to make statistical modeling actually workable (Băbțan, 2020).

2.3.3 Recent Advances: Spatial Models and Image-Based Variables

Of the studies covered in this chapter, Tapia, Chavez-Garzon, Pezoa, Suarez-Aldunate, and Pilleux (2025) is methodologically the most advanced. It compares machine learning models against spatially adjusted hedonic pricing models for Chile's Santiago Metropolitan Region and systematically tests what different groups of explanatory variables actually contribute structural characteristics, neighborhood quality indicators, distance-based location variables, and, notably, image-based features pulled from property photographs via convolutional neural networks. Using five-fold cross-validation, the authors found a baseline model built only on structural variables achieved a mean absolute percentage error (MAPE) of 11.59% and an R^2 of 0.9412. Adding in amenity indicators, neighborhood quality measures, school proximity, and image-derived features brought the MAPE down to 10.07% and pushed R^2 up to 0.9516 (Tapia et al., 2025, p. 18). The numerical gain looks modest on paper, but the authors argue it's practically meaningful given how much money is typically involved in a real estate transaction. They also single out the image-based features as an important driver of the improvement, noting this was the first Chilean study to fold visual property information into an automated valuation model (p. 18).

The study also compares machine learning interpretability techniques specifically SHAP (Shapley Additive Explanations) against conventional econometric models, including ordinary least squares (OLS) and spatial autoregressive (SAR) models that account for spatial dependence in prices. The most influential variables of total floor area, municipal quality, number of bathrooms, proximity to schools came out roughly similarly ranked across every modeling approach the authors tried. Where things diverged was in the estimated direction and size of some variables, school proximity in particular, between the machine learning models and the spatial econometric ones (Tapia et al., 2025, pp. 22–23). The takeaway is a genuinely useful methodological caution: a machine learning model can be highly accurate and still not offer the same kind of analytical interpretation as a traditional econometric model does, especially once spatial relationships aren't explicitly built in.

2.3.4 Historical Origins and Drivers of Intensified Debate

Before moving to professional and regulatory literature in Section 2.4, it's worth setting the academic studies above in a longer historical frame. Renigier-Bițozor et al. (2025) trace automation in real estate valuation back to the 1950s (citing Dimopoulos & Bakas, 2019; Gluac & Rosiers, 2021), with something resembling today's AVMs becoming widespread in the 1980s (citing Gwartney, 1970; Carbone & Longini, 1977; Renigier-Bițozor et al., 2022). AVMs, in other words, aren't purely a product of the recent AI boom. The

hedonic regression models covered in Section 2.3.2 have been developing for decades; the machine learning and image-based techniques in Section 2.3.3 are simply the current stage of that longer development.

Renigier-Biřozor et al. (2025) point to six factors behind the accelerating interest in AVMs and Computer-Assisted Mass Appraisal (CAMA) systems: advances in AI and big data; growing demand for fast, cheap valuations in fast-moving markets; regulatory attention turning toward model governance and bias; better access to digital property data; wider AVM adoption across banking and real estate; and a growing public and professional conversation about what happens to the human valuer's role. Together these help explain why AVM research has picked up pace so quickly even though the underlying technology has been around much longer than that pace would suggest.

The authors also make an interesting argument about resistance to AVM adoption: some of it, they suggest, has less to do with technical evidence than with plain discomfort at technological change. Renigier-Biřozor et al. (2025) point out that AVMs have already improved real estate markets and land administration in many developed countries, which implies that at least some resistance reflects apprehension about disruption rather than a genuine flaw in the technology. Seen that way, the real question isn't whether AVMs become widely used it's when and how. The authors go further, warning that continued resistance risks delaying technology that could genuinely improve how efficiently valuation gets done.

There's also an interesting point about public trust. Renigier-Biřozor et al. (2025) note that skepticism isn't limited to automated systems some clients doubt the objectivity of human valuations too, worried that personal judgment or conflicts of interest might be creeping in. That reframes trust as a challenge both approaches share, rather than an automatic point in traditional valuation's favor. A similar tension shows up among valuation professionals themselves: many recognize what tools that support the valuation process can offer, but they also worry that more automation could shrink job opportunities or demand skills that aren't easy to pick up quickly (Renigier-Biřozor et al., 2025). Both observations line up closely with the discussion of resistance to change in Chapter Three and help explain some of the friction involved in getting AVMs integrated into professional practice.

2.4 Professional and Regulatory Perspectives on AVMs

The studies above are mostly concerned with technical performance. A separate, equally important body of literature, produced by professional and standard-setting bodies, looks instead at governance, transparency, and what AVM adoption means for the profession. That literature matters here specifically because it cares about valuation quality, not just predictive accuracy.

The IVSC's Perspectives Paper (2022) traces how the organization's position on AVMs has evolved, starting with its 2020 Agenda Consultation, which flagged automated valuation as a priority given how widely AVMs were being used across property markets (p. 1). Rather than asking whether AVMs can be accurate, the paper asks whether their output can count as a valuation opinion under the International Valuation Standards (IVS), and under what conditions. Its conclusion: an AVM output only counts as IVS compliant

when a qualified valuer applies the full set of IVS requirements and exercises real professional judgment throughout (IVSC, 2022).

RICS covers similar grounds across two related publications. The 2021 roadmap frames AVMs as an emerging area of practice that needs proper governance rather than resistance (RICS, 2021). Its follow-up, the 2022 Insight Paper Automated Valuation Models (AVMs): Implications for the Profession and their Clients, weighs the efficiency gains against the professional responsibilities' AVMs create. Drawing on a series of international Leaders' Forums, it concludes that whether an AVM is suitable comes down to property type, the purpose of the valuation, data availability, the confidence level required, and risk and that unusual properties or thin comparable data lower confidence and reliability (RICS, 2022, p. 14). One point especially relevant here: valuers don't need to fully understand an AVM's technical workings, but they should be able to judge whether its output looks consistent with what a competent professional valuer would produce (RICS, 2022, p. 15) which lines up closely with the comparative approach this research takes.

Further evidence comes from the University of Oxford's Saïd Business School report, The Future of Automated Real Estate Valuations (AVMs) (2022). It wasn't part of the original proposal's core references, but it offers useful context on how AVMs are used. It estimates roughly 30% of UK mortgage originations used AVMs in 2016, rising to somewhere between 30% and 70% across developed markets by the time the report was written (Saïd Business School, University of Oxford, 2022). Importantly, it also notes AVMs aren't used universally, they tend to show up in lower-risk lending and are rarely relied on for high loan-to-value mortgages or newly built homes, where the financial stakes of getting the valuation wrong are higher (p. 9). All of which reinforces the same point: AVM suitability depends on property type, data quality, and risk, not a blanket fit for every valuation situation.

Renigier-Bițozor, Ache, Dimopoulos, and Janowski (2025), in their FIG Working Week paper for FIG Commission 9, draw a further distinction: between AVMs, mostly used by financial institutions for individual property valuation, and Computer-Assisted Mass Appraisal (CAMA) systems, more commonly used by government agencies for large-scale tax assessment. Both, they argue, should complement rather than replace professional valuation expertise. The paper closes with nine practical recommendations, summarized in Table 2.2, which together sketch a governance framework for using automated valuation technology responsibly and feed directly into the discussion in Chapter Nine.

Table 2.2

The Nine FIG Commission Recommendations for Responsible AI-AVM Integration

#	Recommendation	Core Content
1	Embrace AI as a Complementary Tool	Integrate AI and AVMs to augment human expertise rather than replace it, combining technological efficiency with professional judgment
2	Establish High Data Quality Standards	Develop data quality indicators and international data standards to ensure AVMs produce trustworthy, cross-border consistent outputs
3	Promote Transparency and Explainability	Implement explainable AI (XAI) techniques so AVM processes are transparent, with clear methodologies and understandable outputs that build stakeholder trust
4	Ensure Ethical Use of AI	Adopt ethical guidelines to prevent bias and discrimination in AI-driven valuations, aligning transparency with accountability
5	Continuous Monitoring and Model Updates	Regularly update AVMs to reflect changing market conditions, minimizing inaccuracies as market dynamics evolve
6	Enhance Collaboration Between Valuers and Technologists	Foster partnership between valuation experts and AI developers so AVMs accurately capture market complexity and human behavior
7	Advocate for Clear Regulatory Frameworks	Engage with policymakers to develop balanced regulation, citing the EU AI Act as a global precedent for AI governance in valuation
8	Invest in Professional Development	Encourage valuers to acquire skills in AI and data analytics through ongoing education and training
9	Explore Advanced Technologies for Future Innovation	Investigate blockchain for transparent transaction records, cognitive-based technologies for attribute significance, and VR/AR for interactive property analysis

Note. Adapted from Renigier-Biłozor, Ache, Dimopoulos, and Janowski (2025).

The rest of the recommendations cover maintaining high data quality, improving model transparency and explainability, reducing algorithmic bias through ethical safeguards, monitoring model performance on an

ongoing basis, encouraging collaboration between valuation professionals and technologists, providing clearer regulatory guidance, building up professional skills, and exploring emerging technologies such as blockchain-based transaction records (Renigier-Biřozor et al., 2025). This 2025 publication should not be confused with the 2019 study by Renigier-Biřozor, D'Amato, and Kauko cited in the original proposal it's a separate, later paper, though the overlap in authorship and continuity of research make it a genuinely useful independent source. It's used here as further evidence for a view that keeps recurring throughout the professional literature: AVMs should complement traditional valuation practice, not replace it.

2.4.4 A Four-Dimensional Framework for Market Transparency

Beyond the practitioner recommendations in Table 2.2, Renigier-Biřozor et al. (2025) also offer a structured definition of real estate market transparency, built on the FIG position paper on the subject. Transparency, they argue, means more than information simply being available it requires that data be accessible, traceable, and reliable enough for investors, public institutions, and other market participants to make informed, sustainable decisions (Renigier-Biřozor et al., 2025, citing Ache et al., 2024). They break this into four dimensions: access to information, meaning data should be equally available to all market participants; availability of information, meaning comprehensive data actually exists across different market sectors; quality of information, meaning the data is accurate, current, and consistent; and objectivity of information, meaning market analyses and valuations are free of bias and conflicts of interest.

This framework maps several ideas developed elsewhere in this thesis. The Resource-Based View in Section 3.3 treats data availability as central to AVM performance, which lines up directly with the availability dimension. The IAAO's (2018) data quality requirements, discussed in Section 6.5, sit close to the quality dimension. The IVSC's (2022) position that an IVS-compliant valuation needs professional judgment, covered in Section 2.4.2, connects to the objectivity dimension by insisting that valuation shouldn't rely solely on an automated process without genuine professional oversight. The access dimension adds a wider angle still, pointing to how transparent ownership and transaction data help guard against money laundering, corruption, and tax evasion, consistent with the Financial Action Task Force's guidance (FATF, 2014, as cited in Renigier-Biřozor et al., 2025).

Anti-money laundering isn't the focus of this study, but this strand of market transparency is relevant to the UAE all the same. As noted in Section 1.2, Abu Dhabi drew AED 8.2 billion in foreign direct investment from over 100 nationalities in 2025 (ADREC, 2026), which says something about how important transparent property markets are in a market this internationally connected. Renigier-Biřozor et al. (2025) argue that well-governed AVMs can help here, using large datasets and analytical methods to produce estimates that are more objective and transparent, and to surface market patterns that traditional valuation alone might miss. But they're equally clear that this only works if the AVM operates within clear standards and transparent methods that market participants and regulators can actually trust which is essentially the design philosophy behind the transparent, rule-based HTML-based AVM built for this research and described in Section 7.4.4.

2.5 The RICS Roadmap: A Practitioner-Forum Perspective

One source that hasn't been used as much as it deserves is RICS's (2021) Automated Valuation Models: Roadmap for RICS Members and Stakeholders. It summarizes a series of international Leaders' Forums held under Chatham House rules across London, the Netherlands, Germany, Singapore, Hong Kong, and Sydney. Because participants stay anonymous, the report functions less like a conventional academic source and more like a structured record of practitioner opinion drawn from several jurisdictions at once which is exactly what makes it a useful complement to the academic studies and professional standards already covered: practical, on-the-ground insight into how valuation professionals actually see the opportunities and problems that come with AVM adoption.

2.5.1 The AVM Typology and the Concept of Confidence

The roadmap borrows a classification of AVM types originally developed by Victoria Zillioux of Strategic Development Worldwide, published in RICS's 2009 research paper Integrating Automated Valuation Models with Valuation Services to Meet the Needs of UK Borrowers, Lenders and Valuers (Robson & Downie, cited in RICS, 2021). It sorts AVMs by degree of human involvement, from fully automated models through to those “blended with human input” (RICS, 2021, p. 6), and lines up closely with the IAAO's (2018) taxonomy discussed in Section 2.3.1 a consistent classification that this thesis uses throughout.

Central to this framework is the confidence score, which RICS (2021) defines as a measure of “the accuracy of an AVM's estimate of value.” Confidence tends to run lower, the report explains, for unusual properties or in areas where market data is thin, since reliable value estimation gets harder in both cases (p. 7). Confidence scores are typically built from the relevance, quantity, and recency of comparable data, or from the forecast standard deviation (FSD) of the model relative to a benchmark such as a professional valuation or an actual sale price. But the roadmap flags an important catch: commercial AVM providers in the UK each use different methods and scales for confidence, which makes comparing platforms genuinely difficult (p. 7). That's part of the reasoning behind Chapter Seven's methodological choice building a transparent, purpose-built HTML-based AVM calculator instead of leaning on a proprietary commercial confidence metric.

2.5.2 Documented Uses, Advantages, and Disadvantages

Drawing on an earlier RICS information paper, the roadmap lists ten major AVM applications: mortgage origination and revaluation, assessing properties in arrears, valuation auditing, mass appraisal for property taxation (Computer-Assisted Mass Appraisal, or CAMA), capital tax planning, fraud detection, portfolio and securitization valuation, compensation assessment for public infrastructure projects, cost-benefit analysis for public investment, and lending capital adequacy assessment (RICS, 2021, pp. 8–9). That range makes the point on its own: AVMs go well beyond valuing individual properties. In cases like fraud detection or capital adequacy monitoring, they're doing analytical work that traditional valuation simply has no equivalent for.

The roadmap also lays out the advantages and limitations of AVMs, added to the discussion in the RICS Insight Paper (2022). On the plus side: they integrate with the electronic valuation systems financial

institutions already use, they can surface statistical patterns manual analysis might miss, they cut valuation time and cost, and they can help limit certain kinds of fraud by reducing reliance on any one person's judgment (p. 10). On the other side, the limitations are just as real. AVMs generally skip physical inspection and so tend to assume an average property condition that may not match reality. Add to that limited transparency for end users, the possibility of data manipulation, comparable data that's insufficient or poor quality, uncertainty about where input data came from, and growing reliance on AI models whose internal workings can be hard to explain (p. 10).

That last limitation matters a lot here, because it touches directly on a tension the theoretical framework in Chapter Three explores. More advanced machine learning can push predictive accuracy up while pushing transparency and explainability down. From a professional standpoint, a model that's statistically more accurate isn't automatically the better choice if nobody can clearly explain or justify what it produced. Valuation quality, in other words, must be judged on transparency, explainability, and professional accountability, not predictive performance alone.

2.5.3 A Methodologically Significant Risk: Self-Generating Data

One of the more technically interesting points to come out of the RICS Leaders' Forums is what might be called the self-generation risk. One participant put it plainly: "AVMs could become self-generating if the AVM evidence is reintroduced in the algorithm, which then raises questions about the independence and objectivity of valuation." Their suggested fix was to make "statistically significant non-AVM data... a compulsory element to be part of the AVM model" (RICS, 2021, p. 15). The concern, essentially, is that if an AVM's own past outputs get treated as market evidence and fed back into training or updating the same model, the system can slowly drift away from independently verified transactions quietly eroding the reliability and objectivity of what it produces.

This risk doesn't come up anywhere in the academic studies reviewed in Section 2.3, yet it's a real methodological concern as AVMs spread across property platforms and consumer-facing valuation tools, including services like Bayut's TruEstimate™ (Bayut, 2024). To guard against it, the methodology in Chapter Seven insists that comparable data used in this study's HTML-based AVM comes exclusively from independently recorded market transactions, never from a previous automated valuation output.

2.5.4 The Pace of Disruption: A Cautionary Industry Analogy

One of the more memorable moments in the roadmap draws a parallel with two well-known cases of corporate disruption. It recounts how Blockbuster Video turned down the chance to buy Netflix for \$50 million in 1999 and was bankrupt by 2010 despite running around 9,000 stores, and how Kodak despite inventing the world's first digital camera and holding more than 11,000 patents built up over a century went bankrupt by 2012 having stuck with its film-based business model instead of acting on its own invention (RICS, 2021, p. 13). The roadmap puts the question to its readers directly: "Is this the Valuation industry Kodak moment?" (p. 13). The analogy is more rhetorical than empirical, but it captures a mood that runs

through this practitioner-forum material, and it connects to the Innovation Theory framework in Chapter Three: Rogers's (2003) diffusion model treats the pace of adoption, not just whether adoption eventually happens, as the variable that actually matters, and the roadmap's repeated reach for disruption stories suggests at least part of the profession sees the risk of moving too slowly as being on par with the risk of moving too fast, not obviously smaller.

2.5.5 Regulatory Treatment of AVM Output

A last contribution from the roadmap, tied closely to the distinction drawn in Section 2.4 between automated estimates and professional valuation, concerns how AVM output is treated under the RICS Global Standards. The standards state that “the provision of an automated valuation model (AVM)-derived output or one based on a valuation modelling tool... is regarded as the provision of a written valuation for the purpose of these standards” (RICS, 2021, p. 17, citing RICS Valuation – Global Standards PS 1.4). Within the RICS framework, that settles much of the conceptual ambiguity the IVSC raises about whether an AVM output counts as a valuation: it can, so long as the valuer remains responsible for it and stays “alert to, and aware of, the implications of either accepting or manually modifying an AVM output” (p. 17).

Regulatory treatment of AVMs also varies by jurisdiction, the roadmap notes. Canada, the United States, and Australia have built out more extensive AVM-specific guidance, reflecting more time spent working with the technology. The UK, by contrast, has folded AVMs into broader financial regulation the Financial Conduct Authority's Prudential Sourcebook (BIPRU) and the Prudential Regulation Authority's Building Societies Sourcebook (BSOCS), which requires building societies to maintain reliable property valuation arrangements, AVMs included where appropriate (RICS, 2021).

The roadmap also has something to say about professional education. Rather than pushing for formal accreditation of individual AVM products, which RICS (2021) argues could create unnecessary legal and liability headaches and would be hard to apply consistently across jurisdictions and property types it instead pushes for stronger professional knowledge of AVMs generally. That means improving how well stakeholders understand statistical concepts like confidence levels, correlation, and standard deviation, so valuers and clients can read AVM output properly and hold their own in conversations with data scientists and technologists (p. 16).

It goes further still, recommending that professional qualification and continuing professional development (CPD) programs expand into data science, SQL, database design, statistical modeling, and the basics of machine learning and AI, and even suggesting a dedicated property data scientist career track to reflect how central technology has become to the profession (p. 16). It also stresses standardized property data pointing to the International Property Measurement Standards (IPMS) as an example of the consistency AVM development actually needs and concludes that, since AVMs are now an established part of practice in many countries, professional standards, education, regulation, and training all need to keep evolving alongside the technology.

These recommendations land squarely on the UAE, where ADREC reported a 57.7% jump in licensed real estate professionals during 2025 (ADREC, 2025). That growth has come alongside real digital transformation in the property sector, which only strengthens the case for equipping valuation professionals with the statistical and technological skills RICS recommends. The literature reviewed here doesn't say much about what UAE professional education programs currently cover, but that gap matters for the policy recommendations in Section 9.7.2.

2.6 The Saïd Business School Report: Adoption, Resistance, and Geographic Constraint

Beyond the adoption statistics for the UK mortgage market covered in Section 2.4, the Saïd Business School report also digs into why AVM adoption has been so uneven. This matters here because it ties in closely with the Innovation Theory framework in Chapter Three and adds real depth to how AVM adoption plays out in practice.

2.6.1 Geographic Constraints on Model Scalability

Geographic specificity, according to the report, is one of the main technical limits on how far AVMs can scale. AVMs “exhibit geographic constraints at a sub-county or sub-municipality level,” meaning each model is built for a particular area, and simply extending its coverage tends to hurt performance (Saïd Business School, University of Oxford, 2022, p. 16). To illustrate the scale of the problem, the report notes that “a country the size and complexity of the United Kingdom require approximately 1,000 geographically separate models” (p. 16). One industry expert quoted in the report goes further still, arguing that standard administrative boundaries often don't fit AVMs well: “postcode sectors aren't the best location input for an AVM... manually creating polygons to group broadly similar location factors across a country such as the UK can take up to 7,000 person hours” (p. 16).

This underscores just how much geographic and spatial data matters to AVM development and backs up the Resource-Based View from Chapter Three AVM performance depends not only on transaction data but on having accurate, well-structured geographic information to work with. The bigger and more geographically complex a market gets, the more resource-intensive it becomes to build and maintain reliable location-specific models, which limit both the scalability and the effectiveness of the whole approach.

2.6.2 Professional Resistance and the Hybrid AVM Concept

The report also places current resistance to AVM adoption within a much longer historical pattern. It cites Jaffe's (1986) look at whether the valuation profession had a future in the face of the “microprocessor revolution,” and traces real estate investment valuation models back to the seventeenth-century “estate management surveyors” of English manors (citing Jefferies, 2017) framing today's AVM resistance as another round of a recurring professional reflex rather than something genuinely new. Drawing on Kanter's (1995) general theory of organizational resistance to change, it identifies sources of resistance that map directly

onto AVMs: a “loss of control” felt by valuation professionals as automated tools take over tasks they used to do themselves; “uncertainty” from limited communication between AVM developers, regulators, and valuers; and “concerns about competence,” reflecting the fact that many valuers simply aren't aware of how AVMs could work in their favor rather than against them (Saïd Business School, University of Oxford, 2022, p. 17).

There's also a definitional tension in the adoption debate that bears directly on this thesis's emphasis on integration over substitution. Valuers more open to AVMs, the report notes, tend to see the technology “as a tool no different than a slide rule” that refines rather than replaces the profession under which framing “valuers will benefit from a lot of the mundane and repetitive work being automated, freeing up their time to focus on more appealing work” (p. 18). But that framing sits awkwardly next to how the AVM developer community itself defines the term: “an AVM ceases to be automated as soon as a human gets involved,” meaning an AVM genuinely used as a valuer's tool, with a human reviewing the output, is more accurately what the report calls a “hybrid AVM” (p. 18) rather than an AVM in the strict, fully automated sense. Dr. Andrea Biguzzi, Secretary General of the European AVM Alliance, puts it directly: “In the case of AVMs, the 'A' stands for automated. As soon as you attach a human to it, it becomes what we'd refer to as semi-automated or hybrid. Naturally we recognize and respect the contribution of surveyors, and we welcome close collaboration with them on hybrid valuations” (p. 18). This distinction between a strict AVM and a hybrid AVM runs through the theoretical and methodological treatment of integration in Chapters Three, Six, and Eight, since much of what the professional literature calls “integrating” AVMs with traditional valuation is, by definition, a request to move away from AVMs in their pure form and toward a qualitatively different, hybrid category of tool.

2.6.3 Regulatory Inertia and the Effect of COVID-19

The report's last contribution concerns regulatory inertia, a constraint on AVM diffusion distinct from professional resistance. In the US, it notes, “appraisal waivers” are formally required before an alternative method like an AVM can stand in for a traditional appraisal, and “the coronavirus pandemic increased the rate of appraisal waivers for government-sponsored enterprises Fannie Mae and Freddie Mac” (citing Neal & Goodman, 2020; Di Martino Booth, 2020) though the report is careful to note that “whether the coronavirus pandemic facilitated a permanent nudge toward a higher proportion of appraisal waivers or a temporary one is yet to be determined” (p. 17). A related case of inertia shows up in property tax valuation, where “there has been no revaluation since 1991 in England and 2005 in Wales,” with a planned 2007 revaluation postponed after media coverage suggested it would fall disproportionately on poorer communities (p. 17, citing Weaver & Siddique, 2010; BBC, 2010). Without overstating it, the report suggests that more frequent mass revaluation of a task well suited to AVMs and CAMA-type systems, as discussed in Section 2.5.2 would let practitioners tell genuine market movement apart from valuation anomalies more easily than the current, infrequent revaluation cycle allows.

2.6.4 Four Fundamental Obstacles to AVM Accuracy

Beyond the geographic, professional, and regulatory challenges already discussed, the Saïd Business School report identifies four further factors that limit AVM accuracy no matter the market or the modeling technique. These add to the Resource-Based View in Section 3.3 by pointing to practical constraints that go beyond data availability alone.

The first is real estate's low transaction frequency. Unlike financial assets, which trade constantly, residential property changes hands rarely the report cites the figure that “the average person moves homes every 22.7 years” in the UK (Saïd Business School, University of Oxford, 2022, p. 34, citing Zoopla, 2017). That leaves a genuinely limited pool of verified transactions to build and validate a model on, which makes it harder to establish reliable performance benchmarks in the first place.

The second is market heterogeneity. Property markets vary so much by location that AVMs often need to be built for small geographic areas just to stay accurate but shrinking the geography also shrinks the training data available, creating a real trade-off between local accuracy and having enough data to work with (p. 34). This reinforces the geographic limitations already discussed in Section 2.6.1.

The third is physical characteristics that affect value but rarely get recorded consistently architectural design and garden condition are the report's examples, often missing or documented unevenly, which makes them hard to fold into an automated model (p. 34). The fourth is nearby amenities: parks, schools, busy roads, all of which can move property values noticeably, yet most conventional AVM datasets don't capture them well (p. 34).

All four of this line up with Kok et al. (2017), Bergadano et al. (2019), and Tapia et al. (2025), each of whom found AVM performance improved once richer data hyperlocal amenities, web-collected comparable listings, image-based property features was brought in. The pattern across these studies is consistent: better AVM accuracy comes not just from better algorithms, but from expanding the range and quality of the information feeding into the model.

