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The Role of Artificial Intelligence in Optimizing Real Estate Services

Sayed Faisal Sayed Asemi

Master’s degree in management of services and technology

Supervisor
PhD, Henrique José da Rocha O'Neill, Associate Professor with Habilitation,
Iscte-IUL

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BUSINESS
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Department of Marketing, Strategy, and Operations

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On a personal level, I dedicate this thesis to the people who made this journey possible through their love and support:
To my mother, for her love, sacrifice, and unconditional prayers; all that I achieve is based on her strength.
To my brother, Rafi, for believing in me, encouraging me to study, and motivating me to get this degree.
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RESUMO

Esta pesquisa explora como a Inteligência Artificial está a elevar os serviços imobiliários, a otimizar a avaliação de imóveis, a prever a rentabilidade e a fornecer insights baseados em dados para a previsão do mercado. Ao utilizar modelos baseados em IA, os agentes imobiliários e os investidores podem tomar decisões mais precisas, eficientes e estratégicas para reduzir o risco e melhorar a qualidade global do serviço. Este estudo visa avaliar as capacidades da IA na análise imobiliária, a sua integração com ferramentas digitais existentes e o seu potencial para remodelar as práticas do setor. Com base numa revisão sistemática da literatura orientada pelo PRISMA e numa abordagem de Design Science Research, a tese desenvolve uma estrutura global de apoio à decisão e demonstra-a através de um ambiente de testes em Portugal que utiliza a API idealista.pt para dados e parâmetros.

A plataforma combina dados de mercado, custos e taxas explícitos e uma estimativa transparente de retorno, resultando num ROI líquido e num relatório exportável adequado para os clientes. A avaliação com base num questionário junto dos profissionais do setor indica uma aceitação positiva; os entrevistados reportaram maior confiança quando os detalhes do negócio foram totalmente explicados; o ROI foi ligado a notas explicativas que clarificaram os principais motivadores; a usabilidade e os relatórios foram altamente avaliados, enquanto as oportunidades de melhoria incluem uma cobertura de evidências mais ampla e narrativas mais claras dos motivadores.

A tese contribui com um protótipo de design de IA para apoio à decisão de corretagem, uma demonstração real de mercado e insights reais de utilizadores profissionais. As limitações estão relacionadas com o protótipo de país único e com a amostragem por conveniência. Trabalhos futuros incluem replicação multipaíses, integração de dados mais rica e capacidades melhoradas de explicação e geração de relatórios.

Palavras chave: Inteligência Artificial; Serviços Imobiliários; Avaliação de Imóveis; Tomada de Decisão em Investimento; Previsão de Mercado; IA Explicável

Códigos JEL: C88, R30

ABSTRACT

This research explores about how Artificial Intelligence is elevating real estate services by optimizing property valuation, predicting profitability and providing data driven insights for market forecasting. By using AI driven models, real estate agents and investors can make more accurate, efficient and strategic decisions to reduce risks and improving overall service quality. This study aims to assess AI's capabilities in real estate analytics, its integration with existing digital tools and its potential to reshape industry practices. Building on a PRISMA guided systematic literature review and a Design Science Research approach, the thesis develops a global decision support framework and demonstrates it through a Portugal testbed that uses idealista.pt API for data and parameters.

The platform combines market data, explicit costs and fees and transparent return estimation that results in a Net ROI and an exportable report suitable for clients. Evaluated based on a questionnaire with industry professionals indicates positive acceptance; respondents reported higher confidence when deal details were fully explained, ROI was linked to explanatory notes clarified key drivers; usability and reporting were rated highly, while improvement opportunities include wider evidence coverage and more clear driver narratives.

The thesis contributes a prototype AI design for brokerage decision support, a real market demonstration, and real insights from professional users. Limitations relate to the single country prototype and convenience sampling. Future work includes multi country replication, richer data integration, and enhanced explanation and reporting features.

Keywords: Artificial Intelligence; Real Estate Services; Property Valuation; Investment Decision Making; Market Forecasting; Explainable AI

JEL Codes: C88, R30

GLOSSARY OF ACRONYMS

- **AI**: Artificial Intelligence
- **API**: Application Programming Interface
- **AVMs**: Automated Valuation Models
- **CGT:** Capital Gains Tax
- **DSR**: Design Science Research
- **GDPR**: General Data Protection Regulation
- **HACCP**: Hazard Analysis and Critical Control Points
- **IBS**: ISCTE Business School
- **IMT**: Imposto Municipal sobre as Transmissões Onerosas de Imóveis (Municipal Tax on Onerous Property Transfers)
- **ISCTE**: University Institute of Lisbon
- **JEL**: Journal of Economic Literature
- **JS/TS**: Javascript/Typescript
- **MAE**: Mean Absolute Error
- **MAPE**: Mean Absolute Percentage Error
- **ML**: Machine Learning
- **MSE**: Mean Squared Error (model accuracy metric)
- **N**: Sample size
- **PRISMA**: Preferred Reporting Items for Systematic Reviews and Meta Analyses
- **REBS**: Real Estate Brokerage Services
- **RMSE**: Root Mean Square Error
- **ROI**: Return on Investment
- **SD:** Standard Deviation
- **SHAP:** SHapley Additive exPlanations
- **SLR:** Systematic Literature Review
- **UI:** User Interface
- **VAT**: Value Added Tax
- **XAI**: Explainable Artificial Intelligence

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CHAPTER 1: INTRODUCTION

1.1 Background

Real estate brokerage services (REBS) are a type of real estate intermediary that links buyers and sellers and provides valuation, negotiation, and advisory services that determines the outcomes of transactions and market disclosure (Ferreira, Spahr, Sunderman, Banaitis, and Ferreira, 2017). The industry has over the past decades evolved to a data driven, platform mediated service environment, which is a result of globalization, digitalization, and increased investor expectations (Yavaş, 2007; Barwick and Wong, 2019). REBS have now entered into a global and data enhanced market environment where matching, pricing, negotiation, and transaction assurance is increasingly supported by digital platforms and Artificial Intelligence enabled analytics.

The studies of the brokerage competition point to structural characteristics, including norms of commissions and multi sidedness, that contribute to the quality and transparency of services not only in a single market but across the countries (Barwick and Wong, 2019).

At the same time, technological innovation is transforming decision generation and justification in the brokers and investors. Artificial Intelligence (AI) and machine learning (ML) models build upon the traditional econometric and hedonic models to model complex, nonlinear market dynamics and allow predictive and explainable insights at scale (Zurada, Levitan, and Guan, 2011; Kok, Koponen, and Martínez Barbosa, 2017; Pinter, Mosavi, and Felde, 2020; Calainho, van de Minne, and Francke, 2024). Live comparable data can be incorporated with cost and risk variables via automated valuation models (AVMs), predictive analytics, and explainable artificial intelligence (XAI) to increase transparency, approximate profitability, and negotiating strategy (Hong and Kim, 2022; Schemmer, Hemmer, Kuehl and Schaefer, 2022).

It is against this international context that this thesis examines the ways in which AI can be used to optimize the decision making in REBS on a conceptual and methodological scale that can be globally applied. In order to prove the feasibility empirically, a working prototype is deployed and tested on a single testbed Portugal through the use of available listing data (e.g., Idealista.pt) and well specified local parameters; the results are analyzed in the context of extending to other markets.

1.2 Problem Statement

Although the sector has been digitalized, there is no cohesive decision making by the brokers. Agents often use spreadsheets, subjective information, or third party reports which fail to consider the entire investment cycle. Information asymmetry frequently happens with regard to transaction costs, renovation costs, and resale possibilities, which can diminish the trust and delay the decision making process (Ferreira et al., 2017).

For example; a house that is being sold at a price of €100,000 is hardly the investment cost. When taxes and other fees and legal charges and renovation, and deductions on resale are added the net ROI can vary considerably with expectations. The brokers have a hard time showing investors the whole picture of deal economics without having clear instruments to bring together these variables. This loophole brings about inefficiencies, lack of trust, and low competitiveness in the brokerage process.

1.3 Research Objectives

The aim of the study is to create and test an AI based decision support system in the Portuguese REBS industry.The objectives are:

1. In order to examine the current literature on the use of AI in real estate brokerage, the emphasis should be made on the valuation, negotiation, and investment decision making.
2. To create and test a platform with market data (Idealista.pt API), cost models, and AI valuation to approximate ROI.
3. To test the prototype on professional users (brokers and investors), it is important to test its role in enhancing decision transparency and accuracy.

1.4 Research Question

The thesis is guided by a single research question:

How can Artificial Intelligence optimize decision making in Real Estate Brokerage Services (REBS)?

This question indicates the two fold purpose of learning about the theoretical role of AI and showing how it can be practically useful, in terms of a prototype platform.

1.5 Scope of the Study

This thesis constructs a globally minded framework of AI powered real estate brokerage services and establishes a prototype of the services in Portugal because of the presence of data and API (Idealista.pt). It is not a commercial product, but a proof of concept prototype used in academia.

The study is methodologically a hybrid between a Systematic Literature Review (SLR) that is guided by PRISMA to extract requirements and Design Science Research (DSR) to design, implement, and evaluate the artifact within the Portuguese testbed. This two pronged method gives theoretical foundation and practical confirmation where procedures are expected to be applicable in other markets after replacing local data and parameters. A concise summary of scope and delimitations is provided in Annex 1.A.

1.6 Structure of the Thesis

The thesis is organized into seven chapters and organization of the study is summarized in Figure 1.1, which presents the structure of the thesis and the logical progression.

- **Chapter 1/Introduction:** Background, problem, objectives, question, scope, structure.
- **Chapter 2/Literature Review:** examines REBS from the business and technological perspective.
- **Chapter 3 / Methodology:** Explaining the SLR with PRISMA and the DSR approach.
- **Chapter 4/Results and Framework Design:** Key findings and conceptual AI framework.
- **Chapter 5/Proposal Assessment:** Prototype, functions, and evaluation.
- **Chapter 6/Discussion:** Interpretation, comparison with literature, implications.
- **Chapter 7/Conclusion and Future Work:** Contributions, limitations, and next steps.

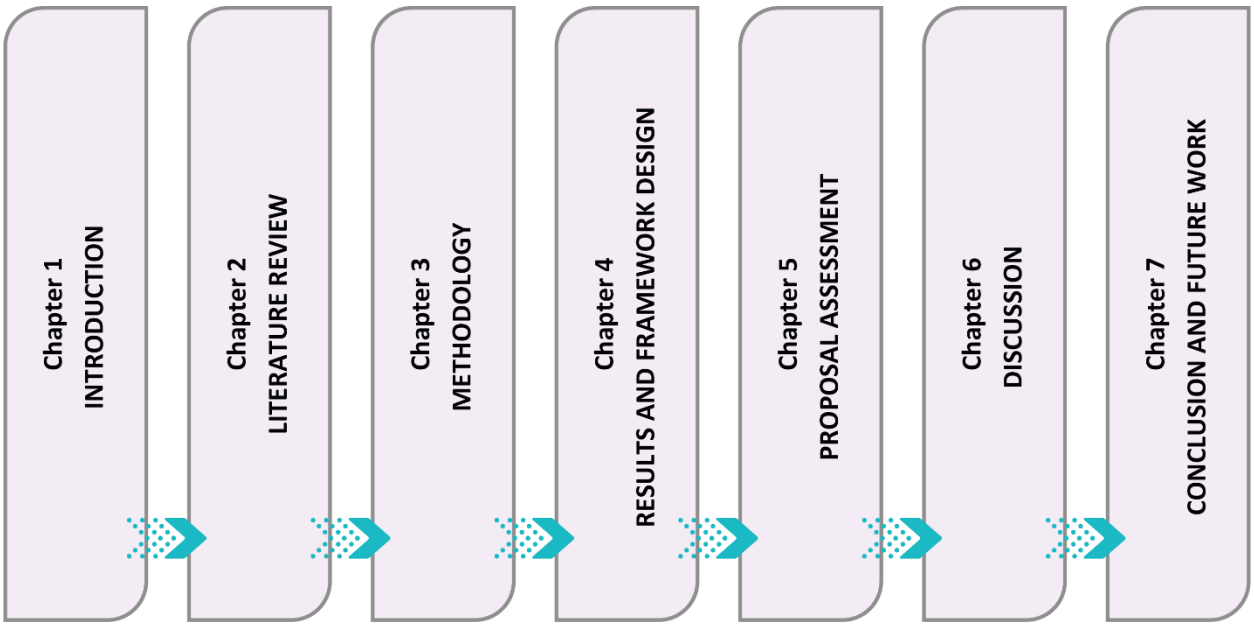


Figure 1.1. Thesis Structure Roadmap

CHAPTER 2: LITERATURE REVIEW

Introduction

This chapter looks at the optimization of decision making in Real Estate Brokerage Services (REBS) with the help of Artificial Intelligence. It is structured in two parts.

Part 1 gives the business viewpoint by defining the REBS industry, stakeholder and incentive mapping, outlining the value chain of brokerage and the cost stack unique to Portugal that the decision tools will have to calculate.

Part 2 introduces technological perspective, which is the synthesis of the data foundations, price indexes, automated valuation models, machine learning methods, explainability, and system governance. The chapter ends with the derivation of design implications that guide the methodology and structure to be designed in the following chapters (Barwick and Wong, 2019; Ferreira et al., 2017; Yavaas, 2007; Hong and Kim, 2022; Calainho, van de Minne, and Francke, 2024; Pinter, Mosavi, and Felde, 2020; Schemmer, Hemmer, Kuhn, and Schaefer, 2022).

The logical connection between these two perspectives is summarized in Figure 2.1, which visually maps how business requirements identified in the literature inform the corresponding technological design choices explored in this chapter.

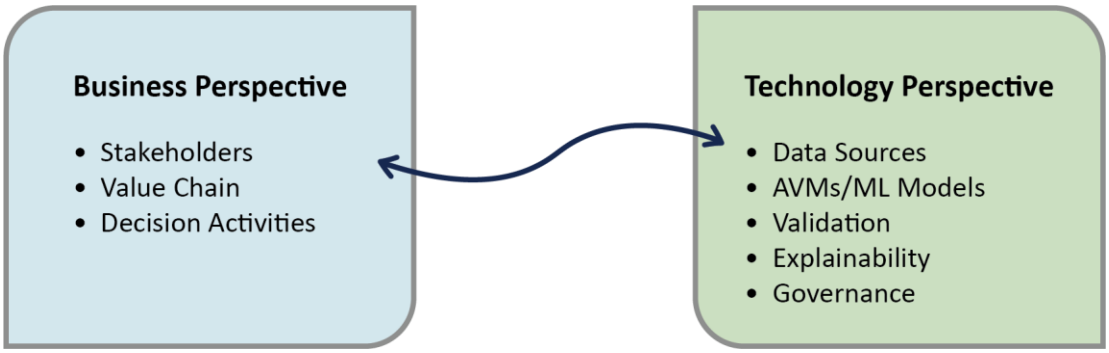


Figure 2.1 Literature review map linking business needs to technical design choices

PART 1: BUSINESS PERSPECTIVE

2.1 REBS industry overview

REBS mediates transactions of high value where the success or failure is based on quality of information, various instructions on prices, negotiation approach and reporting that is auditable. The literature records on going conflicts in brokerage markets including commission standards, dual agency, and limited search by the agent which perpetuate information asymmetries and inconsistent service quality (Barwick &

Wong, 2019; Yavaas, 2007). Such characteristics warrant decision support tools which blend in evidence, set assumptions explicit and standardize professional advice. Additional service evaluation work also demonstrates the idea of clear criteria and traceable points being the core factors in the perceived quality and trust in interactions between brokers (Ferreira et al., 2017).

2.2 Stakeholders and incentives

The main participants are sellers, buyers and investors, brokerage and agents, valuers and inspectors, legal or notary services, government and data providers or listing portals. Goals are partly not coherent among these actors. The commission structure and the multi sided relationship may affect the pricing and time to sale, whereas the disclosure and documentation will reduce the negative impact by explaining the incentives and duties (Barwick and Wong, 2019; Yavaas, 2007). To promote incentive alignment, professional tools with an auditable path between inputs and calculations to outputs enhance the verifiability and comprehension of recommendations by clients (Ferreira et al., 2017). To make these relationships clearer, figure 2.2 illustrates the key factors shaping brokerage service evaluation, while table 2.1 summarizes the main stakeholder groups, their objectives, and related information needs.

Comparable selection and normalization procedures referenced in this section are detailed in Annex 2.C.

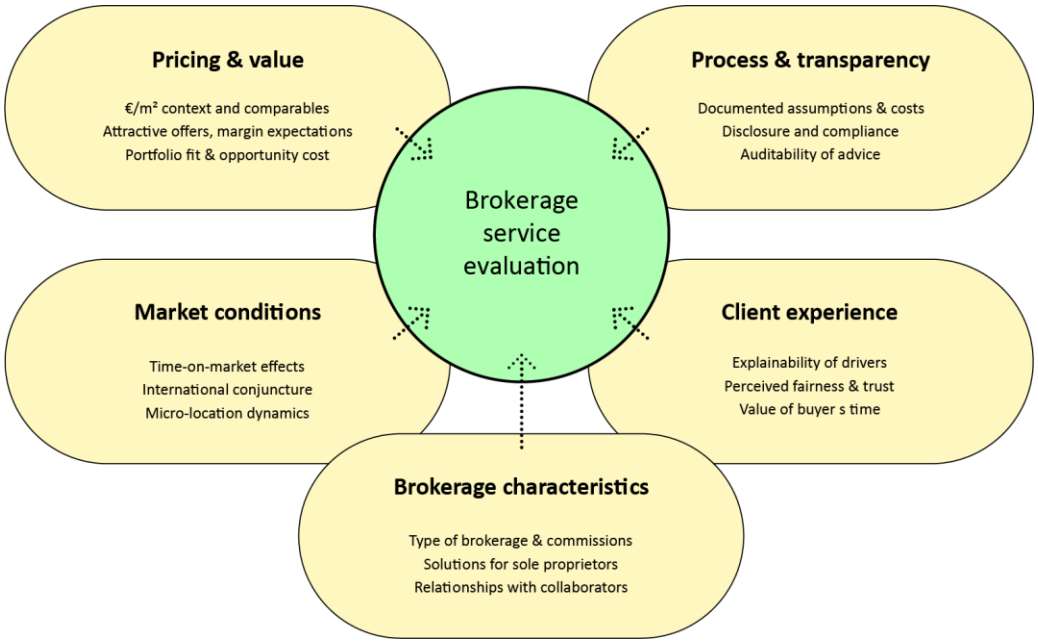


Figure 2.2 Cognitive map of brokerage service evaluation

Caption: Figure 2.2. Thematic synthesis of factors influencing brokerage service evaluation, grouped into five clusters (pricing & value, process & transparency, market conditions, client experience, and brokerage characteristics). Arrows indicate contributions to the overall evaluation.

Table 2.1. Stakeholders, objectives, decisions, and information needs

Stakeholder	Primary objectives	Key decisions	Information needed (examples)
Seller	Maximize net proceeds; time to sale	List price; concessions; agent selection	Comps, €/m² trends, demand signals
Buyer/Investor	Target ROI at risk appropriate price	Offer price; renovation scope; exit	Full cost stack (IMT, Stamp, fees, IVA), comps/indices, resale deductions
Agent/Brokerage	Close with satisfaction & compliance	Pricing advice; negotiation strategy	Comparable filters, index normalization, transparent assumptions
Valuer/Inspector	Independent assessment	Condition/risks; capex ranges	Inspection findings; renovation cost bands
Legal/Notary	Compliance & transfer	Contract terms; registry steps	Fees; timelines; requirements
Authorities	Tax & registry accuracy	Tax assessment; ownership	IMT/Stamp rules; cadastre
Data/Portals	Reliable signals	Data ingestion & quality	Listing metadata; geo features; refresh rates

Caption: *See Annex 2.A for the expanded stakeholder matrix with risks, mitigations, and KPIs.*

2.3 Value chain and decision activities

An investor oriented brokerage process usually takes the following steps: preliminary screening of opportunities, initial deal checks based on comparable properties and the cost of the property in euros per square meter, due diligence costing including IMT, Stamp Duty, professional fees, renovation costs with IVA, negotiation strategy and offer determination, execution and closing with legal and registry steps and exit planning taking into consideration the resale and the capital gains taxation. Both activities are based on justifiable similar selection, time location normalization, and overt assumptions that can be questioned by a client (Ferreira et al., 2017; Barwick and Wong, 2019). The sequential structure of these activities is summarized in Figure 2.3. A full operational specification of the value chain is provided in Annex 2.I.