The report also touches on public perception of AI-based AVMs. It notes that “AI has been marketed as the mysterious 'black box algorithm' that supposedly should provide the best real estate valuation,” yet “due to the limited understanding of the public, AI driven AVMs have not been widely trusted by the industry” (Saïd Business School, University of Oxford, 2022, p. 34). That sits a little at odds with the IAAO's (2018) position that AVM development is “not a black box process.” though the difference seems to come down to two different vantage points. The IAAO is talking about the overall process of building and validating an AVM; the Oxford report is talking about the internal workings of advanced AI and neural network models specifically, whose complexity is exactly what makes them harder to explain and, in turn, harder to trust.

2.7 Analytical Comparison of Previous Studies

Table 2.1 summarizes the studies covered in this chapter in chronological order, alongside their research objectives, methodology, key findings, and relevance to this study.

Table 2.1

Chronological Comparison of Reviewed Studies

Author(s) and Year	Study Objective	Methodology	Key Findings	Relation to Current Research
Kok, Koponen, & Martínez-Barbosa (2017)	Examine the transformation of commercial real estate valuation through big data and machine learning	Machine learning (random forest, gradient boosting) applied to ~54,000 U.S. multifamily assets	Median absolute error of ~9%, outperforming documented traditional appraisal error margins (7.7–13.9% across markets); hyperlocal data adds significant predictive value	Establishes the empirical baseline for AVM accuracy claims and the centrality of data granularity to AVM performance
IAAO (2018)	Establish professional standards for AVM development, calibration, and quality assurance	Standard-based, professional practice review	AVM credibility depends jointly on data quality and analyst competence; AVMs exist on a spectrum from appraiser-assisting to fully automated tools	Provides the operational definition of an AVM and the taxonomy of AVM types used throughout this thesis
Bergadano, Bertilone, Paolotti, & Ruffo (2019)	Develop an adaptive AVM using heterogeneous, web-crawled, and open data sources	Ensemble machine learning (Extra Trees, Random Forest, Bagging) applied to Turin, Italy residential data	Mean error fell from ~€54,400 (baseline hedonic) to ~€21,000 (with comparables); R^2 reached 0.957–0.959; out-of-sample mean error of ~€17,000	Demonstrates that AVM accuracy depends heavily on the richness and diversity of input data, not algorithm choice alone
Renigier-Biłożor, d'Amato, & Kauko (2019)	Review the methodological development of AVMs in the academic literature	Systematic literature review	Bibliographic record only; full text unavailable for this review	Cited per the original proposal's reference list; no independent findings claimed here
Băbțan (2020)	Explore the conceptual basis and feasibility of AVM application in Cluj-Napoca, Romania	Applied, conceptual study with proposed algorithmic design	AVMs framed as complementary to traditional valuation; particularly suited to homogeneous residential property types	Supports the practical case for AVM use in markets with high transaction-type homogeneity
RICS (2021)	Guide RICS members on the professional	Professional policy and analytical roadmap	AVMs require governance, transparency, and professional oversight to be used responsibly	Frames AVM adoption as a governance question rather than a purely technical one

	implications of AVM adoption			
RICS (2022)	Examine practical implications of AVMs for valuers and clients	Analytical review informed by international practitioner forums	AVM suitability depends on property type, data availability, and risk exposure; valuer judgment proposed as the benchmark for AVM quality	Directly supports the comparative, judgment-benchmarked design of this thesis
IVSC (2022)	Assess whether and how AVM outputs can constitute a valuation opinion under IVS	Policy-oriented analytical paper	AVM outputs may be IVS-compliant only where meaningful human oversight is retained throughout the process	Frames the central conceptual tension this thesis investigates: calculation versus professional opinion
Jafary, Shojaei, Rajabifard, & Ngo (2024)	Compare machine learning and deep learning methods for automated land valuation	Comparative empirical study (per bibliographic record)	Full text unavailable for this review; findings not independently verified here	Cited per the original proposal's reference list; included for completeness only
Tapia, Chavez-Garzon, Pezoa, Suarez-Aldunate, & Pilleux (2025)	Compare machine learning and spatially adjusted hedonic models for residential valuation	Cross-validated machine learning (Light GBM) vs. OLS and SAR models, Santiago, Chile	MAPE improved from 11.59% to 10.07% with the addition of image-based variables; R ² rose from 0.9412 to 0.9516; interpretive divergence found between ML and spatial econometric models	Provides the most methodologically rigorous recent benchmark and a direct caution regarding interpretability versus predictive accuracy
Renigier-Bitozor, Ache, Dimopoulos, & Janowski (2025)	Examine the integration of AI with AVMs and CAMAs from a professional governance perspective	Policy-oriented analytical paper, FIG Commission 9	Nine recommendations for responsible AI-AVM integration, centered on complementarity, data quality, transparency, and professional collaboration	Reinforces the complementarity framing central to this thesis's theoretical and practical contribution

Note. Studies marked with an asterisk indicate that only bibliographic information, rather than the full text, was available during this review. Accordingly, no findings beyond those reported in the original research proposal are attributed to these sources.

A few patterns stand out from Table 2.1. First, the full-text studies available consistently show AVMs achieving high predictive accuracy in data-rich residential and multifamily markets, in some cases matching or beating the documented accuracy of traditional valuation (Kok et al., 2017; Bergadano et al., 2019; Tapia et al., 2025). Second, better model performance keeps tracing back to richer input data rather than more

sophisticated algorithms on their own Kok et al. (2017) show the value of hyperlocal variables, Bergadano et al. (2019) show what web-crawled comparable data adds, and Tapia et al. (2025) show the contribution of image-based features. Third, despite coming at the question from different angles, the professional and regulatory literature (IAAO, 2018; RICS, 2021, 2022; IVSC, 2022; Renigier-Bilozor et al., 2025) converges on much the same conclusion: AVMs should support professional valuation rather than replace it and using them well depends on governance and professional oversight issues the more technically focused academic literature tends to give less attention.

2.8 The Research Gap

Three research gaps come out of this literature, and each shapes the design of the present study.

First, the technical literature on AVM performance and the professional literature on AVM governance have largely grown up separately. Kok et al. (2017), Bergadano et al. (2019), and Tapia et al. (2025) show AVMs can be highly accurate under the right data conditions, but none of them systematically compares AVM output against valuations produced by experienced professionals working to established standards such as RICS's or IVSC's. Professional literature, meanwhile, keeps stressing how important that comparison is, without providing much empirical evidence for it.

Second, most of the empirical research sits in mature, data-rich markets the United States, Italy, Chile. That leaves very little evidence on how AVMs perform in a market like the UAE: rapidly developing, digitally transforming, with transaction volumes that are genuinely high, but academic research on AVM performance hasn't caught up.

Third, professional organizations consistently argue for integrating AVMs with traditional valuation rather than replacing valuers outright, but few studies explain how that integration should work in practice. Real questions remain open: what market conditions justify leaning more heavily on AVMs, what kinds of properties AVMs are genuinely less suited to, and what workflow combines automated analysis with professional judgment most effectively.

This study addresses these gaps by comparing AVM-generated outputs against traditional valuation within the UAE real estate market, while also drawing on the perspectives of valuation professionals on how automated and conventional practice might be integrated. Throughout, the comparison is guided by the governance principles and professional standards set out by the IAAO, RICS, and IVSC.

3. THEORETICAL FRAMEWORK

3.1 Introduction

A theoretical framework does two jobs in this study. It gives the phenomenon under investigation a conceptual basis, and it guides how the empirical findings get interpreted by pointing to what kind of evidence would support or undercut a given explanation. The thing this thesis is trying to explain the slow, uneven adoption of Automated Valuation Models within a profession that has traditionally run on expert judgment isn't something technical performance alone can account for. Chapter Two already makes this point: predictive accuracy matters, but it isn't sufficient on its own for adoption to happen. The IVSC, RICS, and IAAO standards all point the same direction, showing that using AVMs effectively depends just as much on data quality, professional governance, and institutional trust. So, this chapter builds its theoretical framework from three complementary angles Innovation Theory, the Resource-Based View, and Data-Driven Decision-Making Theory each covering a different part of the research problem and together grounding the empirical analysis in Chapters Seven and Eight.

3.2 Innovation Theory

3.2.1 Theoretical Foundations

Innovation Theory, most closely associated with Everett Rogers's Diffusion of Innovations, explains how new ideas, technologies, and practices get taken up over time within a social system (Rogers, 2003). Rogers identifies five factors that shape whether an innovation is adopted: relative advantage (is it seen as better than what's already being done), compatibility (does it fit existing values and work practices), complexity (how hard is it to understand and use), trialability (can it be tested before full commitment), and observability (how visible are its benefits to others) (Rogers, 2003). Adoption, in his account, isn't a single event but a process that moves through five stages knowledge, persuasion, decision, implementation, confirmation. Read this way, resistance or slow uptake isn't irrational; it's an ordinary response to uncertainty about whether an innovation fit established professional practice and institutional expectations.

3.2.2 Application to Automated Valuation Models

AVMs map onto Rogers's Innovation Theory neatly. Their relative advantage shows up clearly in the literature covered in Chapter Two Kok et al. (2017), for instance, reported a median absolute error of around 9%, which compares well with the documented variation in traditional commercial appraisals. And yet that technical advantage hasn't translated into universal adoption. Rogers's framework would say this is because adoption depends on more than perceived benefit; it also depends on compatibility with existing professional values and practice. Both the IVSC Perspectives Paper (2022) and the RICS Insight Paper (2022) treat AVMs into professional practice as an ongoing challenge, not a solved problem. The IVSC struggles with reconciling an automated value estimate with the traditional idea of valuation as a professional opinion (IVSC, 2022) a tension between technological innovation and established professional standards that runs through much literature.

The complexity dimension shows up too. RICS (2022) doesn't expect valuers to understand every technical detail of an AVM, but they're still on the hook for judging whether its output is reasonable and consistent with professional judgment. That's a genuine bind: increasingly sophisticated valuation technology sitting alongside a profession that expects transparency and accountability from whatever it uses. It's also why the IAAO (2018) leans so heavily on rigorous model validation, quality assurance, and analyst expertise, rather than treating an AVM's output as automatically trustworthy.

The two remaining dimensions of Rogers's framework trialability and observability help explain the gradual, uneven pattern of AVM adoption the Saïd Business School study documents. AVMs have mostly taken hold first in lower-risk mortgage transactions, where their performance can be tested and evaluated before anyone extends them to riskier lending scenarios (Saïd Business School, University of Oxford, 2022). Innovation Theory, in this study, isn't just a label for classifying AVMs as an innovation; it's doing real work explaining why adoption within the valuation profession has been so uneven, and it grounds the qualitative side of this research by giving a framework for placing the UAE valuation profession somewhere along Rogers's adoption process.

3.2.3 Organizational Resistance: Kanter's Framework

Rogers's diffusion framework is good at explaining how innovations get adopted, but it says less about the psychological and organizational side of resistance to change. Kanter's (1995) theory of organizational resistance, applied to AVMs in the Saïd Business School report discussed in Section 2.6.2, fills that gap. Kanter identifies several typical sources of resistance, three of which map directly onto AVM adoption: loss of control, where professionals feel tasks they used to do themselves are being handed to technology; uncertainty, stemming from poor communication between technology developers and the professionals expected to use their systems; and concerns about competence, the fear that existing knowledge and skill will simply matter less going forward (Kanter, 1995, as cited in Saïd Business School, University of Oxford, 2022, p. 17).

Read alongside Rogers's (2003) Innovation Theory, Kanter's framework fills out the compatibility dimension considerably. Compatibility, it turns out, isn't just about innovation's own characteristics it's about how professionals respond to it. Feeling less in control, being uncertain, worrying about your own competence: any of these can slow adoption on their own, even where the technical case for the technology is already well established.

That matters directly for this study. It suggests that getting AVMs adopted takes more than showing improved valuation accuracy. It also needs real communication between AVM developers and valuation professionals, training that builds confidence in using automated tools, and governance frameworks that keep the valuer's role intact in the final decision, all things RICS, the IAAO, and the IVSC consistently recommend. That's why the qualitative interviews in Chapter Seven are built specifically to probe these three sources of resistance

among UAE valuation professionals, rather than treating skepticism toward AVMs as if it were a purely technical question.

3.2.4 The Hybrid AVM as a Resolution of Definitional Tension

A further wrinkle in the Innovation Theory picture, again from the Saïd Business School report (Section 2.6.2), is a definitional ambiguity that runs through the practitioner literature in Chapter Two. Valuers who welcome AVMs tend to describe them as something like a slide rule a tool that frees up the professional for higher-value work, not a substitute for professional judgment (Saïd Business School, University of Oxford, 2022). That framing doesn't sit comfortably with how the AVM developer community itself defines the term: as one practitioner quoted in the Oxford report puts it, “an AVM ceases to be automated as soon as a human gets involved” (p. 18). What resolves this, per the report, is a third category the “hybrid AVM” that is neither a strictly automated model nor a traditional valuation. This thesis takes the hybrid AVM as an explicit analytical category in the empirical chapters that follow, rather than leaving “integration” as a vague aspiration; seen this way, the Interactive Valuation Application AVM and the Blended or Cascading AVM types the IAAO (2018) defines, discussed in detail in Chapter Nine, are simply two specific, operationally defined versions of the broader hybrid AVM category that both innovation theory and the practitioner literature point toward.

3.3 Resource-Based Theory

3.3.1 Theoretical Foundations

The Resource-Based View (RBV), developed primarily by Barney (1991), explains differences in organizational performance in terms of the resources and capabilities an organization has access to. Barney's argument is that a resource only delivers a sustainable competitive advantage if it's valuable, rare, hard to imitate, and non-substitutable with the VRIN criteria. The RBV was built for strategic management, but its logic transfers to technology adoption just as well: an organization's ability to benefit from a given technology comes down to the quality of the resources behind it, which includes data, technical infrastructure, and human expertise.

3.3.2 Application to Automated Valuation Models

Within the RBV, data is the single most important resource shaping AVM performance. The studies in Chapter Two are consistent on this point: AVM's accuracy tracks the volume, quality, and granularity of the data used to build and calibrate it. Kok et al. (2017) traces much of their model's performance to hyperlocal variables proximity to amenities, crime rates that go beyond the structural variables a standard hedonic model would use. Bergadano et al. (2019) found something similar: enriching the dataset with web-crawled comparable property data cut the mean prediction error from roughly €54,000 to €21,000 using the same algorithms. And Tapia et al. (2025) found that adding image-based property data produced a further improvement on top of that.

Through an RBV lens, what these findings really say is that an AVM's effectiveness isn't set by the algorithm alone but by the quality of the resources feeding it. In markets with comprehensive, reliable transaction data, AVMs can be as consistent as traditional valuation, or even more so. Where market data is thin or

comparable transactions are scarce, the RICS Insight Paper (2022) makes directly the same model's performance is likely to slip, simply because the data resources underneath it isn't there. AVM performance, in other words, depends on the market it's deployed in as much as on the technology itself.

That has a direct implication for this study: AVM performance in the UAE can't just be assumed from results reported elsewhere. It must be tested against the UAE's own transaction records, property characteristics, and market data. The Resource-Based View is used here to explain why AVM performance varies across markets, and it's the reasoning behind the market-specific empirical approach taken in Chapters Seven and Eight.

3.3.3 Geographic Data Infrastructure as a Resource

RBV's relevance to AVMs goes beyond transaction data alone it extends to the broader geographic and administrative infrastructure that automated valuation depends on. The Saïd Business School report, discussed in Section 2.6.1, makes this point clearly. Because AVMs "exhibit geographic constraints at a sub-county or sub-municipality level," a country the size and complexity of the UK need roughly 1,000 separate geographic models. And defining sensible geographic boundaries rather than just relying on administrative units like postcode sectors can take up to 7,000 person-hours for a single country (Saïd Business School, University of Oxford, 2022, p. 16).

Seen through an RBV lens, the critical resource here isn't data alone it's the broader infrastructure needed to organize, manage, and maintain that data in a form usable for automated valuation. That infrastructure is genuinely resource-intensive to build, and it varies a great deal between markets. For the UAE, that means AVM performance depends not just on having transaction data available, but on how mature the supporting geographic and administrative information is: cadastral mapping, district and sub-district boundaries, consistent location classification across data sources. These are the foundations any effective AVM implementation in the UAE market would need to rest on.

3.4 Data-Driven Decision-Making Theory

3.4.1 Theoretical Foundations

The third theoretical lens is Data-Driven Decision-Making (DDD), most closely tied to the work of Brynjolfsson, Hitt, and Kim (2011). They show that organizations using systematic, data-driven decision-making outperform comparable organizations relying mainly on managerial intuition, in terms of productivity. The core idea isn't that data replaces human judgment, it's that data improves decision-making by supplying more consistent, more objective evidence. Along the way, data-driven approaches can reduce certain kinds of bias and inconsistency, while introducing their own problems around data quality, model design, and the limits of what structured data can capture.

3.4.2 Application to Automated Valuation Models

Applied to property valuation, this lens gets at what's at stake in comparing traditional valuation with AVMs. Traditional valuation has always used data comparable sales evidence is data, after all but it uses it inside a fundamentally judgment-led process: the valuer decides which comparables are actually relevant, makes qualitative adjustments for things that resist precise quantification, and brings in contextual knowledge that may never show up in any structured dataset. AVMs flip that balance, folding the analytical process into a systematic, reproducible statistical procedure, at the cost of depending entirely on whatever has been captured, quantified, and made available as structured data. The IVSC's worry that an AVM with no human input might not really constitute a valuation "opinion" in the professional sense (IVSC, 2022) is, seen this way, a specific case of a tension the data-driven decision-making literature has recognized for a long time: structured, algorithmic decisions tend to be more consistent and auditable, but they can also be systematically blind to exactly the qualitative, contextual factors that domain experts consider material.

This tension maps directly onto the empirical pattern from Chapter Two. Tapia et al.'s (2025) finding that machine learning and spatially corrected econometric models can disagree on how to interpret the same variable nearby schools, in their case is a concrete example of how a purely data-driven process can produce something internally coherent but substantively questionable, when the underlying data doesn't fully capture what's actually going on. RICS's (2022) suggestion that a valuer should be able to judge an AVM's output against what "a reasonably competent valuer would be able to produce" is essentially a proposed fix for this same limitation: using professional judgment not to replace the data-driven process, but to check it against an independent, contextually grounded standard. In this research, Data-Driven Decision-Making Theory is used to frame the central comparative question not as "which method is more accurate" in isolation, but as "under what conditions does systematizing the valuation process through data and algorithms actually improve, rather than degrade, the quality of the resulting decision" a framing that treats the technical and professional sides of the AVM debate as one question rather than two.

3.4.3 Explainability and the Behavioral Dimension of Valuation Decisions

Renigier-Biłozor, Ache, Dimopoulos, and Janowski (2025), in the FIG Working Week paper already reviewed in Section 2.4, add a further wrinkle here by discussing the growing use of Explainable Artificial Intelligence (XAI) in AVM and Computer-Assisted Mass Appraisal (CAMA) systems. They describe a shift away from traditional "black box" models toward more transparent approaches feature importance analysis, interpretable algorithms that let users see how different inputs shape the valuation outcome and catch potential bias or error along the way (Renigier-Biłozor et al., 2025). Their argument is that better model transparency builds trust between developers, valuation professionals, and end users, making automated valuation more accountable and more reliable in the process. That supports the Data-Driven Decision-Making framework used here: the balance between predictive accuracy and professional judgment can improve through explainable models rather than opaque ones.

The authors also stress behavioral factors in valuation of something much of the technical AVM literature barely touches. Drawing on earlier work, Renigier-Biřozor and Janowski (2024, as cited in Renigier-Biřozor et al., 2025) argue that current valuation models tend to overlook human behavior, and suggest automated systems should be designed to fit more closely with how people actually think, making them easier to interpret, refine, and use in practice. That complements the IVSC's (2022) position that valuation is fundamentally a professional opinion: buyers, sellers, and lenders don't always behave like perfectly rational decision-makers, so valuation methods arguably need to account for behavioral factors alongside statistical analysis. The authors land on a collaborative model where AI supports human expertise, with professional oversight still essential for anything complex (Renigier-Biřozor et al., 2025).

That collaborative model shows up in the idea of human sovereignty automated systems designed to assist rather than replace the professional decision-maker, so responsibility for the final valuation stays with the human valuer (Renigier-Biřozor et al., 2025). The authors also note that resistance to AVMs is often tangled up with concerns about job security, even though AVMs were originally meant to improve efficiency and cut errors, not eliminate the valuer's role. Some applications discussed in Chapter Two do show AVMs substituting for traditional valuation in specific tasks, but this study isn't trying to settle that debate. Instead, it looks at whether there's a gap between what AVMs are meant to do and how they're used in practice a question explored further through the qualitative interviews with UAE valuation professionals described in Section 7.4.1.

3.5 Integration of the Theoretical Framework

The three perspectives above aren't independent of each other so much as complementary, each explaining a different piece of the shift toward automated property valuation. Innovation Theory explains how AVMs get adopted over time gradually and shaped by how well they fit existing professional practice. The Resource-Based View explains why AVM performance varies across markets, trying successful implementation to the availability of high-quality, detailed, reliable data. Data-Driven Decision-Making Theory speaks to the bigger picture: the trade-off between the consistency and transparency data-driven methods offer and the contextual judgment that still sits at the center of professional valuation.

Together, these three give this study its theoretical grounding for the research questions and hypotheses. Innovation Theory suggests AVM adoption in the UAE valuation profession will happen gradually, taking hold faster where data is rich and where the risk of model error is lower consistent with what the Sařd Business School study found elsewhere. The Resource-Based View says AVM performance in the UAE needs to be judged against the country's own data environment, not assumed from results reported in other markets. And Data-Driven Decision-Making Theory suggests the comparison between traditional valuation and AVMs should go beyond predictive accuracy, toward how the strengths of each approach might complement each other which is the conceptual basis for the integration-focused analysis that runs through this thesis's empirical chapters.

This integrated framework is set out in Figure 3.1, showing how the three theoretical perspectives relate to one another, the variables each one governs, and the outcome they converge on valuation quality which is the dependent focus of this research.



Figure 3.1. Integrated Theoretical Framework. Author's own construction.

Ultimately, what this research finds may help improve valuation practice by pointing to the most effective ways of combining human expertise with data-driven technology.

4. FROM THEORY TO PRACTICE A BRIDGE TO THE EMPIRICAL CHAPTERS

4.1 Purpose of This Chapter

The previous two chapters laid the academic, professional, and theoretical groundwork for this study Chapter Two through the literature on traditional valuation and AVMs, Chapter Three through the theoretical lenses used to explain why AVM adoption has been so uneven. Before turning to the operational workflows of traditional valuation and AVMs in Chapters Five and Six, and the research methodology in Chapter Seven, it's worth pausing to spell out how all of this connects. That's the point of this short chapter: to tie literature, theory, and empirical investigation together into one coherent argument rather than leaving them as separate discussions sitting side by side.

4.2 The Logical Structure of the Thesis

The argument running through this thesis unfolds in four connected steps. The first, laid out in Chapter Two, establishes the empirical foundation. The studies reviewed there Kok et al. (2017), Bergadano et al. (2019), Băbțan (2020), Tapia et al. (2025) consistently show that AVM performance depends less on how sophisticated the algorithm is than on the quality, richness, and completeness of the underlying data. The professional literature, meanwhile, the IAAO (2018), the IVSC Perspectives Paper (2022), the RICS Roadmap (2021) and Insight Paper (2022) arrive at much the same conclusion from a different angle: AVMs should complement professional valuation judgment, not replace it.

The second step, in Chapter Three, supplies the theory behind these findings. The Resource-Based View explains why data quality is the key factor in AVM performance. Innovation Theory, backed by Kanter's (1995) theory of organizational resistance and the hybrid AVM concept discussed in the Saïd Business School report, explains why AVM adoption has moved unevenly across markets, property types, and professional settings. Data-Driven Decision-Making Theory frames the trade-off at the heart of it all: the consistency and transparency automated systems offer against the contextual judgment a professional valuer brings.

The third step, in Chapters Five and Six, puts these empirical and theoretical foundations into practice by reconstructing how traditional valuation and AVMs work, step by step, rather than just comparing their final numbers. That means looking at the sequence of activities each approach involves and pinpointing where professional judgment, or methodological control, gets applied. That operational groundwork feeds directly into the fourth step, the empirical investigation in Chapter Seven understanding how each method functions is what lets this study asks not just whether traditional valuation and AVMs differ, but why.

4.3 Formal Statement of the Study Hypotheses

Before turning to the workflow analysis and research methodology in the chapters that follow, it's worth stating the hypotheses that guide this study up front, since they get referenced throughout the empirical analysis. The main hypothesis addresses the central research question from Section 1.5: whether Automated Valuation Models (AVMs) and traditional valuation methods differ significantly in valuation accuracy and

efficiency. The alternative hypothesis (H1) holds that there is a statistically significant difference between AVMs and traditional property valuation methods on accuracy and efficiency; the null hypothesis (H0) holds that no such difference exists.

To dig into this more precisely, the main hypothesis splits into four sub-hypotheses, each tied to one of the research questions from Section 1.3 and summarized in Table 4.1. The first covers accuracy: H1.1 states that AVM use significantly improves valuation accuracy compared with traditional methods, while H0.1 states AVMs have no statistically significant effect on accuracy. The second covers efficiency: H1.2 proposes that AVMs significantly improve the speed and efficiency of the valuation process, while H0.2 states that no significant improvement exists. The third examines data quality and AVM performance, tying directly to the Resource-Based View discussed in Section 3.3: H1.3 states there is a statistically significant relationship between the availability and quality of real estate data and AVM accuracy, while H0.3 states no such relationship exists. The fourth covers integration: H1.4 proposes that combining AVMs with traditional valuation significantly improves the overall reliability of property valuations, while H0.4 states that integration produces no statistically significant improvement.