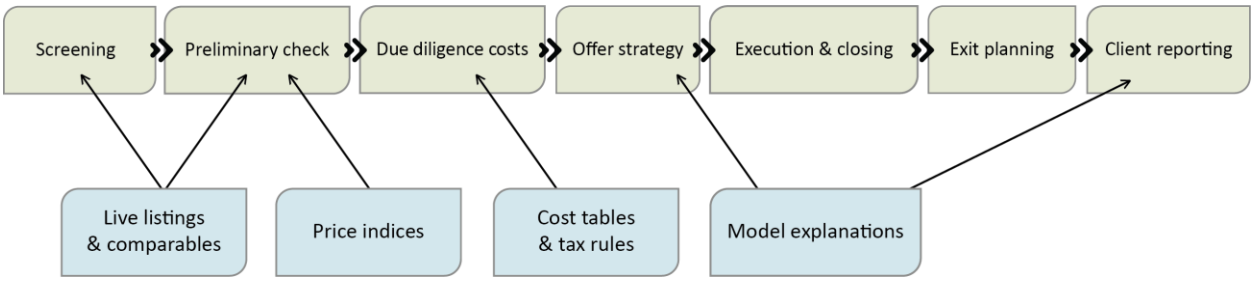


Figure 2.3 REBS value chain and evidence inputs

2.4 Portuguese cost stack

In Portugal, a decision complete advice involves an end to end costing of the transaction and project. Important ones are IMT transfer tax, Stamp Duty on acquisition, notary and registry fees, legal fees, brokerage commissions with IVA where necessary and renovation costs with IVA of those properties that need works. The selling agency commission with IVA, transfer fees and any capital gains tax on the realized gain after allowable deductions are normally deducted at the exit. The overall acquisition cost, overall project cost, and, finally, the Net ROI to be used by investors are calculated based on the combination of these items (Ferreira et al., 2017; Safronov, 2017). Cost schedules and calculation formulas of the Portuguese case are presented in more detail in Annex 2.B.

The heterogeneity of the market in the micro locations of Lisbon and Porto, as well as the time dependent environment, puts the risk of biased benchmarks in case costs and prices are not regularly normalized. Professional practice thus combines full cost modeling with comparable selection that is transparent and index based to adjust the time to the decision date, maintaining auditability and enhancing the interpretability of pricing advice provided to investors (Ferreira et al., 2017; Barwick and Wong, 2019; Safronov, 2017).

2.5 Implications for requirements

The business perspective suggests four requirements for professional decision support:

R1: decision completeness with full cost lines to Net ROI.

R2: provenance and dating for comparables and indices with clear filters.

R3: explainability with accessible driver views and calculation narratives.

R4: negotiation alignment through offers back solved to target ROI. (Ferreira et al., 2017; Barwick & Wong, 2019). Risk and bias considerations that inform these requirements are summarized in Annex 2.G.

Note: *These preliminary requirement labels are refined in Chapter 4 into their operational design form R1 Decision Completeness, R2 Explainability, R3 Verifiable Evidence, and R4 Investor-grade Reporting to align the conceptual insights from the literature with the artifact's design requirements.*

PART 2: TECHNOLOGICAL PERSPECTIVE

2.6 Data foundations and price indices

REBS requires high quality decision support data relies on organized property data, and processes that make observations comparable over time and place. The major categories are property items like typology, area that it can be used, condition, age, parking and energy type, geospatial location like coordinates and neighborhood, and transaction or listing data like dates, asking or closing price, and days on market. In the case of the Portuguese market, the option of curated portal data and the explicit description of search windows, filters, and timestamps allow the professionals to screen and benchmark the data reliably (Ferreira et al., 2017; Safronov, 2017). All the definitions of variables employed in this chapter are listed in Annex 2.F.

The observed prices depend on market conditions on various dates and in different heterogeneous micro locations. To prevent biased benchmarks, the literature suggests the adoption of price indices to normalize over time and where feasible, also over space. Classical methods are hedonic indices and repeat sales models. In the recent evidence, machine learning can be used to help with index construction by not only capturing nonlinearity but also richer interactions and create interpretable index series that can be applied in practice (Calainho, van de Minne, and Francke, 2024). The index application process, normalization formula and the selection of base period is recorded in Annex 2.D.

Similar selection and normalization are complementary to use of index. A defensible process then selects comparables of the candidate on property type, size band, condition and proximity, adjusts the valuation date with time adjustment using the selected index and tunes up the residual heterogeneity with the help of neighborhood indicators or distance weighting. The protocol used in this case defines search radii, time windows, outlier rules on the amount spent on m2, minimum sample size, and weighting limits to avoid over representation by a single similar, and filters and identifiers are fully audited (Ferreira et al., 2017). The entire similar selection and normalization procedure is defined in Annex 2.C.

The preparation of data usually follows four steps as illustrated in Figure 2.3, which shows how these activities are positioned within the REBS value chain and linked to their supporting evidence inputs. The first is ingestion and unification to consolidate listing or transactions based on trusted sources and retain consistent identifiers, dates and coordinates. Second, cleaning and harmonization to eliminate duplicates, standardize units and typologies and managing outliers with transparent rules. Third, extract

hedonic variables (effective area and age bands, encode calendar effects and neighborhood structure), and calculate accessibility measures using feature engineering. Fourth, record keeping to maintain query strings, filters, index identifiers, and exclusion reasons, and, therefore, maintain auditability in client facing reporting (Ferreira et al., 2017). Non traditional cues like mobility or telecommunication footprints can be useful to augment location information, as soon as they are verified in terms of bias and stability, but they cannot be used in a professional environment without careful testing and reporting of constraints (Pinter, Mosavi, and Felde, 2020).

The construction of the index is based on an estimation step where the prices or log prices are estimated using a series of features and time effects. Using machine learning aided methods, tree ensemble or other nonlinear regressors are trained via cross validation. This is followed by the derivation of the index by normalizing time effects of predictions to a base period and time chaining. Validation consists of stability backtesting, sensitivity analysis to feature sets and sample windows, and error measures like RMSE, MAE and MAPE. There are two uses of indices in the Portuguese context. To start with, they adjust similar prices to the day of decision in dynamic sub markets like Lisbon and Porto. Second, they have a reference series to track the market changes in holding periods and to match the assumptions of the exit with the observed trends (Calainho, van de Minne, and Francke, 2024; Ferreira et al., 2017; Safronov, 2017). The end to end steps for constructing and applying these indices are summarized in Figure 2.4 which diagrams the machine learning enhanced price index workflow from data preparation through estimation, normalization, and validation.

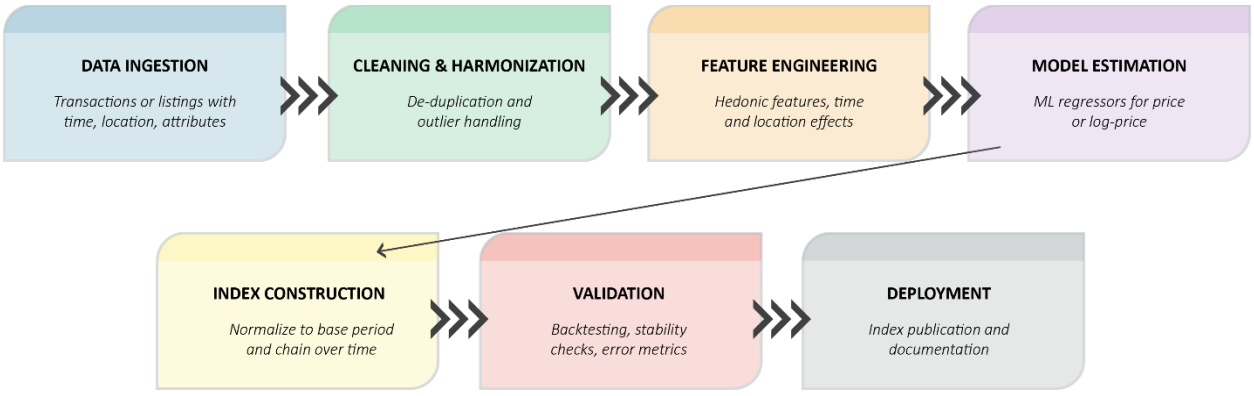


Figure 2.4 Machine learning enhanced real estate price index workflow

2.7 Automated valuation models and hybrid evidence stacks

Automated valuation models are valuation models that deterministically estimate the market value using features. Hybrid stacks with similar selection and index normalization and machine learning estimators can stabilize predictions by neighborhood and time in a brokerage environment and maintain a defensible range of valuation. Literature records that machine learning methods are able to exceed hedonic thresholds, under suitable feature engineering and validation, this will warrant its application to professional processes that not only demand precision but also transparency. (Hong & Kim, 2022; Pinter et al., 2020). Feature definitions and data types referenced here follow Annex 2.F.

2.8 Machine learning methods and validation metrics

The most common algorithms used in all the sets reviewed are the Random Forests, gradient boosting families (XGBoost and Gradient Boosting Regressor), support vector regression, k-nearest neighbors, and model stacking or ensembling. Random Forest and boosting are often reported to work well on nonlinear price trends using tabular features, and stacking can be used to improve performance in case predictors have complementary structures (Hong and Kim, 2022). The reported measures are R2 of the variance explained and error measures, namely RMSE, MAE and MAPE. Fair comparison requires constant evaluation procedures that correct data partitions.

Threats to validity and mitigation checks for model evaluation are summarized in Annex 2.G.

2.9 Explainable AI and stakeholder trust

Explainability methods like SHAP value analysis can be used to balance the output of the model with market explanations by demonstrating the contribution of features both globally and locally. Explainability is also a key focus in appraisal oriented prototypes, which are the focus of user trust, documentation and error analysis, and can be easily incorporated without affecting predictive performance when models are properly instrumented. (Schemmer et al., 2022). User centric evaluation constructs adopted later are defined in Annex 2.H.

2.10 From methods to systems

The literature of end to end systems integrates both data ingestion, model inference, and explanation interfaces as well as client friendly report exports. The mechanisms of governance comprise time stamped comparables, versioned assumptions and settings and reproducible calculations. At the scale of a

brokerage, tree based models can often have strong out of sample performance with complexity manageable compared to deep learning alternatives, which justifies their applicability to professional use with limited data budgets. (Hong & Kim, 2022; Schemmer et al., 2022).

Process governance, provenance, and reproducibility expectations per value chain stage are detailed in Annex 2.I. Operational rules for indices and comparables are consolidated in Annex 2.D and Annex 2.C, respectively.

2.11 Design implications for the proposed framework

The synthesis suggests that four conditions are needed on a professional REBS decision tool: decision completeness (Net ROI full cost stack, through Portugal); provenance (time stamped comparables, explicit filters, index identifiers and base periods); explainability (driver views linking comps, context on step by step costs, and negotiation aligned offer prices, back solved); and negotiation alignment (offer structures aligned with investor ROI targets and market evidence) (Ferreira et al., 2017; Barwick & Wong, 2019; Safronov, 2017; Schemmer et al., 2022). These four conditions and their implementation logic are summarized in Table 2.2, which maps each requirement to the corresponding system component and the evaluation constructs later applied in Chapter 5.

Procedural details are in Annex 2.B (costs), Annex 2.C (comparables), Annex 2.D (indices), Annex 2.F (features), Annex 2.G (risks), and Annex 2.I (value chain). The relationship between the reviewed evidence and the resulting design requirements is consolidated in Figure 2.5, tracing how specific findings in the literature justify each requirement used later in the framework and illustrating the traceability from business and technological evidence to the system's conceptual design.

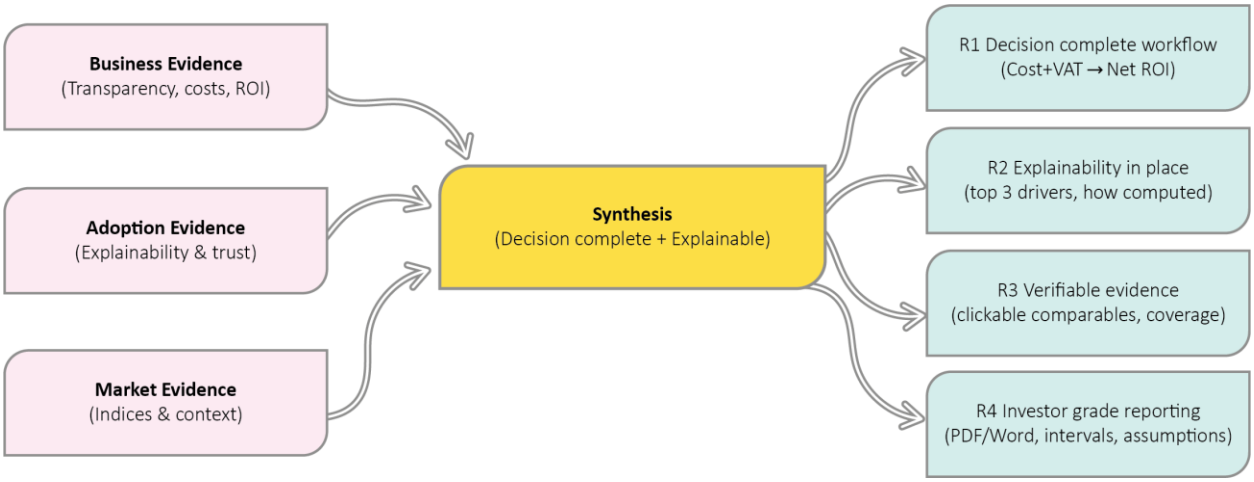


Figure 2.5. Traceability from evidence to design requirements

Table 2.2. Design implications mapped to requirements, components, and evaluation constructs

Requirement	Design implication	Implementation element	Evaluation construct
R1 Decision completeness	Compute full Portugal cost stack through Net ROI	Cost engine for IMT, Stamp Duty, fees, renovation with IVA, resale deductions, CGT	Usefulness; Efficiency
R2 Provenance	Time stamped comps and indices with reproducible filters	Comparable selector with query logs; index identifier and base period in outputs	Trust; Interpretability
R3 Explainability	Show drivers and calculation narratives	Driver view for comps and €/m² context; step by step cost breakdown	Interpretability; Trust
R4 Negotiation alignment	Back solve offer price from target ROI with scenarios	Offer strategy module with sensitivity panels	Usefulness
R5 Governance	Versioning of rules, indices, and reports with exportable audit trail	Assumptions registry; versioned reports; export hash	Trust

Caption: *Table 2.2. Synthesis of design implications linking business requirements to concrete components and to evaluation constructs used in Chapter 5.*

2.12 Chapter bridge

The second chapter elaborates the systematic literature review protocol that was based on PRISMA and the design science research process that converts the requirements identified in Chapter 2 into an implemented framework and an empirical test with professionals.

CHAPTER 3: METHODOLOGY

3.1 Research design and methodological stance

This study combines a Systematic Literature Review (SLR) guided by a PRISMA flow and counts and a Design Science Research (DSR) approach to design, build, and evaluate an AI enabled decision support artifact for Real Estate Brokerage Services (REBS). The SLR identifies and synthesizes contributions on REBS decision making, valuation models, and explainability to derive design requirements (R1-R4). DSR then instantiates these requirements in a prototype and evaluates it with practitioners, consistent with learning oriented, evidence tracing brokerage processes (Ferreira, Spahr, Sunderman, Banaitis, & Ferreira, 2017) and prior DSR style prototyping in real estate analytics (Schemmer, Hemmer, Kühl, & Schäfer, 2022). This mixed SLR+DSR stance aligns with recent artefact oriented work in real estate appraisal and decision support.

The integration between the systematic literature review and the design science research processes is illustrated in Figure 3.1, which depicts the overall methodological backbone adopted for this study. Figure 3.2 complements this by showing the sequential research workflow from the identification of relevant literature to the evaluation of the prototype. It clarifies how the SLR produces theoretical evidence and design requirements (R1-R4), which are then operationalized through the DSR cycle of *build*, *demonstrate*, and *evaluate*. This visualization emphasizes the traceability and coherence between each methodological phase, ensuring that the artifact's construction and validation remain grounded in systematically derived evidence.

Detailed methodological artefacts are compiled in Annexes 3.A-3.N for transparency and reproducibility.

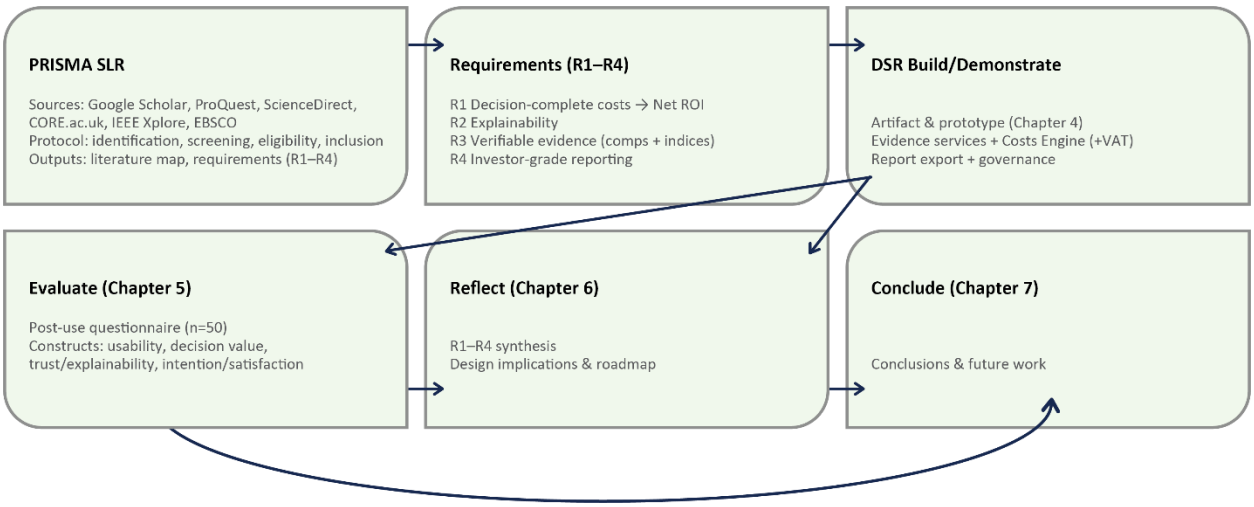


Figure 3.1. Methodological backbone (PRISMA SLR + DSR)

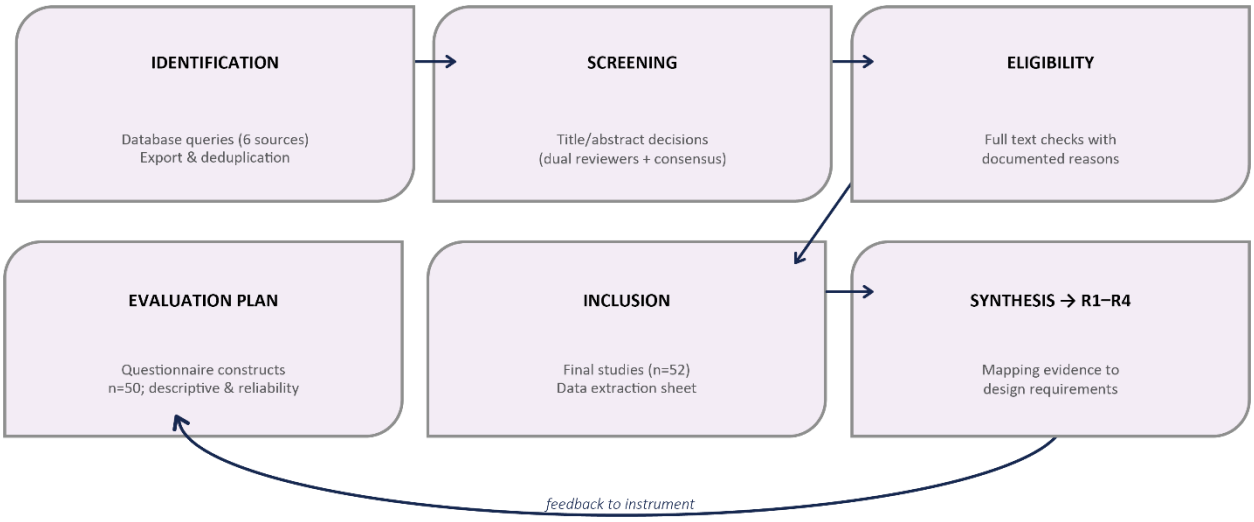


Figure 3.2. Research workflow (from identification to evaluation).

3.2 Systematic Literature Review (SLR)

3.2.1 Objectives and scope

The SLR maps two complementary lenses: (i) business/industry work on REBS actors, decision activities, information needs, and transparency frictions (Yavaş, 2007; Barwick & Wong, 2019; Ferreira et al., 2017); and (ii) technological work on AI/ML, automatic valuation models (AVMs), price indices, feature engineering, and explainability (Calainho, van de Minne, & Francke, 2024; Hong & Kim, 2022; Pinter, Mosavi, & Felde, 2020; Schemmer et al., 2022).

The PRISMA aligned protocol and scope are documented in Annex 3.A (SLR Protocol).

3.2.2 Sources and search strategy

Searches covered Google Scholar, ProQuest, ScienceDirect, CORE.ac.uk, IEEE Xplore, and EBSCO (EN/PT). A representative scaffold adapted per database was: *("real estate" OR "real estate brokerage" OR broker OR realtor OR "estate agency") AND (decision OR valuation OR "price index" OR ROI OR appraisal) AND ("artificial intelligence" OR "machine learning" OR AVM OR "explainable AI" OR XAI OR explain).* Backward/forward snowballing was performed from full text eligible studies (following best practice for literature synthesis in the RE/AVM domain; e.g., Hong & Kim, 2022; Calainho et al., 2024).

Database specific query strings and date ranges appear in Annex 3.A, and the data extraction fields are listed in Annex 3.D.

3.2.3 Identification and PRISMA counts

Records were exported, consolidated, and deduplicated before screening.
Aggregate PRISMA counts are: identified = 46,026; duplicates removed = 43,183; screened = 2,843; full text assessed = 233; included = 51 . The screening process is illustrated in Figure 3.3, which presents the PRISMA flow of identification, screening, eligibility, and inclusion of studies.