Chapter Eight tests these hypotheses, and Chapter Nine discusses them against the research questions and theoretical framework. H1.4 is addressed mainly through the qualitative side of the mixed-methods design described in Section 7.2.2, since judging the reliability of an integrated valuation approach needs the perspective of experienced valuation professionals, not just quantitative analysis.

These hypotheses also trace back to the theoretical framework in Chapter Three. H1.1 and H1.2 test the core claim underlying the AVM literature that automation can improve valuation accuracy and efficiency. H1.3 is a direct test of the Resource-Based View, asking whether AVM performance in the UAE depends on data availability and quality. And H1.4 tests the central argument running through both the professional literature and Innovation Theory: that AVMs add the most value not by replacing traditional valuation, but by combining automated analysis with professional judgment for a more reliable result.

4.4 Why the Workflow Reconstruction Matters Methodologically

It's worth explaining why this thesis devotes two full chapters to workflow reconstruction before getting to the empirical methodology, since that's a departure from most of the literature in Chapter Two. Even technically advanced studies like Tapia et al. (2025) go into real depth on model design and performance but say comparatively little about how AVM output gets folded into valuation practice. That's a reasonable choice for a technically focused study, but it leaves a real gap for this one Research Question 5, on how AVMs can be integrated with traditional valuation, can't be properly answered without knowing exactly where in the valuation process that integration would happen.

Chapters Five and Six close that gap by reconstructing the workflows of traditional valuation and AVMs using the IAAO's (2018) AVM development standard and the RICS Global Standards for traditional valuation. Together they produce two directly comparable step-by-step workflows that Chapter Nine's analysis builds

on. Setting the traditional workflow (Table 5.1) against the automated one (Table 6.1) makes it possible to pinpoint exactly where a hybrid approach could be introduced most effectively.

This also reflects a broader principle in comparative research. Judging AVMs purely on performance measures like mean absolute percentage error treats both traditional and automated valuation as “black boxes” and ignores the process behind the result. That kind of comparison has its uses, but it isn't enough for a study concerned with valuation quality rather than prediction accuracy alone. As Section 2.4 and Section 5.6 discuss, valuation quality depends on more than the final estimate professional judgment, auditability, compliance with valuation standards, and using the right basis of value all matters too. The workflow reconstructions in Chapters Five and Six exist precisely to connect valuation outcomes back to the processes that produced them.

4.5 Mapping the Research Questions to the Thesis Structure

To give a clear picture of how the study is put together, Table 4.1 maps each of the five research questions from the original proposal to the chapter or chapters where it's primarily addressed. Treat this as a guide rather than a claim that each question lives in exactly one chapter as Section 4.2 explains, the argument builds progressively, and most research questions get examined across several chapters.

Table 4.1

Mapping Research Questions to Thesis Chapters

Research Question	Primary Chapter(s)	Supporting Theoretical Lens
RQ1: What are the methodological differences between traditional valuation and AVMs?	Chapters Two, Five, and Six	Data-Driven Decision-Making Theory
RQ2: How do AVMs influence valuation accuracy and efficiency relative to traditional methods?	Chapters Two, Seven, and Eight	Resource-Based View
RQ3: What technological, data-related, and methodological challenges affect AVM implementation?	Chapters Two and Six	Resource-Based View; Innovation Theory

RQ4: What is the relationship between automated valuation techniques and overall valuation quality and reliability?	Chapters Two, Five, Six, and Nine	Data-Driven Decision-Making Theory
RQ5: How can AVMs be effectively integrated with traditional valuation methods?	Chapters Three, Six, and Nine	Innovation Theory; the hybrid AVM concept (Section 3.2.4)

This mapping also explains why some chapters, Five and Six especially, support more than one research question rather than just one. They supply the procedural and operational groundwork the empirical analysis builds on. RQ1 and RQ4 both lean on the detailed workflow reconstructions in these chapters, since answering either question means understanding how the valuation processes actually differ in practice. Chapter Eight compares outcomes, but the workflow analysis in Chapters Five and Six is what explains the methodological differences, and the quality and reliability considerations, that an outcomes-only comparison can't fully capture on its own.

4.6 Overview of the Remaining Chapters

With that structure in place, the rest of the thesis runs as follows. Chapter Five reconstructs the traditional property valuation workflow across four stages: instruction and scope of work, inspection and data collection, selecting and applying the valuation approach, and review, reconciliation, and reporting. Chapter Six lays out the corresponding automated workflow, distinguishing the one-time model development process the nine stages the IAAO (2018) defines from the repeated model application process, and introduces the statistical quality measures used throughout this study: the Coefficient of Dispersion (COD), Coefficient of Variation (COV), Price-Related Differential (PRD), and Coefficient of Price-Related Bias (PRB).

Chapter Seven sets out the research methodology: design, study population, sampling strategy, data collection instruments, the expert interview guide, the HTML-based AVM calculator, data collection procedures, analytical methods, and the steps taken to ensure reliability and validity. Chapter Eight presents the empirical findings qualitative results from a structured survey of thirteen valuation professionals, and a quantitative comparison of AVM and manual valuations for nine Abu Dhabi residential units, evaluated using IAAO performance measures. Chapter Nine closes the thesis by discussing these findings against the research questions and hypotheses, pulling together the literature review, theoretical framework, and workflow analysis into the study's conclusions and recommendations.

5. THE TRADITIONAL VALUATION WORKFLOW

5.1 Introduction

Before setting traditional property valuation against Automated Valuation Models (AVMs), it helps to understand how each process plays out in practice. Chapter Two covers what traditional valuation produces its accuracy, consistency, cost but says relatively little about the sequence of activities behind it. This chapter fills that gap, reconstructing traditional valuation as a structured workflow based on the RICS Global Standards, the International Valuation Standards (IVS), and the professional literature covered throughout this thesis.

This workflow does two things. It gives the automated valuation process in Chapter Six something concrete to be compared against, and it pinpoints exactly where professional judgment carries the most weight which in turn clarifies what, specifically, is hardest for an AVM to replicate.

5.2 Stage One: Instruction and Scope of Work

Traditional valuation starts when a client a lender, property owner, company, or government authority requests a valuation for a property or portfolio. Before any work begins, the RICS Global Standards require the valuer and client to agree formal terms of engagement that spell out the scope of the assignment: the valuer's identity and status, the property being valued, the purpose of the valuation, the basis of value, the valuation date, how far the investigation will go, and any assumptions or special assumptions that apply (RICS, 2022).

This isn't just paperwork. It sets the scope and responsibilities of the whole assignment and becomes the benchmark against which the valuation's quality and adequacy get judged later. If a valuation is ever challenged, one of the first questions is whether the work matched the agreed scope.

The IAAO's (2018) AVM standard has a similar principle, requiring the scope of work to define the assumptions, limiting conditions, and hypothetical conditions the model applies. The implementation differs, though. In traditional valuation, scope is negotiated individually between valuer and client for each assignment. An AVM, by contrast, runs on a scope fixed during model development, applying the same assumptions and procedures consistently across every property it evaluates.

5.3 Stage Two: Property Inspection and Data Collection

Physical inspection is probably the single most distinctive stage of traditional valuation, and the one that separates it most clearly from anything automated. The RICS Insight Paper (2022) notes that COVID-19 forced valuers toward remote and virtual inspection out of necessity, but these were treated as temporary workarounds rather than a permanent substitute for visiting the property (p. 12). During an inspection, the valuer takes in the property's condition, layout, construction quality, visible defects, maintenance needs, and other things a structured dataset simply doesn't capture well natural light, the surrounding environment,

road noise, neighborhood quality, proximity to amenities, all judged through professional experience rather than a spreadsheet.

Alongside the inspection, the valuer gathers supporting documents and market information: title deeds, floor plans, planning approvals, lease agreements where relevant, and, crucially, evidence of recent comparable transactions. The IAAO (2018) sorts of valuation information into three categories: property data (the asset's physical characteristics), location data (geographic, demographic, land-use information), and market data (sales transactions, rental information, replacement costs) (p. 6). Traditional valuation relies on these same categories the difference is in how they get used. A valuer weighs the relevance and quality of available information property by property, choosing the best comparable evidence and deciding which location factors matter. An AVM, by contrast, applies one predefined data structure and one set of standardized rules across every property in the model.

5.4 Stage Three: Selection and Application of the Valuation Approach

Once the information is in hand, the valuer picks the approach, or combination of approaches, that fits the property and the purpose of the valuation, as discussed in Section 2.2. For residential property, sales comparison is usually the method of choice: the valuer finds recently sold comparable properties and adjusts their sale prices for differences from the subject property location, size, condition, age, amenities. That adjustment step leans heavily on judgment. Market evidence guides it, but there's no universal formula for pricing a sea view or a marginally better location; valuers rely on experience and a feel for local market conditions to make that call.

For income-producing property, income capitalization is the standard method. The valuer estimates the property's net operating income (NOI) and converts it to market value using a capitalization rate drawn from comparable market transactions. The basic formula is:

$$MV = NOI / R$$

where MV is market value, NOI is net operating income, and R is the capitalization rate (IAAO, 2018, p. 28). For more complex assets, valuers may instead use discounted cash flow (DCF) analysis, which estimates future income and expenses over a specified holding period and discounts those cash flows to their present value. Gross Income Multipliers (GIM) and Gross Rental Multipliers (GRM) may also be used where appropriate (IAAO, 2018, p. 28). In practice, the mathematical calculations are straightforward; the critical task is selecting a realistic income estimate and an appropriate capitalization rate that reflects current market conditions, property type, location, and investment risk.

Where comparable sales are scarce, specialized or unique properties especially the cost approach steps in instead. This estimates the current cost of replacing or reproducing property, deducts depreciation and obsolescence, and adds back land value. The IAAO (2018) expresses this as:

$$MV = \pi GQ \times [(1 - BQD) \times RCN + LV]$$

where RCN represents replacement or reproduction cost new, LV is land value, BQD represents depreciation, and πGQ reflects general qualitative adjustments such as market conditions and location (IAAO, 2018, p. 25). Although the calculation itself is mechanical, the accuracy of the result depends on the valuer's professional judgment when estimating replacement cost and assessing physical, functional, and economic depreciation based on the property's condition.

In practice, valuers rarely rely on just one approach. The primary result usually gets checked against a secondary approach, and any meaningful gap between the two gets investigated before a final value is settled on. This cross-checking is what makes the valuation more reliable it ties the final estimate to both market evidence and professional judgment, rather than alone.

5.5 Stage Four: Review, Reconciliation, and Reporting

Once there's an initial estimate, the valuer checks it for reasonableness and internal consistency against previous valuations of the same property, recent comparable transactions, and, for mortgage lending, the proposed loan amount. None of this is meant to steer the outcome; it's there to flag anything that needs a closer look while keeping the valuer's professional independence intact.

The last stage is writing the report. Under the RICS Global Standards, it has to spell out the basis of value, the assumptions and special assumptions used, the valuation approach applied, the evidence considered, and the valuer's own professional opinion of value (RICS, 2022) with enough detail that another qualified valuer could follow exactly how the final figure was reached.

This reporting stage matters precisely because it makes the valuation transparent, auditable, and professionally defensible. As Section 2.4 discusses, the IVSC (2022) treats this ability to document and justify a professional opinion as one of the key things separating traditional valuation from a fully automated system, where keeping that same level of transparency and accountability is harder without meaningful human oversight somewhere in the process.

5.6 Bases of Value and the Limits of Standardization

One thing not yet covered is the basis of value what, exactly, the valuer's professional opinion is meant to represent. The IVS define a basis of value, sometimes called a standard of value, as “the fundamental premises on which the reported values will be based” (IVS 104, as cited in IVSC, 2022, p. 12). The one most relevant here, since it's the basis most commonly used in secured lending, is Market Value: “the estimated amount for which an asset or liability should exchange on the valuation date between a willing buyer and a willing seller in an arm's length transaction, after proper marketing and where the parties had each acted knowledgeably, prudently and without compulsion” (IVSC, 2022, p. 12).

A key part of that definition is highest and best use the use, per the IVS, that would generate the greatest value from a market participant's perspective. Working this out takes judgment: the valuer has to weigh whether the property's current use is really its maximum potential, or whether redevelopment opportunities, alternative permitted uses, or site-specific constraints should shift the valuation. The IVSC (2022) argues this stays genuinely difficult for a fully automated system, since AVMs run on predefined rules and limited investigation which is why the Perspectives Paper questions whether current residential AVMs are sophisticated enough to assess highest and best use to the standard IVS requires.

The IVSC draws a broader line here too, between an automated estimate and a professional valuation. Every IVS basis of value is expressed as a valuer's opinion, so a fully automated residential AVM can't, on its own, produce a Market Value opinion only a human valuer can form a professional opinion (IVSC, 2022, p. 12). This is a conceptual point, not a comment on how good technology currently is: no matter how accurate an AVM gets, its output stays a calculation rather than a professional opinion under the IVS. That said, the IVSC does allow a valuer to use AVM results as an input, provided the final opinion is genuinely the valuer's own professional judgment.

The IVS reporting requirements reinforce this. IVS 103 requires a valuation report to disclose every assumption, special assumption, significant uncertainty, and limiting condition that materially affects the valuation (IVSC, 2022, p. 11). An AVM might be able to generate a standardized report, but the IVSC questions whether it can explain the reasoning behind its assumptions, or judge their impact, across every possible scenario. That's exactly what the reporting stage in Section 5.5 is for documenting the evidence, assumptions, and reasoning behind the final opinion of value.

The IVSC does offer a practical middle ground, though. The Perspectives Paper suggests that when a valuer is involved from the start, inspection findings can feed into a semi-automated valuation model, potentially producing better results than either a fully manual or fully automated approach alone (IVSC, 2022, p. 11). That's essentially the hybrid valuation concept discussed in Sections 3.2.4 and 6.3: rather than reviewing an AVM's output after the fact, the valuer's judgment gets built into the process itself, letting qualitative, site-specific information feed the model rather than sitting outside it.

5.7 Summary of the Traditional Workflow

Table 5.1 pulls together the four stages of this workflow and marks where professional judgment enters at each one. It's the basis for comparison with the automated workflow in Chapter Six together, Tables 5.1 and 6.1 give a clear framework for setting the two approaches side by side, feeding into the discussion of their complementary roles in Chapter Three and again in Chapter Eight.

Table 5.1

Stages of the Traditional Valuation Workflow

Stage	Principal Activity	Point of Professional Judgment
1. Instruction and scope of work	Agreement of terms of engagement: asset, purpose, basis of value, valuation date, assumptions	Negotiating and fixing the scope of work for the specific assignment
2. Inspection and data collection	Physical inspection of the property; gathering of comparable transactions, locational, and documentary data	Judging which qualitative, non-tabulated factors (condition, light, noise, neighborhood) are material
3. Selection and application of approach	Choosing between sales comparison, income, and cost approaches; making comparable adjustments or building a cash flow model	Quantifying the value impact of attribute differences between the subject and comparable properties
4. Review, reconciliation, and reporting	Cross-checking the result; preparing a reasoned, auditable valuation report	Forming and articulating a final, defensible professional opinion of value

What this chapter's workflow shows is that professional judgment doesn't sit at one stage of traditional valuation, it runs through the whole thing. It shapes how the scope of work gets defined, how property and market data get collected and interpreted, how comparable evidence gets selected and adjusted, and how the final report gets written and justified. That continuous presence of judgment is what defines traditional valuation, and it's the point of comparison for the automated workflow in the next chapter.

6. THE AUTOMATED VALUATION WORKFLOW

6.1 Introduction

Chapter Five reconstructed traditional valuation as a workflow driven by professional judgment; this chapter does the same for Automated Valuation Models (AVMs). In one sense AVMs are easier to pin down, since the IAAO (2018) sets out a standardized nine-step framework for developing and implementing them. But unlike traditional valuation, the AVM process runs on two levels: a model development workflow, carried out once to design, train, and calibrate the model, and a model application workflow, repeated every time the finished model values an individual property. Traditional valuation, by contrast, runs the whole process from scratch for every single assignment. That distinction built once, applied many times, versus performed start to finish for each property is one of the fundamental differences between the two approaches, and it structures the rest of this chapter.

6.2 The Model Development Workflow

6.2.1 Scope of Work

Like traditional valuation, AVM development starts with a clear scope of work. The IAAO (2018) says this should specify the property type, the geographic area the model will cover, and the procedures needed for development and implementation, along with the assumptions, special limiting conditions, and hypothetical conditions the model rests on (p. 6).

One assumption is that the IAAO flags as important: most AVMs simply assume the property's current use already is its highest and best use (p. 6). That's different from traditional valuation, where the valuer assesses whether current use is the most valuable use. Unless an AVM is specifically built to evaluate alternative land uses, this assumption just gets baked in automatically.

6.2.2 Identification and Acquisition of Property Data

Next comes identifying and collecting the data the AVM needs. As in Chapter Five, the IAAO (2018) sorts of valuation data into property data (physical characteristics), location data (demographic, land-use, geographic information), and market data (sales transactions, rental information, replacement costs), drawn from five main sources: internal organizational databases, government agencies, third-party data providers, public information sources, and client-supplied data.

This stage does more to determine AVM performance than almost anything else. Chapter Two is consistent on this: input data quality and richness shapes model accuracy more than algorithm choice alone. Kok et al. (2017) found hyperlocal information from non-traditional sources improved predictive accuracy significantly; Bergadano et al. (2019) found enriching the dataset with web-crawled comparable transactions cut mean prediction error by more than 50%.

6.2.3 Exploratory Data Analysis

Once collected, the data goes through exploratory analysis checking completeness, consistency, missing values, and outliers, analyzing distributions, tracking market trends over time, and generally checking the dataset (IAAO, 2018).

This stage has no real counterpart in manual valuation a professional valuer doesn't normally run formal statistical analysis on comparable sales before starting a valuation. But the purpose is similar. Just as an experienced valuer uses judgment to spot an unusual or unreliable comparable, exploratory data analysis lets an AVM catch these problems systematically, through statistics, before the model even gets built.

6.2.4 Stratification

Next is stratification: grouping properties into relatively homogeneous categories by property type (residential, commercial, industrial, agricultural), physical attributes, value range, or location (IAAO, 2018).

The point is to shrink variation within each group while maximizing the difference between groups, which lets the model produce more accurate, more reliable estimates.

The IAAO (2018) notes that geographic stratification works especially well where property types and housing styles are fairly consistent within an area (p. 7) which lines up with the Resource-Based View from Chapter Three: an AVM's effectiveness depends on the market's characteristics and the underlying data quality, not just the modeling technique.

6.2.5 Determination of Data Representativeness

Before model specification begins, the developer must check whether the available data actually represents the properties the AVM is meant to value. As the IAAO (2018) puts it, “the available sales may limit representativeness and applicability of the AVM model” (p. 7). If the transaction data on hand doesn't reflect the target market, the model built from it isn't going to produce reliable estimates.

This stage drives home one of this study's central themes: AVM performance rests fundamentally on the quality and representativeness of the underlying data. In market segments with thin transaction activity or too few comparable sales, the data simply may not support a reliable model, no matter how sophisticated the statistical or machine learning technique behind it.

6.2.6 Model Specification

Model specification is where the developer settles on the AVM's mathematical structure and picks which variables to include this is where the approaches from Chapter Two become operational. A developer working from traditional hedonic pricing typically goes with a linear or log-linear additive model, as Bergadano et al. (2019) describe. Developers using modern machine learning might instead reach for decision trees, random forests, gradient boosting, or other advanced algorithms, along the lines of Kok et al. (2017) and Tapia et al. (2025).

Mathematical forms of model specification. The IAAO (2018) sets out several mathematical formulations for implementing the cost, sales comparison, and income approaches inside an AVM essentially showing how traditional valuation methods translate into statistical models.

For the cost approach, the IAAO proposes a hybrid model combining land value, building characteristics, and general market adjustment factors (p. 25). It also stresses that where commercial cost databases are used, the model developer is still responsible for calculating them to local conditions and understanding the assumptions behind the underlying cost data a reminder that professional expertise doesn't disappear just because the framework is automated.

For sales comparison, the IAAO distinguishes a comparable sales model, which adjusts the prices of comparable properties, from a direct market model, which can take three forms (IAAO, 2018, p. 26):

- Additive (linear) model, where market value is estimated as a constant plus the weighted sum of selected variables.
- Multiplicative (log-linear) model, where variables combine multiplicatively to capture proportional and non-linear relationships more effectively.
- Hybrid model, combining additive and multiplicative elements for more flexibility in representing market behavior (IAAO, 2018, pp. 26–27).

These mathematical forms map onto the evolution of AVMs traced in Chapter Two. Traditional hedonic pricing models correspond to the additive direct market model, while newer machine learning approaches Kok et al. (2017), Tapia et al. (2025) use non-parametric algorithms that skip the step of fixing a mathematical relationship in advance.

The HTML-based AVM calculator described in Section 7.4.4 adopts the additive direct market model for this study. More advanced machine learning could well achieve higher predictive accuracy given enough data, but the additive model was chosen because it's transparent, easy to interpret, and can be built with standard spreadsheet regression functions which fit the study's emphasis on transparency and explainability throughout.

6.2.7 Model Calibration

Calibration is where the AVM estimates the coefficients for each selected variable and checks whether those relationships are both statistically significant and logically sound. According to the IAAO (2018), this means estimating coefficients, testing their significance, and confirming the results actually make sense a model should show a positive relationship between property size and value, say; if a larger property came out lower-valued, that would flag a problem with the specification or the data.

Calibration is really the analytical core of AVM development, the step where the model learns how property characteristics relate to market value. Traditional hedonic models typically get there through ordinary least squares (OLS) regression; more advanced machine learning models instead use iterative algorithms like decision trees, random forests, or gradient boosting to pick out complex patterns in the data, as Chapter Two discusses.

6.2.8 Quality Assurance

Before an AVM goes live, and at regular intervals afterward, it has to be checked against established standards of accuracy and consistency. The IAAO (2018) does this through statistical tests and ratio studies, comparing the model's estimated values against the actual sale prices of a separate group of properties that weren't used in calibration.

The IAAO recommends several statistical measures for this, covering not just predictive accuracy but consistency and reliability across property types and market conditions too. The main ones are introduced in

Section 6.4, since they form the basis of professional AVM quality assurance rather than functioning purely as accuracy scores.

6.2.9 Model Application and Value Review

The last stage of AVM development is model implementation. Once calibrated and validated, the model goes live for operational use, though it stays subject to ongoing monitoring and periodic review. The IAAO (2018) is explicit that specification, calibration, and quality assurance are iterative: “these processes are repeated until statistical diagnostics are satisfactory” (p. 6). In practice, that means an AVM gets refined repeatedly until it clears the required performance bar before deployment.

This iterative pattern is exactly what separates AVM development from the traditional workflow in Chapter Five. A traditional valuation generally runs a linear sequence per assignment; AVM development instead cycles through refinement, testing, and validation repeatedly before a single model is judged fit to value large numbers of properties.

6.3 The Model Application Workflow and AVM Typology

Once an AVM has been developed and validated, it starts estimating individual property values. Here, the IAAO's (2018) classification of AVM types, introduced in Section 2.3.1, matters a great deal, since it distinguishes application workflows by how much human involvement each one has.

A Preliminary Data AVM produces an initial estimate that a professional valuer reviews and folds into a broader valuation. An Interactive Valuation Application AVM goes further, letting the valuer review, modify, and validate the model's output using their own judgment. A Repetitive AVM applies the same calibrated model repeatedly over time, updating values as new transactions and economic data arrive without full recalibration though the IAAO (2018) warns that delaying recalibration too long can hurt reliability. A Blended or Cascading AVM combines the output of two or more valuation models through a single interface, letting users draw on the strengths of each, though the IAAO cautions this introduces the risk of user influence over the final estimate, since how the models get combined can shape the result (p. 5). And a Research AVM exists for testing, academic research, or planning, rather than supporting actual transactions.

This classification makes clear that AVM applications aren't standardized one standardized process but a range of workflows differing mainly in how much human review is involved. The RICS Roadmap (2021) backs this up, distinguishing fully automated models from blended approaches that combine automation with professional judgment a framework RICS describes as one of the most widely used ways of categorizing AVM applications in practice.

The RICS Insight Paper (2022) takes this further, presenting AVM use as a continuous spectrum rather than a handful of discrete categories. At one end sit fully automated systems that process properties without human

intervention except to flag cases falling outside predefined confidence limits, which then get referred elsewhere. At the other end, AVMs function purely as decision-support tools supplying comparable sales, market information, or quality checks within a process that is still largely driven by professional judgment (p. 13).

In between, RICS identifies several intermediate approaches combining automation with different levels of inspection: desktop valuations relying entirely on available data and imagery; drive-by inspections with an external visual assessment; remote or virtual inspections over video; traditional on-site inspections; and structured property inspections carried out by non-valuers following procedures a qualified valuation professional designed (p. 13). Each reflects a different trade-off between efficiency, cost, and how much professional judgment can realistically be applied.

RICS (2022) also raises an organizational point worth noting: where AVM-supported desktop valuation teams are highly centralized, reviewers may not know the local market well enough to apply sound professional judgment. That's especially relevant in geographically diverse markets, and it reinforces the local-expertise argument made in Sections 2.6.1 and 6.2.4. In the UAE, where property markets vary considerably across emirates and districts, any centralized AVM review process needs reviewers who actually know the specific market a given property sits in.

The RICS Insight Paper also raises a question of professional accountability: can one valuer meaningfully oversee a very large volume of automated valuations in a short window? Even where human review technically satisfies professional requirements, an unrealistic workload can undercut genuine case-by-case judgment (p. 13). The paper also stresses that property condition remains critical to any valuation and recommends that AVM-supported workflows spell out clearly how condition gets assessed and folded in. That reinforces a central argument of this thesis: transparency must extend past the mathematical model itself, to the qualitative judgments that are, or aren't, captured within an AVM-supported workflow.