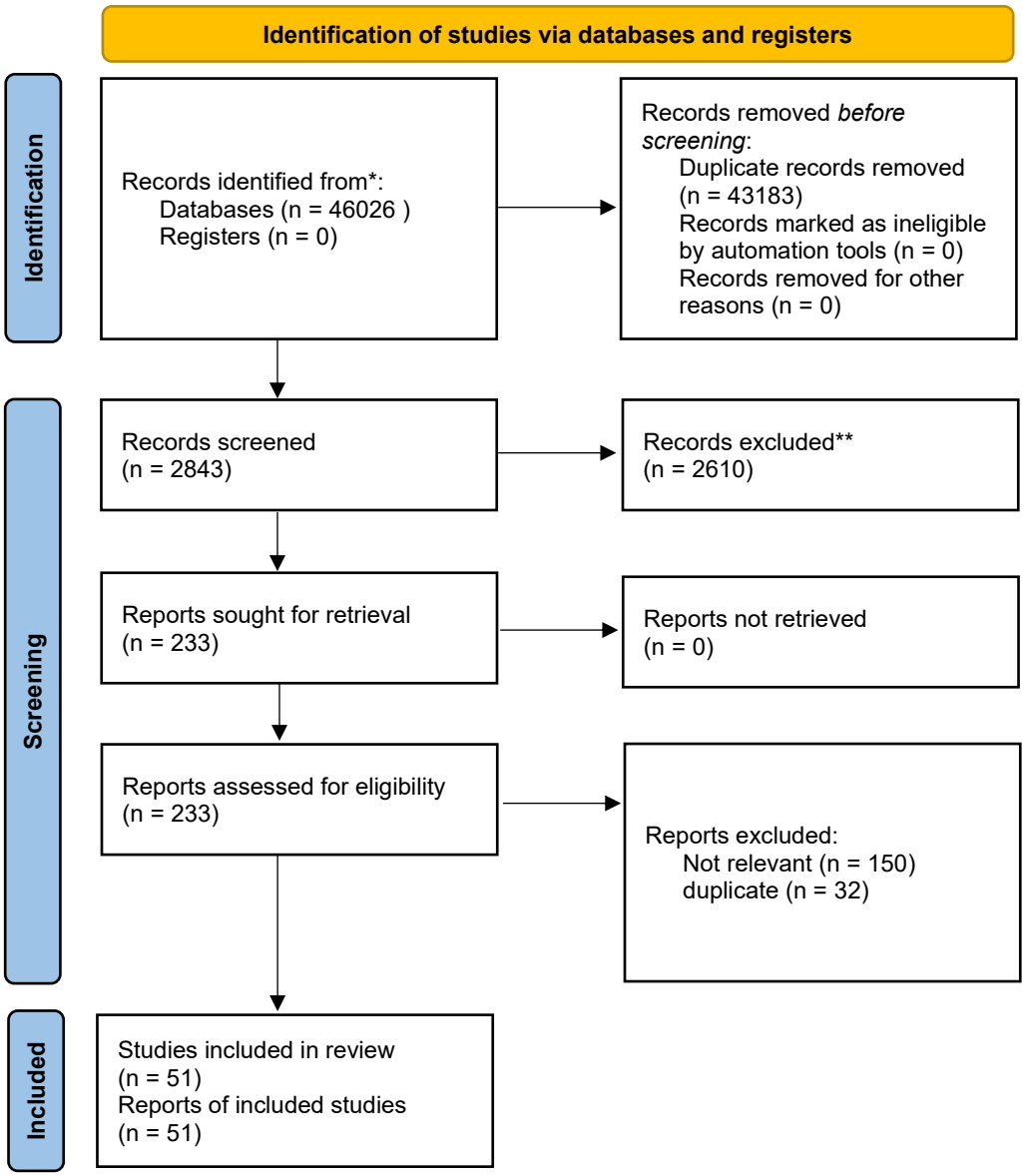


Figure 3.3. PRISMA flow diagram for systematic reviews

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71
The archival PRISMA flow (Figure A3.M.1) and per-database tallies (Table A3.M.1) are provided in Annex 3.M (Figures and Tables).

3.2.4 Screening and quality appraisal

Predefined criteria (Table 3.1) were used to screen two stage (titles/abstracts followed by full texts). The dual reviewers did not collaborate with each other; any disagreement was solved by consensus. Reason codes were recorded at eligibility (major reasons: not relevant to REBS decision/AI valuation; duplicate). An informed narrative weight was based on a study type quality appraisal sensitive to context/question clarity; data adequacy; method transparency; validity/credibility; decision support relevance, which is consistent with appraisal emphases in RE valuation/analytics studies (Hong & Kim, 2022; Pinter et al., 2020).

Screening decision codes are described in Annex 3.B, and the study type sensitive appraisal rubric is detailed in Annex 3.C.

3.2.5 Data extraction and synthesis

For each included study we extracted bibliographic data, setting, study type (AVM/index/decision process/DSR), features/data, validation, and decision support takeaways. The synthesis translated evidence into R1-R4:

- **R1 Decision complete analysis:** end to end costs/taxes to Net ROI, reflecting advisory needs in brokerage (Ferreira et al., 2017).
- **R2 Explainability:** "how computed," drivers, and explicit assumptions to address trust/credibility (Schemmer et al., 2022).
- **R3 Verifiable evidence:** comparables normalized with local price indices and provenance (Calainho et al., 2024; Hong & Kim, 2022).
- R4 Investor grade reporting: clear exports supporting client communication (Ferreira et al., 2017).

The extraction process followed a structured protocol to ensure consistency and traceability across all stages of the review. The main elements of this protocol including databases searched, inclusion and exclusion criteria, screening process, and PRISMA counts are summarized in Table 3.1, which consolidates the operational details of the SLR and supports the transparency of subsequent analyses.

Table 3.1. SLR protocol (summary)

Element	Summary
Sources	Google Scholar; ProQuest; ScienceDirect; CORE.ac.uk; IEEE Xplore; EBSCO
Languages	English, Portuguese
Inclusion	Peer reviewed REBS decision making; valuation/AVMs; decision support/explainability in real estate
Exclusion	Construction/FM only without brokerage decision relevance; non academic items; theses misaligned with REBS
Screening	Title/abstract → full text; dual reviewers; consensus; reason coded exclusions
PRISMA counts	46,026 identified; 43,183 duplicates; 2,843 screened; 233 full text; 51 included

The extraction template is reproduced in Annex 3.D, and the evidence coverage summary for R1-R4 (n=51) is reported in Annex 3.F.

3.3 Design Science Research (DSR) approach

3.3.1 Problem identification and objectives (R1-R4)

The SLR showed fragmented tools, opacity in valuations, and weak investor reporting issues echoed in brokerage and competition literatures (Yavaş, 2007; Barwick & Wong, 2019). Objectives were formalized as R1-R4 (above).

The problem→objectives→requirements traceability is mapped in Annex 3.G (DSR Traceability Matrix).

3.3.2 Build → Demonstrate

The construction phase translated the conceptual requirements into a tangible artifact. Following the design principles identified through the literature review and design science process, the prototype was implemented as a web based decision support system integrating analytical and explanatory components. The artifact developed in this research, further detailed in Chapter 4, was implemented as a web based prototype designed to operationalize the identified requirements. Its backend was developed in *Python* and integrates several core modules, including a cost calculation engine that incorporates value added tax (VAT), a net return on investment (ROI) computation pipeline, a dynamic report generator, and an explainability service that traces each calculation step. The frontend, developed in *JavaScript/TypeScript*, provides the user interface for data input, visualization of comparable properties and price indices,

detailed cost breakdowns, ROI results, and a negotiation support tool that allows scenario adjustments and report export.

This configuration allows the artifact to simulate the complete decision process of a real estate brokerage transaction—from data input and evidence analysis to the generation of transparent ROI reports—thereby demonstrating the feasibility and coherence of the proposed framework within a real world technological environment. This "build and evaluate" posture mirrors DSR prototypes in real estate analytics (Schemmer et al., 2022) and supports learning oriented decision processes (Ferreira et al., 2017). The structure of the questionnaire evaluation and its link to the prototype demonstration are summarized in Figure 3.4, illustrating how participant feedback was gathered and analyzed.

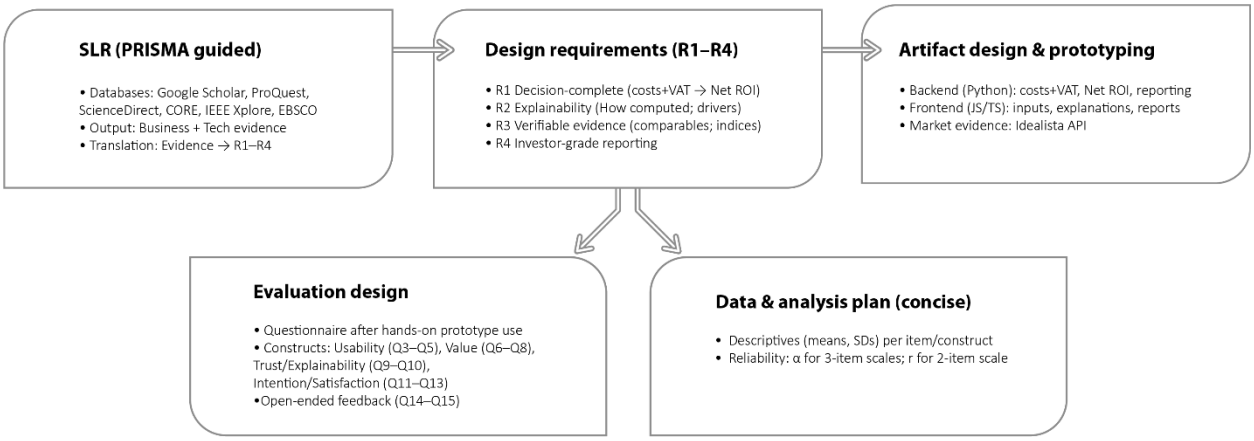


Figure 3.4. Research workflow from SLR to evaluation

More detailed and demonstration materials are presented in Annex 3.N.

3.4 Artifact scope and data

The prototype is scoped to the Portuguese market in a pilot configuration and targets investment oriented acquisitions, with an option to include renovation scenarios. The evidence base combines listing comparables with local price indices, while configuration tables encode tax and fee schedules required for cost computation. Users provide core inputs (location, size, asking price, and a renovation toggle), after which the system returns a net ROI along with an investor grade report; a negotiation helper can also generate a counter offer consistent with a target ROI. These design choices reflect established practice in the literature, which emphasizes comparable based valuation complemented by contextual indices and transparent reporting (Calainho, van de Minne, & Francke, 2024; Hong & Kim, 2022).

3.5 Evaluation design (questionnaire study)

3.5.1 Participants and procedure

N= 50 professionals (agents, brokers, investors) used the prototype and then answered the questionnaire. Responses were anonymous and consented.

3.5.2 Instrument and constructs

The evaluation instrument was intentionally designed to remain concise while capturing the key perceptual dimensions relevant to decision support systems. It consisted of thirteen Likert type items (rated from 1 to 5) and two open ended questions, organized around five main constructs: perceived usefulness and decision value, efficiency, interpretability and clarity, trust and explainability (operationalized through two specific items, Q9 trust and Q10 transparency), and overall satisfaction or intention to use. This configuration ensured coverage of both functional and perceptual aspects of system evaluation, in alignment with validated constructs commonly employed in the literature on decision support and explainable artificial intelligence (Ferreira et al., 2017; Schemmer et al., 2022).

3.5.3 Analysis plan

The analysis plan adopts descriptive and reliability procedures with explicit benchmarks. Descriptive statistics are reported at both item and construct levels (means and standard deviations), with benchmark means of 3.5 considered acceptable and 4.0 targeted. Cronbach's alpha (α) is computed for constructs comprising three or more items, while the inter item Pearson correlation (r) is used for the two item Trust/Explainability pair, with the alpha equivalent approximated as $\alpha \approx 2r/(1+r)$. Qualitative evidence from open ended responses is thematically coded to enrich and contextualize the quantitative findings, following reporting practices in Hong & Kim (2022) and Pinter et al. (2020).

3.6 Validity, reliability, and ethics

The methodological rigor of this research is supported by the transparent documentation of the PRISMA screening process and the inclusion of detailed selection criteria, both recorded in Annex E. The design science approach further strengthens the study's reliability by maintaining explicit traceability between the four system requirements (R1-R4), their implementation within the artifact, and the corresponding constructs used during evaluation (Ferreira et al., 2017; Schemmer et al., 2022).

Several limitations are acknowledged. These include constraints related to database coverage and language scope during the literature search, the use of a non probability professional sample for the evaluation phase, and the reliance on perceptual, post session measures rather than longitudinal data. Each of these limitations is explicitly addressed and mitigated in Chapters 5 to 7, ensuring that the overall methodological framework remains coherent, transparent, and ethically sound.

3.7 Chapter summary

This chapter established the integrated methodological foundation of the research by combining the Systematic Literature Review (SLR) guided by the PRISMA protocol with the Design Science Research (DSR) approach. It reported the PRISMA screening counts and criteria, defined the four system requirements (R1-R4), and delimited the artifact's scope while outlining the evaluation procedures that are further developed in Chapters 4 to 6. The methodological workflow was supported by Figures 3.1 to 3.4 and the complementary documentation contained in Annexes 3.A to 3.N, ensuring transparency, reproducibility, and alignment between theoretical evidence and prototype implementation.

3.8 Chapter bridge

This chapter has established the PRISMA guided SLR and Design Science Research approach, reported counts of PRISMA and derived requirements (R1-R4), the dissertation proceeds to Chapter 4 where the requirements are converted into a concrete framework and working prototype. The following chapter elaborates the architecture, data flows and modules (evidence/indices, costs and taxes, valuation with explainability, and reporting) which apply the methodology outlined here.

CHAPTER 4: RESULTS AND FRAMEWORK DESIGN

4.1 Chapter overview

This chapter turns the literature derived requirements (R1-R4) into a concrete framework and a working prototype for REBS decision support. We specify the architecture and services (Costs & Taxes and Net ROI, Comparables & Indices, Explainability, and Reporting), describe data and auditability, present the UI, and demonstrate the artifact in use. The design is grounded in brokerage structure and service quality research and in AI/ML studies on valuation, indices, and explainability (Yavaş, 2007; Barwick & Wong, 2019; Ferreira, Spahr, Sunderman, Banaitis, & Ferreira, 2017; Calainho, van de Minne, & Francke, 2024; Hong & Kim, 2022; Pinter, Mosavi, & Felde, 2020; Schemmer, Hemmer, Kühl, & Schäfer, 2022).

4.2 Requirements recap from Chapters 2-3

Guided by the systematic review and the problem analysis in Chapters 2-3, the framework is anchored on four design requirements: R1 Decision Completeness (an end to end pipeline from costs/fees/taxes to proceeds and net ROI, enabling a clear buy/sell call); R2 Explainability (transparent drivers and an explicit "How computed" assumptions panel), R3 Verifiable Evidence (defensible valuation logic using comparables, normalization and indices, with validation metadata), and R4 Investor grade Reporting (client/audit ready outputs that surface assumptions, comparables and sensitivity). Table 4.1 summarizes each requirement, representative evidence, and the concrete design hooks used in the artifact.

Table 4.1. Design requirements (R1-R4) distilled from the literature, with representative evidence and design implications.

Req.	Concise definition	Key evidence (examples)	Implication for the artifact
R1	End to end costs/fees/taxes → proceeds → Net ROI for a buy/sell call.	REALM appraisal (IEEE); Ho, Tang & Wong (2021); Hong & Kim (2022); REBS templates.	Costs & Taxes engine + Net ROI pipeline.
R2	Make results explainable: drivers + "How computed" assumptions.	Lorenz (2023); Zhao, Chetty & Tran (2019, IEEE); Teoh (2022);	Explainability service + Assumptions panel.
R3	Verifiable evidence: comps, normalization, indices, validation.	Pinter (2020); Tchuente & Nyawa (2022); Gao (2022); Lin (2021);	Comparables & Indices service + stored metrics.
R4	Investor grade reporting: assumptions, comps, sensitivity, clear export.	REBS templates; Chou (2022); report workflow (Chiasson et al., 2023)	Reporting layer (PDF/DOCX) with tags & notes.

4.3 Architecture of the framework and prototype

The artifact follows a layered architecture to separate concerns and support auditability. As illustrated in Figure 4.1, the framework integrates five layers data, processing, application services, presentation, and governance, ensuring modularity and traceability across the system. The specific roles of each layer and their connection to the design requirements (R1-R4) are summarized in Table 4.2, which outlines how analytical, evidential, and reporting components interact to deliver decision complete and explainable outputs.

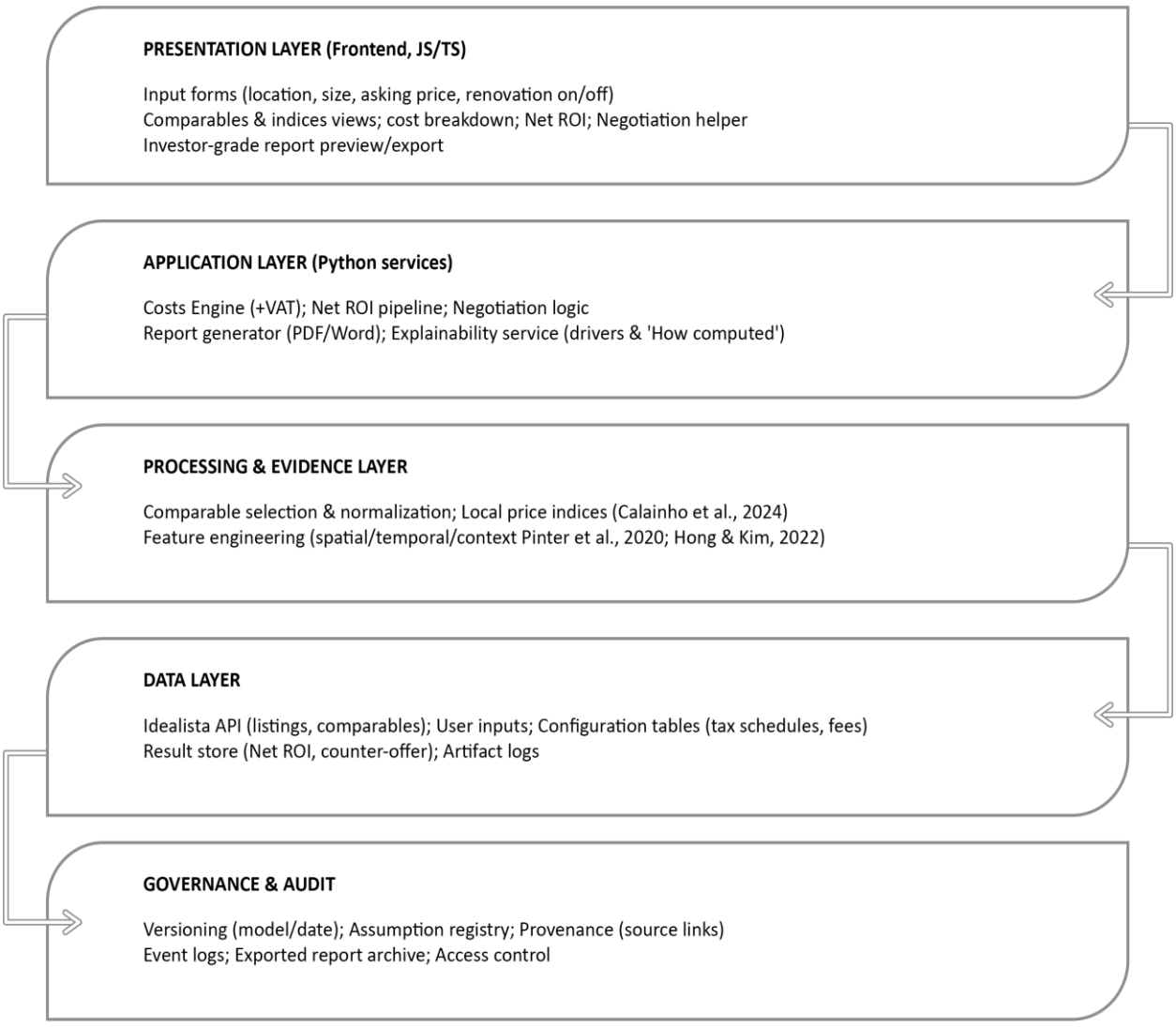


Figure 4.1. AI-enabled REBS decision support architecture (layers & components)

Table 4.2. Component responsibility map

Layer	Key components	Responsibilities
Presentation	Web UI (JS/TS)	Collect inputs; show comparables/indices; show costs & Net ROI; negotiation helper; export report.
Application services	Costs Engine (+VAT); Net ROI pipeline; Negotiation; Reporting; Explainability	Compute line items and total costs; aggregate to Net ROI; compute counteroffer for a target ROI; generate investor grade report; expose *How computed* and top drivers.
Processing & evidence	Comparable selection & normalization; Local indices; Feature engineering	Select and normalize comparables; apply local index context; enrich with spatial/temporal/contextual features.
Data	API & stores	Pull Idealista listings; store inputs, costs, ROI results, reports; configuration tables (rates/fees).
Governance	Audit & control	Versioning (model/date); assumption registry; provenance (links to sources); access and event logs.

Note. "Governance" appears below as an architecture layer (versioning, assumptions, provenance) to support auditability; it is not specified as a separate requirement (the formal set is R1-R4).

Citations: design separates evidence, calculation, and communication concerns consistent with decision process guidance (Ferreira et al., 2017) and explainable analytics (Schemmer et al., 2022). Use of indices and spatial features aligns with Calainho et al. (2024), Hong and Kim (2022), and Pinter et al. (2020).