6.4 Confidence Scores and Performance Measurement in the Application Workflow

One feature of the automated workflow with no real counterpart in traditional valuation is the confidence score, which signals how reliable an AVM's estimate is. RICS (2021) defines it as reflecting “the accuracy of an AVM's estimate of value,” with lower scores typically showing up where a property has unusual characteristics or sits in an area with thin market data, making the estimate genuinely less certain (p. 7). Confidence scores are usually built from the quality, quantity, and recency of comparable data, or from the model's forecast standard deviation (FSD) relative to a benchmark like an actual sale price or professional valuation. But different commercial AVM providers score confidence differently, RICS notes, which makes cross-platform comparison difficult (p. 7) part of why this study leans so heavily on transparency instead.

Behind the confidence score sits a broader set of statistical quality measures the IAAO (2018) defines for evaluating AVM performance. One of the most common is the Coefficient of Dispersion (COD), measuring how much estimated values vary from actual sale prices across a group of properties lower COD means more

consistent performance. The Coefficient of Variation (COV) is another dispersion measure, generally more sensitive to extreme values than COD.

The Price-Related Differential (PRD) checks whether an AVM systematically over- or under-values properties across price ranges. The IAAO (2018) puts the acceptable range at roughly 0.98 to 1.03: above 1.00 signals regressivity, where higher-priced properties tend to be undervalued relative to lower-priced ones; below 1.00 signals progressivity, the reverse pattern.

A related measure, the Coefficient of Price-Related Bias (PRB), gives a more statistically robust read on vertical equity by examining how valuation errors relate to property value. The IAAO (2018) recommends PRB stay between -0.05 and 0.05 , with anything outside -0.10 to 0.10 signaling serious vertical bias.

These measures matter for two reasons. First, they show AVM performance can't be judged on a single accuracy statistic MAE, MAPE, and R^2 assess overall predictive performance, but PRD and PRB check whether the model performs fairly across different value ranges. Second, the IAAO points out that these statistics come from samples, not entire populations, so they carry sampling error, and confidence intervals should ideally accompany them (p. 17). That's part of the methodological basis for the inferential statistics used in Chapter Seven, rather than relying on descriptive performance measures alone.

6.5 Data Quality Standards in AVM Development

Everything in the development stages above rests on the quality of the underlying data, which is exactly why the IAAO (2018) gives data quality its own dedicated section. The standard splits data into quantitative floor area, bedroom count, land size, measurable and relatively objective and qualitative, like property condition, construction quality, or maintenance level, which are more subjective but still matter a great deal for value (p. 9).

This distinction matters because qualitative characteristics must be converted into standardized categories or numerical variables before a statistical model can use them at all. A human valuer can size up a property's overall condition through inspection and judgment directly; an AVM needs those same observations translated into structured data it can process. Getting qualitative information represented accurately is one of the harder parts of AVM development, and it has no real equivalent in the traditional workflow from Chapter Five.

The IAAO (2018) also gives practical guidance on whether there's enough data to build a reliable model: at least five sales observations per independent variable, and ideally fifteen (p. 10). That's a simple enough benchmark, an AVM with eight independent variables, should ideally rest on at least 40 transaction records, with 120 preferred. Chapter Seven uses this guideline when assessing the sample size needed for the HTML-based AVM calculator.

The IAAO also stresses data verification: analysts should confirm that variables expected to drive value floor area, location show the statistical relationships they'd expect, using tools like correlation matrices and regression statistics (t-tests, F-tests). If an expected relationship doesn't show up, the standard suggests the likely culprit is poor or insufficient data, not a flaw in established valuation principles (p. 9).

Finally, the standard addresses the growing use of externally sourced and web-scraped data. Where developers use it, they should understand the source's structure, put quality control in place for when website formats change, have a way of handling missing or inconsistent data, and make sure data ownership, licensing, and legal requirements are all satisfied (p. 10). That's directly relevant to the web-crawled comparable data Bergadano et al. (2019) used a reminder that enriched data can genuinely improve AVM performance while also bringing real data-governance responsibilities with it.

6.6 Calibration Techniques and the Role of Location

Back to calibration, introduced in Section 6.2.7: the IAAO (2018) is clear this is iterative, not a single step. The developer specifies the model, calibrates it, tests performance, adjusts the specification where needed, recalibrates, and repeats until quality assurance standards are met (p. 11). The standard also stresses that calibration accuracy depends on more than the statistical technique chosen data quality and analyst expertise matter just as much: “data integrity and the skill level of the analyst contribute to the accuracy of any calibration technique” (p. 11), tying calibration technology and human expertise together closely. That supports the Resource-Based View from Chapter Three, which argues AVM performance rests on organizational resources and human capability, not algorithms alone.

The standard also covers time series analysis, used to capture how property values shift over time long-term trends, seasonal effects, market cycles. This matters especially when calibration data spans several years, or when a Repetitive AVM keeps generating valuations over a long stretch without full recalibration. Since property markets don't move uniformly, the IAAO recommends separate time adjustment factors for different property types and geographic markets rather than one blanket adjustment across a whole region (p. 12) particularly relevant to the UAE, where price movements vary considerably across emirates, and even between districts in the same city.

Among the model specification decisions the IAAO covers, how location gets treated matters a lot. A more detailed location analysis can reduce the need for extra variables that only indirectly capture location effects, and geographic stratification works best where property types and housing styles stay consistent within an area (p. 12) lining up closely with the geographic constraints discussed in Section 2.6.1.

The IAAO also shows how an apparent location premium can sometimes really be explained by other, correlated property characteristics. If a neighborhood commands higher prices mainly because most of its properties are in excellent condition, a well-specified model that explicitly includes a condition variable should pick that up without needing extra location adjustments (p. 12). This is a real advantage of formal

AVM specification: it can separate the true drivers of value, rather than crediting location for price differences that are actually caused by something else measurable.

6.6.1 Time Series Methods for Time-Adjusting Sale Prices

The IAAO (2018) also describes five methods for building the time trend factors introduced in Section 6.6 practical techniques for tracking how property values move over time, and for adjusting historical sales to reflect current conditions: value-per-unit analysis, re-sales analysis, sales-to-assessment or sales-to-AVM-value ratio trend analysis, median or mean value per period analysis, and time-of-sale variables built directly into the model (p. 32).

Value-per-unit analysis tracks changes in unit prices price per square meter or square foot over time. It's simple to understand and easy to graph, the IAAO notes, but it has a real limitation: it doesn't account for other factors affecting value, like age, construction quality, or condition (p. 32).

Re-sales analysis uses properties sold more than once during the study period, comparing successive sale prices to estimate the rate of market change. The IAAO warns this can overstate market appreciation if the property was significantly renovated between sales, and that repeat-sale properties may not represent the wider market well, limiting how broadly the method applies (p. 32).

A third method, sales-to-AVM-value ratio trend analysis, compares actual sale prices against values the AVM previously generated; how this ratio shifts over time signals market movement. Its advantage, per the IAAO, is that it controls for many property characteristics already captured in the AVM, isolating time trends more cleanly than simple value-per-unit analysis though its reliability then depends on the AVM's own quality, since an inaccurate model can distort the trend analysis right along with it (p. 32).

The median or mean value per period method groups sales into short intervals, usually one to three months, calculates the average or median price for each, and uses that to build a trend line adjusting historical transactions to the valuation date. It's widely used, but it shares value-per-unit analysis's limitation of not explicitly accounting for other value-driving characteristics (p. 32).

Finally, time-of-sale variables can be built directly into the valuation model itself, letting market condition changes get estimated as part of calibration rather than through a separate adjustment factor.

The standard closes with a practical point: time trend factors built from historical sales can be projected forward for a while, but their reliability drops the further out you go. Trend adjustments need regular updating as a result reinforcing the case for periodic recalibration made earlier in this chapter (p. 32).

6.6.2 The Centrality of the Sales Comparison Approach in AVM Modeling

The IAAO (2018) wraps up its discussion of AVM modeling by reaffirming the three traditional valuation approaches: sales comparison is preferred whenever there's enough sales data, with cost and income reserved for cases where comparable sales evidence is thin or unavailable (p. 32).

This matches the empirical studies in Chapter Two. Kok et al. (2017), Bergadano et al. (2019), Băbțan (2020), and Tapia et al. (2025) all build their AVMs primarily around the sales comparison approach rather than cost- or income-based models professional standards and academic research agreeing on the central role of market transaction data in modern automated valuation.

The IAAO closes with a line that sums up much of this chapter: automation doesn't replace professional expertise; it just relocates where that expertise gets applied. As the standard puts it, “whether automated or appraiser derived, all market analysis relies on the quality and experience [of the] real estate appraisers/valuers” (p. 32). Successful AVMs, in other words, depend as much on the people who design, calibrate, validate, and maintain them as on the algorithms themselves which fits neatly with the comparative workflow analysis in Chapters Five and Six: professional judgment doesn't disappear, it just shows up mainly during model development and oversight rather than in each individual valuation.

6.7 Market Analysis and the Treatment of Limited Data

One last piece of AVM development the IAAO (2018) covers, and one especially relevant to the UAE, is market analysis under limited transaction data. Effective market analysis, per the standard, means identifying the property type being valued, defining the valuation's purpose (mortgage lending, investment analysis, property taxation), deciding how to handle limited data, choosing the right valuation approach, identifying the property characteristics that matter most for value, and factoring in relevant geographic and economic conditions (p. 13). Several of these steps closely mirror the scope-of-work and data collection stages of traditional valuation from Chapter Five, a reminder that both approaches are, in the end, wrestling with many of the same questions, just through different procedures.

The IAAO also gives practical guidance for when transaction data falls short. When sales or economic information is limited, the standard recommends expanding the dataset with transactions from multiple years, adjusted for time to reflect current conditions, and, where appropriate, using independent appraisals of unsold properties as supplementary benchmark data (p. 13).

This is directly on the methodology in Chapter Seven. The UAE property market records a high overall transaction volume, but certain property types or geographic sub-markets can still have thin comparable sales. Where the available data falls short of the sufficiency thresholds discussed in Section 6.5, the HTML-based AVM calculator may draw on multi-year transaction data adjusted for market trend rather than relying on a single year's transactions alone following the IAAO's (2018) recommendation and discussed further among the study's limitations in Chapter Nine.

6.8 Calibration Transparency and Spatial Adjustment Methods

The IAAO (2018) closes its discussion of calibration with an observation that speaks directly to one of the recurring worries about AVMs: transparency. “This standard encourages AVM market analysts and clients to understand that AVM development is not a black box process; instead, it is based on well-defined concepts

surrounding the appraisal process” (p. 30). That's a notable claim, since the same standard also acknowledges that advanced techniques like artificial neural networks have internal workings that are genuinely hard to interpret so the IAAO is drawing a line between the transparency of the overall development process and the transparency of the specific algorithms used within it.

In other words, even where a given calibration technique is inherently hard to explain, the AVM workflow as a whole scope of work, data collection, exploratory analysis, stratification, specification, calibration, quality assurance still rests on established valuation principles. This process-versus-algorithm distinction runs throughout this thesis. The HTML-based AVM calculator built in Chapter Seven is designed to be transparent at both levels, though the IAAO's point is that a transparent development process alone already goes a long way toward addressing the governance and accountability concerns raised in professional literature.

The IAAO also goes into real detail on location adjustment methods. Two broad approaches stand out. The first uses geo-economic areas properties grouped into zones defined by roads, natural boundaries, or administrative divisions which the IAAO describes as the traditional, still most widely used way of building location into a valuation model (p. 31).

The second approach works directly from each property's geographic coordinates. Rather than slotting a property into a predefined zone, the model applies spatial smoothing to estimate a location adjustment from its exact position, then feeds that in as an additional explanatory variable (p. 31).

The standard also covers Geographically Weighted Regression (GWR), a more advanced spatial technique that lets model coefficients vary by location. Instead of assuming a feature like an extra bedroom has the same effect everywhere, GWR allows that effect to genuinely differ between neighborhoods or market areas what the IAAO calls spatially heterogeneous effects (p. 31).

More broadly, the standard sets out several location-based modeling frameworks: spatial regression models such as spatial lag and spatial error models, regression models with location variables built in, multi-stage location adjustment models, random forest models that include location as an explanatory variable, and spatial interpolation techniques like kriging (p. 31).

This gives a useful framework for reading the spatial models covered in Chapter Two. The Spatial Autoregressive (SAR) model Tapia et al. (2025) use, for instance, falls under the IAAO's broader category of spatial regression models. Their finding that SAR and machine learning models disagree on location-sensitive variables like school proximity should be read, then, as a comparison between two alternative spatial modeling techniques, not as some general failure of spatial analysis itself.

6.9 Ratio Studies and the Temporal Dimension of Quality Assurance

Another important piece of AVM quality assurance, particularly relevant to the Repetitive AVM discussed in Section 6.3, is monitoring performance over time. The IAAO (2018) notes that “samples may become less

representative in dynamic markets” (p. 16), meaning an AVM calibrated on historical data can gradually lose accuracy as conditions shift. Unlike traditional valuation, where each valuation is done independently for a specific date, an AVM can keep generating estimates for months or years after calibration without being fully updated so performance can genuinely deteriorate if market trends move significantly in the meantime.

The IAAO's answer is periodic quality assurance throughout the model's operational life, rather than relying only on validation results from development. Developers should regularly check model performance to catch time-related errors and decide when recalibration is needed (p. 16) AVM quality assurance, in short, is ongoing, not a one-time box to tick.

The main tool for this ongoing monitoring is the ratio study, which the IAAO defines as a statistical comparison between estimated property values and observed sale prices or other calibration benchmarks (p. 16). Ratio studies measure both central tendencies, how closely estimates track market values on average and uniformity; how consistent performance is across different properties.

The standard is also careful to flag a limitation: ratio studies say a lot about an AVM's overall quality, but they don't guarantee any individual valuation is accurate. A model can perform well across a large sample and still get specific properties badly wrong. That backs up the point made in Section 2.5.1, where RICS (2021, 2022) notes AVM reliability varies by individual property characteristics even when the overall model statistics look fine.

The IAAO further recommends running sales-based ratio studies regularly, since they rely on actual market transactions rather than subjective opinion, and testing quality using holdout samples excluded from calibration particularly useful for checking vertical equity through the PRD and PRB measures discussed in Section 6.4 (p. 16).

For this study, that guidance reinforces the approach taken in Chapter Seven, where the HTML-based AVM calculator is evaluated on separate training and validation data. It also points to a real limitation of the research: since the empirical analysis is based on data collected at a single point in time, the resulting performance measures reflect the model's condition in the UAE market during the study period, not a permanent verdict on AVM performance generally. This limitation is discussed further in Chapter Nine.

Finally, the IAAO addresses confidence score standardization directly, acknowledging that different commercial AVM providers calculate confidence differently and that no industry-wide standard exists meaning confidence scores from different systems can't always be compared directly, even when they claim to measure the same thing (p. 16). The IAAO deliberately doesn't endorse any one commercial methodology, a position consistent with RICS's (2021) own observation that confidence scores vary substantially between providers. Both reinforce this thesis's methodological choice to build a transparent, fully documented HTML-based calculator rather than lean on proprietary confidence measures whose inner workings can't be independently checked.

6.10 Summary of the Automated Workflow

Table 6.1 summarizes the automated valuation workflow set out in this chapter, distinguishing the one-time model development process from the repeated application process and marking the main point of methodological control at each stage the automated counterpart to the points of professional judgment identified for each traditional valuation stage in Table 5.1.

Table 6.1
Stages of the Automated Valuation Workflow

Stage	Principal Activity	Point of Methodological Control
Development: scope of work	Defining property type, geographic area, and modeling assumptions	Fixing assumptions (e.g., current use = highest and best use) uniformly in advance
Development: data acquisition	Gathering property, locational, and market data from internal, government, and third-party sources	Determining which data sources and variables are included
Development: exploratory analysis and stratification	Reviewing data quality and distributions; grouping properties into homogeneous strata	Identifying and excluding outliers; defining stratification boundaries
Development: specification and calibration	Choosing the model's mathematical form; estimating variable coefficients	Selecting model architecture (hedonic, ensemble, gradient-boosted, etc.)
Development: quality assurance	Testing the model against holdout data using COD, COV, PRD, and PRB statistics	Setting acceptance thresholds for statistical reliability
Application: value generation	Running the calibrated model against an individual property's data	Selecting the AVM type (Preliminary Data, Interactive, Repetitive, Blended, or Research)
Application: confidence assessment	Generating a confidence score or forecast standard deviation for the output	Deciding how much human review the output requires before use

Set against Table 5.1, the differences between the traditional and automated workflows become clear. In traditional valuation, professional judgment runs through the entire process and gets repeated for every

property. The automated workflow instead concentrates most of the decision-making in model development data selection, market stratification, model specification, calibration, validation. Once the model is built, the application stage is largely standardized and needs minimal case-by-case intervention, except in workflows like the Interactive Valuation Application AVM, where professional judgment is deliberately built back in through human review.

What this distinction really shows is that the difference between the two approaches isn't just how much judgment is involved it's where that judgment gets applied. Traditional valuation embeds judgment throughout every individual valuation; an AVM concentrates it during model development and reintroduces it only selectively during application. That difference is one of the key analytical foundations for the comparative discussion in Chapter Nine.

7. RESEARCH METHODOLOGY

7.1 Introduction

This chapter lays out the research design and methodology behind the study's objectives, research questions, and hypotheses. Getting the methodology right matters because it's what lets the findings in Chapter Eight be read with confidence, and lets future researchers understand, replicate, or build on the work. It covers the research type and approach, the study population and sampling strategy, the data collection instruments, the data collection procedures, the analytical techniques, and the steps taken to ensure reliability, validity, and ethical compliance.

This chapter describes the research methodology in its final, implemented form. The research design, sampling strategy, data collection instruments, and analysis plans were carried through to completion. The qualitative strand was completed through a structured survey of thirteen valuation professionals from Jordan, Saudi Arabia, and the UAE. The quantitative strand was completed through a comparative analysis of AVM and traditional manual valuations for nine residential units across three Abu Dhabi districts, evaluated using the HTML-based AVM calculator described in Section 7.4.4. Chapter Eight presents the actual empirical findings arising from both strands.

Research on property valuation and AVMs has grown substantially alongside advances in big data, machine learning, and digital real estate systems. The studies here are organized chronologically, oldest to newest, since that ordering makes the field's development easy to trace starting from general discussions of automation and moving toward the more advanced comparative and AI-based valuation models seen today.

7.2 Type and Approach of the Research

7.2.1 Type of Research

This study counts as applied and explanatory research. It's applied because the goal is to address a practical problem, not generating theory for its own sake. Robson and McCartan (2016) define applied research this way, as producing findings that can inform decisions and improve practice. The practical problem here is straightforward: real estate professionals, lenders, and policymakers in the UAE currently have very little locally derived evidence to guide decisions about when AVMs are appropriate, how reliable their output is compared with traditional valuation, and how the two approaches might be combined effectively.

It's also explanatory, since the goal isn't just spotting whether traditional and AVM-based valuation differ, but explaining why. Specifically, it looks at how data availability and quality, property characteristics, and market conditions shape the comparative performance of the two approaches. Saunders, Lewis, and Thornhill (2019) define explanatory research as examining causal relationships between variables rather than simply describing what's observed which is exactly the aim here: identifying the conditions under which AVMs perform well, and how those conditions shape whether they're suitable for integration into UAE valuation practice.

7.2.2 Research Approach: A Mixed-Methods Design

This study uses a mixed-methods design, specifically the convergent parallel design Creswell and Plano Clark (2018) describe: qualitative and quantitative data collected during the same phase, analyzed independently, then brought together when interpreting the findings. That fits well here, since the study needs to address both the technical performance of AVMs and the professional perspectives around their adoption.

This mixed-methods choice ties directly back to the theoretical framework in Chapter Three. The quantitative strand tests whether AVM-generated values differ significantly from traditional valuations, using the HTML-based AVM calculator described in Section 7.4.4. The qualitative strand explores how experienced valuation professionals perceive AVMs, what concerns them, and how they view integrating automated tools into practice. Together, the two strands give complementary evidence on valuation quality from both a technical and a professional angle.

A convergent parallel design was chosen over a sequential one because the qualitative and quantitative components are meant to address different aspects of the same problem rather than build on each other. Neither dataset shapes or refines the other; both are collected and analyzed independently, then compared and integrated in Chapter Nine. That lets the study check how far measured AVM performance actually lines up with, or diverges from, what valuation professionals perceive and experience.

This choice also answers directly to the gap identified in Chapter Two. Academic literature has mostly focused on AVM predictive performance; professional and regulatory literature has focused on governance, transparency, and practitioner judgment, two bodies of work that have developed largely on separate tracks. Combining quantitative performance evaluation with qualitative evidence from valuation professionals, in one research framework, is this study's attempt to bring those separate perspectives together into a fuller picture of what AVMs actually mean for property valuation practice in the UAE.

7.3 Study Population and Sample

7.3.1 Study Population

The study population splits into two groups, matching the qualitative and quantitative strands. The qualitative population covers professionals and stakeholders working in property valuation and real estate analysis in the UAE RICS-registered or otherwise accredited valuers, real estate analysts at financial institutions or valuation firms, and professionals in real estate regulatory or data institutions. The quantitative population covers the universe of residential property transactions recorded in the selected UAE markets, along with the corresponding traditional valuation records where they exist.

7.3.2 Sampling Strategy and Sample Size

For the qualitative strand, this study uses purposive sampling selecting participants for their professional expertise and direct experience with traditional valuation, AVMs, or both (Patton, 2015). That fits the goal here, which isn't statistical representation of the UAE real estate profession but detailed insight from people

who actually know the subject matter. A target of 8 to 12 participants was originally proposed, in line with established guidance on thematic saturation in semi-structured interview studies Guest, Bunce, and Johnson (2006) found most major themes surface within the first twelve interviews, with relatively few new ones after that. In practice, the survey landed thirteen valid respondents, just over that target range, including both professionals whose work leans traditional and those with hands-on AVM or property analytics experience (see Section 8.2.1).

For the quantitative component, an initial sample of approximately 60 to 100 residential property transactions was originally proposed, broadly comparable to the out-of-sample validation conducted by Bergadano et al. (2019), who evaluated model performance using 58 independent properties. Access to matched traditional valuation records for the UAE market ultimately constrained the achievable sample to nine residential units, drawn from three Abu Dhabi districts: Yas Island, Al Saadiyat Island, and Al Rahah, and spanning unit sizes of 43.5 m² to 904.95 m². Each unit was matched, where available, with its recorded selling price and/or latest official valuation amount, and with a traditional manual valuation prepared by a qualified practitioner, to enable direct comparison against the estimates generated by the HTML-based AVM calculator. Given the modest size of this achieved sample relative to the IAAO (2018) minimum of 30 observations recommended for statistically reliable assessment ratio analysis, the quantitative results reported in Chapter Eight are treated as indicative and exploratory rather than as a statistically robust validation of either method. This limitation is acknowledged and discussed further in Section 7.7 and Section 9.6.

7.4 Research Tools and Instruments

This research uses three categories of instrument: a semi-structured expert interview guide, a structured review of an existing commercial AVM platform as a contextual reference point, and a purpose-built HTML-based AVM calculator developed specifically for the empirical comparison at the heart of this study.

7.4.1 Expert Interview Guide and Structured Survey Instrument

The qualitative instrument is a semi-structured interview guide built around four themes drawn directly from the research questions and the theoretical framework in Chapter Three. The first covers current valuation practice participants' views on the strengths and limitations of traditional methods. The second covers perceptions of AVMs: their advantages, limitations, data quality requirements, model transparency, and how suitable they are for different property types, echoing the issues raised in the professional literature reviewed in Chapter Two.

The third theme digs into the organizational and professional challenges of AVM adoption, informed by Innovation Theory Rogers's (2003) relative advantage, compatibility, and complexity, alongside Kanter's (1995) account of organizational resistance through loss of control, uncertainty, and competence concerns, as discussed in Section 3.2.3. The fourth asks participants how AVMs might be integrated with traditional

practice, rather than treating the two as substitutes speaking directly to Research Question Five and Hypothesis H1.4 on hybrid valuation workflows.

The interview guide follows Kvale and Brinkmann's (2009) semi-structured approach: a common core of questions keeps interviews consistent, while open-ended questions let participants bring in their own professional experience and perspectives the research design might not have anticipated.

To widen participation beyond the interviews, these same four themes were also developed into a structured survey administered as an online Google Form. Where the interviews aim for depth, the survey gives a standardized way of collecting responses from a broader group of practitioners, combining closed-ended questions, five-point Likert-scale items, and short open-response questions.

The survey is meant to generate quantitative evidence on practitioners' attitudes toward AVMs perceived benefits and limitations, barriers to adoption, and views on integrating automated and traditional methods. Responses are analyzed with descriptive statistics (frequencies, percentages, mean Likert scores), with cross-tabulations added where sample size allows, to check whether perceptions vary by years of experience, primary area of practice, or familiarity with AVM technology.

The questionnaire runs across six sections, summarized in Table 7.1, with the complete instrument reproduced as the online Google Form survey in Appendix A.

Table 7.1
Structure of the Survey Instrument

Section	Content	Question Type	Theoretical Linkage
A. Respondent Profile	Role, years of experience, primary valuation background, organization type, emirate of practice	Categorical, single select	Sampling stratification (Section 7.3.2)
B. Traditional Valuation Practice	Current methods used, perceived strengths and limitations, typical turnaround time, frequency of physical inspection	Likert scale (1–5), single-select, short numeric entry	Chapter Five (traditional workflow)
C. AVM Awareness and Use	Familiarity with AVM platforms, frequency of use, perceived accuracy,	Likert scale (1–5), single-select, multi-select	Chapter Six (automated workflow); Section 2.3

	perceived data quality concerns		
D. Perceived Advantages and Disadvantages of AVMs	Rating of specific advantages and disadvantages drawn directly from the RICS (2021) Roadmap taxonomy (Section 2.5.2)	Likert scale (1–5) per item	Section 2.5.2; Section 3.3 (Resource-Based View)
E. Adoption Attitudes and Resistance	Rogers's (2003) relative advantage, compatibility, complexity, trialability, and observability dimensions; Kanter's (1995) loss of control, uncertainty, and competence concerns	Likert scale (1–5) per item	Section 3.2 (Innovation Theory)
F. Integration and Future Outlook	Preferred balance between automated and traditional methods by property type; open-ended suggestions for responsible integration	Single-select matrix; open response	Section 3.2.4 (hybrid AVM); research question five

Sections D and E's survey items were built by directly operationalizing concepts from the literature in Chapter Two and the theoretical framework in Chapter Three, rather than inventing new constructs every statement traces back to an established finding in the academic or professional literature.