4.4 Backend services (Python)

This section describes the computational services that operationalize R1 Decision Completeness and contribute to R2-R4 by ensuring that both the cost calculation process and the resulting ROI outputs are transparent and reproducible.

The backend of the prototype was developed in Python 3.11, using several complementary frameworks and libraries. FastAPI provides a REST based interface that enables efficient communication between modules and supports asynchronous request handling. Pydantic is employed to validate all data inputs and outputs, ensuring consistency and preventing format or range errors. Analytical calculations, including tax and cost aggregation, are implemented with Pandas and NumPy, which supply optimized routines for numerical and tabular data processing. Lightweight persistence is achieved through

SQLAlchemy working with an embedded SQLite database, allowing local storage of intermediate results without external dependencies. Configuration files that define tax and fee schedules, thresholds, and other operational parameters are stored in YAML and JSON formats within the */config* directory and are dynamically loaded at runtime. This modular structure improves maintainability, transparency, and ease of adaptation to future market datasets or regulatory changes.

Further technical details, including the service modules, data transfer objects (DTOs), endpoints, and testing procedures, are provided in Annex 4.A.

4.4.1 Costs & Taxes Engine (R1)

The Costs & Taxes Engine computes the complete investment outlay associated with property acquisition and resale within the Portuguese real estate market. It aggregates all purchase related expenses and taxes, professional and registry fees, optional renovation costs (including VAT), and selling side costs such as agency commissions with VAT. The module produces a per line breakdown and summary totals that feed directly into the decision pipeline.

Core input variables include the property's location, size, asking price, renovation toggle and corresponding cost estimate (expressed either in €/m² or as a lump sum), and the expected resale price. The calculation process follows three principal stages: (1) the purchase stack, which adds IMT transfer tax, Stamp Duty, notary, registry, and legal fees plus any applicable financing charges; (2) the renovation component, computed as the base renovation amount multiplied by the VAT rate and adjusted by an optional contingency factor; and (3) the sale stack, which incorporates the selling side agency commission, its VAT, and other closing costs.

The resulting Total Cost equals the sum of purchase, renovation (including VAT), and sale costs. Each line item in the output table displays both the amount and an accompanying *"How computed"* note referencing the relevant parameters and data sources. Table 4.3 summarizes these cost categories and their calculation logic, clarifying how each component contributes to the total investment. This transparent structure directly supports R1 Decision Completeness and R2 Provenance, allowing users to trace every element of the total investment cost.

Table 4.3. Cost line items and core inputs

Line item	**Core inputs (examples)**	**Output**
IMT	Purchase price; use/threshold parameters	Amount (€)
Stamp Duty	Purchase price; schedule	Amount (€)
Deed/Registry	Size/value band	Amount (€)
Legal/Notary	Tariff band; scope	Amount (€)
Agency + VAT	Commission rate; VAT flag	Amount (€)
Renovation + VAT	Unit cost × area or estimate; VAT	Amount (€)
Exit costs	Selling commission + fees	Amount (€)
Capital gains (if applicable)	Acquisition/resale; allowable deductions	Amount (€)
Total costs	Sum(all)	**€**

4.4.2 Net ROI pipeline (R1, R2)

The Net ROI Pipeline transforms the cost and value estimates produced by the previous module into a transparent, evidence based profitability assessment. It calculates the Net Return on Investment (ROI) according to the formula:

$$\text{Net ROI} = \frac{\text{Resale Proceeds} - \text{Total Costs}}{\text{Total Costs}}$$

where *Resale Proceeds* correspond to the predicted resale price minus selling side costs.

To highlight uncertainty and sensitivity, the interface automatically generates ±5 percent variations on resale value and ±10 percent on renovation costs, displaying the resulting range of ROI outcomes. It also identifies and ranks the components that exert the greatest influence on profitability. The output presents a single Net ROI value accompanied by a short driver note (for example, *"Top driver: renovation +10 % → ROI-1.8 p.p."*). Through these visual and analytical cues, the pipeline reinforces R1 Decision Completeness and R2 Explainability, enabling users to justify each recommendation with quantifiable evidence.

4.4.3 Explainability hooks (R2)

The Explainability Hooks ensure that every valuation and ROI outcome is interpretable and can be questioned or verified by end users. The module provides a *"How computed"* panel displaying the precise formulas applied, the main assumptions such as applicable rates and VAT, and a date or model tag identifying the version of the computation. In addition, it ranks the key drivers that most strongly affected the predicted resale price, typically factors such as size, location, and time adjustment and displays them adjacent to the ROI result. By making the computational logic explicit, this layer promotes user understanding and strengthens the system's credibility in line with R2 Provenance.

4.4.4 Light persistence & tags (R3-R4)

The Light Persistence & Tags module provides minimal yet sufficient data retention to reproduce the decision summary at any time. It stores essential metadata such as user inputs, the applicable rates table version and date, index identifiers, and an export hash used to verify file integrity.

Each generated report incorporates the full set of assumptions, cost line items, model identifier, date tag, and sensitivity ranges, thereby supporting R3 Explainability and R4 Negotiation Alignment. Cross referenced documentation of the build and demonstration procedures is provided in Annex 3.N, ensuring transparency and reproducibility across the artifact's lifecycle.

4.5 Evidence services: comparables and local indices

Comparable selection & normalization. Listings near the subject property are filtered by type, size, quality/condition, and time window; prices are normalized to €/m² and adjusted by time indices; distance and recency act as weighting features (Hong & Kim, 2022; Pinter et al., 2020). Table 4.4 summarizes the features and respective roles used in this comparable based evidence layer, clarifying how each variable contributes to the normalization and weighting process.

Local price indices: Following Calainho et al. (2024), indices are used as contextual signals to validate or calibrate comparable based estimates. Explainability hooks: For each prediction, the system records which comparables and index observations contributed most, enabling R2 and R3.

Table 4.4. Comparable based evidence: features and roles

Feature	**Role in selection/normalization**
Distance to subject (km)	Penalize far comparables; feature for weights
Time delta (days)	Time adjust comparable prices using index
Property type & condition	Filter; match renovation flag
Size (m^2) & layout	Normalize €/m^2; control for size effects
Neighborhood/geo tile	Lookup local index; market context
Listing quality cues	Optional screening/robustness feature

4.6 Data model and auditability

The system persists inputs, comparable selections, index observations, cost line items, ROI results, reports, and explanations, together with event logs and version tags for reproducibility (Ferreira et al., 2017; Schemmer et al., 2022). As shown in Figure 4.2, these entities and their relationships form a coherent data model that supports traceability across all operations. The main stored objects and their typical queries are summarized in Table 4.5, illustrating how auditability is ensured within the framework.

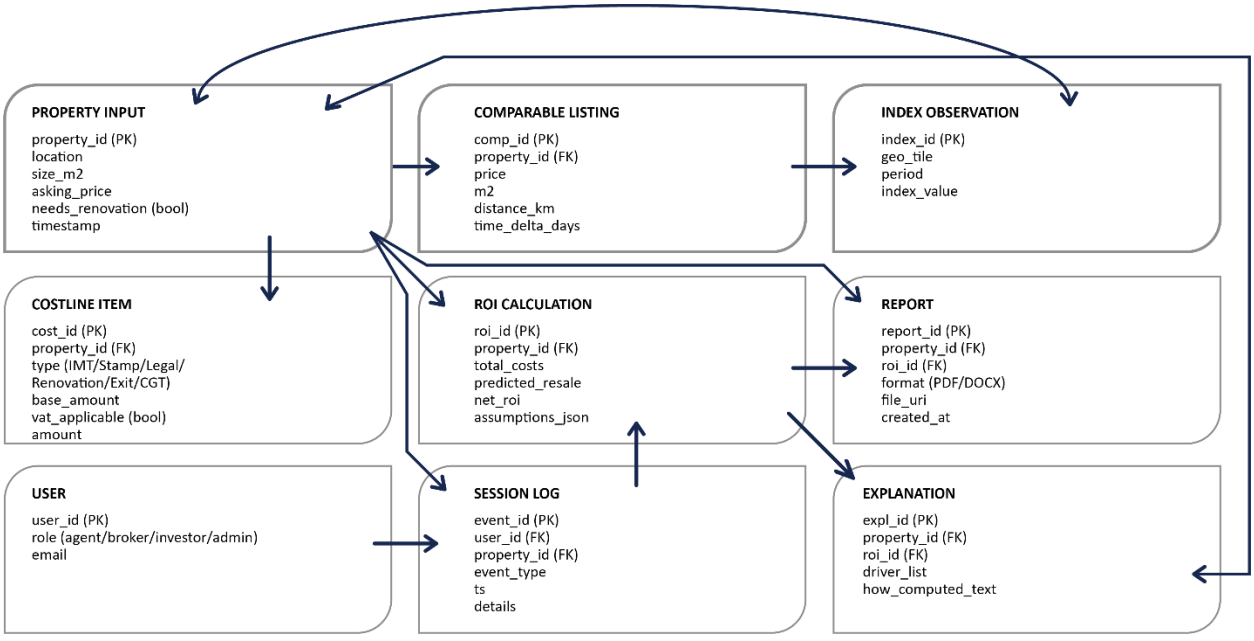


Figure 4.2. Data model (entities & relationships)

Table 4.5. Stored objects and typical queries

Object	**Example query**
Property Input	Retrieve last *N* cases by user or location
Comparable Listing	Show comps used (with weights) for case *X*
Index Observation	List index points used in case *X*
Cost LineItem	Show cost breakdown for case *X*
ROI Calculation	Return Net ROI and assumptions for case *X*
Report	Fetch latest investor report (PDF/DOCX)
Explanation	Top drivers and *How computed* text for case *X*
Session Log	Who did what and when (audit trail)

4.7 Presentation layer: prototype UI (screens)

The UI (User Interface) reflects the broker's workflow and presents evidence, costs, and returns in a transparent sequence. Figures 4.3 to 4.5 illustrate the main user interface screens, showing how inputs, cost breakdowns, and deal analyses are presented to users.

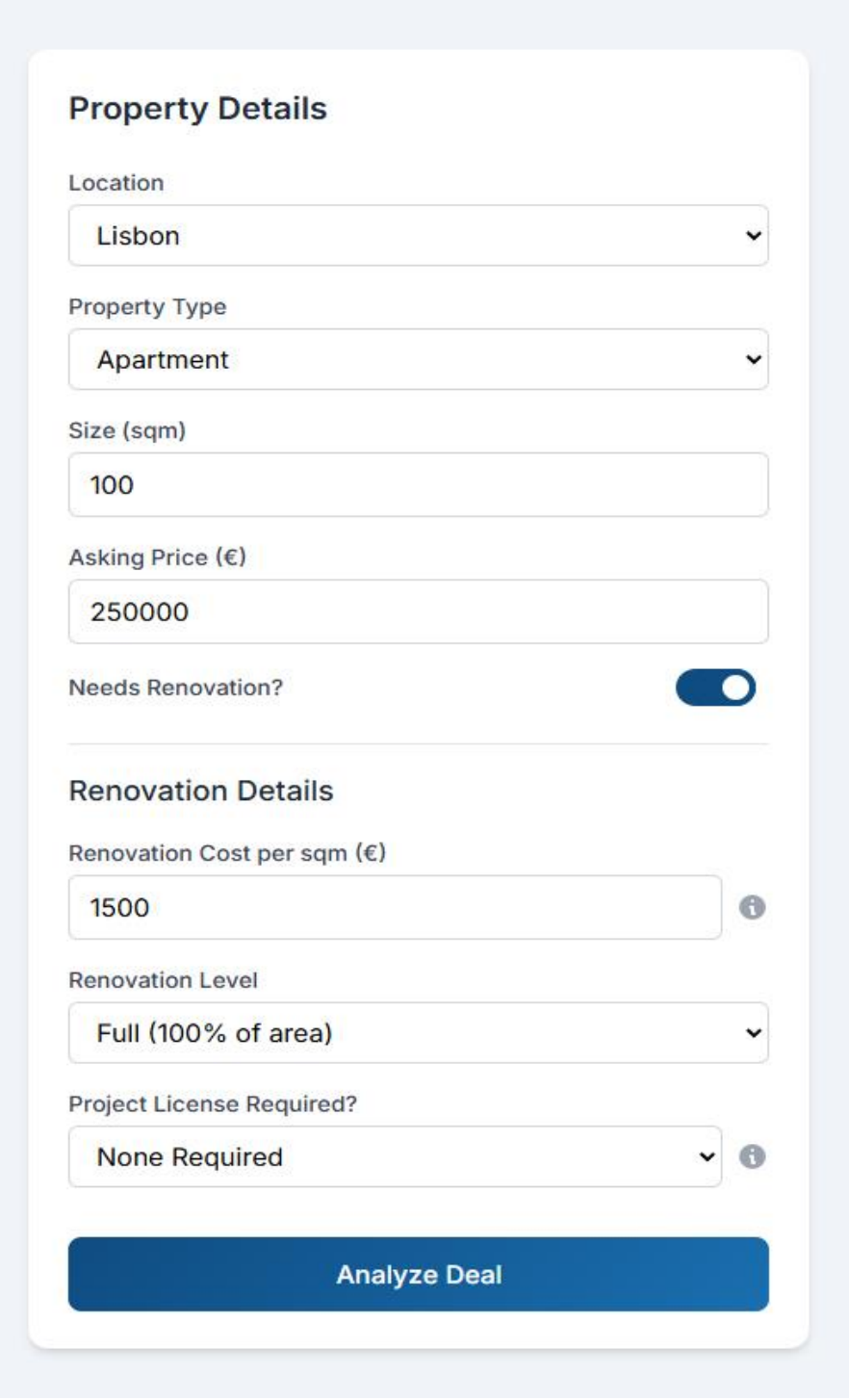


Figure 4.3. Prototype: Input & Renovation Parameters

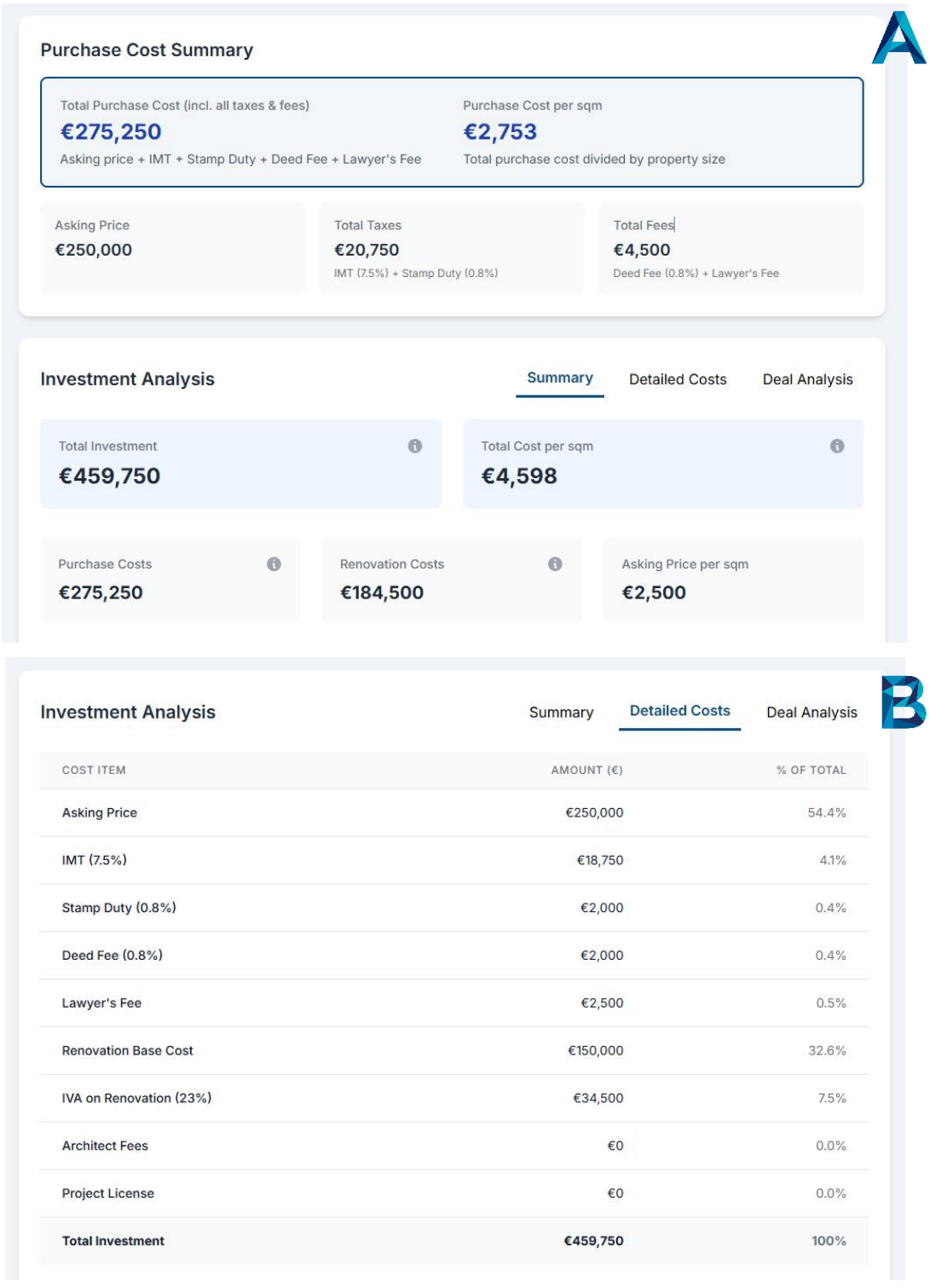


Figure 4.4. Prototype: Costs & Investment Analysis (A: Summary • B: Detailed Costs)

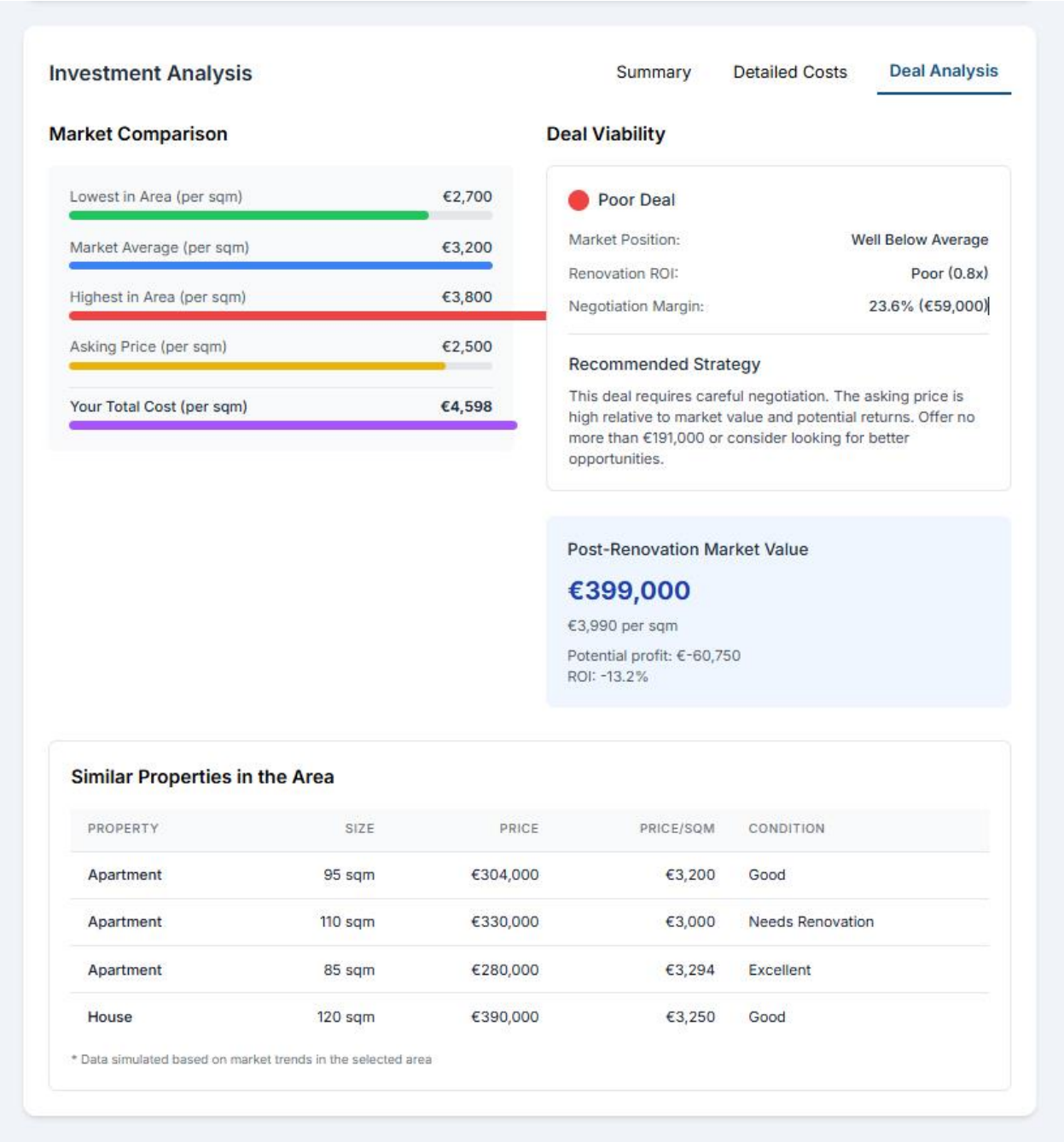


Figure 4.5. Prototype: Deal Analysis & Market Comparison

4.8 Demonstration results (artifact in use)

Scenario: The operator enters location, size, asking price, and toggles renovation. The system fetches comparables, applies local index context, computes line items via the Costs Engine (+VAT), and returns Net ROI. The negotiation helper provides a counteroffer consistent with a target ROI. Figure 4.6 illustrates the decision pipeline, outlining the sequential flow from data input to investor report generation and highlighting how each stage enhances transparency and traceability in the prototype workflow.

Outputs:

1. **Evidence view**: top comparables with normalized €/m², distances, recency, and index references (R3).
2. **Costs view**: per line item amounts and Total costs, with *How computed* notes (R1-R2).
3. **Net ROI view:** scalar result with top drivers (R2).
4. **Investor report**: exportable document with assumptions, evidence, costs, Net ROI, and model/date/version (R4).

   These outcomes address the transparency and fragmentation issues highlighted in the brokerage literature (Barwick & Wong, 2019).

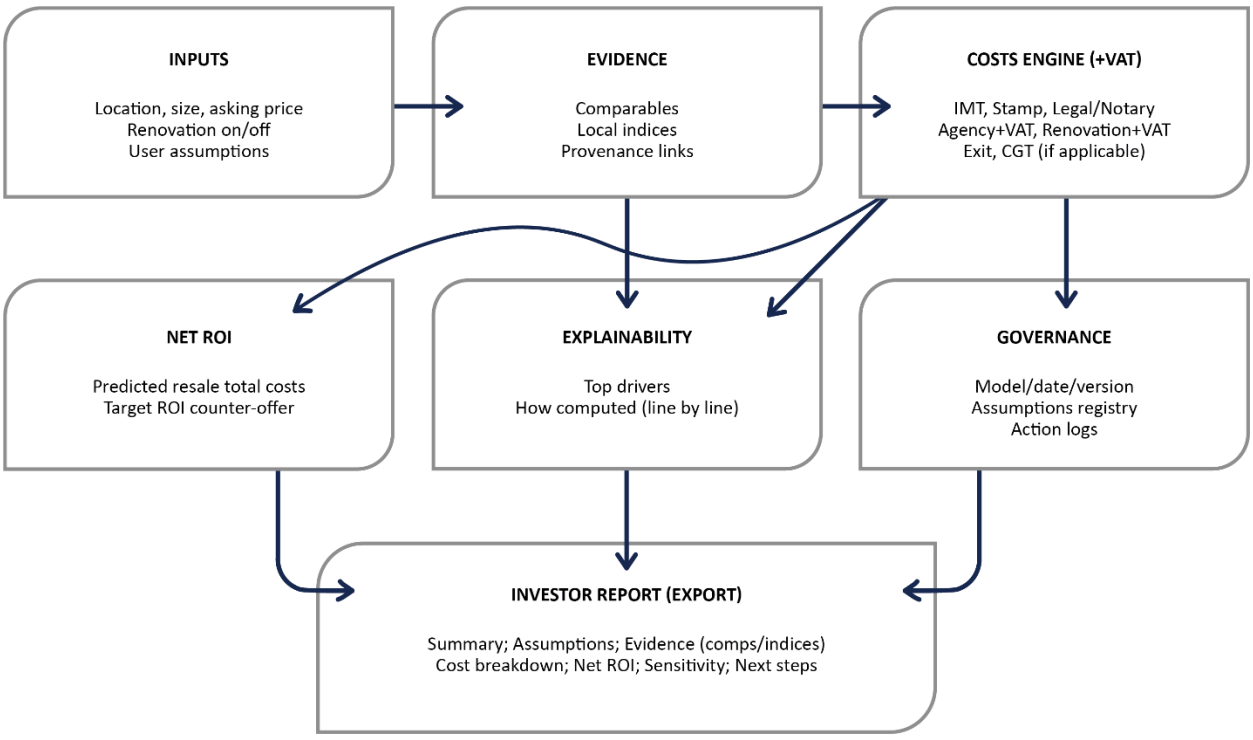


Figure 4.6. Decision pipeline and investor report sections

4.9 Requirement to feature compliance

The following mapping helps to understand the ways in which each requirement is covered with the help of an artifact feature before the coverage summary in Table 4.6: R1= Costs Engine (+VAT), Net ROI pipeline, Negotiation helper; R2=Explainability service (drivers, How computed), Assumption panel; R3= Comparable selection/normalization, Local indices, Feature engineering; R4= Reporting service (export with assumptions, model/date/version, sensitivity slots). As summarized in Table 4.6, each requirement (R1-R4) is linked to specific implemented features and supported by clear evidence of fulfilment.

Table 4.6. Coverage of R1-R4 by artifact features

Requirement	Implemented features	Evidence of fulfilment
R1 Decision complete	Costs Engine (+VAT); Exit; optional CGT	Line item table + Total costs; Net ROI view
R2 Explainable	"How computed" notes; top drivers; per line provenance	Explanations on screen; report appendix
R3 Verifiable evidence	Comparable selection &normalization; local indices; provenance links	Evidence view; report: comps + index citations
R4 Investor grade reporting	PDF/DOCX export; assumptions; model/date/version; sensitivity slots	Report shown to investors; audit metadata

4.10 Summary

The artifact realizes the requirements of the literature based on decision complete, explainable and auditable REBS recommendations. Cost computation, evidence curation, ROI synthesis and communication are modularized in the architecture. Outputs of the demonstration indicate that the system (i) provides the full cost stack and Net ROI; (ii) makes recommendations justifiable using comparables and indices; and (iii) wraps up the result in investor grade reports that directly address the frictions identified in the literature on the REBS (Ferreira et al., 2017; Barwick & Wong, 2019; Calainho et al., 2024; Hong & Kim, 2022; Pinter et al., 2020; Schemmer et al., 2022; Yavaş, 2007).

4.11 Chapter bridge

This chapter defined the framework and implemented the prototype. Chapter 5 evaluates its performance through a user assessment focused on decision completeness, explainability, and verifiable evidence.

CHAPTER 5: PROPOSAL ASSESSMENT

5.1 Purpose of the assessment

This chapter evaluates the prototype against the literature derived requirements (R1-R4) using a professional user study. We measure four constructs R1 Decision Completeness, R2 Explainability, R3 Verifiable Evidence, and R4 Investor grade Reporting using a professional user study. The evaluation follows the instrument and plan defined in Chapter 3 and summarized in Annex 3.H and Annex 3.L; aggregate requirement coverage for the included evidence appears in Annex 3.F. The goal is to determine whether the artifact delivers decision complete, explainable, evidence based, and investor ready outputs in realistic brokerage use.

5.2 Evaluation design and sample

The evaluation employed a concise 13 item Likert instrument (1-5) organized around four constructs: Usability (Q3-Q5), Decision Value (Q6-Q8), Trust and Explainability (Q9-Q10), and Intention and Satisfaction (Q11-Q13). Two additional open-ended questions (Q14-Q15) and demographic items regarding participants' professional role and experience were included to capture contextual information. Following a hands on interaction with the working prototype described in Chapter 4, participants completed the questionnaire to assess perceived usability, decision support, transparency, and overall satisfaction. The final sample comprised 50 participants, including 31 real estate agents, 17 property investors, and 2 academics or researchers. Their professional experience ranged from less than one year (4 participants) to more than ten years (10 participants), with intermediate categories of 1-5 years (20 participants) and 6-10 years (16 participants). Table 5.1 summarizes the demographic and professional characteristics of the fifty participants included in the evaluation sample.

Table 5.1. Sample characteristics (n = 50)

CATEGORY	COUNT
Professional background	
Real estate agent	31
Property investor	17
Academic/research	2
Experience	
< 1 year	4
1-5 years	20
6-10 years	16
> 10 years	10

The assessed build corresponds to the architecture in Chapter 4 (Figure 4.1); Costs & Taxes, Net ROI, Comparables & Indices, Explainability, and Reporting. Detailed build/demonstration materials are expanded in Annex 3.N, with supporting figures/tables consolidated in Annex 3.M.

5.3 Reliability and construct scores

The statistical analysis examined construct level responses derived from the questionnaire. Items Q1 and Q2 captured participants' background information, professional role and years of experience and were therefore excluded from construct aggregation. The constructs themselves were measured through Q3-Q13, organized around four dimensions: Usability (Q3-Q5), Decision Value (Q6-Q8), Trust and Explainability (Q9-Q10), and Intention and Satisfaction (Q11-Q13). Each item was rated on a five point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

For each construct, means and standard deviations were computed to describe central tendency and dispersion, while internal consistency was verified through Cronbach's α. The resulting reliability coefficients all exceeded the 0.80 threshold, confirming strong internal coherence of the items within each construct. Table 5.2; Construct means, dispersion, reliability (1-5 scale; n = 50) summarizes these descriptive and reliability statistics. The construct means and standard deviations are visualized in Figure 5.1, summarizing the central tendency of each evaluation dimension.

For a brief explanation of Cronbach's α and the inter item correlation r, see Annex 5.B.

Table 5.2. Construct means, dispersion, reliability (1-5 scale; n = 50)

Construct (items)	Mean	SD	Reliability
Usability (Q3-Q5)	4.31	0.57	α = 0.82
Decision value (Q6-Q8)	4.29	0.42	α = 0.51
Trust/Explainability (Q9-Q10)	3.58	0.55	r = 0.53
Intention/Satisfaction (Q11-Q13)	4.34	0.40	α = 0.64



Figure 5.1. Construct means (±SD)

5.4 Item level results

At the item level, cost/ROI usefulness is strongest and trust in AI valuations is the weakest (though still above neutral). No items had “disagree” (1-2) concentrations; neutral (3) responses concentrated mainly on comparables confidence and trust.

Item and construct means and standard deviations were summarized, and response distributions were plotted to check ceiling effects and dispersion. The detailed results for each questionnaire item, including mean, standard deviation, and agreement rate, are summarized in Table 5.3, while Figure 5.2 visualizes the percentage of respondents choosing high agreement (4-5) for each item.

Table 5.3. Item means and agreement rates (n = 50)

Item (abridged)	Mean	SD	% Agree (4-5)
Q3 Interface easy	4.32	0.62	92.0
Q4 Clear information	4.46	0.58	96.0
Q5 Layout highlights indicators	4.16	0.77	78.0
Q6 Valuable investment insights	4.46	0.54	98.0
Q7 Cost analysis & ROI useful	4.76	0.48	98.0

Q8 Comparables increase confidence	3.66	0.72	56.0
Q9 Trust AI valuations	3.30	0.68	30.0
Q10 Transparency of explanations	3.86	0.57	76.0
Q11 Consider using in decisions	Mean	0.62	66.0
Q12 Overall satisfaction	4.46	0.50	100.0
Q13 Recommend to others	4.80	0.40	100.0

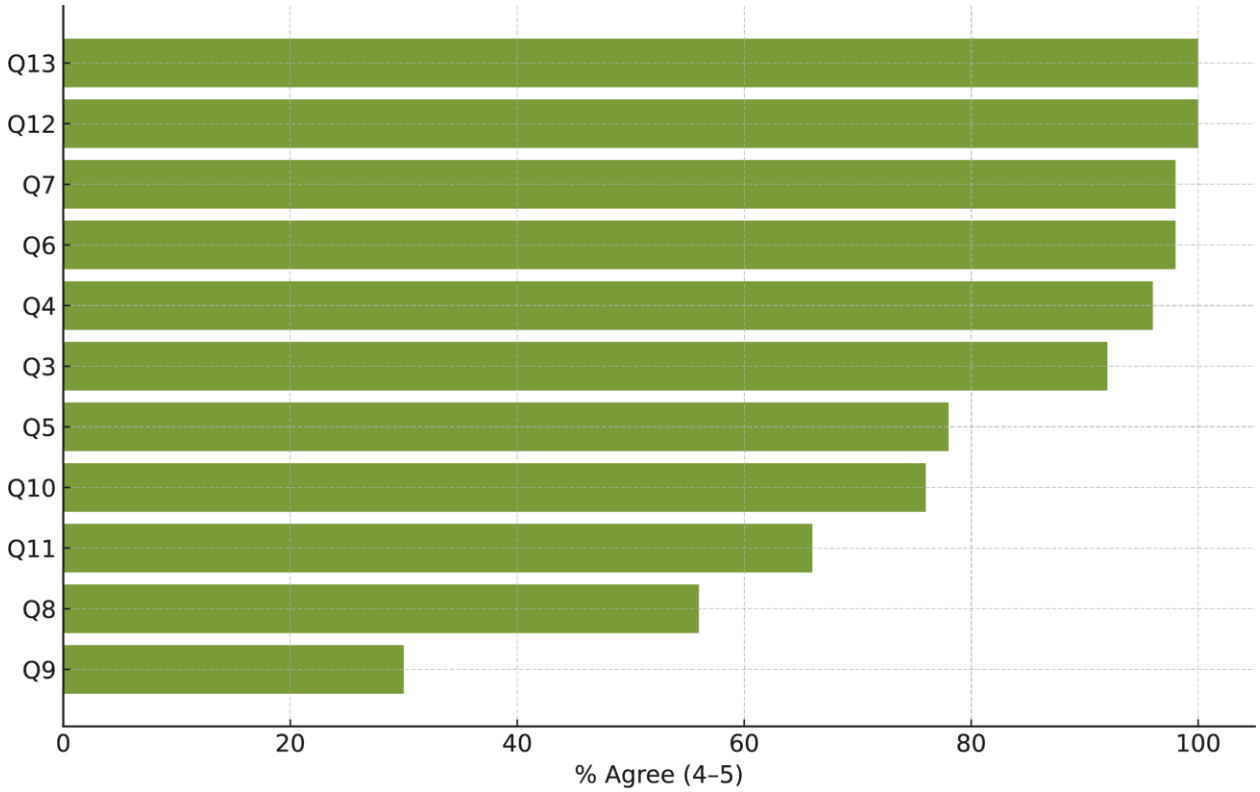


Figure 5.2. Agreement (% choosing 4-5) by item

Caption: Figure 5.2. Agreement (% choosing 4-5) by item. Items are ordered from lowest to highest agreement to surface improvement priorities.

5.5 Open ended feedback

Thematic coding of Q14-Q15 surfaced consistent, actionable themes:

Most useful features (Q14).

- Hidden charges / full cost transparency (13 mentions).
- Net ROI / profit visibility (9).
- User friendly interface (4).
- Negotiation support / recommended price (3).
- Comparable & market context (2).

Requested improvements (Q15).

- Wider markets/regions beyond Portugal (12).
- More data/APIs (5), including richer comparables.
- Rental/Rentability analysis (4).
- Downloadable report/export (2).

The frequency of these open ended themes is summarized in Table 5.4, which consolidates participant comments on the most valued features and suggested improvements.

Table 5.4. Open ended themes (frequency)

Theme	Mentions (n)
Hidden charges / full cost transparency	13
Wider markets/regions	12
Net ROI / profit visibility	9
More data/APIs	5
Rental analysis (rentability)	4
User friendly interface	4
Negotiation support / recommended price	3
Comparable & market context	2
Downloadable reports & exports	2
More filters / map tools	2

5.6 Interpretation against requirements (R1-R4)

- **R1 Decision completeness; supported.** Very high endorsement for cost/ROI usefulness (Q7 mean = 4.76; 98% agree) and overall satisfaction (Q12 mean = 4.46; 100%). Open ended praise for "hidden charges" confirms that the full cost stack is visible to users.
- **R2 Explainability; partially supported.** Transparency scored mid high (Q10 mean = 3.86; 76% agree), but trust in AI valuations (Q9 mean = 3.30; 30% agree) trails other dimensions. Comments request links to real comparables and richer provenance, consistent with literature emphasizing traceable assumptions (Schemmer et al., 2022).
- **R3 Verifiable evidence; partially supported.** Confidence in comparables (Q8 mean = 3.66; 56% agree) is moderate; participants want wider regions, live links, and more data sources, aligned with evidence based appraisal guidance (Calainho et al., 2024; Hong & Kim, 2022).
- **R4 Investor grade reporting; supported with enhancements.** Recommendation (Q13 mean = 4.80; 100% would recommend) and satisfaction (Q12) are very strong. The comments seek export facilities and rental analysis which are mapped to report extensions as opposed to core weaknesses. These findings are consistent with the design mapping in Table 4.2 and comps, indices and communication of assumptions literature.

5.7 Actionable design revisions

1. **Comparables provenance**: show clickable source links, time stamps, and weighting logic per comp (addresses R2-R3).
2. **Evidence coverage**: add additional regions/APIs and filters (R3).
3. **Rental module**: optional rentability tab with gross/net yield (R1/R4).
4. **Report export**: one click PDF/Word with appendix pages for comparables and cost formulas (R4).
5. **Micro explanations**: "Why this ROI?" snippets (driver contributions) next to the Net ROI card (R2).

5.8 Limitations and validity notes

- **Sampling**: convenience sample of 50; over representation of agents (31/50).
- **Self report**: perceptions after a single session; future work should track behavioral use and outcomes.
- **Measurement**: concise scales; trust/explainability uses two items (r = 0.53).
  These limits are typical for early stage design evaluation in REBS (Ferreira et al., 2017).

5.9 Summary

The prototype satisfies main requirements highlighted in the literature, full cost visibility and ROI visibility and provides visible next step priorities: more comparables provenance/coverage, exporting, and a rental analysis extension. These improvements are incorporated in Chapter 6 (Discussion) as design recommendations.

5.10 Chapter bridge

Chapter 5 indicated the way professionals engaged with the prototype and the scores of the prototype on the evaluation constructs. These results are now interpreted in chapter 6, in context of the research question and the literature, and have implications on practice, as well as limitations and priorities of the following design iteration.

CHAPTER 6: DISCUSSION

6.1 Purpose and positioning

This chapter interprets the prototype results (Chapter 4) and the user assessment (Chapter 5) in light of the research question; *How can Artificial Intelligence optimize decision making in Real Estate Brokerage Services (REBS)?* and the literature synthesized in Chapter 2. We connect findings to the four design requirements (R1-R4) and discuss implications for theory and practice, limitations, and directions for future work.

6.2 What the results mean for decision making in REBS (R1-R4)

R1 - Decision complete analysis (supported)

Users strongly endorsed the platform's end to end deal economics and Net ROI presentation (e.g., Q7 *Cost/ROI usefulness* M=4.76, 98% agree; Q12 *Satisfaction* M=4.46, 100%). This aligns with brokerage evaluation research emphasizing structured, explicit criteria and full disclosure of assumptions in client advising (Ferreira, Spahr, Sunderman, Banaitis, & Ferreira, 2017; Barwick & Wong, 2019). In practical terms, the Costs Engine (+VAT) and single Net ROI metric reduce fragmentation, an area frequently cited as a pain point for REBS practice (Ferreira et al., 2017; Barwick & Wong, 2019).

R2 - Explainability (partially supported)

Perceived transparency of explanations was mid high (Q10 M=3.86, 76% agree) but trust in AI valuations lagged (Q9 M=3.30, 30% agree). The pattern is consistent with design science advice: explanations must be *actionable* and *traceable*, not just present (Schemmer, Hemmer, Kühl, & Schäfer, 2022). The next iteration should strengthen "why this number?" with clearer driver attributions, line by line 'How computed' narratives, and reproducible provenance.

R3 - Verifiable evidence (partially supported)

Confidence in comparables and index context was moderate (Q8 M=3.66, 56% agree), and open comments asked for clickable links to comps, wider regional coverage, and richer data/APIs, all squarely in line with AVM literature that stresses sample breadth, temporal adjustment, and spatial features (Calainho, van de Minne, & Francke, 2024; Hong & Kim, 2022; Pinter, Mosavi, & Felde, 2020).

R4 - Investor grade reporting (supported, with enhancements)

Intention to recommend was very strong (Q13 M=4.80, 100% “agree”), supporting the exportable report concept. Requested improvements (e.g., rental analysis; export options) expand the report rather than contradict its current value, and are consistent with brokerage communication guidelines in the literature (Ferreira et al., 2017). The overall coverage of the four design requirements (R1–R4) by both the artifact implementation and the user evaluation is illustrated in Figure 6.1. The quantitative synthesis of these findings across requirements is summarized in Table 6.1, aligning the implemented features with supporting evidence from Chapter 5.