Section D, on the perceived limitations of AVMs, draws on concerns raised in the RICS (2021) Roadmap: the absence of physical inspection in most AVM processes, uncertainty about the quality and origin of underlying data, reduced explainability as machine learning models get more sophisticated, and the lack of standardized confidence-score methodology across commercial AVM providers. These show up as Likert-scale statements, letting respondents indicate how much they agree or disagree with each concern.

Section E operationalizes Rogers's (2003) five innovation attributes directly each item maps to one dimension of Diffusion of Innovations theory: relative advantage, compatibility, complexity, trialability, observability. That one-to-one mapping means the results can be read not just as measures of practitioner attitude toward AVMs, but within the Chapter Three theoretical framework, letting each dimension of innovation adoption be examined on its own.

Building the survey this way strengthens its content validity every question trace to a specific concept or finding in the literature, so a reviewer can verify it measures established theoretical and empirical constructs rather than relying on subjective judgment or face validity alone. The complete questionnaire, all items, response scales, and skip logic included, is reproduced in Appendix A as the ready-to-administer online Google Form survey used to actually collect the data, with responses recorded automatically in a linked Google Sheet in a format suitable for the descriptive and inferential analyses described in Section 7.6.2.

7.4.2 Aggregation and Analysis Procedure for the Structured Survey

After participants completed the survey described in Section 7.4.1, responses were recorded automatically in a linked Google Sheet, one respondent per row and one survey question per column, following the structure in Table 7.1. Thirteen valid responses came in total. This standardized format made data management straightforward and supported the descriptive and comparative statistics reported in Chapter Eight.

The consolidated dataset feeds descriptive statistics for each item means and standard deviations for Likert-scale responses, frequencies and percentages for the categorical variables in Section A with subgroup analysis where sample size allows. Mean scores on the compatibility construct (E2), for instance, might be compared between respondents whose experience is mainly traditional and those with hands-on AVM experience, giving an empirical check on whether perceived compatibility actually varies by professional background, as the Innovation Theory framework in Chapter Three would predict.

Because each item ties to a specific theoretical construct, the resulting analysis can be read within the study's conceptual framework rather than as a pile of isolated statistics. Section E's five Innovation Theory items (E1–E5) map directly onto Rogers's (2003) innovation attributes relative advantage, compatibility, complexity, trialability, observability and looking at them together indicates roughly where AVM adoption currently sits within the UAE valuation profession. High relative advantage (E1) scores paired with lower compatibility (E2) and trialability (E4) scores, say, would suggest practitioners recognize AVM benefits but haven't yet worked them into routine practice a pattern consistent with the early stages of innovation diffusion.

The three items drawn from Kanter's (1995) theory of organizational resistance (E6–E8) get analyzed together too, to identify what's actually driving resistance to AVM adoption rather than just confirming that resistance exists. Is it mainly loss of professional control, uncertainty about the technology, or anxiety about competence? That distinction matters practically, since each points to a different fix: loss-of-control resistance calls for stronger governance, uncertainty calls for better communication between developers and valuation professionals, and competence concerns call for training and education. These findings link directly to the recommendations developed in Chapter Nine.

7.4.3 Reference Review of an Existing AVM Platform

As a contextual reference rather than a primary data source, this study reviews the Bayut TruEstimate™ platform, an AI-based AVM generating property value estimates from location information, property

characteristics, and market transaction data in the Dubai real estate market (Bayut, 2024) included to show a practical, real-world example of how AVM technology is currently used in the UAE.

To be clear, TruEstimate™ isn't the analytical tool for this study's empirical work; the quantitative analysis relies exclusively on the HTML-based AVM calculator built for this research. The review of TruEstimate™ is purely contextual, illustrating the kind of information and output typical of commercially available, consumer-facing AVM platforms: estimated market value, comparable property identification, price-per-square-foot indicators, historical price trends, and estimated rental yields (Bayut, 2024).

Including this regional example ties the theoretical and methodological discussion to an AVM already operating in the UAE market and shows how a contemporary commercial AVM presents its output to end users a useful reference point when interpreting the findings and recommendations in later chapters.

7.4.4 HTML-Based AVM Calculator

The main quantitative research instrument is a purpose-built, browser-based AVM application developed specifically for this study. Building a custom HTML application, rather than relying on an existing commercial platform, was a deliberate methodological choice. As RICS (2022) notes, the algorithms and calculations behind commercial AVM platforms are generally proprietary, which limits how much a valuer or researcher can actually examine about how an estimate was produced or why an unexpected result occurred. A fully self-contained, transparent web application, by contrast, lets every input variable, calculation, weighting, and comparable-selection step be documented, inspected, and replicated addressing the transparency concerns raised throughout the professional literature in Chapter Two.

The application runs on a real transaction dataset of 3,609 verified property records from four residential projects (Project1 through Project4) in the Great Amman municipality, spanning 2017–2026. Each record carries a full set of attributes unit area, balcony area, floor level, bedroom and bathroom count, construction status, construction age, sell age, developer identity, recorded selling price depth that supports both a rigorous AVM valuation and a meaningful comparable-property search, consistent with Kok et al. (2017) and Bergadano et al. (2019), both of whom found predictive accuracy improves substantially with richer datasets.

The AVM calculates the estimated market value using the following formula, applied to each subject property identified within the dataset:

$$\text{AVM Estimated Value} = \text{Gross Area (m}^2\text{)} \times \text{Calculated Price per m}^2$$

where Gross Area is the sum of the unit's net internal area (UNIT_AREA) and its balcony area (UNIT_BALCONY_AREA), and the Calculated Price per m² is derived from the dataset by computing the mean of (Valuation Amount ÷ UNIT_AREA) across all records within each project. This produces a fixed, project-level price per m² that reflects prevailing market conditions for each development. The application of the

calculated rate to the gross area rather than the net area alone ensures that all habitable and semi-habitable space is reflected in the valuation estimate, consistent with the area measurement practices adopted in the Jordanian residential market.

Table 7.2

Calculated Project Price per m² (Derived from Dataset)

Project	Community	Calculated PPM (JOD/m ²)
Project1	AMS3	1,928.44
Project2	AMS3	1,981.89
Project3	AMS1	2,181.11
Project4	AMS1	2,181.11

The application runs across two main screens. The first, the Property Input Screen, identifies the subject property through nine cascaded dropdowns Municipality, City, Neighborhood, Community, Project, Land Number, Building Number, Floor Number, Unit Number each automatically populated based on the previous selection, so only valid combinations in the dataset are reachable. Once all nine are filled in, a preview panel summarizes the unit's key attributes net area, gross area, balcony area, bedroom and bathroom count, construction status, construction age, developer identity, transaction year letting the user confirm they've picked the right property before proceeding.

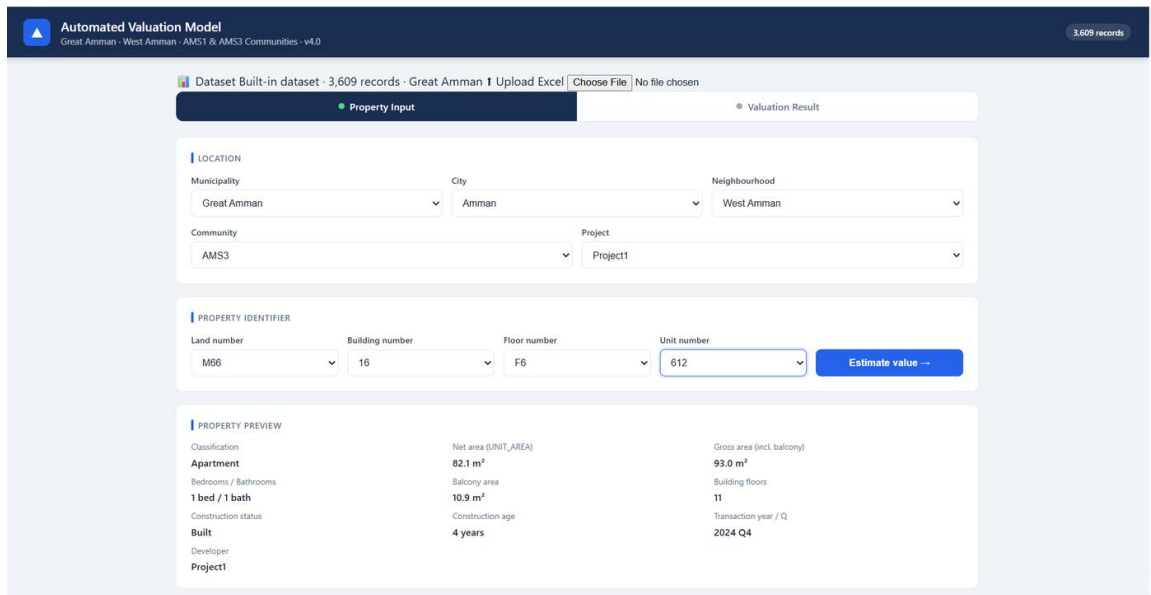


Figure 7.1

Property Input Screen: Nine cascaded dropdowns and property preview panel

The second screen, the Valuation Result Screen, generates automatically on submission and shows the AVM output in two parts. The first displays four headline figures: the AVM Estimated Market Value on a gross-area basis, the Confidence Score as a percentage, and the difference between the AVM estimate and the property's recorded selling price, in both absolute (JOD) and percentage terms. Confidence is calculated as a composite of a fixed base value, a component weighted by the number of comparables identified (up to twenty), and a component reflecting the quality of the top comparable as a fraction of the maximum possible similarity score, capped at 95 percent to reflect the inherent uncertainty of any automated valuation done without a physical inspection.

The second component presents a ranked comparable properties table. Comparables are selected using a weighted similarity scoring system with a maximum of 110 points across eight criteria: same project (+40), same community (+20), same land number (+10), unit area within 10% (+15), same bedroom count (+10), same floor level (+8), transaction year within one year (+7), same classification (+5), same bathroom count (+3), and same building number (+2). Only properties scoring at least 20 points are included, with up to 25 displayed in descending order.

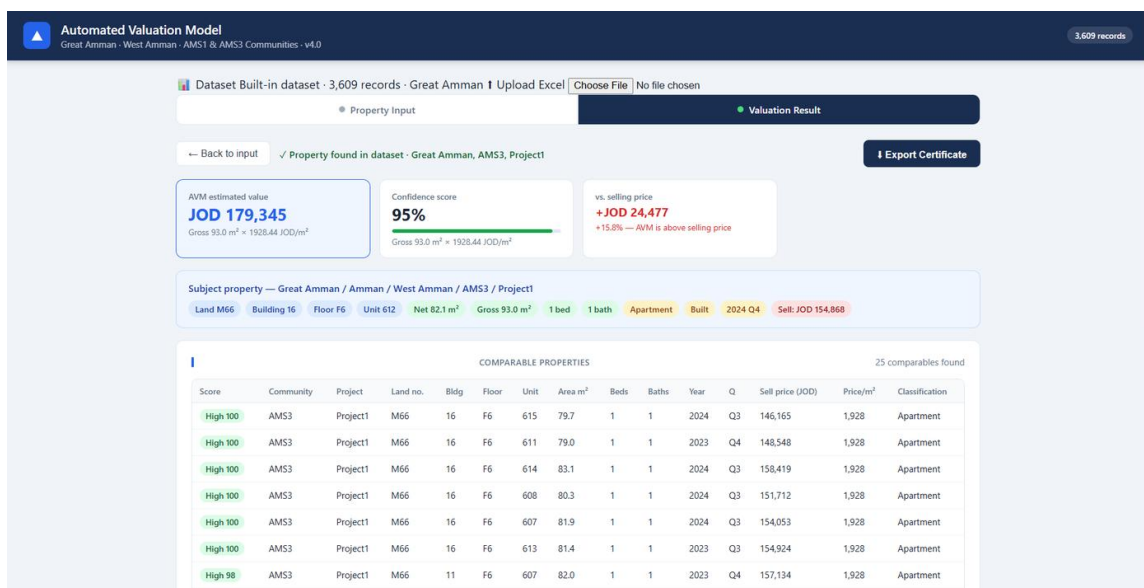


Figure 7.2

Valuation Result Screen

Table 7.3

Comparable Property Similarity Scoring Criteria

Similarity Criterion	Points Awarded
Same project	+40 points
Same community (if different project)	+20 points
Same land number	+10 points
Unit area within 10% of subject	+15 points
Unit area within 10–20% of subject	+10 points
Unit area within 20–35% of subject	+5 points
Same bedroom count	+10 points
Same floor level	+8 points
Transaction year within 1 year	+7 points
Transaction year within 1–3 years	+3 points

Similarity Criterion	Points Awarded
Same unit classification	+5 points
Same bathroom count	+3 points
Same building number	+2 points
Maximum possible score	110 points

Figures 7.1, 7.2, and 7.3 demonstrate the end-to-end valuation workflow for a single subject property. Figure 7.X shows the Property Input Screen with all nine dropdowns populated and the preview panel confirming the subject property's details before valuation. The preview panel presents both the net area (82.1 m²) and the gross area inclusive of the balcony (93.0 m²), making the area basis behind the AVM calculation fully visible. Figure 7.X+1 shows the Valuation Result Screen: an AVM estimated value of JOD 179,345 for the selected unit (Project1, building 16, Floor F6, Unit 612), derived from a gross area of 93.0 m² multiplied by the calculated project price per m² of JOD 1,928.44. The confidence score is 95 per cent, the recorded selling price is JOD 154,868, and 25 comparables are listed with similarity scores. Figure 7.X+2 shows the exported valuation certificate.

The Export Certificate function generates a PDF certificate directly within the browser without server-side processing. The certificate presents the AVM estimated value, the gross-basis price per m², the confidence score with a visual bar, the complete property identification and attribute summary, the transaction data including the selling price and its difference from the AVM estimate, a summary of the top five comparable properties, a methodology statement confirming the gross-area calculation basis, a unique reference number, the date and time of issue, and a prominent disclaimer that the output is an informational estimate only and does not represent a formal RICS or IVS-compliant valuation report.

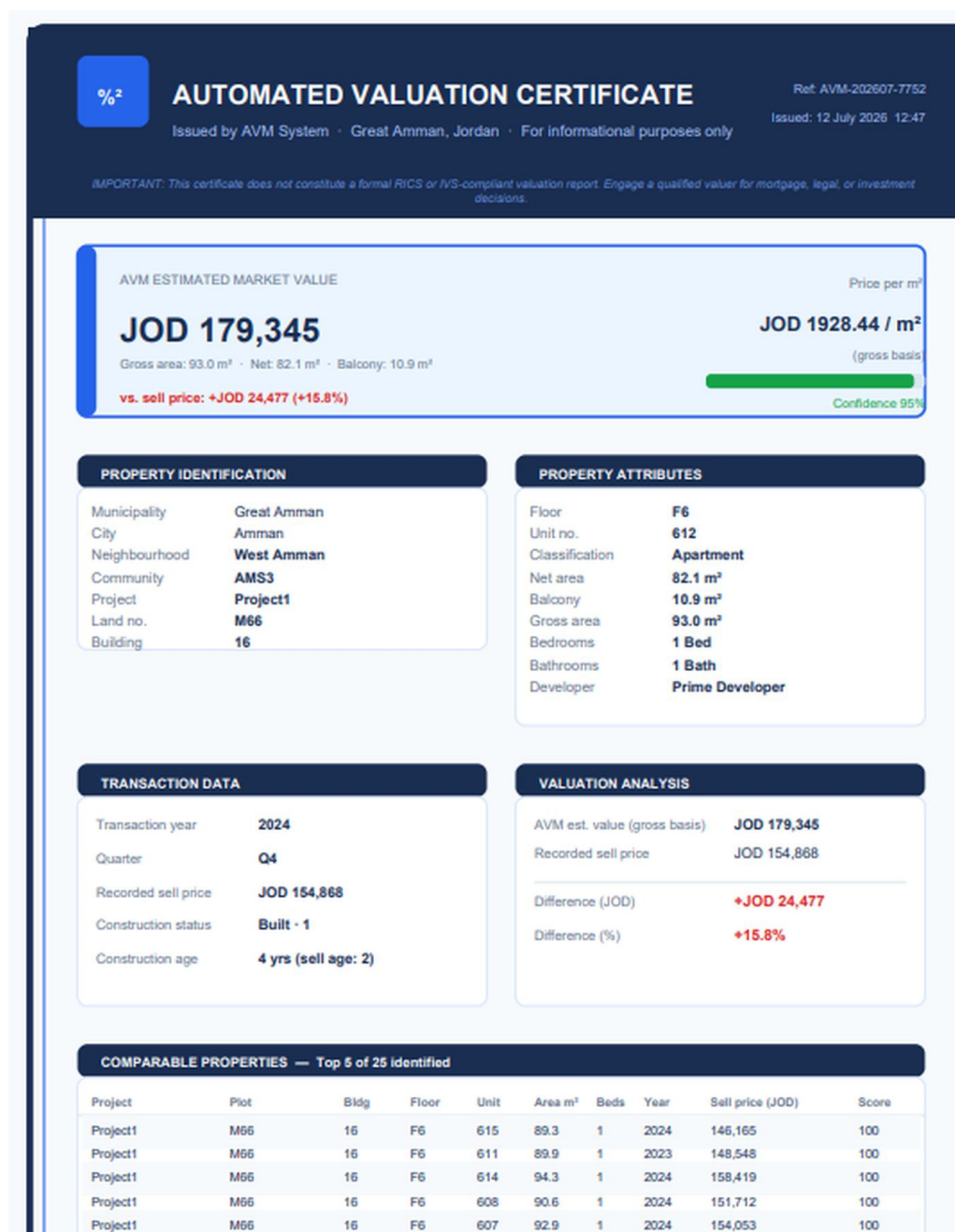


Figure 7.2

Exported Valuation Certificate

www.midocean.edu.km

Comoros Address: (Headquarters) Midocean university, 8764+GH9 Matelec street, BP 684 Moroni, RP 98123 Moroni, Comoros

The application is built to run as a fully self-contained HTML file, loadable in any modern browser without installation or a network connection useful for field settings or institutional environments with limited internet access. The embedded dataset is compressed within the file and decompressed in the browser at runtime, fitting the full 3,609-record database into roughly 150 kilobytes. It also has an Excel Upload feature letting future users swap in an updated or different transaction database in the same column format, so the AVM framework can be applied to other markets or time periods without touching the application code on upload, it automatically recalculates the project-level price per m², rebuilds the dropdown navigation, and applies the gross-area formula, keeping the methodology consistent regardless of dataset.

The choice to calculate a project-level price per m² applied to gross area, rather than deriving an estimate through machine learning, reflects the same transparency and interpretability priorities behind the calibration technique discussed in Section 7.4.5 and the MRA assumptions in Section 7.4.6. The application, in other words, is consistent with the study's overall methodological framework, one that prioritizes explainability, replicability, and meaningful comparison with traditional professional practice over squeezing out maximum predictive accuracy.

7.4.5 Justification for the Choice of Calibration Technique

Note: Sections 7.4.5 and 7.4.6 describe the original methodological design considered for calibrating the AVM application, which envisaged a Multiple Regression Analysis (MRA)-based calibration drawing on a three-tier variable structure. Following iterative development work, the implemented application instead adopts the transparent, project-level price-per-m² approach described in Section 7.4.4 calculated as the mean of Valuation Amount ÷ UNIT_AREA per project and applied to the subject property's gross area rather than a full MRA calibration. This departure was made because a single, auditable project-level rate could be explained and verified in its entirety without recourse to a fitted statistical model, offering an even higher degree of transparency than an MRA specification would provide, while the modest number of price-determining attributes recorded per project made a full regression specification unnecessary for producing a stable estimate. The methodological reasoning set out below remains relevant to the study's overall framing, in that it explains why a simpler, fully transparent calculation method was ultimately preferred over an opaque machine-learning approach; it should, however, be read as an account of the study's design rationale rather than as a literal description of the calibration technique implemented in the final application.

Choosing Multiple Regression Analysis (MRA) over more advanced machine learning techniques like gradient boosting or ensemble learning for calibrating the AVM application needs explicit justification. Chapter Two shows that sophisticated machine learning models can push predictive accuracy higher, but that's not the primary goal here the aim is a valuation model that's transparent, interpretable, and genuinely comparable to traditional valuation practice. The IAAO (2018) standard offers a useful frame for this choice through its own comparison of MRA against Artificial Neural Networks (ANNs).

The IAAO (2018) describes MRA as examining the relationship between a dependent variable and multiple independent variables through linear or curvilinear estimation. Beyond generating value predictions, it produces a full set of diagnostic statistics the coefficient of determination (R^2), adjusted R^2 , standard error of the estimate, coefficient of variation, and significance tests like t-tests and F-tests (p. 29) letting analysts judge overall model performance, weigh individual variables, and compare alternative specifications.

MRA's advantages, per the standard: it's widely accepted and well understood, backed by readily available software including Excel's own regression functions, and its output is highly interpretable an analyst can explain exactly how each variable shapes the estimated value (p. 29). Its main drawbacks are that interpreting the results properly needs real statistical knowledge, and complex nonlinear relationships usually need explicit mathematical transformation before MRA can model them well (p. 30).

The IAAO contrasts this with Artificial Neural Networks (ANNs), which can model linear and nonlinear relationships simultaneously through an iterative process that keeps adjusting internal weights to minimize prediction error. That architecture lets neural networks pick up on genuinely complex relationships and patterns that conventional regression might miss entirely (p. 30).

The trade-off, though, is that a neural network's calculations happen inside a hidden layer, making the relationship between inputs and outputs hard to interpret. Without a clearly defined model structure, it's harder to explain how any individual variable actually contributed to the final estimate (p. 30) a limitation that echoes the transparency concerns raised in both the RICS (2021) Roadmap and the IVSC (2022) Perspectives Paper, both of which stress explainability and professional accountability wherever automated valuation is used.

Against that backdrop, choosing MRA for the HTML-based AVM calculator was a deliberate methodological decision, not a technological limitation. The calculator was designed first and foremost as a transparent research instrument, where every variable, coefficient, and calculation step can be inspected and checked. MRA delivers exactly that: explicit coefficients, significance tests, and clearly interpretable relationships between explanatory variables and property value well suited to a comparative study where the point isn't just producing estimates but understanding and explaining how they're produced.

This does involve a genuine trade-off. The calculator is unlikely to match the predictive accuracy of the more advanced machine learning models in Chapter Two, particularly Tapia et al.'s (2025) image-enhanced gradient boosting model. But the added transparency and interpretability MRA offers fits this study's goals better methodological clarity, professional accountability, and a meaningful comparison between automated and traditional valuation. This trade-off is acknowledged as a limitation and discussed further in Chapter Nine.

7.4.6 MRA Assumptions and Their Implications for This Study

Any MRA model's reliability rests on several statistical assumptions the IAAO (2018) spells out explicitly, so the data collection and analysis procedures here are designed to satisfy those assumptions wherever possible, with any shortfall reported transparently rather than glossed over.

Per the IAAO (2018), predictive accuracy depends on having complete, reliable data, a calibration sample that represents the wider population the model will be applied to, and a dataset split into a training sample for development and an independent holdout sample for validation (p. 29) all incorporated directly into this study's training and validation procedure described in Section 7.5.3.

The standard also lists the statistical assumptions behind regression-based calibration: residuals should be normally distributed; they should show homoscedasticity, meaning prediction-error variance stays roughly constant across the property value range (heteroscedasticity, its opposite, means errors grow or shrink systematically with value); and explanatory variables shouldn't be excessively multicollinear so correlated with each other that their individual effects on value can't be reliably separated. The IAAO recommends checking multicollinearity through correlation analysis before final calibration (p. 29).

These assumptions matter directly here. Homoscedasticity in particular ties closely to the Price-Related Differential (PRD) and Price-Related Bias (PRB) measures discussed in Section 6.4 if prediction errors grow systematically as property values rise, the model is likely to show unacceptable PRD or PRB values, signaling inconsistent performance across market segments. Different lens, same underlying issue: uneven predictive accuracy across the price distribution.

Multicollinearity matters just as much here, given the calculator's three-tier variable structure described in Section 7.4.4. Since the market and enrichment variables are meant to capture distinct sources of information, the analysis plan includes a full correlation matrix before calibration, to catch variables that are too closely correlated and therefore redundant. Where that happens, highly correlated variables get removed, combined, or otherwise adjusted to keep the model stable and the regression coefficients statistically reliable and interpretable.

7.5.1 Qualitative Data Collection

Interviews are conducted individually, in person or by video call depending on what works for the participant, each expected to run 30 to 60 minutes. With consent, interviews are audio-recorded and transcribed verbatim to support accurate thematic analysis, with field notes taken alongside to capture context the audio alone wouldn't convey.

7.5.2 Quantitative Data Collection

Property transaction data comes from the relevant UAE property transaction registry or registries, supplemented where possible with the corresponding traditional valuation reports for the same properties

enabling a direct comparison between professional valuation outcomes and the HTML-based AVM calculator's estimates.

Where no directly matched traditional valuation report exists, the study instead uses professionally prepared sales-comparison estimates for comparable properties matched on location, property type, size, and other relevant characteristics so the traditional-valuation benchmark stays grounded in recognized professional practice (RICS, 2022) rather than informal or researcher-generated estimates.

To protect the dataset's integrity, the study builds in a specific safeguard against the self-generation risk raised during the RICS Leaders' Forums and discussed in Section 2.5.3. One forum participant put it directly: "AVMs could become self-generating if the AVM evidence is reintroduced in the algorithm," undermining the independence and objectivity of future valuations the recommended fix being that statistically significant non-AVM data stay a compulsory part of AVM development (RICS, 2021, p. 15).

So every comparable transaction feeding the HTML-based AVM calculator is, wherever possible, verified as either an independently recorded market transaction or a professionally prepared traditional valuation. Estimates from existing commercial AVM platforms including consumer-facing tools like Bayut TruEstimate™ (Bayut, 2024) are never used as calibration data. That keeps the calculator trained exclusively on independent market evidence, not on previous automated estimates, avoiding the kind of recursive feedback that could artificially reinforce whatever the model already outputs.

This safeguard reflects a broader principle running through the study: an AVM's quality and credibility depend not just on how much data is available, but on the independence, provenance, and reliability of the data actually used to build and validate it.

7.5.3 Pilot Testing of Instruments

Before real data collection starts, both instruments go through pilot testing to check clarity, functionality, and fit for purpose.

The semi-structured interview guide gets reviewed first by the study's academic supervisors and, where possible, one or two experienced valuation professionals who won't take part in the main study checking the questions for clarity, relevance to the research objectives, and whether they actually generate useful responses. Feedback from this stage feeds back into the guide's wording, sequencing, or structure as needed, consistent with the research design set out in the original proposal.

The HTML-based AVM calculator gets piloted too, before it's applied to the full dataset testing an initial subset of transactions with known market outcomes to check the calculator's functionality, verify formulas and calculations, and catch any structural or computational errors, along with confirming the input variables process correctly and the output is logically consistent. Anything that turns up gets fixed before the calculator goes into the main quantitative analysis, strengthening the reliability of the findings that follow.

7.6 Data Analysis Techniques

7.6.1 Qualitative Analysis

The interview data is analyzed thematically, following Braun and Clarke's (2006) six-phase framework chosen because it's systematic enough to be rigorous but flexible enough to actually work with qualitative data's patterns of meaning.

The analysis starts with familiarization: reading through the transcripts repeatedly to build an overall sense of what participants said. Next comes generating initial codes, systematically identifying and labeling text segments relevant to the research questions. Third, related codes get grouped into candidate themes representing broader patterns in the data.

Fourth, those themes get reviewed and refined against both the coded extracts and the full dataset, to make sure each one genuinely reflects what participants said. Fifth, the final themes get defined and named, with a clear sense of what each one means and how it relates to the research objectives. Sixth and last, the analytical narrative in Chapter Eight interprets these themes against the literature, theoretical framework, and research questions.

Coding starts from the four thematic areas already built into the interview guide (Section 7.4.1) traditional valuation practice, perceptions of AVMs, barriers to adoption, and opportunities for integrating AVMs with traditional methods but stays open to themes that weren't anticipated in the guide's design, in keeping with Braun and Clarke's (2006) view of thematic analysis as flexible rather than strictly deductive.

7.6.2 Quantitative Analysis

The quantitative analysis runs in three stages. The first two follow the analytical approaches common in the academic AVM literature from Chapter Two; the third applies the formal quality assurance measures the IAAO (2018) recommends, discussed in Section 6.4. Together, they let the study assess both the HTML-based AVM calculator's predictive performance and its professional reliability.

The first stage descriptively compares the values the HTML-based AVM calculator generates against the traditional valuation benchmarks, using the same metrics common in previous AVM research Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2) the same ones Bergadano et al. (2019) and Tapia et al. (2025) use, so this study's findings can be set directly against the existing international literature.

The second stage tests the study's hypotheses through inferential statistics, using paired-sample tests to compare the AVM calculator's estimates against the traditional valuation results. A paired-samples t-test applies where the valuation differences are roughly normally distributed; where that assumption doesn't hold, the non-parametric Wilcoxon signed-rank test steps in instead. These analyses are the statistical basis for testing the main hypothesis (H1) and its sub-hypotheses from Chapter Four.

The third stage goes beyond conventional predictive accuracy, applying the formal AVM quality assurance measures the IAAO (2018) recommends checking not just how accurate the model is on average, but how consistently and fairly it performs across different categories of property.

The Coefficient of Dispersion (COD) measures how consistent valuation performance is within each property group from the stratification stage described in Section 6.2.4 lower COD means more consistent estimates.

The Price-Related Differential (PRD) checks whether the model systematically over- or under-values properties at different points in the price distribution, and, where sample size allows, the Coefficient of Price-Related Bias (PRB) gives a more statistically robust read on vertical equity. Per the IAAO (2018), PRD between 0.98 and 1.03 signals acceptable vertical equity; outside that range suggests systematic bias toward either lower- or higher-priced properties.

Where the final dataset is large enough, confidence intervals get reported alongside each quality assurance statistic too, following the IAAO's (2018) point that statistics calculated from a sample are estimates of unknown population parameters and should be read together with some measure of sampling uncertainty.

Adding this third analytical stage sets this study apart from much of the existing academic literature, which typically judges AVM performance on aggregate error measures alone. Bringing in the IAAO's professional quality assurance framework means checking not just whether the HTML-based AVM calculator produces accurate estimates, but whether it shows the consistency, reliability, and fairness expected of an AVM operating in real professional practice.

7.7 Reliability and Validity

Reliability and validity get addressed separately for the qualitative and quantitative strands, since each rests on different epistemological standards (Creswell & Plano Clark, 2018).

For the qualitative strand, trustworthiness follows Lincoln and Guba's (1985) four criteria: credibility, dependability, confirmability, and transferability.

Credibility rests on several things. The semi-structured interview guide gets reviewed by the study's academic supervisors and pilot-tested with experienced valuation professionals before real data collection starts. The structured survey instrument, meanwhile, is drawn directly from the theoretical framework and literature in Chapters Two and Three, so every item traces back to an established concept or empirical finding rather than the researcher's own assumptions which is what strengthens the credibility of the qualitative evidence here.

Dependability comes from applying Braun and Clarke's (2006) six-phase thematic analysis consistently across every interview transcript a structured framework that keeps coding and theme development following the same systematic procedure throughout.

Confirmability rests on keeping a full audit trail of the analytical process interview transcripts, coding decisions, theme development, supporting quotations, all retained so the link between the raw data and the final interpretation can be independently checked.

Transferability comes from reporting the study context and participant characteristics in detail: years of professional experience, valuation background, organizational affiliation, emirate of practice, alongside the UAE property market context laid out in Chapter One enough for a reader to judge how far these findings might apply to other professional settings or comparable markets.

For the quantitative side, validity comes down to content validity, construct validity, and criterion validity together.

Content validity comes from aligning the calculator's input variables with what previous research has consistently identified as driving AVM performance structural, market, and enrichment variables based on Kok et al. (2017), Bergadano et al. (2019), and the variable framework in Section 7.4.4, keeping the model grounded in the current state of AVM literature.

Construct validity asks whether the calculator actually estimates market value as a theoretical concept, rather than some other measure of property price. To make sure it does, the calculator is built explicitly around the IVS definition of Market Value discussed in Section 5.6, so its output corresponds as closely as possible to the valuation concept professional practice actually uses.

Criterion validity comes from evaluating the calculator against internationally recognized measures used throughout the AVM literature Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2) which lets this study's findings be compared directly with Bergadano et al. (2019), Tapia et al. (2025), and the other studies in Chapter Two. The model is also evaluated against the IAAO's (2018) quality assurance measures Coefficient of Dispersion (COD), Price-Related Differential (PRD), and, sample size permitting, the Coefficient of Price-Related Bias (PRB) extending the evaluation past predictive accuracy into model consistency and distributional fairness.

Reliability on the quantitative side comes from several complementary steps. The HTML-based AVM calculator gets pilot-tested on a subset of transactions with known outcomes before it's applied to the full dataset, as described in Section 7.5.3. The workbook formulas then get independently checked for computational accuracy and internal consistency. Before final calibration, the assumptions behind Multiple Regression Analysis get tested through statistical diagnostics multicollinearity checks among explanatory variables, homoscedasticity checks on the regression residuals steps that keep the regression coefficients stable and reduce the odds the model produces inconsistent estimates on different samples from the same population.

Together, these qualitative and quantitative procedures are meant to keep this study's findings credible, reliable, and methodologically sound and to let its results be read within internationally accepted research practice and compared directly against the academic and professional literature covered in Chapter Two.

7.8 Ethical Considerations

This research follows established ethical principles for studies involving human participants. Every participant gets a clear explanation of the study's purpose, that participation is voluntary, and that they can withdraw at any stage without penalty. Written informed consent is obtained before each interview, including explicit consent for audio recording where that applies.

To protect participant confidentiality, interview responses are anonymized during transcription, and reporting participants are identified by generic descriptors (Participant 1 – Senior Valuer, say) rather than names, employers, or other identifying detail, and any organizational reference that could reasonably identify a person or institution gets removed or generalized.

Property transaction data from official UAE property registries or other institutional sources is used solely for academic research. All datasets are anonymized before analysis, so neither individual properties nor the parties involved can be identified in the reported findings. Electronic data, interview recordings, transcripts, and supporting materials are stored securely with password protection, accessible only to the researcher and academic supervisors, and used exclusively for this study in line with applicable institutional research ethics requirements.

Beyond these standard safeguards, two considerations matter particularly given the UAE property market and the data this research relies on.

First, given the discussion of beneficial ownership transparency and anti-money laundering requirements in Section 2.4.4, any transaction records from institutional property registries are handled carefully so that no personally identifiable ownership information is kept beyond what the valuation analysis actually needs. The research focuses on property characteristics, transaction prices, and valuation outcomes, not the identities of buyers, sellers, or owners so any identifying information in the original datasets gets removed or anonymized before analysis.

Second, since the structured survey may reach respondents across multiple organizations within a relatively small UAE valuation profession, respondent anonymity gets particular attention at the reporting stage. Demographic variables like years of experience, organization type, valuation specialization, and emirate of practice can, combined, unintentionally point to a specific respondent's identity. Survey results are therefore reported only in aggregate, with demographic categories collapsed into broader groupings where the sample size is limited, to prevent indirect identification consistent with accepted disclosure-control practice in social science research.

Together, these procedures are meant to keep the study within accepted ethical standards for informed consent, confidentiality, privacy, data security, and handling sensitive information responsibly, while maintaining the transparency and integrity academic research is expected to have.

8. FINDINGS AND ANALYSIS

8.1 Introduction

This chapter presents the findings from both strands of the study, reflecting the convergent mixed-methods design set out in Chapter Seven. Section 8.2 covers the qualitative findings from the structured survey of thirteen real estate valuation professionals from Jordan, Saudi Arabia, and the UAE. Section 8.3 covers the quantitative analysis, comparing AVM estimates from the purpose-built HTML application against traditional manual valuations for nine residential units across three Abu Dhabi districts, evaluated using the IAAO performance measures from Chapter Seven. Section 8.4 reports the hypothesis testing results, Sections 8.5 and 8.6 cover the integration of findings and the IAAO quality assurance assessment, and Section 8.7 draws preliminary conclusions.

8.2 Qualitative Findings

8.2.1 Participant Profile

Thirteen professionals in total completed the structured survey. Table 8.1 summarizes their demographic profile across the six Section A variables.

Table 8.1 Respondent Profile (n = 13)

Variable	Category	n	%
Professional Role	Chartered / Registered Valuer	2	15.4%
	Real Estate Analyst	2	15.4%
	AVM / Data Analytics Specialist	2	15.4%
	Academic / Researcher	2	15.4%
	Other	5	38.5%
Years of Experience	Less than 2 years	1	7.7%
	2–5 years	1	7.7%
	6–10 years	1	7.7%
	11–20 years	5	38.5%
	More than 20 years	5	38.5%
Primary Background	Predominantly traditional	5	38.5%
	Mixed both approaches	6	46.2%
	Predominantly AVM-based	1	7.7%

Variable	Category	n	%
	Limited direct experience	1	7.7%
Organization Type	Government / regulatory body	7	53.8%
	Real estate developer	3	23.1%
	Protech / AVM provider	1	7.7%
	Other	2	15.4%
Country of Practice	Jordan	6	46.2%
	Saudi Arabia	6	46.2%
	United Arab Emirates	1	7.7%
RICS Accreditation	Yes	1	7.7%
	No	12	92.3%

What stands out about this sample is its seniority: ten of the thirteen respondents (76.9%) report eleven or more years of professional experience, five of them more than twenty. That concentration of experienced practitioners gives the qualitative responses real weight, since these are perspectives grounded in deep familiarity with traditional valuation workflows and, in several cases, direct exposure to AVM technology. Government and regulatory body respondents make up more than half the sample (53.8%), which fits the study's institutional framing around how AVM adoption decisions get made in regulatory and supervisory contexts across the GCC and Levant. The geographic spread Jordan (46.2%), Saudi Arabia (46.2%), UAE (7.7%) covers three markets at broadly similar stages of AVM awareness and regulatory development, and only one respondent holds RICS accreditation, in line with the generally lighter formal credentialing in GCC and Levant valuation markets compared with Europe.

8.2.2 Traditional Valuation Practice

Respondents reported handling a median of five traditional valuations a month (range: 1–15, with some responses given in Arabic numerals and converted to their numeric equivalents), and a median turnaround of three working days for a standard residential valuation (range: 2–10 days) both figures matching the 3–10-day industry norm built into the research design, and confirming these are active practitioners doing regular traditional valuation work. Table 8.2 reports the mean scores and standard deviations for the four Likert-scale items.

Table 8.2 Section B: Traditional Valuation Practice -Likert Responses (n = 13)

Item	Statement (abbreviated)	Mean	SD	Interpretation
B3a	Physical inspection is essential to reliable valuation	4.54	0.66	Strong agreement
B4	Sales comparison is most frequently used for residential	3.77	1.24	Moderate agreement
B5	Valuer inconsistency is a meaningful concern	3.77	0.73	Moderate agreement
B6	Cost/time of traditional valuation is a significant constraint	3.69	0.48	Moderate agreement

B3a comes out as the highest-rated item by a clear margin ($M = 4.54$, $SD = 0.66$), reflecting near-universal agreement that physical inspection is indispensable to a reliable valuation eleven of thirteen respondents scored it 4 or 5, and nobody scored it below 3. That matters methodologically: since an AVM works purely from transactional data and can't inspect a property, this near-consensus represents a real, widely held professional reservation about how complete a fully automated output can actually be. The moderate agreement on B6 ($M = 3.69$, $SD = 0.48$) confirms that cost and time constraints are a recognized limitation of traditional practice to the efficiency rationale that draws even manual-method practitioners toward AVM adoption.

8.2.3 AVM Awareness and Use (Section C)

Twelve of the thirteen respondents (92.3%) reported at least slight familiarity with AVMs, five moderately familiar, four very familiar, one not at all though notably, nobody described themselves as an AVM expert. Six respondents (46.2%) have never personally used an AVM platform; three use one occasionally and three frequently, so direct operational engagement ranges from mere awareness to regular use. Table 8.3 presents the four Likert evaluative items.

Table 8.3 Section C: AVM Awareness and Use Likert Responses (n = 13)

Item	Statement (abbreviated)	Mean	SD	Interpretation
C3	AVM estimates are generally close to traditional valuer outputs	3.23	0.73	Neutral to moderate agreement
C4	Concerned about data quality / provenance of AVM platforms	3.31	1.03	Neutral to moderate agreement
C5	Aware of confidence scores alongside AVM outputs	3.08	0.64	Neutral
C6	AVMs more suitable for residential than commercial property	3.23	0.83	Neutral to moderate agreement

The neutral-to-moderate means across all four Section C items suggest measured, cautious engagement with AVM technology rather than either enthusiasm or rejection. The moderate agreement on C3 ($M = 3.23$) shows that practitioners aren't widely convinced AVM estimates are reliably equivalent to a professionally prepared valuation a reservation the quantitative findings in Section 8.3 back up. And the near-neutral awareness of confidence scores (C5, $M = 3.08$) suggests AVM output quality metrics aren't yet being communicated effectively in these markets, consistent with RICS's (2021) own observation that confidence-score conventions remain applied inconsistently across providers.

8.2.4 Advantages and Disadvantages of AVMs (Section D)

Section D drew on seven statements from the RICS (2021) Roadmap taxonomy; Table 8.4 reports the results.

Table 8.4 Section D: Advantages and Disadvantages of AVMs Likert Responses ($n = 13$)

Item	Statement (abbreviated)	Mean	SD	Expected range
D1	AVMs save meaningful time, money, and resources	3.92	0.86	4–5
D2	AVMs integrate easily into lender platforms	3.69	0.75	4
D3	Absence of physical inspection is a significant limitation	3.92	1.04	4–5
D4	AVM data provenance is often difficult to verify	3.69	0.85	4
D5	AI sophistication makes AVM outputs harder to explain	3.08	0.86	3–4
D6	Confidence-score differences complicate fair comparison	3.77	0.83	4
D7	AVMs help reduce fraud by removing human discretion	3.77	1.24	3

Two items tie for the highest mean: D1 (time and cost savings, $M = 3.92$) and D3 (absence of physical inspection, $M = 3.92$). That pairing is worth noting practitioners are weighting AVMs' main operational advantage and their most substantive methodological limitation equally, which anticipates the hybrid integration preferences that show up in Section F. D5's relatively lower score (explainability, $M = 3.08$) may reflect limited direct exposure to advanced machine-learning AVMs in these markets, where simpler hedonic or rules-based systems are more common. D7 (fraud reduction, $M = 3.77$, $SD = 1.24$) has the highest variance of any D-section item, reflecting genuinely split opinion on whether removing human discretion helps prevent fraud or actually creates an accountability risk.

8.2.5 Adoption Attitudes- Innovation Theory Constructs (Section E)

Section E operationalizes Rogers's (2003) five diffusion attributes (E1–E5) and Kanter's (1995) three resistance dimensions (E6–E8); Table 8.5 presents the results.

Table 8.5 Section E: Innovation Theory Constructs/ Likert Responses ($n = 13$)

Item	Construct (Rogers / Kanter)	Mean	SD
E1	Relative Advantage: AVM speed/cost advantage	4.23	0.83
E2	Compatibility: AVM consistent with current approach	3.15	1.21
E3	Complexity: AVM outputs difficult to understand	2.77	0.93
E4	Trialability: opportunity to trial AVM before use	2.62	1.39
E5	Observability: can observe peers using AVMs	2.69	0.95
E6	Loss of Control: AVM use reduces professional control	2.92	0.95
E7	Uncertainty: developer communication limited/unclear	3.31	0.75
E8	Competence: confidence using AVM alongside judgement	3.77	0.73

The Rogers attributes trace a clear adoption gradient. Relative advantage (E1, $M = 4.23$) is the second-highest mean in the entire survey, confirming broad recognition of AVM efficiency benefits. Compatibility (E2, $M = 3.15$) sits near-neutral AVMs aren't yet fully woven into professional practice, but they're not seen as fundamentally incompatible with it either. More strikingly, trialability (E4, $M = 2.62$) and observability (E5, $M = 2.69$) are the two lowest-scoring items across all 23 Likert questions in the survey, reflecting how early-stage AVM adoption still is in Jordan and Saudi Arabia: most practitioners simply haven't had much direct exposure to AVM tools, or much visibility into how peers use them. In Rogers's (2003) diffusion model, these are exactly the factors that most reliably predict adoption barriers, and their low scores explain the cautious, qualified endorsement seen throughout the survey rather than genuine enthusiasm.

Among the Kanter dimensions, loss of control (E6, $M = 2.92$) sits below the scale midpoint, suggesting practitioners don't widely feel AVM adoption threatens their professional autonomy a more encouraging finding than the strong B3a result on physical inspection might have suggested. Uncertainty about developer communication (E7, $M = 3.31$) confirms AVM providers haven't explained their methodologies well in these markets. And competence (E8, $M = 3.77$, reverse-worded) suggests practitioners feel broadly capable of incorporating AVM output into their workflow given the chance an encouraging sign for technology-supported hybrid practice.

8.2.6 Integration Preferences and Future Outlook (Section F)

Section F asked respondents to identify the most appropriate integration balance between traditional and automated valuation across four property categories; Table 8.6 presents the frequency distribution.

Table 8.6 Section F: Preferred Integration Balance by Property Type (n = 13)

Category	Fully Traditional	Mostly Traditional	Balanced Hybrid	Mostly AVM	Fully Automated
F1: Standard residential (data-rich)	3 (23.1%)	1 (7.7%)	6 (46.2%)	0 (0%)	3 (23.1%)
F2: Atypical / unique residential	3 (23.1%)	3 (23.1%)	5 (38.5%)	1 (7.7%)	1 (7.7%)
F3: Commercial / income-producing	2 (15.4%)	5 (38.5%)	4 (30.8%)	1 (7.7%)	1 (7.7%)
F4: Mortgage (low LTV)	2 (15.4%)	6 (46.2%)	2 (15.4%)	3 (23.1%)	0 (0%)

For standard residential property in data-rich communities (F1), the balanced hybrid model draws the single largest share (46.2%), broadly matching what the literature would predict. Responses get more cautious for atypical residential property (F2): 46.2% favor traditional or mostly traditional practice, recognizing that AVM reliability drops once comparable evidence gets thin. For commercial property (F3), 54% prefer mostly or fully traditional approaches, confirming this asset class is widely seen as unsuited to primary AVM reliance. And the mortgage scenario (F4) shows the highest share of mostly-traditional preferences (46.2%), reflecting the legal accountability mortgage valuations carry and the correspondingly lower tolerance for estimates that can't be fully certified. Together, these results point to a differentiated integration model, one that scales AVM reliance to property type, data richness, and the regulatory weight of the valuation's purpose.

F5 Open Text: Key Conditions for AVM Reliance

Ten substantive open-text responses came in. Thematic analysis identified three clusters:

Theme 1 Data currency and accuracy:

Data quality and recency was the precondition cited most often. Respondents said the AVM must use “accurate and updated data” (R3) and that outputs should be validated against “known units” (R1); one respondent specified the need for “field data collection associated with the property” (R6) all pointing to the same view, that AVM data pipelines need to incorporate current local market evidence.

Theme 2 Model validation:

Three respondents, independently, wanted the AVM “trained and tested to read and analyze input data correctly before giving output” (R5, R10), with “inputs must be verified” (R7) essentially describing an engineering quality assurance framework for AVM deployment.

Theme 3 Methodological appropriateness by asset type:

One respondent noted that commercial properties “need all available historical information surrounding” the subject, while residential units benefit from a “comparable approach with adjustable method” (R9) reinforcing the same property-type differentiation seen across F1–F4.

8.3 Quantitative Findings: AVM vs. Traditional Manual Valuation

8.3.1 Transaction Sample

The quantitative strand draws on nine Abu Dhabi residential units across three districts: Yas Island (four units), Al Saadiyat Island (four units), Al Rahah (one unit). Most units have valuation estimates from three sources: the HTML-based AVM application built for this study, a traditional manual valuation from a qualified practitioner, and, where available, the recorded selling price and/or latest official valuation amount. Table 8.7 presents the full sample.

Table 8.7 Sample Units: Attributes and Valuation Estimates (AED)

#	District	Area m ²	Beds	Sell Price	Official Val.	AVM	Manual Val.
1	Yas Island	165.83	2	2,679,030	2,957,910	2,398,550	2,366,328
2	Yas Island	43.50	Studio	749,982	754,986	660,160	603,989
3	Yas Island	99.85	2	1,241,259	1,959,856	1,633,146	1,567,885
4	Al Saadiyat	149.00	2	—	5,834,840	4,290,402	5,098,542
5	Al Rahah	208.52	4	—	3,873,259	3,133,468	3,098,607
6	Al Saadiyat	89.01	1	1,895,400	2,027,381	3,337,554	3,696,276
7	Yas Island	254.73	4	3,568,500	4,543,619	5,873,928	3,634,895
8	Al Saadiyat	527.53	5	7,641,700	—	16,960,258	6,960,490
9	Al Saadiyat	904.95	5	58,693,540	28,912,570	55,418,552	23,130,057

The sample covers a wide range of unit sizes (43.5 m² to 904.95 m²) and property values (AED 604k to AED 58.7M recorded), spanning studio, one-, two-, four-, and five-bedroom units across three districts a heterogeneity that reflects the diversity of the Abu Dhabi premium residential market and lets the analysis test both overall method performance and how unit complexity and size specifically affect relative accuracy. Seven of the nine units have a recorded selling price, enabling direct market-referenced comparison; the

remaining two (Units 4 and 5) have no recorded sell price and are evaluated against the latest official valuation amount only.

8.3.2 Performance Metrics: Deviation from Recorded Selling Price

Table 8.8 reports the percentage deviation of AVM and manual estimates from the recorded selling price for the seven units with available market evidence, alongside the IAAO assessment ratios (estimate ÷ sell price).

Table 8.8 Deviation Analysis: AVM and Manual vs. Recorded Selling Price (7 units)

Unit	District	AVM Deviation	AVM Ratio	Manual Deviation	Manual Ratio
1	Yas Island	-10.5%	0.895	-11.7%	0.883
2	Yas Island	-12.0%	0.880	-19.5%	0.805
3	Yas Island	+31.6%	1.316	+26.3%	1.263
6	Al Saadiyat	+76.1%	1.761	+95.0%	1.950
7	Yas Island	+64.6%	1.646	+1.9%	1.019
8	Al Saadiyat	+121.9%	2.219	-8.9%	0.911
9	Al Saadiyat	-5.6%	0.944	-60.6%	0.394
Mean	—	+38.0%	1.380	+3.2%	1.032
Median	—	+31.6%	1.316	-8.9%	0.911
Mean Abs. Dev.	—	46.0%	—	32.0%	—

The AVM's mean absolute deviation from the recorded selling price comes to 46.0%, against 32.0% for the manual method meaning the manual valuation lands closer to market evidence on average across this sample. That gap is driven mainly by AVM performance on the larger, more complex properties: for Units 7, 8, and 9 the three largest, at 254.73 m², 527.53 m², and 904.95 m² respectively the AVM's deviations run +64.6%, +121.9%, and -5.6%, against +1.9%, -8.9%, and -60.6% for the manual valuations. The pattern suggests the AVM's gross-area multiplier amplifies error for premium-sized or premium-location properties, where area alone doesn't capture the market premium tied to a specific view, floor level, or amenity access.