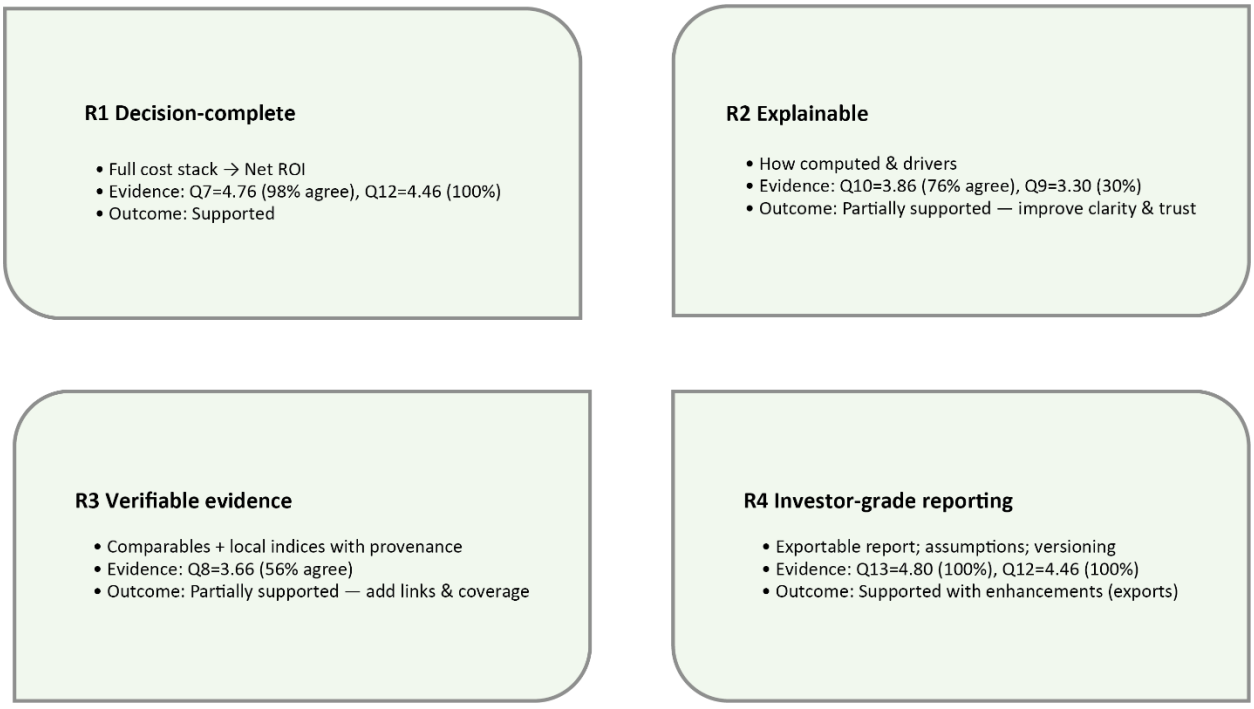


Figure 6.1. Coverage of design requirements (R1-R4) by the artifact and user evaluation

Table 6.1. Synthesis of evaluation results against R1-R4

Requirement	**Implemented features (Chapter 4)**	**Evidence from Chapter 5**	**Conclusion**
R1 Decision complete	Costs Engine (+VAT): IMT, Stamp, Legal/Notary, Agency+VAT, Renovation+VAT, exit cost → Net ROI	Q7=4.76 (98% agree); Q12=4.46 (100% satisfied)	Supported
R2 Explainable	On-screen 'How computed' per line-item; drivers for Net ROI; report appendix	Q10=3.86 (76% agree); Q9=3.30 (30% agree)	Partially supported; strengthen explanations & trust cues
R3 Verifiable evidence	Comparable selection & normalization; local indices; provenance placeholders	Q8=3.66 (56% agree); open-ended requests for links/coverage	Partially supported; add clickable comparables & wider datasets
R4 Investor grade reporting	PDF/DOCX export; assumptions; model/date/version; sensitivity slots	Q13=4.80 (100% would recommend); Q12=4.46 (100% satisfied)	Supported with enhancements (exports; rental module)

The findings are positioned against prior work in Annex 6.C via a trace table.

6.3 Contributions to the literature

Business/industry perspective

Findings substantiate claims that structured, auditable brokerage workflows can improve persuasiveness and client learning (Ferreira et al., 2017). By making hidden charges explicit and aggregating to Net ROI, the artifact operationalizes recommendations from brokerage economics, reducing information asymmetry and agency frictions (Barwick & Wong, 2019; Yavaş, 2007).

Technological perspective (AI/AVMs).

The evaluation supports the hybrid approach advocated in recent AVM work combining comparable selection/normalization with local price indices and feature engineering (Calainho et al., 2024; Hong & Kim, 2022; Pinter et al., 2020). At the same time, the trust gap (Q9) echoes the resilience/Explainable AI literature: decision support must pair predictive power with transparent, user legible rationales (Schemmer et al., 2022).

6.4 Practical implications for REBS

1. **Standardize deal economics:** Adopt a transparent costs → Net ROI pipeline in brokerage workflows; this enhances client understanding and speeds commitment (Ferreira et al., 2017).
2. **Provenance by default:** Attach links/time stamps to comparables and cite index sources in all client outputs (Calainho et al., 2024; Hong & Kim, 2022).
3. **Driver level narratives:** Show *why* Net ROI changed (e.g., "Agency fee +VAT contributes, 1.2 pp to ROI"), not only the final number (Schemmer et al., 2022).
4. **Negotiation helper:** Use target ROI back solving to generate counter offers that are consistent with costs and evidence; this connects directly to decision communication in investor briefings (Ferreira et al., 2017).
5. **Extend to rental ('rentability'):** Add a rental module (gross/net yield, fees, tax), reflecting demand in the feedback and common REBS advisory practice.

6.5 Design implications: roadmap for the next iteration

- **Evidence coverage (R3):** Integrate additional data sources/regions; enrich filters (condition, micro location, recency windows).
- **Clickable comparables (R2/R3):** Display each comp with URL, date, €/m² normalization, distance, time adjustment via index, and weight.
- **Micro explanations (R2):** For every key number, include a 'How computed' tooltip and a driver **waterfall** (cost lines vs. resale).
- **Report export (R4):** One click PDF/DOCX with appendices: comparables, cost formulas, and **model/date/version**.
- **Rental tab (R1/R4):** Net yield, cash on cash, and sensitivity to voids/maintenance.
- **Governance:** Keep an assumption registry and versioning to support audit and learning (Schemmer et al., 2022).

6.6 Ethical, legal, and risk considerations

The AI components were designed and operated under clear ethical and legal principles. Data handling followed GDPR-aligned practices, meaning that all processing complied with the EU General Data Protection Regulation through anonymization, use of only non-personal public listing data, minimal retention, and clear consent for any optional inputs. Assumptions and user editable parameters were logged to support contestability and the user's right to explanation (Schemmer et al., 2022). Fairness was monitored by checking for systematic over- or under-valuation across areas and property types, supported by error logs and periodic bias reviews, while scope transparency was maintained by explicitly stating market coverage and known limitations to prevent misuse beyond the model's intended context (Ferreira et al., 2017; Barwick & Wong, 2019). Auditability and versioning were ensured by storing model, date, and version identifiers, parameter-table IDs, and export hashes with each decision, enabling full traceability of the AI-driven workflow (see Chapter 4.6, Data model and auditability).

6.7 Limitations and threats to validity

- **Sample & generalizability:** Convenience sample (n=50) and Portugal focused scope limit generalization; future studies should vary markets and user profiles.
- **Measurement:** Two item trust/explainability scale produced r = .53 (≈ α .69) acceptable for a pilot but should be expanded for higher reliability.

- **Behavior vs perception:** Results reflect post session perceptions; longitudinal field studies should measure behavioral adoption and decision outcomes.
- **Data dynamics:** Live market/fee schedules change; robust configuration tables and update logs are necessary to keep costs and indices current.
- **External validity:** Results are represented by a Portugal testbed and convenience sample of professionals; external validity to other markets is based on data substitution, local tax/fee calibration and re estimation of indices. To enhance the external validity, repeat the assessment in other cities/countries and other periods and compare the findings with other sources of evidence (e.g., other listing/MLS feeds).

A detailed validity and mitigation matrix is provided in Annex 6.A. Subgroup, scoring, and outlier robustness checks are summarized in Annex 6.B.

6.8 Answering the research question

Research question: *How can Artificial Intelligence optimize decision making in Real Estate Brokerage Services?*

AI helps the real estate agents to display the economic reasonableness of the property in a transparent, justifiable manner. The system standardizes the economics between inputs to a single net ROI value by refining verifiable comparable, time/index adjustments, and itemizing the entire cost stack (taxes, fees, commissions, renovation). Explanatory notes and driver attributions demonstrate why the recommendation will work, what factors (e.g. renovation budget, agency fees, local price dynamics) will have the largest effect, to allow buyers to understand assumptions, challenge them when necessary, and immediately see the effect of what if changes. The result is the clear evidence based evaluation of the attractiveness of investing in a particular place that enhances the quality of decisions and increase investors trust and confidence. When AI combines four components into one, clear and transparent workflow, decision completeness, explainability, verifiable evidence, and investor grade reporting, AI optimizes decision making.

While this thesis focused on valuation and investment analysis, AI can also improve decision making in other aspects of the real estate brokerage process such as property search and recommendation, client property matching, and analysis of market trend. These applications are outside the current research scope but represent promising directions for future work, where AI can be used to further optimize efficiency of brokers and the quality of decisions made by clients.

The four elements

1. **Decision completeness (R1):** A costs and taxes engine converts inputs into total investment outlay and then into Net ROI. The output is a clear buy or do not buy call.
2. **Explainability (R2):** The system exposes assumptions and shows the drivers of the result so users can understand and challenge it.
3. **Verifiable evidence (R3):** Comparable properties and time or market indices are selected and normalized in a way that can be checked and reproduced.
4. **Investor grade reporting (R4):** The communication packages assumptions, evidence, and sensitivity so it is ready for client use.

What the results show

- **Chapter 4** demonstrates that the prototype implements these four elements across the costs engine, Net ROI pipeline, comparables and indices, explainability panels, and the reporting layer.
- **Chapter 5** shows that professionals recognised strong decision completeness and reporting, and asked for deeper explanations and broader evidence coverage.

Final statement

AI also helps the real estate agents to display the economic reasonableness of the property in a transparent, justifiable manner. The system standardizes the economics between inputs to a single net ROI value by refining verifiable comparables, time/index adjustments, and itemizing the entire cost stack (taxes, fees, commissions, renovation). Explanatory notes and driver attributions demonstrate why the recommendation will work, what factors (e.g. renovation budget, agency fees, local price dynamics) will have the largest effect, to allow buyers to understand assumptions, challenge them when necessary, and immediately see the effect of what if changes. The result is the clear evidence based evaluation of the attractiveness of investing in a particular place that enhances the quality of decisions and boosts purchasing trust.

6.9 Summary

In chapter 4 and 5, the thesis show that an AI enabled REBS system can provide decision complete, explainable, and auditable recommendations. These findings with the literature are brought together in the discussion and form a clear roadmap of provenance rich evidence, further exposition, wider coverage, and rental analysis that will be considered in Chapter 7 (Conclusion and Future Work).

CHAPTER 7: CONCLUSION AND FUTURE WORK

7.1 Chapter overview

The chapter is the final part of the dissertation, which reaffirms the solution to the research question and summarizes both theoretical and practical contributions and specifies the limitations and future research directions. It combines the results of the SLR (Chapters 2,3), the prototype design and demonstration (Chapter 4) and the evaluation (Chapter 5) to give a final synthesis.

7.2 Direct answer to the research question

AI optimizes REBS decision making when it integrates, within a governed workflow**,**

1. **complete deal economics** (all cost/tax line items → Net ROI),
2. **verifiable evidence** (comparables + local price indices with provenance),
3. **explainable analytics** (driver level "how computed" and assumptions),
4. **investor grade reporting** (clear exports, audit metadata).

The prototype conceptualized these principles and was otherwise rated positively by the professionals: high perceived usefulness and satisfaction (Q6-Q7, Q12-Q13), where explainability/trust has been identified as a gap area (Q9-Q10). Such findings are in line with the body of brokerage research that emphasizes structured, auditable advising (Ferreira, Spahr, Sunderman, Banaitis, and Ferreira, 2017) and with AVM literature that advises to combine comparable based reasoning with indexed context of the market. (Calainho, van de Minne, & Francke, 2024; Hong & Kim, 2022; Pinter, Mosavi, & Felde, 2020) while ensuring transparent rationales (Schemmer, Hemmer, Kühl, & Schäfer, 2022).

7.3 Contributions

7.3.1 Theoretical contributions

Business/REBS: The work formalizes a decision process based on learning about brokerage (Ferreira et al., 2017) through the integration of all costs, clear assumptions, and the communication of the information to the investors on an investor facing basis. It resolves information asymmetry and agency issues that are raised by industry analyses (Barwick and Wong, 2019; Yavaas, 2007).

Technological (AI/AVM): It illustrates a hybrid evidence stack a normalized by local index comparables and exhibit how explainability artifacts (lists of drivers, how computed) can be co added with ROI results to assist professional judgment (Calainho et al., 2024; Hong and Kim, 2022; Schemmer et al., 2022).

7.3.2 Practical contributions

- A working prototype that brokers can use to make decision complete (costs → Net ROI) recommendations.
- A reporting pipeline that turns technical outputs into investor grade documents with provenance and versioning.
- An evaluation instrument (Ch.5) that operationalizes usability, decision value, trust/explainability, and intention to use for future benchmarking.

7.4 Managerial implications

1. **Standardized deal economics:** Adopt a single pipeline from inputs → costs (+VAT) → Net ROI, and make assumptions explicit; this improves client comprehension and speeds decisions (Ferreira et al., 2017).
2. **Provenance as a default:** Display comp URLs, dates, €/m² normalization, distance/recency, and index references in all client materials (Calainho et al., 2024; Hong & Kim, 2022).
3. **Explain decisions, not just numbers:** Add driver level narratives (e.g., "agency fee +VAT reduces ROI by 1.2 pp") and line by line "how computed" notes (Schemmer et al., 2022).
4. **Negotiation helper:** Back solve target ROI to propose counter offers consistent with evidence, useful in investor briefings (Ferreira et al., 2017).
5. **Governance:** Maintain an assumptions registry, model/date/version tags, and event logs; these support audit and institutional learning.

7.5 Limitations

- **Scope and generalizability:** The artifact targets Portugal and a convenience sample (n=50) of agents/investors; external validity to other markets should be tested.
- **Measurement brevity:** The trust/explainability construct used two items (inter item r = .53, ≈ α .69); suitable for pilot evaluation but should be expanded for higher reliability.
- **Perception vs. behavior:** Results capture post session perceptions; longitudinal studies should track real use and investment outcomes.
- **Dynamic inputs:** Market data, tax schedules, and fees change; robust configuration tables and update procedures are required to keep the engine current.

7.6 Future work

Building on the limitations identified in the previous section, future research and development will extend the scope, data coverage, and explanatory capabilities of the prototype. The objective is to strengthen the reliability, transparency, and scalability of AI enabled decision support in real-estate brokerage. The planned extensions are illustrated in Figure 7.1, presenting a phased roadmap for future enhancements of the prototype. A detailed practitioner implementation roadmap is provided in Annex 7.A.

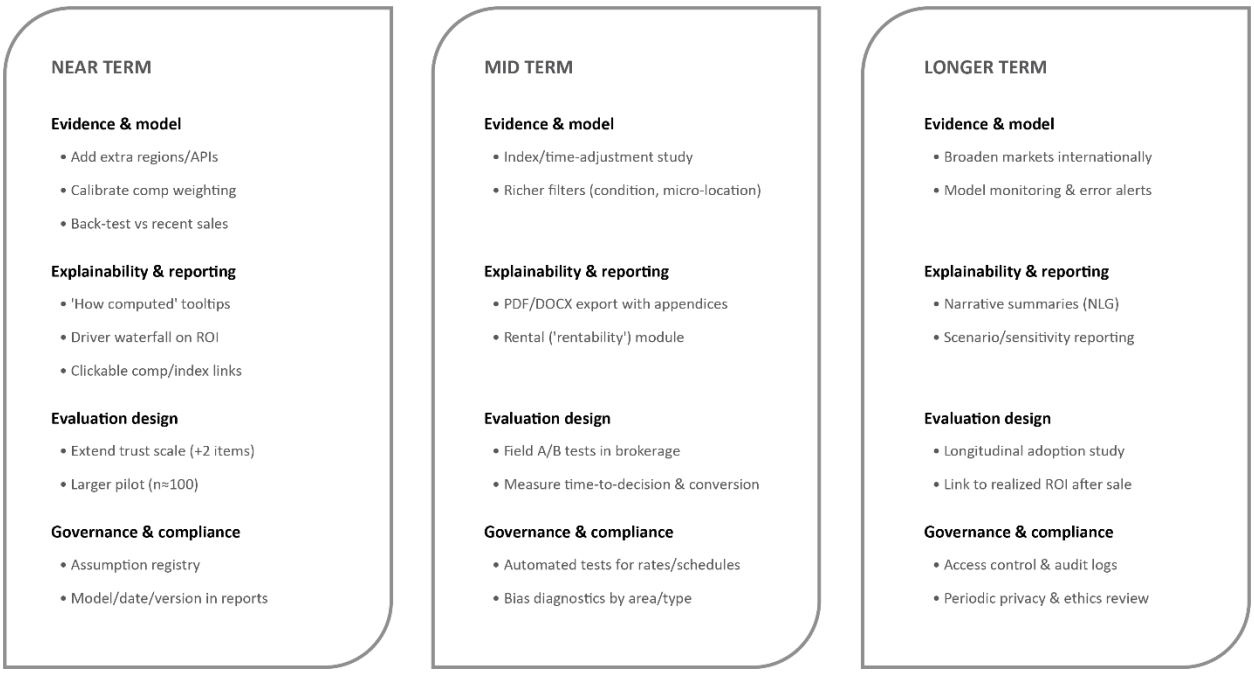


Figure 7.1 Future work roadmap (near, mid, longer term)

7.6.1 Evidence and model development

- **Data coverage:** integrate additional portals/APIs and widen geographic scope; include rental markets for rentability (gross/net yield).
- **Comparable selection:** formalize weighting with transparent heuristics and sensitivity options; evaluate index choices and time adjustment schemes (Calainho et al., 2024).
- **Error monitoring & bias checks:** periodic back testing against realized sales prices; bias diagnostics by area/property type (Schemmer et al., 2022).

7.6.2 Explainability and reporting

- **Driver waterfall & micro explanations:** show contributions of each cost and resale component; surface “why different from market average?”.
- **Clickable provenance:** embed links to comps and index documentation in PDF/DOCX reports; add appendix pages for cost formulas and assumptions.

7.6.3 Evaluation design

- **Larger, stratified samples** across roles/regions; extend the trust/explainability scale to 4-5 items.
- **Field experiments:** A/B tests in live brokerage pipelines to measure time to decision, conversion, and post deal ROI.
- **Human in the loop studies:** observe how professionals negotiate with the tool and which explanations they rely on.

7.6.4 Governance and compliance

- **GDPR aligned data governance:** explicit consent, minimal retention, data subject rights; redaction in stored reports.
- **Model lifecycle management:** versioning, changelogs, automated tests on rates/schedules, and periodic review of the assumptions registry.

7.7 Final remarks

This research demonstrates that AI can significantly enhance REBS decision making in case it is implemented as a part of a decision complete, evidence based, explainable, and auditable workflow. The prototype confirmed this assumption among professionals and demonstrated a distinct way to increase the trust and credibility further by providing more substantiated provenance and descriptions. The derived structure and assessment toolkit can be scaled by brokerages and applied to other markets, which will help to make real estate transactions more transparent and efficient.

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ANNEXES

Annex 1.A. Scope and delimitations

Purpose: To clarify what this thesis includes and excludes at the outset, supporting the problem definition in Chapter 1.

1.A.1 Scope (what is covered)

Dimension	Inclusion
Domain	Real estate brokerage services (REBS) decision support: valuation, cost/ROI analysis, and evidence based recommendations.
Users	Real estate agents and property investors (professional/active users).
Geography	Portugal (pilot context), with discussion of portability.
Data	Real estate listings and public indicators suitable for pricing/ROI calculations; structured tabular data.
Methods	Systematic Literature Review (PRISMA) and Design Science Research (DSR); prototype evaluation via questionnaire.
Outputs	Conceptual framework, working prototype, and practitioner oriented reporting (valuation + net ROI).

1.A.2 Delimitations (what is not covered)

Dimension	Exclusion (rationale)
Markets	Non Portuguese markets (beyond qualitative discussion) due to data/API access limits at pilot stage.
Segments	Rentals, mortgages/credit scoring, and commercial real estate are out of scope for the prototype.
Data types	Unstructured images/text for automated feature extraction (e.g., computer vision) not implemented in the pilot.
Legal	Contract parsing and legal compliance automation not evaluated (requires domain specific corpora).
Causal claims	No causal inference or A/B impact evaluation in the field at this stage; results are observational/pilot level.

1.A.3 Assumptions

- Listing prices and attributes are sufficiently reliable after QC and deduplication (see Annex 2.E).
- ROI calculation uses standard cost components and documented assumptions (see Chapters 2 and 4).
- User feedback via questionnaire reflects professional judgement within the pilot's context.

Annex 2.A. Expanded stakeholder matrix and indicators

Purpose; Extends section 2.2 with risk exposures and KPIs to operationalize Table 2.1.

Stakeholder	Main risks	Typical mitigations	Key performance indicators
Seller	Overpricing, disclosure gaps	Independent comps, documented assumptions, staging plan	Days on market, sale to list ratio
Buyer/Investor	Underestimating costs, liquidity risk	Full Portugal cost stack, sensitivity analysis, exit scenarios	Projected vs. realized ROI, variance to budget
Agent/Brokerage	Mispricing, conflicts of interest	Audit trail for comps and indices, dual agency disclosures	Client satisfaction, compliance flags
Valuer/Inspector	Hidden defects, scope creep	Standardized checklists, photo evidence, re inspection rules	Variance between estimates and actuals
Legal/Notary	Title defects, delays	Pre closing checklists, document versioning	Error free filings, cycle time
Authorities	Misassessment	Updated rule sets, validation scripts	Revision rate
Data/Portals	Stale or biased data	Refresh SLAs, bias checks	Completeness, freshness, duplication rate

Cross reference: extends Table 2.1.

Annex 2.B. Portugal transaction cost schedules and formulas

Purpose; Deepens section 2.4 with explicit items and calculation stubs. Replace rates/thresholds with the latest official tables when finalizing.