For the standard-sized units (1, 2, and 3), the two methods perform comparably mean absolute deviations of 18.0% (AVM) versus 19.2% (manual) suggesting broadly equivalent performance in the standard residential segment. The larger deviations for Units 3, 6, and 7, on both methods, trace mostly to the time gap between the recorded selling price and the valuation date: Unit 3's sell price dates to February 2019 and Unit 7's to

December 2020, both before the significant Abu Dhabi residential price appreciation that took off from 2022 onward. In these cases, both methods are correctly tracking current market conditions rather than an outdated transaction price.

8.3.3 IAAO Statistical Quality Assurance Measures

Table 8.9 presents the IAAO assessment ratio statistics for both methods, computed across the seven units with recorded selling prices.

Table 8.9 IAAO Assessment Ratio Statistics

Measure	AVM	Manual Valuation	IAAO Standard (Residential)
Median Assessment Ratio	1.316	0.911	0.90 – 1.10
Mean Assessment Ratio	1.380	1.032	—
Coefficient of Dispersion (COD)	31.6%	33.7%	≤ 15.0%
Price-Related Differential (PRD)	1.223	1.881	0.98 – 1.03
Mean Absolute Deviation	46.0%	32.0%	—

Neither method clears the IAAO's (2018) residential performance standards on this sample. The AVM's median assessment ratio of 1.316 points to a systematic tendency to overshoot the recorded selling price by roughly 31.6% at the median well outside the acceptable 0.90–1.10 range. The manual valuation's median ratio of 0.911 just clears the lower boundary of that range, suggesting professionally prepared estimates are broadly calibrated to market levels at the median, though the extreme under-assessment of Unit 9 (ratio = 0.394) skews the distribution substantially.

Both methods show COD well above the IAAO's 15% threshold (AVM: 31.6%; Manual: 33.7%), pointing to high dispersion in assessment ratios relative to the median. The AVM's PRD of 1.223 signals some vertical inequity it tends to over-assess relative to selling price particularly for mid-range units (3, 6, and 7), while converging more closely for the highest-value unit (9, ratio = 0.944). The manual method's PRD of 1.881 is inflated by that same extreme under-assessment of Unit 9 (ratio = 0.394), reflecting how hard it is to manually value the largest, most complex asset in the sample.

Note: at nine units, this sample sits well below the IAAO's (2018) recommended minimum of 30 observations for statistically reliable assessment ratio analysis. These results should be read as indicative of performance tendencies and exploratory in nature, consistent with the preliminary character of this strand of the research; their limitations are discussed further in Chapter Nine.

8.4 Hypothesis Testing

The study's main hypothesis and four sub-hypotheses, formally stated in Section 4.3 as H1.1/H0.1 through H1.4/H0.4, are evaluated below based on the combined qualitative and quantitative evidence.

Main Hypothesis

H0: There is no significant difference in valuation accuracy between the AVM application and traditional manual valuation when applied to UAE residential property.

The quantitative evidence provides qualified support for rejecting H0, with the rejection being strongest for larger and more complex properties. For standard residential units (Units 1–3), mean absolute deviations are broadly comparable (AVM: 18.0%; Manual: 19.2%). For larger premium units (Units 6–9), the methods diverge substantially: the AVM's gross-area multiplier produces systematic overestimation for high-value or complex assets, while the manual method demonstrates greater flexibility in applying market-context adjustments though also producing a severe underestimate for Unit 9 (–60.6%). Accordingly, H0 is not rejected for standard residential property but is rejected for complex, large, or premium-location assets.

Sub-Hypotheses

H1.1/H0.1 (Accuracy): Not supported overall, though qualified support emerges for standard residential property. Across the full nine-unit sample, the AVM's mean absolute deviation from recorded selling price (46.0%) is considerably higher than the manual method's (32.0%), driven almost entirely by Units 6–9. For standard-sized units (1–3), the two methods are closely comparable (18.0% versus 19.2%), providing localized support for H1.1 restricted to data-rich, standard property, but not for the sample as a whole.

H1.2/H0.2 (Efficiency): Supported. E1 (M = 4.23) and D1 (M = 3.92) confirm broad practitioner recognition of AVM speed and cost advantages, with E1 recording the second-highest mean score across all 23 Likert items surveyed.

H1.3/H0.3 (Data availability and AVM performance Resource-Based View test): Strongly supported. AVM deviations for Units 7, 8, and 9 (+64.6%, +121.9%, and –5.6% respectively) are substantially larger than for Units 1 and 2 (–10.5% and –12.0%), and 54% of survey respondents favor traditional or mostly traditional approaches for commercial and atypical properties where comparable evidence is thinner. This pattern is consistent with the fundamental limitation of a gross-area multiplier calibrated on project-level data: it cannot capture the property-specific quality differentials that richer, unit-level data or a physical inspection would register. Secondary evidence points the same way: the AVM's Coefficient of Dispersion (31.6%) is only marginally lower than the manual method's (33.7%), and neither meets the IAAO threshold, indicating that data availability constrains both methods similarly once comparable evidence becomes scarce. Qualitatively,

B5 (M = 3.77) confirms moderate concern about inter-valuer inconsistency, reinforcing the data-driven motivation for standardization that underlies the Resource-Based View.

H1.4/H0.4 (Integration): Supported. Hybrid approaches command the largest single-category support for standard residential property (F1: 46.2%), and no property type attracts majority support for full automation. The qualitative themes particularly the prominence of physical inspection (B3a, M = 4.54) and the low trialability and observability scores (E4, E5) further explain why practitioners favor cautious, supervised integration over unilateral AVM reliance, supporting the proposition that combining AVMs with traditional valuation improves overall reliability.

8.5 Integration of Qualitative and Quantitative Findings

Three principal areas of convergence emerge between the survey findings and the valuation comparison.

First, both strands confirm that AVM performance is strongly property-type dependent. The quantitative results show AVM and manual performance converging for small standard units and diverging substantially for larger premium assets. The qualitative survey respondents articulate an equivalent gradient in integration preferences, from hybrid endorsement for standard residential property (F1: 46.2% hybrid) to predominantly traditional preferences for commercial assets (F3: 54% traditional or mostly traditional).

Second, the survey's strongest finding near-universal agreement that physical inspection is essential (B3a, M = 4.54) is directly corroborated by the quantitative evidence. The AVM's largest errors occur precisely for properties where location-specific quality factors (premium views, floor level, amenity access) are most influential but cannot be captured by a project-level price-per-m² rate applied to gross area.

Third, the low trialability (E4, M = 2.62) and observability (E5, M = 2.69) scores from the survey reflect the novelty of systematic AVM application in the Jordan and Saudi Arabia markets. The quantitative comparison itself represents one of the first structured evaluations of AVM accuracy against market evidence in this regional context, and the moderate familiarity distribution (C1) suggests that practitioner reservations reflect limited exposure rather than principled rejection a distinction that has important implications for the technology adoption recommendations developed in Chapter Nine.

8.6 Application of the IAAO Quality Assurance Framework

Table 8.10 consolidates the IAAO quality measures and their interpretation for both methods.

Table 8.10 Consolidated IAAO Quality Assurance Summary

Measure	AVM Result	Manual Result	IAAO Standard	Assessment
Median Ratio	1.316	0.911	0.90–1.10	AVM over-assesses; Manual near lower boundary

Measure	AVM Result	Manual Result	IAAO Standard	Assessment
Mean Ratio	1.380	1.032	—	AVM consistent overestimation; Manual near-neutral
COD	31.6%	33.7%	≤ 15%	Both exceed threshold; high sample heterogeneity
PRD	1.223	1.881	0.98–1.03	AVM mild upward bias; Manual distorted by Unit 9
MAD vs. Sell	46.0%	32.0%	—	Manual closer to market on average

The elevated COD for both methods (AVM: 31.6%; Manual: 33.7%) traces largely to the wide heterogeneity of the nine-unit sample and the time gap between historical selling prices and current valuations. Both findings point the same direction: neither method can be certified against IAAO quality standards for institutional use on this sample, and both would need validation against a larger, more homogeneous dataset with contemporaneous market evidence before any formal assessment-ratio endorsement. The PRD looking worse for the manual method (1.881) than the AVM (1.223) reflects the manual method's severe under-assessment of Unit 9 specifically the most complex, highest-value unit in the sample rather than a systematic bias across the whole population.

8.7 Preliminary Conclusions

This chapter's findings speak to each of the study's five research questions and ground the broader discussion in Chapter Nine. The qualitative survey of thirteen experienced professionals shows AVM adoption attitudes in Jordan, Saudi Arabia, and the UAE shaped by a clear recognition of efficiency advantages, alongside real concerns about data quality, the absence of physical inspection, and very limited hands-on experience trialing or observing AVM tools. The quantitative comparison of AVM and manual valuations for nine Abu Dhabi units shows both methods performing comparably for standard residential property, while the AVM's gross-area multiplier approach introduces larger systematic errors for complex, large, or premium-location assets cases where location-specific quality factors simply can't be captured by a project-level price rate alone.

Together, these findings support a nuanced, differentiated conclusion: the AVM and traditional manual valuation work as complementary instruments, not substitutes for each other. For standard, data-rich residential transactions, the AVM gives an efficient, broadly accurate initial estimate that can meaningfully cut cost and turnaround time, provided it's subject to mandatory professional review. For complex, premium, or atypical assets, the manual method with its capacity for physical inspection and property-specific market adjustment produces estimates that are, on average, closer to recorded market prices and more responsive

to qualitative factors transactional data alone can't capture. The theoretical, practical, and regulatory implications of all this are developed in Chapter Nine.

9. DISCUSSION, CONCLUSION, AND RECOMMENDATIONS

9.1 Introduction

This chapter pulls together everything developed across the thesis the literature in Chapter Two, the theoretical framework in Chapter Three, and the methodology in Chapters Five through Eight to address the research questions and hypotheses introduced in Chapter One and formalized in Chapter Four, and to spell out what this study actually contributes to understanding AVMs within the UAE real estate sector.

The empirical data collection described in Chapter Seven has been completed. Chapter Eight presents the actual findings arising from both strands of the research: a structured survey of thirteen valuation professionals from Jordan, Saudi Arabia, and the UAE, and a comparative analysis of AVM and traditional manual valuations for nine residential units across three Abu Dhabi districts. The present chapter interprets these findings in relation to the literature reviewed in Chapter Two, the theoretical framework developed in Chapter Three, and the research questions and hypotheses introduced in Chapter One and Chapter Four.

Accordingly, the sections that follow evaluate each research question and hypothesis using the collected data, compare the results with the international literature, assess the extent to which the theoretical expectations developed in Chapter Three are supported, and present the study's conclusions, practical implications, recommendations, and limitations.

9.2 Discussion in Relation to the Research Questions

Research Question 1, on the methodological differences between traditional valuation and AVMs, can largely be answered from the literature in Chapter Two and the theoretical framework in Chapter Three, independent of the empirical data. Traditional valuation, as RICS (2022) and the IVSC (2022) define it, is fundamentally a professional process the valuer applies expert judgment through sales comparison, income, or cost approaches to reach a reasoned opinion of value, selecting comparable evidence, making qualitative adjustments, and weighing factors that a structured dataset might never capture. AVMs, by the IAAO's (2018) and IVSC's (2022) definitions, generate estimates through systematic statistical or machine learning techniques applied to previously collected data, ranging from conventional hedonic regression to more advanced ensemble learning and gradient boosting (Kok et al., 2017; Bergadano et al., 2019; Tapia et al., 2025). The real methodological difference, then, isn't about whether data gets used both approaches lean heavily on market information but how it gets interpreted: traditional valuation runs on individualized professional judgment, while an AVM formalizes the relationship between inputs and outputs into a consistent, reproducible computational process.

Research Question 2, concerning the effect of AVMs on valuation accuracy and efficiency relative to traditional valuation methods, is addressed directly by the quantitative comparison reported in Chapter Eight. Kok et al. (2017) reported a median absolute error of approximately 9% for a machine learning AVM applied to multifamily properties in the United States, and Tapia et al. (2025) achieved a Mean Absolute

Percentage Error of approximately 10% using advanced machine learning techniques in the Chilean housing market; both figures are considerably lower than the AVM's own overall mean absolute deviation of 46.0% observed in this study. However, the present findings are not directly comparable to these benchmarks, since both international studies were calibrated on datasets several orders of magnitude larger than the nine-unit Abu Dhabi sample analysed here. Disaggregating the result clarifies the pattern: for the three standard-sized units in the sample (Units 1–3), the AVM and manual method perform comparably, with mean absolute deviations of 18.0% and 19.2% respectively, figures broadly consistent with the accuracy levels reported by Kok et al. (2017) and Tapia et al. (2025) for data-rich, standard property segments. For larger or more complex units (Units 6–9), the AVM's gross-area multiplier approach produces markedly larger deviations, while the manual method supported by physical inspection and property-specific adjustment remains closer to recorded market evidence on average (32.0% mean absolute deviation overall versus 46.0% for the AVM). Efficiency-related survey evidence corroborates the accuracy findings: E1 ($M = 4.23$) and D1 ($M = 3.92$) confirm strong practitioner recognition of the AVM's speed and cost advantages, even where its point-estimate accuracy trails the manual method for complex assets. Taken together, these results indicate that, under UAE market conditions and within the constraints of the achieved sample, AVM performance approaches that of traditional valuation for standard residential property but declines for larger, atypical, or premium-location assets, a pattern consistent with the Resource-Based View developed in Chapter Three.

Research Question 3, which investigates the technological, data-related, and methodological challenges affecting AVM implementation, is addressed extensively within the professional literature reviewed in Chapter Two. The IAAO (2018) identifies data quality, model specification, calibration, and continuous quality assurance as the principal technical requirements for successful AVM development. Similarly, RICS (2022) highlights limitations associated with atypical properties, limited comparable evidence, and inconsistent data quality, while the IVSC (2022) raises broader conceptual concerns regarding whether an automated model can produce a valuation opinion in the professional sense required by international valuation standards. The qualitative findings reported in Chapter Eight confirm that these internationally documented challenges are similarly experienced within the Jordan, Saudi Arabia, and UAE valuation profession: near-universal agreement that physical inspection remains essential (B3a, $M = 4.54$), moderate concern regarding AVM data provenance (D4, $M = 3.69$), and, most notably, very low trialability (E4, $M = 2.62$) and observability (E5, $M = 2.69$) scores, the two lowest of all 23 Likert items surveyed, indicating that limited direct exposure to AVM tools, rather than principled rejection of the technology, is the predominant market-specific barrier to adoption in these markets.

Research Question 4, on the relationship between AVMs and overall valuation quality and reliability, ties closely to the theoretical framework in Chapter Three. Under Data-Driven Decision-Making Theory, valuation quality can't be judged on predictive accuracy alone transparency, auditability, explainability, and the capacity to incorporate qualitative professional judgment all matters too, and RICS (2022) and the IVSC (2022) both stress this consistently. That's why the empirical component here was designed to evaluate both

the numerical agreement between AVM and traditional valuation estimates and practitioners' own perceptions of valuation quality professional confidence in a valuation outcome is about more than statistical accuracy alone.

Research Question 5, which examines how AVMs can be effectively integrated into traditional valuation practice, represents the central practical objective of the present research. Professional literature reviewed throughout Chapter Two consistently advocates a complementary relationship between automation and professional judgment. Guidance published by RICS (2021, 2022), the IVSC (2022), and Renigier-Bițozor et al. (2025) emphasizes that AVMs should enhance rather than replace the role of the professional valuer. This conclusion is further supported by the theoretical framework developed in Chapter Three. The Resource-Based View suggests that the effectiveness of AVMs depends fundamentally on the availability of high-quality market data, while Innovation Theory predicts that adoption will occur progressively in areas where automation demonstrates clear advantages without undermining professional practice. Together, these perspectives suggest that successful implementation is unlikely to involve a single universal workflow. Instead, the appropriate balance between automated analysis and professional judgment is expected to vary according to property type, market conditions, transaction complexity, and data availability. The evidence from Chapter Eight addresses this directly: survey respondents favour a balanced hybrid model most strongly for standard, data-rich residential property (F1: 46.2% balanced hybrid), while preferring predominantly traditional approaches for commercial and income-producing assets (F3: 54% traditional or mostly traditional) and mortgage valuations (F4: 46.2% mostly traditional). The quantitative results confirm this same gradient empirically, with AVM and manual performance converging for standard units and diverging for larger, premium-location, or atypical assets, identifying data richness and property-type complexity as the key determinants of where automated tools and professional expertise are most effectively combined within the UAE property valuation environment.

9.3 Discussion in Relation to the Study Hypotheses

The study's main hypothesis and its four associated sub-hypotheses, introduced in Chapter Four, are evaluated below using the actual empirical evidence reported in Chapter Eight, drawing on the comparative analysis of AVM and manual valuations for nine Abu Dhabi residential units and the structured survey of thirteen valuation professionals from Jordan, Saudi Arabia, and the UAE.

The main hypothesis (H1/H0), which examines whether there is a statistically significant difference between Automated Valuation Models (AVMs) and traditional valuation methods in terms of valuation accuracy, is evaluated using the deviation and assessment-ratio evidence reported in Section 8.3. For standard residential units (Units 1–3), AVM and manual valuations produce broadly comparable mean absolute deviations from the recorded selling price (18.0% versus 19.2%), providing no basis to reject H0 for this segment of the market. For larger, premium, or atypical units (Units 6–9), the two methods diverge substantially, with the AVM recording a considerably higher overall mean absolute deviation (46.0%) than the manual method (32.0%); H0 is therefore rejected for complex, large, or premium-location assets. This differentiated result

rather than a uniform acceptance or rejection of H_0 across the whole sample is itself among the principal substantive findings of the quantitative strand and is consistent with the property-type-contingent view of AVM performance developed throughout this thesis.

Sub-hypothesis H1.1/ $H_{0.1}$, concerning valuation accuracy, is evaluated using the IAAO assessment-ratio statistics reported in Section 8.3.3. Neither method satisfies the IAAO (2018) residential performance thresholds on this sample: the AVM's Coefficient of Dispersion of 31.6% and the manual method's 33.7% both exceed the 15% ceiling, and both methods' Price-Related Differentials (1.223 and 1.881 respectively) fall outside the 0.98–1.03 acceptable range. $H_{0.1}$ is therefore not rejected in the strict IAAO sense for either method, although the manual method's median assessment ratio (0.911) lies closer to the acceptable 0.90–1.10 range than the AVM's (1.316). Both results are qualified by the small sample size, discussed further in Section 9.6.

Sub-hypothesis H1.2/ $H_{0.2}$, relating to valuation efficiency, is supported by the qualitative evidence reported in Section 8.2: E1 ($M = 4.23$), the second-highest mean score among all 23 Likert items surveyed, and D1 ($M = 3.92$) confirm broad practitioner recognition that AVMs deliver meaningful time and cost savings relative to traditional valuation, even where, as shown above, their point-estimate accuracy trails the manual method for complex assets.

Sub-hypothesis H1.3/ $H_{0.3}$, which examines the relationship between data availability and AVM performance and provides the most direct empirical test of the Resource-Based View developed in Chapter Three, could not be evaluated in its originally envisaged form. As explained in Section 7.4.5, the implemented AVM application adopts a transparent, project-level price-per- m^2 approach rather than the multi-tier, regression-calibrated variable structure originally proposed, so the planned comparison of predictive performance across base, market, and enrichment variable tiers was not possible. Related evidence nonetheless bears on the same underlying proposition: the pattern documented in Section 8.3, whereby AVM accuracy is closely comparable to the manual method for standard, data-rich units but deteriorates markedly for larger, atypical, or premium-location units where a single project-level rate cannot capture property-specific quality differentials, provides indirect support for the Resource-Based View's central claim that AVM effectiveness depends primarily on the richness and specificity of the underlying data rather than on calibration technique alone.

Sub-hypothesis H1.4/ $H_{0.4}$, concerning the integration of Automated Valuation Models with traditional valuation practice, is supported by the combined interpretation of the quantitative and qualitative findings. Hybrid approaches command the largest single-category support for standard residential property (F1: 46.2% balanced hybrid), and no property type attracts majority support for full automation, while the prominence of physical inspection (B3a, $M = 4.54$) and the low trialability and observability scores (E4, E5) further explain why practitioners favour cautious, supervised integration over unilateral AVM reliance. This triangulation

confirms that integration is regarded as both statistically sensible, given the accuracy patterns reported above, and practically acceptable to valuation professionals operating within the UAE market.

Collectively, the testing of these hypotheses provides the empirical mechanism through which the theoretical expectations developed in Chapter Three are evaluated. The results indicate that the proposed relationships between data quality, professional judgment, valuation accuracy, operational efficiency, and hybrid valuation practice are supported within the UAE context in a differentiated, property-type-contingent form rather than as a uniform verdict favouring either method, thereby addressing the principal objectives of the present research.

9.4 Discussion in Relation to the Workflow Comparison

One notable contribution here is the detailed comparison of the traditional and automated workflows reconstructed in Chapters Five and Six. Setting Table 5.1 against Table 6.1 surfaces something the literature in Chapter Two only addresses implicitly: the main difference between traditional valuation and AVMs isn't really how much professional judgment gets applied, but at what stage of the process it gets applied.

In traditional valuation, judgment is spread across the whole workflow. Valuers exercise discretion defining the scope of work, inspecting the property, selecting and adjusting comparable evidence, choosing the valuation approach, reconciling different value indications, and writing the final report and since the whole workflow repeats independently for every assignment, that judgment gets applied continuously, property by property.

An AVM, by contrast, concentrates most of its judgment during model development. Decisions on data selection, variable specification, market stratification, calibration technique, and quality assurance all get made once, during construction, by the analysts and developers building the model. Once those decisions are baked in, applying the AVM operationally needs comparatively little case-specific intervention, especially in a fully automated setup so professional expertise shifts from repeated per-valuation judgment toward designing, calibrating, validating, and governing the model itself.

That has real practical implications for integrating AVMs into professional practice. Rather than asking generically how much human review an AVM needs, the workflow comparison points to a sharper question: at which stage of the process does professional judgment actually add the most value? The answer will likely differ by the valuation's purpose, the data available, and how automated the process already is.

Seen this way, the IAAO's (2018) AVM typology Preliminary Data, Interactive Valuation Application, Repetitive, Blended or Cascading, Research reads less as a set of different computational techniques and more as different ways of positioning professional judgment within the automated process, distinguished mainly by how much human involvement there is and when it happens.

This also sharpens the IVS discussion from Section 2.4. The IVSC (2022) distinguishes a valuer who just reviews or validates an AVM output after the fact from one who exercises real professional judgment during the process itself and only the latter, in the IVSC's view, produces a valuation opinion that actually meets IVS requirements.

Read alongside the IAAO's typology, this suggests the Interactive Valuation Application AVM where the valuer actively reviews, evaluates, and where needed modifies the output sits much closer to an IVS-compliant valuation than a Preliminary Data AVM, where the estimate might just get accepted with minimal professional intervention. What matters isn't whether an AVM gets labeled “hybrid” or “valuer-assisted” it's whether real professional judgment stays an integral part of the process.

For valuation firms, financial institutions, and regulators in the UAE, this has real governance implications. Policy on AVM use should focus less on whether human involvement exists at all, and more on its nature, timing, and substance making sure professional judgment gets applied at the stages of the process where it does the most for valuation quality, regulatory compliance, and accountability. That's consistent with the broader complementarity framework running through this thesis: AVMs as decision-support tools that enhance professional expertise, not replace it.

9.5 Contribution of the Study

Grounded in the completed qualitative survey and quantitative valuation comparison reported in Chapter Eight, the thesis makes contributions at the academic, theoretical, and practical levels.

On the academic side, this study addresses a gap that runs throughout Chapter Two. Plenty of international research evaluates AVM predictive performance, but comparatively little sets AVMs against traditional professional valuation within one unified professional standards framework and the UAE is genuinely underrepresented in that literature, which leans heavily on markets like the United States, Italy, and Chile. Building a comparative framework specifically for the UAE gives future empirical work a foundation in a region that differs substantially in market maturity, data availability, and regulatory structure.

On the theoretical side, this study integrates Innovation Theory, the Resource-Based View (RBV), and Data-Driven Decision-Making Theory into one framework explaining both AVM adoption and AVM performance. Rather than treating technology adoption, data quality, and valuation quality as separate research streams, the framework shows how they actually complement each other in explaining why AVMs perform differently across markets and why adoption moves at different speeds across professional settings. As far as the author is aware, these three theoretical perspectives haven't previously been combined this way for a comparative study of traditional valuation and AVMs.

Practically, the research is meant to generate evidence that helps valuation professionals, financial institutions, regulators, and policymakers in the UAE make better-informed decisions offering locally

grounded guidance on when AVMs can be deployed effectively, what limitations need recognizing, and what governance arrangements keep automated valuation consistent with professional standards.

The theoretical contribution goes beyond simply stacking existing theories together. Innovation Theory has traditionally explained technology adoption mostly through Rogers's (2003) diffusion attributes relative advantages, compatibility, complexity. This thesis sharpens that picture by folding in Kanter's (1995) more granular account of organizational resistance, treating loss-of-control resistance, uncertainty-driven resistance, and competence-anxiety resistance as analytically distinct mechanisms. That gives a more nuanced read on how professionals respond to AVM adoption different kinds of resistance call for different organizational interventions, not one generic strategy for winning people over.

The Resource-Based View also gets extended beyond its conventional use in strategic management. Rather than treating competitive advantage as something built purely from resources an individual firm owns, this study treats the broader market data ecosystem transaction databases, geographic information systems, cadastral infrastructure, administrative data quality as the real strategic resource behind AVM performance. In automated valuation, performance depends not just on proprietary algorithms but on how mature and reliable the surrounding market-wide information infrastructure actually is, much of which no single organization controls on its own. That's a useful theoretical explanation for the considerable variation in AVM performance the international literature reports across different countries.

Another contribution comes from the workflow-based comparison in Chapters Five and Six. Reconstructing both processes in procedural detail shows that the real difference between traditional valuation and AVMs isn't really how much professional judgment gets applied overall, but where it gets applied. Traditional valuation spreads judgment across every stage of an individual assignment; an AVM concentrates it during model design, calibration, and governance, before applying the finished model to large numbers of properties. That workflow lens gives a more operational handle on integration than the broader idea of "complementarity" that shows up so often in the professional literature.

Building on that workflow analysis, the study further distinguishes between different forms of human involvement in AVM-supported valuation by linking the IAAO's (2018) workflow classifications with the IVSC's (2022) requirements for a compliant valuation opinion. What matters, this comparison suggests, isn't simply whether a human reviews an automated valuation, but the timing, nature, and substance of that involvement giving a practical basis for deciding where professional judgment should sit within an automated workflow to satisfy both efficiency goals and international valuation standards.

Finally, the thesis makes a conceptual contribution through how it treats transparency. Rather than treating transparency as one single characteristic of an AVM, it develops a multidimensional framework covering access, availability, quality, and objectivity of information letting concerns usually lumped together under "AVM transparency" get analyzed separately. Within that framework, better data availability needs investment in market information infrastructure; better data quality needs robust verification and quality

assurance; better access depends on the right institutional data-sharing arrangements; and preserving objectivity depends on governance that keeps genuine professional oversight in place. Separating these dimensions gives a more structured way of understanding transparency as a set of related but distinct governance challenges, each needing its own institutional and regulatory response rather than one universal fix.

9.6 Limitations of the Study

Several limitations are worth acknowledging here not because they diminish the value of the study, but because they mark the boundaries within which its conclusions should be read and point toward useful directions for future research.

The principal limitation of the quantitative strand is the small sample size of nine residential units, substantially below the IAAO (2018) minimum of 30 observations recommended for statistically reliable assessment ratio analysis. As noted in Section 8.3.3, neither the AVM nor the manual valuation satisfies the IAAO's Coefficient of Dispersion or Price-Related Differential thresholds on this sample, and both sets of results should accordingly be treated as indicative and exploratory rather than as a definitive validation or rejection of either method's compliance with professional performance standards.

A second limitation concerns the qualitative component of the study. The achieved survey sample of thirteen respondents is consistent with established guidance regarding thematic saturation in qualitative research and is appropriate for generating rich professional insights; however, it is not intended to provide statistical representation of the wider population of valuation professionals across Jordan, Saudi Arabia, and the UAE. The sample is also geographically uneven, with Jordan and Saudi Arabia together accounting for 92.3% of respondents and the UAE itself, the market at the centre of the quantitative strand, contributing only a single respondent. Accordingly, the qualitative findings should be interpreted as providing depth of understanding regarding regional practitioner perspectives rather than statistically generalizable, UAE-specific conclusions.

The quantitative sample of nine residential units, while sufficient to illustrate the comparative methodology and to reveal a clear property-type gradient in relative performance, encompasses only three Abu Dhabi districts and remains substantially smaller than the datasets employed in several international studies reviewed in Chapter Two. For example, Kok et al. (2017) calibrated their models using approximately 54,000 multifamily properties, and the AVM application itself draws on a 3,609-record Jordanian dataset for its underlying price-per-m² calibration, even though only nine units were available for the direct AVM-versus-manual comparison reported in Chapter Eight. Consequently, the comparative performance results reported in this study should be interpreted cautiously, particularly the finding that AVM accuracy declines for larger and premium-location units, which rests on evidence from only four such units (Units 6–9) and would benefit from replication using a larger, more homogeneous sample of 30 to 100 units within a single district to enable more statistically robust IAAO ratio analysis.

This limitation is reinforced by the data sufficiency guidance provided by the IAAO (2018), which recommends a minimum ratio of five observations for every independent variable included within a regression model, with fifteen observations per variable considered preferable. As discussed in Section 7.4.5, this guidance was one of the considerations that led to the implemented application adopting a single, project-level price-per-m² calculation rather than the originally envisaged multi-variable regression specification, since a nine-unit comparison sample could not, in any case, have supported reliable estimation of a multi-variable model. Future work with an expanded transaction sample could revisit the originally proposed regression-based specification on a more statistically defensible basis.

Another limitation relates to the design of the HTML-based AVM application itself. The application adopts a gross-area price-per-m² approach specifically to maximize methodological transparency, interpretability, and reproducibility, in preference to the multiple regression specification originally envisaged and discussed in Section 7.4.5. While this design choice aligns closely with the objectives of the present research, it is inherently less sophisticated than both a fitted regression model and the more advanced machine learning architectures employed in recent studies, including gradient boosting, random forests, deep learning, and image-enhanced models such as those developed by Tapia et al. (2025). This is precisely the trade-off documented empirically in Chapter Eight: a single project-level rate cannot capture the property-specific quality differentials that a fitted model or a physical inspection would register, which is the principal reason the AVM's deviations widen for larger and premium-location units. Consequently, the predictive performance of the application should not be interpreted as representing the maximum capability of contemporary AVM technology. Instead, it should be understood as providing a transparent and academically reproducible benchmark against which traditional valuation methods can be compared.

The reliance on a single, deterministic project-level rate also introduces its own methodological constraint, distinct from the regression-based limitations originally anticipated in Section 7.4.6. Because the rate is fixed at the project level, it cannot flexibly accommodate within-project variation driven by floor level, view, or unit-specific finishes, and may struggle to capture highly nonlinear relationships between property characteristics and value unless these are captured through the comparable-property ranking mechanism described in Section 7.4.4. As noted by the IAAO (2018), more flexible regression or machine learning approaches can accommodate complex nonlinear relationships more effectively, although they often do so at the expense of the transparency this study prioritized.

The scope of the research limits how far its findings generalize. The study focuses exclusively on the UAE, with empirical analysis centered on market conditions during the study period. Property markets move fast, the UAE's especially, given the substantial growth in transaction volumes and values documented in recent years so an AVM calibrated on data from one period could well see its predictive performance decline if applied to meaningfully different market conditions without recalibration. That's consistent with the IAAO's (2018) own guidance that AVM performance needs continuous monitoring, since calibration samples grow steadily less representative in a dynamic market.

There's also a contextual limitation tied to the UAE market's distinctive structure. Unlike many of the international markets covered in the literature, where AVM development has historically been driven by mortgage lending, UAE property transactions are predominantly cash-financed. As Chapter One discusses, that likely shapes both practitioner attitudes toward AVMs and the institutional contexts automated valuation gets deployed in so adoption patterns observed in the UAE may not match those reported in more mortgage-dependent jurisdictions, and direct international comparisons should be made carefully.

Finally, it's worth remembering that AVMs themselves keep evolving quickly. Advances in artificial intelligence, computer vision, geospatial analytics, explainable AI, and increasingly comprehensive property datasets will likely push AVM capability beyond what's reflected in the literature reviewed here. So, these findings should be read as capturing where AVM development in the UAE currently stands, not as a permanent verdict on the technology's long-term capability continued research will be needed as both the technology and the UAE property market keep developing.

9.7 Recommendations

9.7.1 Recommendations for Practice

Grounded in the completed empirical findings reported in Chapter Eight, together with the literature and theoretical framework developed throughout this thesis, the following recommendations are proposed for real estate professionals and institutions operating in the UAE market. Valuation firms and financial institutions should consider structuring AVM deployment around the data-richness principle highlighted by the Resource-Based View (Section 3.3.2): prioritizing automated valuation for property types and market segments with dense, well-documented transaction histories, while reserving traditional, judgment-led valuation for atypical properties or thinly traded segments, consistent with the practitioner guidance articulated in the RICS Insight Paper (2022). Institutions adopting AVM platforms should also invest in the kind of methodological transparency that this thesis's own HTML-based calculator was designed to model, ensuring that valuation professionals retain the ability to inspect and understand the basis of automated outputs rather than treating them as opaque, authoritative figures directly addressing the concern documented by RICS (2022) regarding valuers' limited visibility into commercial AVM platforms.

A further practice recommendation follows directly from the IVS compliance distinction discussed in Section 9.4: institutions should check their internal AVM governance policies to confirm that anything labeled “valuer-assisted” or “hybrid” genuinely involves the valuer applying substantive judgment to the AVM's output, rather than just validating or rubber-stamping a number the model already produced. Given the IVSC's (2022) explicit position that validation-only review doesn't count as an IVS-compliant valuation, any institution relying on AVM-assisted workflows where IVS compliance is expected certain mortgage lending or

financial reporting contexts among them should audit its workflows against this specific distinction, rather than assuming a human reviewer's mere presence is enough.

A third recommendation concerns the self-generation risk from Section 2.5.3: institutions building or commissioning AVM tools for the UAE market should make it a matter of internal data governance policy that comparable transaction data feeding any such model comes from genuine, independently verified market transactions rather than previous AVM outputs the same safeguard this thesis's own methodology adopts in Section 7.5.2. As AVM-derived estimates become more widely available through consumer platforms like Bayut's TruEstimate™ (Bayut, 2024) and other emerging UAE PropTech offerings, the risk of these estimates getting inadvertently treated as market evidence in later modeling is likely to grow rather than shrink this deserves proactive governance attention now, not a reactive fix later.

These three recommendations connect directly to several of the nine FIG Commission 9 recommendations summarized in Table 2.2. The first, structuring AVM deployment around data richness, extends FIG Recommendation 2 (high data quality standards) into a specific, property-type-contingent deployment policy. The second, auditing the substance of human review in hybrid workflows, turns FIG Recommendation 1 (embracing AI as complementary rather than substitutive) into a concrete, auditable governance criterion. The third, guarding against self-generating data, extends FIG Recommendation 2's data quality concern into the specific UAE PropTech context this thesis examines. UAE institutions wanting a fuller practice-level framework may want to consult the full nine-recommendation set directly several remaining items, continuous model monitoring (Recommendation 5), collaboration between valuers and technologists (Recommendation 6), and investment in professional development (Recommendation 8) among them, speak to the organizational and human-capital side of AVM adoption that sits somewhat outside this thesis's primary focus on valuation-quality comparison, but complements the practice recommendations developed here naturally enough.

9.7.2 Recommendations for Policy and Regulation

The findings here suggest several recommendations for the regulatory authorities and professional organizations overseeing valuation practice in the UAE.

First, UAE regulatory bodies and professional associations should consider building locally tailored guidance for AVM governance. The IAAO (2018), RICS (2021, 2022), and IVSC (2022) standards provide a valuable international foundation, but they were built mainly for markets with different regulatory environments, property information systems, and financing structures. A UAE-specific framework should build on that international foundation while adapting it to the country's own institutions, property data infrastructure, licensing framework, and market characteristics.

That guidance should spell out clearly when AVM-generated valuations are appropriate for different professional applications. Rather than one universal policy, regulators could set risk-based guidance that differentiates valuation purposes by the consequences of getting it wrong following the usage patterns the

Saïd Business School (2022) report documents, leaning more on AVMs where the stakes are lower, while transactions carrying higher financial or regulatory risk keep requiring more extensive professional involvement.

The UAE property market's distinctive structure also deserves specific regulatory attention. As this thesis has discussed throughout, property transactions in Abu Dhabi and Dubai are predominantly cash-funded, quite different from many international markets where AVM development has historically been driven by mortgage lending. Governance frameworks built mainly around mortgage-oriented valuation systems may not transfer directly to the UAE without adjustment regulatory guidance should recognize that local AVM applications may lean more heavily toward portfolio valuation, taxation, market monitoring, and investment analysis, and institutional decision-making than toward mortgage underwriting alone.

Another important recommendation concerns clarifying the IVS compliance status of AVM-assisted valuations in the UAE. Since professional valuation practice here draws on both the IVS and the RICS Global Standards, local regulators and professional bodies would do well to issue explicit guidance on when AVM-supported valuations satisfy professional requirements clarifying the IVSC's (2022) distinction between substantive professional judgment and mere validation of an automated output. Clear expectations on how much professional review different valuation contexts need would improve consistency across the profession and give valuation firms, financial institutions, auditors, and market participants more certainty.

Finally, regulatory frameworks should push for transparent governance and accountability in how AVMs get deployed. Institutions using AVMs should be expected to document the data sources, calibration procedures, quality assurance measures, confidence metrics, and professional review processes behind their valuation outputs governance practice that would strengthen confidence in automated valuation technology while keeping its development consistent with internationally recognized standards and the specific needs of the UAE real estate market.

9.7.3 Recommendations for Future Research

The most immediate direction for future research is the expansion of the empirical work undertaken within this thesis. The nine-unit quantitative sample and thirteen-respondent survey reported in Chapter Eight are sufficient to reveal a clear property-type gradient in relative AVM performance, but a larger, IAAO-compliant sample of 30 to 100 residential units within a single Abu Dhabi district, together with a UAE-weighted expert sample, would allow the research questions and hypotheses developed in this thesis to be re-evaluated with considerably greater statistical confidence and to support formal assessment-ratio certification of either method.

Beyond that immediate priority, several other research directions follow from this study. Future work could extend the comparative framework here beyond residential property into commercial, industrial, hospitality, and mixed-use real estate, where valuation complexity, market dynamics, and data availability all look quite

different giving a broader picture of how AVMs perform across the different segments of the UAE real estate market.

Future studies should also test more advanced AI and machine learning techniques against larger UAE-specific datasets. The HTML-based multiple regression model built for this research was chosen deliberately for its transparency and interpretability, but a bigger dataset would allow comparison against more sophisticated approaches gradient boosting, random forests, deep neural networks, spatial machine learning, computer vision, image-enhanced valuation models along the lines of Tapia et al. (2025) to see how much additional algorithmic sophistication actually improves predictive performance under UAE market conditions.

Longitudinal AVM adoption is another area worth investigating. As technology, the regulatory frameworks, and the property data infrastructure keep evolving, practitioner attitudes and organizational adoption patterns will likely shift to a longitudinal study would show how acceptance, trust, governance practice, and professional roles change over time as automated valuation becomes more embedded in professional practice.

The workflow-based framework developed in Chapters Five and Six could also be applied well beyond residential valuation. Future research could use the same workflow comparison approach for other real estate processes where automated analysis and professional judgment interact property registration, building data management, digital cadastral systems, valuation quality assurance, property taxation, and related administrative processes within the UAE's evolving digital real estate ecosystem contributing to a broader understanding of how automation gets integrated responsibly into professional real estate practice while keeping accountability and regulatory compliance intact.

Another promising direction is bridging technical AVM research and professional valuation practice more directly. This thesis has shown that the academic literature on predictive modeling and the professional literature on valuation governance have largely developed on separate tracks. Future research could close that gap by pairing advanced technical model development with direct participation from practicing valuers, regulators, lenders, and industry stakeholders throughout the research process collaboration that would strengthen both the practical relevance of technical AVM research and the evidence base professional valuation organizations draw on when developing future guidance and standards.

Finally, future research should keep exploring Explainable Artificial Intelligence (XAI) in property valuation. As Chapters Two and Three discuss, making automated valuation models more transparent and interpretable has become an increasingly important research priority studying how explainability techniques affect practitioner trust, regulatory acceptance, model governance, and valuation decisions would be a valuable extension of the framework developed here, and would support responsible AI adoption within the real estate profession more broadly.

9.8 Concluding Remarks

Discussion of AVMs often gets framed as a choice between professional expertise and technological automation, as if one is destined to replace the other eventually. The evidence in this thesis, together with the theoretical framework in Chapter Three, points to a more balanced conclusion. Traditional valuation and AVMs aren't really competing alternatives, their complementary approaches whose relative effectiveness depends on the market data available, the property being valued, and the purpose of the valuation. Given that, the real question isn't whether automation should replace professional judgment, but how the strengths of both can be combined to improve valuation quality, consistency, and efficiency.

One striking thing to come out of the literature review is how consistently the major international standard-setting bodies actually agree. The IAAO, RICS, and IVSC developed their guidance independently, for different professional contexts, yet they converge on much the same fundamental principles: AVMs offer real benefits in efficiency, scalability, and analytical consistency, but those benefits depend on high-quality data, robust governance, transparent methodology, and genuine professional oversight. Across all three frameworks, human expertise isn't treated as obsolete it's treated as essential to responsible valuation practice.

Building on that international consensus, one of this thesis's main contributions is the workflow-based comparison in Chapters Five and Six. Rather than judging traditional valuation and AVMs purely on their final outputs, the research reconstructs each process step by step and shows that the real distinction between them is where professional judgment gets applied. Traditional valuation embeds judgment throughout every stage of an individual assignment; an AVM concentrates most of that judgment during model design, calibration, validation, and governance, before it's applied to individual properties. That's a more operational way of understanding integration than the broad idea of "complementarity" that shows up so often in the professional literature, and it gives a practical framework for identifying where professional expertise actually adds the most value within an automated process.

Within the UAE context, this thesis gives a structured foundation for understanding how AVMs might be introduced in a way that reflects both international best practice and local market conditions. The integrated theoretical framework, the comparative workflow analysis, the transparent HTML-based valuation application and its accompanying survey instrument, together with the completed nine-unit valuation comparison and thirteen-respondent survey reported in Chapter Eight, give an evidence-based foundation for the larger-scale future empirical work outlined in Section 9.7.3.

More broadly, this research argues that the future of property valuation shouldn't be framed as a contest between human valuers and automated systems. It's better understood as an ongoing process of designing valuation workflows that combine the analytical strengths of data-driven technology with the contextual understanding, professional judgment, ethical responsibility, and accountability that valuation practice still depends on. Getting that balance right will take continued investment in data quality, transparent model

development, appropriate regulatory oversight, and professionals equipped to work alongside increasingly sophisticated valuation technology.

Ultimately, the empirical findings reported in Chapter Eight reinforce rather than overturn the central argument advanced throughout this thesis. The most effective valuation systems are unlikely to be those that rely exclusively on either automation or professional judgment. Rather, they will be those that integrate both approaches within a carefully designed governance framework that recognises the strengths and limitations of each, adapts to the characteristics of the market in which they operate, and preserves the professional accountability that underpins confidence in valuation practice. It is this balanced, context-sensitive perspective that this thesis offers as its principal contribution to the continuing development of Automated Valuation Models within the real estate profession.

10. References

Băbțan, S.-I. (2020). Automated valuation model for residential real estates. EasyChair Preprint No. 2780.

Bayut. (2024). TruEstimate™ property valuation tool. Retrieved from <https://www.bayut.com/property-market-analysis/tru-estimate/>

Bergadano, F., Bertilone, R., Paolotti, D., & Ruffo, G. (2019). Learning real estate automated valuation models from heterogeneous data sources. arXiv preprint arXiv:1909.00704.

International Association of Assessing Officers (IAAO). (2018). Standard on Automated Valuation Models (AVMs). Kansas City, MO: IAAO.

International Valuation Standards Council (IVSC). (2022). Automated valuation models: Perspectives paper. London: IVSC.

International Valuation Standards Council (IVSC). (2022). Automated valuation models: Perspectives paper (print edition). London: IVSC.

Jafari, P., Shojaei, D., Rajabifard, A., & Ngo, T. (2024). Automated land valuation models: A comparative study of machine learning and deep learning methods based on influential factors. *Cities*, 151, 105115.

Kok, N., Koponen, E., & Martínez-Barbosa, C. A. (2017). Big data in real estate? From manual appraisal to automated valuation. *Journal of Portfolio Management*, 43(6), 202–211.

Renigier-Bițozor, M., Ache, P., et al. (2019). Automated valuation models in real estate appraisal: Methodological developments and practical implications. FIG Working Week Conference Proceedings.

Royal Institution of Chartered Surveyors (RICS). (2021). Automated valuation models: Roadmap for RICS members and stakeholders. London: RICS.

Royal Institution of Chartered Surveyors (RICS). (2022). RICS valuation – Global standards (Red Book). London: RICS.

Royal Institution of Chartered Surveyors (RICS). (2022). RICS valuation – Global standards (Arabic translation). London: RICS.

Royal Institution of Chartered Surveyors (RICS). (2022). Automated valuation models: Industry insights report. London: RICS.

Tapia, J., Chavez-Garzon, N., Pezoa, R., Suarez-Aldunate, P., & Pilleux, M. (2025). Comparing automated valuation models for real estate assessment in the Santiago Metropolitan Region using machine learning algorithms and hedonic pricing. PLOS ONE, 20(3), e0318701.

Abu Dhabi Real Estate Centre. (2025). Abu Dhabi real estate market report 2025.
https://adrec.gov.ae/en/Market_Reports

Abu Dhabi Real Estate Centre. (2026). Abu Dhabi Real Estate Centre releases 2025 real estate performance numbers, with a record AED 142 billion in transactions recorded across the market.
<https://adrec.gov.ae/en/news/news-item-1---abu-dhabi-real-estate-centre-releases-2025-real-estate>

Dubai Land Department. (2024). Dubai's real estate sector recorded AED761 billion in transactions in 2024.
<https://dubailand.gov.ae/en/news-media/dubai-s-real-estate-sector-records-aed761-billion-in-transactions-in-2024>

Dubai Land Department. (2025). Dubai real estate transactions exceed AED431 billion in H1 2025.
<https://www.mediaoffice.ae/en/news/2025/july/20-07/dubai-real-estate-transactions-exceed-aed431-billion-in-h1-2025>

Financial Action Task Force. (2014). Transparency and beneficial ownership [Guidance]. <https://www.fatf-gafi.org/en/publications/Fatfrecommendations/Transparency-and-beneficial-ownership.html>

Global Property Guide. (2026). United Arab Emirates' residential property market analysis 2026.
<https://www.globalpropertyguide.com/middle-east/united-arab-emirates/price-history>

Jefferies, S. (2017). Real estate investment valuation: A historical perspective. Royal Institution of Chartered Surveyors.

Kok, N., Koponen, E.-L., & Martínez-Barbosa, C. A. (2017). Big data in real estate? From manual appraisal to automated valuation. The Journal of Portfolio Management, 43(6), 202–211.
<https://doi.org/10.3905/jpm.2017.43.6.202>

11. Appendices

11.1 APPENDIX A: SURVEY INSTRUMENT

The structured survey instrument described in Section 7.4.1 (summarized in Table 7.1) was originally designed as a standalone Excel workbook, “AVM_Research_Survey-V6_0.xlsx”, accompanying this document. The workbook contains ten worksheets: a List sheet holding the dropdown reference values used for data validation; an Instructions cover sheet; Section A (Respondent Profile); Section B (Traditional Valuation Practice); Section C (AVM Awareness and Use); Section D (Perceived Advantages and Disadvantages of AVMs, drawn directly from the RICS, 2021, Roadmap taxonomy discussed in Section 2.5.2); Section E (Adoption Attitudes, operationalizing Rogers's, 2003, Innovation Theory diffusion attributes and Kanter's, 1995, resistance dimensions as discussed in Sections 3.2.2 and 3.2.3); Section F (Integration and Future Outlook); a Summary sheet that automatically calculates mean Likert scores and other descriptive results as responses are entered; and a Multi-Respondent Data sheet for aggregating completed responses across the full survey sample.

For actual data collection, the same question set, section structure, and response scales were reproduced as an online Google Form, which is the version referenced as the data collection instrument in Section 7.4.1. Administering the survey online rather than through the Excel workbook made it possible to reach respondents across Jordan, Saudi Arabia, and the UAE without requiring them to install or return a spreadsheet file, while preserving the exact item wording, Likert scales, and skip logic built into the original Excel design. Every closed-ended item in the Excel workbook uses data validation to constrain responses to the defined scale or category list, and every analytical formula in the Summary sheet has been verified to produce zero calculation errors, including for the blank, not-yet-completed template. The thirteen completed responses collected through the Google Form are provided separately as raw response data in Appendix D.

11.2 APPENDIX B: HTML-BASED AVM APPLICATION

The purpose-built Automated Valuation Model application described in Section 7.4.4 is provided as a standalone file, “AVM_Application_V9_0.html”, accompanying this thesis. The application is a fully self-contained HTML file that runs in any modern web browser without installation, an internet connection, or server-side processing, and embeds the complete 3,609-record transaction dataset described in Section 7.4.4 in compressed form.

The file implements the two-screen workflow described in Section 7.4.4: a Property Input Screen using nine cascaded dropdown menus (Municipality, City, Neighborhood, Community, Project, Land Number, Building Number, Floor Number, Unit Number) to identify the subject property, and a Valuation Result Screen that calculates the estimated market value as $\text{Gross Area} \times \text{Calculated Price per m}^2$, generates a confidence score, ranks comparable properties using the weighted similarity scoring system set out in Table 7.X+1, and allows the result to be exported as a PDF valuation certificate. An Excel Upload facility also allows the embedded dataset to be replaced with an alternative transaction database in the same column format, so the same

application can, in principle, be re-applied to other markets or time periods without modifying the underlying code.

11.3 APPENDIX C: SAMPLE VALUATION RESULTS DATASET

The dataset underlying the quantitative comparison presented in Section 8.3 (Tables 8.7 through 8.10) is provided as “AVM_Vs_Manual_Sample_Result_V2_0.xlsx”, accompanying this thesis. The workbook records the nine Abu Dhabi residential units evaluated in this study, drawn from Yas Island, Al Saadiyat Island, and Al Rahah, together with each unit's district, unit area, number of bedrooms, last recorded selling price, latest official valuation amount and date, the HTML-based AVM application's estimated value, and the corresponding traditional manual valuation.

This is the source data from which the deviation percentages, IAAO assessment ratios, and quality assurance statistics (COD, PRD, PRB) reported in Section 8.3 were calculated, and it is provided so that these calculations can be independently verified or extended.

11.4 APPENDIX D: SURVEY RESPONSE DATA

The raw responses collected through the online Google Form survey described in Section 7.4.1 and Appendix A are provided as “AVM_vs__Traditional_Valuation-Research_Survey__Responses_V2_0.xlsx”, accompanying this thesis. The workbook contains thirteen completed responses across the thirty-eight substantive survey questions spanning Sections A through F, together with a timestamp for each submission. Consistent with the bilingual design of the survey instrument, each question column header is recorded in both English and Arabic.

This file is the underlying dataset for the demographic profile reported in Table 8.1 and the Likert-scale results reported in Tables 8.2 through 8.6 in Section 8.2, and is provided so that the descriptive statistics reported in Chapter Eight can be independently verified.