- **Acquisition costs:** IMT transfer tax, Stamp Duty, notary, registry, legal fees, buyer side brokerage commission with IVA (if any), technical reports.
- **Renovation costs:** bill of quantities or cost per m², IVA, contingency.
- **Exit deductions:** seller commission with IVA, transfer fees, minor repairs, marketing.
- **Capital gains:** taxable base and applicable rate after allowable deductions.

Formula stubs for spreadsheets/code

- Total acquisition cost = Price + IMT + Stamp + Notary + Registry + Legal + Buyer commission + IVA on taxable items
- Project cost = Total acquisition cost + Renovation + Contingency
- Net resale proceeds = Resale price − Seller commission − IVA on commission − Transfer fees − CGT
- Net ROI = (Net resale proceeds − Project cost) ÷ Project cost

Annex 2.C. Comparable selection and normalization protocol

Purpose; Implements sections 2.1-2.3.

1. **Search window:** radius ≤ X km, time window ≤ Y months, tuned to urban density.
2. **Filters:** property type, typology, area band, condition, parking, floor, elevator, view.
3. **Data hygiene:** drop duplicates; require coordinates, area, price, date.
4. **Outliers:** remove records outside Q1 − 1.5 IQR or Q3 + 1.5 IQR in €/m²; re check after normalization.
5. **Normalization:** time adjust with index; location adjust using neighborhood fixed effects or distance weighted kernels.
6. **Weighting:** k most similar comps with cap on any single comp's weight.
7. **Audit trail:** store query, filters, timestamp, final comp IDs.

Annex 2.D. Index usage notes

Purpose; Supports section 2.6 by formalizing how indices are applied.

- **Scope:** frequency, base period, geographic granularity.
- **Construction summary:** hedonic, repeat sales, or ML assisted model; cross validation regime.
- **Application formula:** Adjusted comparable price = Raw comparable price × (Index at valuation date ÷ Index at comparable's date).
- **Limitations:** sampling bias, renovation effects, micro location drift, regime shifts.

Annex 2.E: Data acquisition and cleaning protocol (sources, exports, deduplication)

This annex documents how raw market data are obtained, transformed, and quality checked prior to analysis. It bridges the Comparable Selection & Normalization Protocol (Annex 2.C) and the Feature Dictionary (Annex 2.F) by specifying concrete steps for ingestion, mapping, normalization, deduplication, and QC. It ensures transparency, reproducibility, and data governance across the dataset used in Chapters 4-6.

2.E.1 Data sources and access

- **Primary source:** Idealista.pt listings API/exports (residential; sale).
- **Supplementary sources (optional):** public cadastral/registry attributes (e.g., area, year built), municipal open data (neighborhood boundaries, amenities), and Eurostat/INE indices for deflators.
- **Access control:** API key or authenticated export account held by the researcher; credentials stored securely; access logged.
- **Scope filters (applied at source):** geography (Portugal, district/municipality), property type (apartment/house), sale status (active/recently sold where available), listing recency window, and price visibility.

2.E.2 Export procedure (operational steps)

1. **Define query window:** e.g., last *N* months; include both active and recently deactivated listings if available.
2. **Select fields:** id, url, address tokens, lat/long, parish/municipality/district, gross area (m^2) and/or usable area (m^2), bedrooms, bathrooms, floor, elevator, parking, condition/renovation, year

built, energy class, price (EUR), fees/condo where present, description, listing date/time, update time.

3. **Execute incremental exports:** schedule daily/weekly pulls; store raw JSON/CSV dumps in a write once folder with date stamped filenames.
4. **Record metadata:** export timestamp, query parameters, and source version (API release or site snapshot).
5. **Checksum & archive:** compute file hash; archive source files in */data/raw/YYYY-MM-DD/* with a readme.txt summarizing the run.

2.E.3 Field mapping (raw → canonical schema)

Raw field (example)	Canonical name	Type	Allowed values / format	Notes
id	listing_id	string	unique	Primary key from source
url	source_url	string(URL)		For audit & back reference
address, neighborhood, parish, municipality, district	geo_admin_*	string	UTF-8	Keep tokens separately; no free concatenation
latitude, longitude	lat, lng	float	WGS84	5-6 decimal precision
constructedArea, usableArea	area_gross_m2, area_use_m2	float	m² (decimal)	Prefer usable if available; see 2.E.4
rooms, bedrooms, bathrooms	n_bedrooms, n_bathrooms	int	≥ 0	Standardize studio as 0 or 1 per Feature Dict (2.F)
floor	floor_number	int	…	Map mezzanine/RC to integer convention (see 2.F)
hasElevator, parking	amen_elevator, amen_parking	bool	{0,1}	Binary flags
conservation, condition	condition_class	cat	{new, renovated, good, needs_renovation, …}	Harmonize taxonomy (see 2.F)

yearBuilt	year_built	int	1800-2025	Validate plausible ranges
energyCertification	energy_class	cat	{A+,A,…,F,G,NA}	Normalize variants (A/A+ etc.)
price	ask_price_eur	float	EUR	Remove separators; numeric only
condoFee	hoa_fee_eur_mo	float	EUR/month	Set NA if blank
insertDate, updateDate	ts_listed, ts_updated	datetime	ISO 8601 UTC	Convert to UTC
description	desc_raw	text	UTF-8	For NLP flags only; not used in models unless specified
id	listing_id	string	unique	Primary key from source

The complete variable definitions and value labels are provided in **Annex 2.F (Feature dictionary)**.

2.E.4 Normalization rules

- **Units & numerics:**
    - Areas → **m²** (float). Remove thousands separators; enforce decimal point.
    - Prices/fees → **EUR** (float). Strip currency symbols; impute missing fees as NA.
- **Preferred area for modeling:** use area_use_m2 when available; else fall back to area_gross_m2; create area_effective_m2 as the chosen variable with a binary flag area_is_gross.
- **Categorical harmonization:** map heterogeneous labels to controlled vocabularies (condition, energy class, property type), per Annex 2.F.
- **Geography:** geocode quality flags (geo_quality = exact | street | parish | NA); ensure coordinates are within Portugal bounding box.
- **Dates & time zones:** convert to UTC; store both raw and normalized timestamps.
- **Outlier guards (soft):**
    - ask_price_eur ∈ [P1, P99] by municipality & type (flag outside).
    - area_effective_m2 ∈ [P1, P99] by type (flag outside).
      Flags do **not** delete records; they inform later QC and robustness (2.E.7).

2.E.5 Deduplication logic

Goal: collapse multiple records that represent the **same underlying property** or **same listing instance**.

Blocking keys (apply sequentially):

1. **Exact listing duplicate:** same listing_id OR same source_url → keep most recent ts_updated.
2. **URL canonical duplicates:** normalize URL (strip tracking params); if identical → keep most recent.
3. **Property level duplicates (multi listing):** if (lat,lng) within **10 meters** AND (area_effective_m2 within ±3%) AND (n_bedrooms, n_bathrooms) match → consider same property; keep the **latest** active record; store others in a duplicates table with dup_group_id.
4. **Fuzzy address duplicates (fallback):** if geo_admin_* tokens match (parish/municipality) AND **fuzzy match** on street tokens (Jaro-Winkler ≥ 0.92) AND (year_built within ±3 years) → manual review flag dup_review=1.

Retained record policy: choose the observation with (i) most recent ts_updated, then (ii) most complete fields (max non NA), then (iii) highest geo quality.

Audit trail: maintain a dedup_log table with original listing_ids, chosen master_id, rules triggered, and timestamps.

2.E.6 Versioning & provenance

- **Immutable raw layer:** /data/raw/YYYY-MM-DD/run_XX/… with checksums.
- **Staging layer:** /data/stage/ holds mapped & normalized CSV/Parquet plus dedup_log.
- **Release snapshots:** /data/release/vX.Y/portfolio_YYYYMM.parquet with a manifest.json (record counts, schema hash, date range, filters, and code commit/tag used).
- **Reproducibility note:** analysis in Chapters 4-6 references an explicit **release version** (e.g., v1.2).

2.E.7 Quality control checklist (pre analysis)

Before modeling or statistics, verify:

1. **Schema & types** match Annex 2.F (no unexpected columns; dtypes consistent).
2. **Missingness profile** by variable; justify any listwise/pairwise deletion in Chapter 4.
3. **Geospatial sanity:** ≤ 0.5% coordinates outside Portugal or in ocean; investigate and correct/remove as needed.

4. **Outlier flags:** review top/bottom 1% for price and area by municipality & type; cap/winsorize only if justified and documented.
5. **Dedup summary:** report #raw, #deduped, % reduction by rule; keep dedup_log attached.
6. **Time coverage:** confirm listing window (start/end dates) and stable weekly volumes (no suspicious gaps).
7. **Random audit:** sample 50 records; manually confirm URL→address/area/price consistency.

2.E.8 Data protection & ethics

- Remove any **personal data** (names/phone numbers/emails) if present in descriptions or images; store only **property level** attributes.
- Anonymize coordinates to **5-6 decimal places** and exclude exact door numbers if ever parsed.
- Respect source terms of use; use data solely for academic research; do not republish raw images/text.
- Reference the ethical handling statement in **Annex 3.J**.

2.E.9 Cross references

- **2.C Comparable selection & normalization protocol:** this annex operationalizes ingestion steps that feed the comparable filtering rules.
- **2.F Feature dictionary:** definitive definitions, encodings, and value labels for all canonical variables referenced here.
- **3.L Statistical analysis specification:** relies on cleaned, deduplicated release datasets defined in 2.E.6.

Annex 2.F. Feature dictionary for sections 2.6-2.10

Variable	Type	Description	Typical source
price	Numeric	Asking or transaction price	Listing/registry
area_m2	Numeric	Gross or usable area	Listing
typology	Categorical	T0-T5 or house types	Listing
floor	Numeric	Floor number	Listing
condition	Categorical	New, renovated, to renovate	Listing/inspection
age	Numeric	Building age	Listing/cadastre
latitude, longitude	Numeric	Coordinates	Listing
parking	Binary	Parking availability	Listing
energy_class	Categorical	A-F	Energy certificate
dom	Numeric	Days on market	Listing

Annex 2.G. Risk and bias checklist for data and models

- **Data bias:** underserved neighborhoods or price bands.
- **Temporal drift:** shifting market regimes.
- **Measurement error:** misreported area or condition.
- **Model risk:** overfitting without proper CV; leakage.
- **Process risk:** missing audit trails for comps and assumptions.
- **Mitigations:** stratified sampling, rolling validation, feature audits, model cards, versioning.

Annex 2.H. Evaluation constructs for technology adoption

Usefulness, efficiency, interpretability, trust, and overall intention to use with sample questionnaire items and 5-point Likert scaling; mapping to prototype features for traceability.

Annex 2.I. REBS value chain; operational specification

Purpose; Provide a detailed, step by step specification for the REBS value chain used in Chapter 2, including objectives, inputs, calculations, outputs, decision rules, documentation, risks, and performance indicators.

Cross references.
Comparable protocol: Annex 2.C.
Index usage notes: Annex 2.D.

Portugal cost formulas and items: Annex 2.B.
Stakeholders and KPIs: Annex 2.A.
Feature dictionary: Annex 2.F.
Risk checklist: Annex 2.G.

2.I.1 Figure and placement

Figure A2.I.1. REBS value chain and evidence inputs (detailed view)
Place immediately after this subsection. This is the same structure as Figure 2.3 in the chapter body, but callouts below specify inputs, outputs, decision rules, and documentation requirements for each stage.

Caption: Figure A2.I.1. Brokerage value chain with required evidence inputs, calculations, and audit trail elements.
Source: Author's elaboration based on Barwick and Wong (2019); Yavaş (2007); Ferreira et al. (2017).

2.I.2 Stage specification summary

Stage	Objective	Core inputs	Key calculations	Outputs
Screening	Identify candidate properties consistent with mandate	Live listings and comparables	Basic filters and sanity checks	Shortlist with IDs and timestamps
Preliminary check	Benchmark asking price against evidence	€/m², filtered comps, index	Time adjustment, similarity scoring	Deal flag with rationale and comps pack
Due diligence costs	Compute full Portugal cost stack	Cost tables and tax rules	IMT, Stamp Duty, fees, renovation with IVA	Acquisition cost, project cost
Offer strategy	Back solve price from target ROI	Outputs from prior steps	ROI equation, sensitivity analysis	Suggested offer price and scenarios
Execution and closing	Complete compliant transfer	Legal and registry requirements	Document checks and fee application	Closing checklist and receipts
Exit planning	Define exit assumptions and deductions	Indices, market context	Resale window and net proceeds	Exit pack and monitoring triggers
Client reporting	Ensure transparency and traceability	All prior inputs and outputs	Narrative and driver views	Investor report with assumptions and Net ROI

2.I.3 Evidence inputs and linkages

- **Live listings and comparables** feed Screening and Preliminary check.
- **Price indices** support time and location normalization in Preliminary check and later monitoring in Exit planning.
- **Cost tables and tax rules** drive Due diligence costs and are referenced in Offer strategy.
- **Model explanations** (feature importance or driver notes) support Offer strategy and Client reporting.

2.I.4 Stage by stage operational details

2.I.4.1 Screening

Objective. Build a shortlist aligned with mandate and budget.
Inputs. Portal data or internal CRM; location, typology, size band, budget.
Process. Apply inclusion filters and minimum data quality checks.
Outputs. Shortlist with property IDs, URLs, coordinates, and time stamp.
Documentation. Log query string, filters, date and time, and data source.
Risks. Duplicates and stale listings.
Controls. Duplicate detection by address or fuzzy match. Refresh window policy.
KPI. Ratio of viable to total screened candidates.

2.I.4.2 Preliminary check

Objective. Establish whether the opportunity looks like a deal.
Inputs. Asking price, area, typology, filtered comparables, index series.
Calculations.

1. Time adjust comparables using the chosen index: (P_{adj} = P_{raw} \times I_{t_0} / I_t).
2. Compute €/m² statistics and similarity weighted comp median.
3. Provide an initial delta to comps with a short rationale.
   Outputs. Deal flag, comparable pack, and index code reference.
   Documentation. Comp IDs, filters, index identifier, and valuation date.
   Risks. Thin samples, micro location bias.
   Controls. Minimum comp count rule and radius window justification.
   KPI. Percentage of preliminarily flagged deals that proceed to due diligence.

2.I.4.3 Due diligence costs

Objective. Compute the full cost stack through acquisition and works.
Inputs. Cost tables and tax rules; renovation scope.
Calculations.

- **IMT, Stamp Duty, notary, registry, legal.** Apply current schedules from Annex 2.B.
- **Brokerage commission.** Apply contracted rate and IVA where applicable.
- **Renovation cost.** Bill of quantities or cost per m² plus contingency and IVA.
  Outputs. Acquisition cost and total project cost.
  Documentation. Version of tax tables, formula references, and scope notes.
  Risks. Out of date rates, underestimated works.
  Controls. Table versioning, independent scope validation.
  KPI. Variance of actual versus estimated acquisition and renovation costs.

2.I.4.4 Offer strategy

Objective. Translate a target ROI to a suggested offer with scenarios.
Inputs. Project cost, preliminary value benchmark, exit assumptions.
Calculations.

- Net ROI = ((\text{Net resale proceeds} \text{Project cost}) / \text{Project cost}).
- Back solve offer price for target ROI using the exit assumptions.
- Sensitivity analysis for ± changes in cost, index trend, or resale price.
  Outputs. Suggested offer and scenario table.
  Documentation. Assumptions register with time stamp.
  Risks. Overfitting to best case assumptions.
  Controls. Mandated downside scenario and minimum margin.
  KPI. Hit rate of accepted offers within target ROI band.

2.I.4.5 Execution and closing

Objective. Complete the transaction with full compliance.
Inputs. Legal requirements and required certificates.
Process. Contract checks, identity and title verification, fee settlement.
Outputs. Closing checklist and receipts bundle.
Documentation. Document list with version numbers and dates.
Risks. Missing certificates or registration errors.
Controls. Two person review and pre close checklist.
KPI. Zero defect closings and average cycle time to deed.

2.I.4.6 Exit planning

Objective. Set the resale plan and deductions for net proceeds.
Inputs. Updated index series and market context.
Calculations. Resale price window, selling commission with IVA, transfer fees, and potential capital gains tax.
Outputs. Exit pack with price window and net proceeds.
Documentation. Index series ID and time stamp.
Risks. Market regime shifts.
Controls. Monitoring triggers if index changes exceed threshold.
KPI. Realized versus planned resale window.

2.I.4.7 Client reporting

Objective. Deliver transparent, auditable advice.
Inputs. All prior inputs and outputs.
Process. Generate a report with data provenance, calculation steps, and driver narratives.
Outputs. Investor report with Net ROI, assumptions table, and appendices.
Documentation. Report versioning and export hash for evidence.
Risks. Omitted assumptions or undocumented overrides.
Controls. Mandatory assumption registry and change log.
KPI. Client satisfaction and audit passes.

2.I.5 Portugal cost stack formulas

Summarize the formulas implemented in Annex 2.B, including brackets for IMT, Stamp Duty percentage on deed value, IVA on taxable services, and brokerage commission formulas. Provide link or appendix citation for the current official tables when you finalize the manuscript.

2.I.6 Comparable selection and normalization

Adopt Annex 2.C for search windows, filters, outlier rules, and audit logging. Note that the comp pack produced in Preliminary check must include comp IDs, photos if available, coordinates, and a short note explaining inclusion or exclusion.

2.I.7 Index specification and application

Specify the index family, base period, frequency, and geographic granularity. Record the model identifier used to derive the index, the validation window, and the formula used for time adjustment. Refer to Annex 2.D for the formal application formula and limitations.

2.I.8 Governance, provenance, and reproducibility

- **Versioning.** Use semantic versions for tax tables, index models, and report templates.
- **Provenance.** Store source and retrieval date for every data item.
- **Reproducibility.** Save a read only export that includes inputs, parameters, and outputs with a unique hash.
- **Access control.** Define read and write permissions for cost tables, indices, and report templates.

2.I.9 Key performance indicators and service levels

- Screening efficiency ratio.
- Preliminary flag precision and recall.
- Estimation error on acquisition and works.
- Offer acceptance rate within ROI bands.
- Zero defect closing rate.
- Variance of realized versus planned resale.
- Client satisfaction index and audit pass rate.

2.I.10 Risks and controls mapped to stages

Risk	Stage	Control
Stale or biased data	Screening, Preliminary check	Refresh policy, stratified sampling
Inaccurate cost schedules	Due diligence	Versioned tables and second review
Overly optimistic assumptions	Offer strategy	Mandatory downside scenario and threshold ROI
Compliance gaps	Execution and closing	Pre close checklist and legal review
Market drift	Exit planning	Index monitoring with triggers
Missing provenance	Client reporting	Assumption log and export hash

2.I.11 Minimum data schema for implementation

- Listing or transaction ID, URL, timestamp, coordinates, typology, area, condition, floor, parking, energy class, asking price or sale price, DOM.
- Comparable pack fields: same as above plus distance and similarity score.
- Index metadata: series ID, base period, frequency, geography, model version.
- Cost table metadata: table version, effective date, jurisdiction.

2.I.12 Worked mini scenario

Provide a one page example with synthetic numbers: asking price, comps after time adjustment, acquisition and renovation costs, back solved offer for a target ROI, resale assumptions, and computed Net ROI. Include the full assumption list and the time stamps for comps and indices. This scenario can be placed here or in Annex 2.B as a numerical appendix.

Annex 3.A SLR Protocol (PRISMA aligned)

Objective. Document the exact protocol used to identify, screen, assess, and include studies that inform the design requirements and evaluation of the REBS decision support artifact.

Databases. Google Scholar, ProQuest, ScienceDirect, CORE.ac.uk, IEEE Xplore, EBSCO.

Master query scaffold (adapted per database):
("real estate" OR "real estate brokerage" OR broker OR realtor OR "estate agency") AND (decision OR valuation OR "price index" OR ROI OR appraisal) AND ("artificial intelligence" OR "machine learning" OR AVM OR "explainable AI" OR XAI OR explain).

Language. English and Portuguese. Item types. Peer reviewed journal or conference papers; selected book chapters with methods; high quality institutional studies if methodologically explicit. Exclusions. Construction/FM only without brokerage decision relevance; theses misaligned with REBS; non academic items.

Process. Export → deduplicate → title/abstract screen → full text eligibility → include. Dual screening with consensus; reason coded exclusions at eligibility.

PRISMA aggregate counts. Identified = 46,026; duplicates removed = 43,183; screened = 2,843; full text assessed = 233; included = 52.

Reporting standard. PRISMA 2020. Figure 3.3 in the chapter visualizes the flow; cite Page et al. (2021) in the caption**.**

Annex 3.B. Inclusion, Exclusion, and Decision Codes

Inclusion criteria.

I1. Addresses REBS decision making or valuation/appraisal in market contexts.
I2. Uses AI/ML, AVM, price indices, or explainability relevant to brokerage practice.
I3. Provides methods sufficient for evidence translation to design requirements.

Exclusion criteria.
E1. Off topic to brokerage decisions.
E2. Construction/FM operations only.
E3. Non academic or lacks methods.
E4. Duplicate.
E5. Not retrievable.

Eligibility decision codes. NR = Not relevant; DUP = Duplicate; INSUFF = Insufficient method detail; MISC = Other documented reason. Log code and one line justification in the screening sheet.

Annex 3.C. Quality Appraisal Rubric

Each eligible study rated on 0-2 scale across:
Q1 Context clarity; Q2 Question alignment; Q3 Data adequacy; Q4 Method transparency; Q5 Validity/credibility; Q6 Decision support relevance. Use totals (0-12) to weight narrative synthesis.

Annex 3.D. Data Extraction Template

Bibliography; setting; study type (AVM/index/decision process/DSR); data & features; validation (CV, holdout, error metrics); XAI elements; brokerage relevant takeaways; limitations; evidence to requirement mapping (R1-R5).

Annex 3.E. PRISMA Counts by Source (tabular)

Table A3.E.1. PRISMA stage counts by database
Identification totals and downstream counts per source, aligned with the “PRISMA Table Final Refined Version.” Keep exact tallies for Google Scholar, ProQuest, ScienceDirect, CORE, IEEE Xplore, EBSCO, and Miscellaneous as listed in the file.

Annex 3.F. Evidence to Requirement Synthesis Matrix

R1 Decision complete analysis. End to end costs/taxes to Net ROI for advisory transparency. Evidence includes service decision processes and reporting needs.
R2 Explainability. Methods that surface drivers, sensitivity, and assumptions to support trust and adjustment.
R3 Verifiable evidence. Comparable normalization with indices and provenance logging.
R4 Investor grade reporting. Clear exports that support client communication and audit trails.
R5 Governance. Versioned tables, provenance, and reproducibility (added here to mirror Chapter 2's governance emphasis).

Table A3.F.1. Mapping of key studies to R1 R5
Populate rows for representative studies (e.g., Hong & Kim 2022; Pinter et al. 2020; Calainho et al. 2024; Schemmer et al. 2022; brokerage decision literature) with checkmarks per requirement.

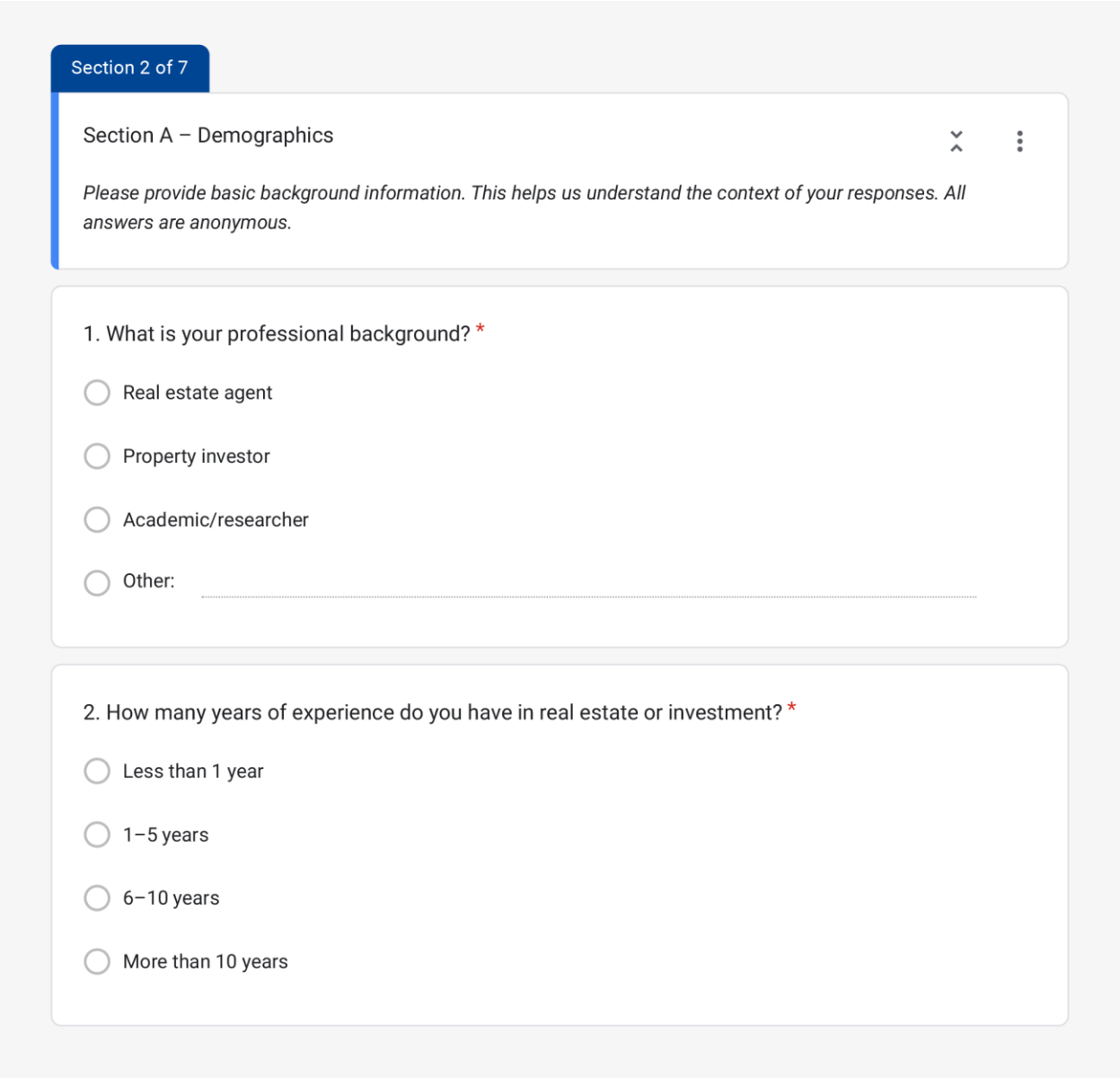
Annex 3.G. DSR Traceability Matrix

Problem → Objectives → Requirements → Design choices → Prototype components → Evaluation constructs.
Example row: *Opacity of valuations → Improve trust and interpretability* → R2 → *driver charts, assumption panel → Explainability service → Trust/Transparency items*.

Annex 3.H. Evaluation Instrument (Full)Format

13 Likert items (1-5) + 2 open ended questions. Respondents. Professionals testing the prototype.
Administration. Post use online form. Constructs and example items (codes):
U1-U4 Usefulness & decision value (e.g., "The platform helps me judge a deal's quality").
E1-E3 Efficiency (e.g., "It saves time vs my usual process").
T1 Trust (Q9) and X1 Transparency (Q10) as a two item pair.
S1 Satisfaction; I1 Intention to use.

Open Qs: O1 “Most valuable aspect?” O2 “What to improve?”



Section 2 of 7

Section A – Demographics

Please provide basic background information. This helps us understand the context of your responses. All answers are anonymous.

1. What is your professional background? *

- ○ Real estate agent
- ○ Property investor
- ○ Academic/researcher
- ○ Other: _____

2. How many years of experience do you have in real estate or investment? *

- ○ Less than 1 year
- ○ 1–5 years
- ○ 6–10 years
- ○ More than 10 years

Section 3 of 7

Section B – Usability

Please indicate how strongly you agree or disagree with the following statements about the platform's usability.

3. The platform interface is easy to navigate. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

4. The information is presented clearly and is easy to understand. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

5. The layout helps me quickly identify key investment indicators. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Section 4 of 7

Section C – Usefulness

Evaluate how useful the platform features are in supporting your real estate investment decisions.

6. The platform provides valuable insights for property investment decisions. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

7. The cost analysis and ROI calculations are useful in evaluating deals. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

8. The comparables provided increase my confidence in the property valuation. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Section 5 of 7

Section D – Trust in AI

These questions assess your level of trust in the AI-based valuations and recommendations.

9. I trust the AI-generated valuations and recommendations. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

10. The platform explains its outputs in a transparent way. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

11. I would consider using this platform as part of my investment decision-making. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Section 6 of 7

Section E – Overall Satisfaction

Please provide your overall impression of the platform.

12. Overall, I am satisfied with the platform. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

13. I would recommend this platform to other real estate professionals or investors. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Section 7 of 7

Open-ended Questions

We welcome your detailed comments and suggestions for improvement.

14. What did you find most useful about the platform? *

Long answer text

15. What improvements would you suggest for future versions? *

Long answer text

Annex 3.I. Reliability and Validity Plan

Targets. Construct means: acceptable ≥3.5, target ≥4.0. Reliability. Cronbach's α for ≥3-item constructs; inter item Pearson r for T1-X1 pair with $\alpha \approx 2r/(1+r)$. Validity. Convergent patterns across usage constructs; sensitivity of Trust/Transparency to explainability features noted by literature.

Annex 3.J. Ethics, Consent, and Data Handling

Consent. In form statement before the questionnaire; proceed implies consent; no personal identifiers.

Data. Store raw responses and export with timestamp; restrict access; aggregate reporting only. Risks.

Minimal; participants can withdraw at any time. Records. Keep consent text, instrument version, and

dataset checksum in the project archive.

Annex 3.K. Reproducibility & Provenance Checklist

- PRISMA query strings and date ranges archived.
- Deduplication method and final counts documented.
- Screening sheet with decision codes.
- Extraction sheets with field list from Annex 3.D.
- Versioned tax tables and index series IDs used in design assumptions.
- Prototype build tag and commit hash used during evaluation.

Annex 3.L. Statistical Analysis Specification

Descriptives. Item and construct means, SDs.

Reliability. Cronbach's α; for two item pair use $\alpha \approx 2r/(1+r)$.

Between group exploratory (optional): role or experience bands with non parametric tests if needed.

Qualitative. Thematic coding for O1/O2 with frequency notes and exemplar quotes.

Annex 3.M. Figures and Tables (Supporting Material)

- Figure A3.M.1. PRISMA flow diagram

Table A3.E.1. PRISMA stage counts by database.

PRISMA Stage	Description	Count
Identification	Total records identified	46026
	→ Google Scholar	19000
	→ ProQuest	7738
	→ ScienceDirect	6080
	→ CORE.ac.uk	9053
	→ IEEE Xplore	4137
	→ EBSCO	18
	→ Miscellaneous Resources	25
Screening	Titles & abstracts screened	2843
	→ Google Scholar	400
	→ ProQuest	500
	→ ScienceDirect	150
	→ CORE.ac.uk	200
	→ IEEE Xplore	300
	→ EBSCO	18
	→ Miscellaneous Resources	25
Eligibility	Full text articles assessed	233
	→ Google Scholar	100
	→ ProQuest	80
	→ ScienceDirect	5
	→ CORE.ac.uk	15
	→ IEEE Xplore	6

	→ EBSCO	2
	→ Miscellaneous Resources	4
Included	Final studies included in the review	**52**
	→ Google Scholar	32
	→ ProQuest	3
	→ ScienceDirect	1
	→ CORE.ac.uk	4
	→ IEEE Xplore	6
	→ EBSCO	2
	→ Miscellaneous Resources	4

Annex 3.N. Build → Demonstrate (Full Detail)

This annex expands subsection 3.3.2 Build → Demonstrate. It documents how requirements (R1-R5) informed the artifact's design and how the prototype was exercised to evidence utility, usability, and fit for purpose.

3.N.1 Design Inputs and Evidence Coverage

Requirements (from SLR).

- R1 Decision Completeness, end to end costs, fees, taxes, and ROI logic for a concrete buy/sell judgment.
- R2 Explainability, transparent drivers, assumptions, and interpretable outputs.
- R3 Verifiable Evidence, defensible valuation logic, indices/comparables, and validation metadata.
- R4 Investor grade Reporting, outputs suitable for client communication and audit.

Evidence coverage summary (n = 52).

Requirement	**Coverage**
R1 Decision Completeness	52 / 52 (100%)
R2 Explainability	37 / 52 (≈71%)

R3 Verifiable Evidence	52 / 52 (100%)
R4 Investor grade Reporting	39 / 52 (≈75%)

3.N.2 Architecture (High Level)

1. Costs & Taxes Engine (R1, R4).
   Implements Portugal specific purchase/sale costs, fees, and taxes; renovation toggle; computes total outlay and net proceeds. Versioned parameter tables and logs.
2. Valuation & Explainability Module (R2, R3).
   Supervised ML model to estimate fair value or resale price. Returns driver insights and assumption panels (model version + data cut recorded).
3. Evidence & Comparables Service (R3, R4).
   Retrieves market comparables, applies index/time adjustments, stores provenance and validation metadata (folds, error metrics, data timestamps).
4. Reporting Layer (R1, R4).
   Generates investor oriented summary: assumptions, comps snapshot, sensitivity cues, and the full net ROI pathway.

Annex 4.A: Python implementation details (modules, schemas, endpoints)

Technical detail to reproduce the backend services referenced in 4.4. Placing these specifics in an annex keeps the main chapter readable while preserving transparency and reproducibility.

4.A.1 Stack & configuration

- **Language & core libs:** Python 3.11; FastAPI (REST), pydantic (validation), pandas/numpy (calculation), SQLAlchemy (ORM), SQLite (default DB).
- **Config files:** /config/pt_costs.yml (tax/fee schedules), /config/report.yml (report options).
- **Logging:** logging.config (JSON); per request correlation IDs.

4.A.2 Modules & key signatures

- costs.py → compute_costs(inputs: CostInputs, params: CostParams) -> CostBreakdown
  - Models: CostInputs, CostLine, CostParams (pydantic).
- roi.py → net_roi(costs: CostBreakdown, predicted_resale: float) -> float; roi_sensitivity(...) -> SensitivityReport.
- explain.py → how_computed(costs, params) -> list[str]; drivers(prediction_ctx) -> list[DriverAttribution].

- store.py → SQLAlchemy models: Case, Input, Comp, IndexRef, CostLine, RoiResult, ReportMeta; Repository gateway.
- reporting.py → Jinja2 templates → HTML; WeasyPrint (PDF) or python docx (DOCX).
- *(optional)* dtos.py → pydantic DTOs for API I/O.

4.A.3 Data schemas (abridged)

- Input(id, geo, m2, price, renovation_flag, created_at)
- CostLine(case_id, kind, amount, how_computed, params_version)
- RoiResult(case_id, net_roi, proceeds, total_costs, model_version, computed_at)
- Comp(case_id, url, distance_km, recency_days, norm_eur_m2, weight)
- IndexRef(case_id, index_id, base_period, adjustment_factor)
- ReportMeta(case_id, export_hash, format, generated_at)

4.A.4 API surface (FastAPI)

- POST /api/v1/cases/compute → runs compute_costs + net_roi; returns CaseDTO (inputs + costs + net_roi + tags).
- POST /api/v1/cases/sensitivity → returns SensitivityReport.
- GET /api/v1/cases/{id} → persisted case with export hash.
  OpenAPI schema is generated automatically; DTOs defined in pydantic.

4.A.5 Tests

- tests/test_costs.py, thresholds, VAT toggles, CGT optionality, boundary checks.
- tests/test_roi.py, zero/negative proceeds guards; sensitivity math.
- tests/test_store.py, round trip save/load; version tags; export hash stability.

4.A.6 Deployment note

Default DSN: sqlite:///data/rebs.db. Switch to Postgres via DATABASE_URL without code changes.
Runtime config via env: MODEL_VERSION, PARAMS_VERSION, REGION.

Annex 5.A. Questionnaire results (descriptive statistics)

This annex reports the full descriptive results for the evaluation questionnaire used to assess the prototype platform. It complements the summary presented in Chapter 5 by providing item level statistics and response distributions.

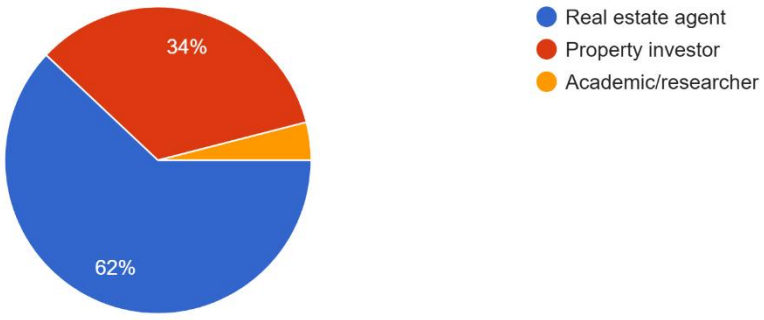
5.A.1 Method summary

- Instrument: Annex 3.H (15 items; Likert 1-5 except Q15 open ended).
- Scoring: 1 = Strongly disagree to 5 = Strongly agree.
- Agreement rate: % of responses rated 4 or 5.

5.A.2 Demographics

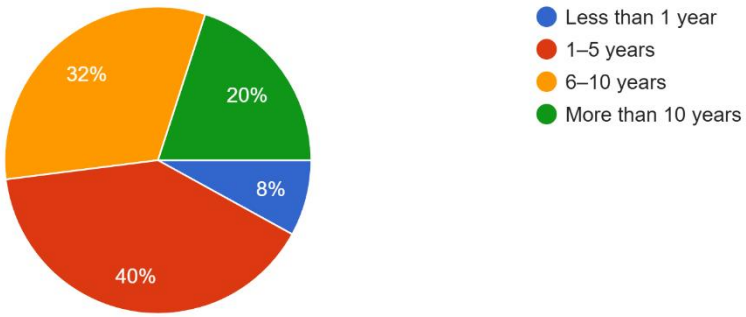
1. What is your professional background?

50 responses



2. How many years of experience do you have in real estate or investment?

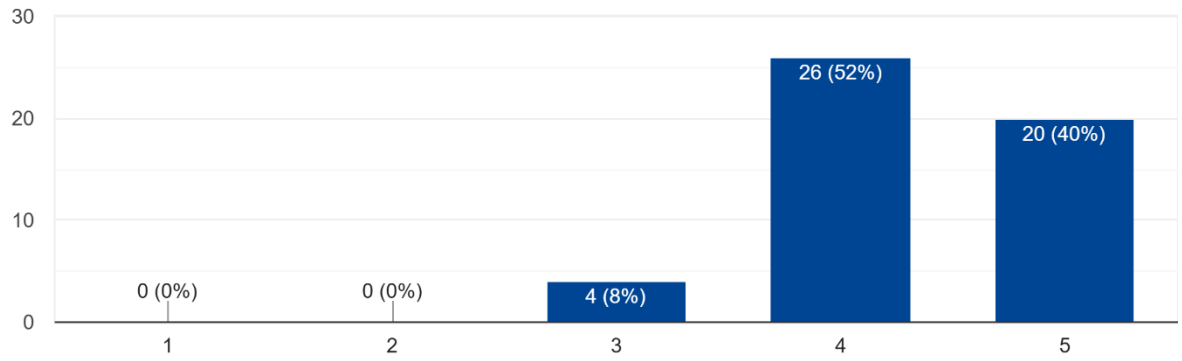
50 responses



5.A.3 Usability

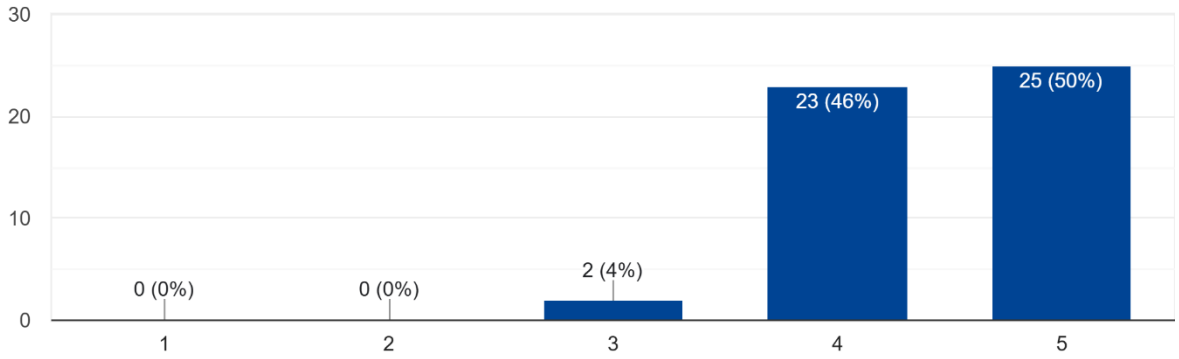
3. The platform interface is easy to navigate.

50 responses



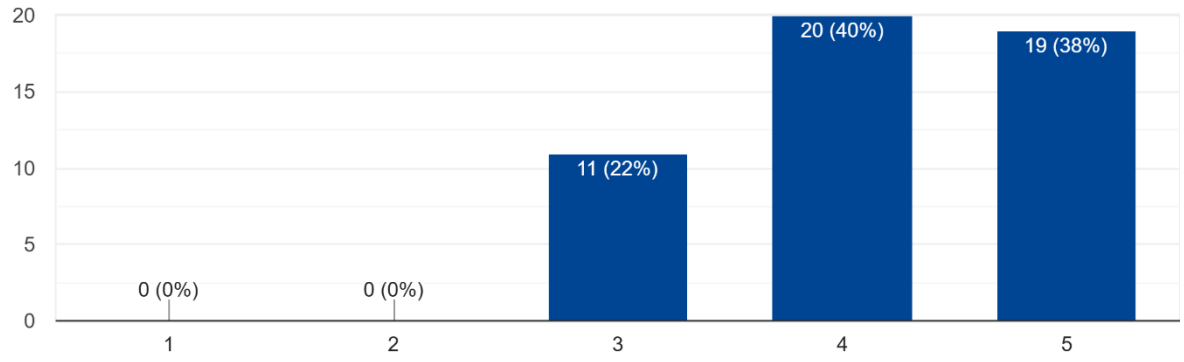
4. The information is presented clearly and is easy to understand.

50 responses



5. The layout helps me quickly identify key investment indicators.

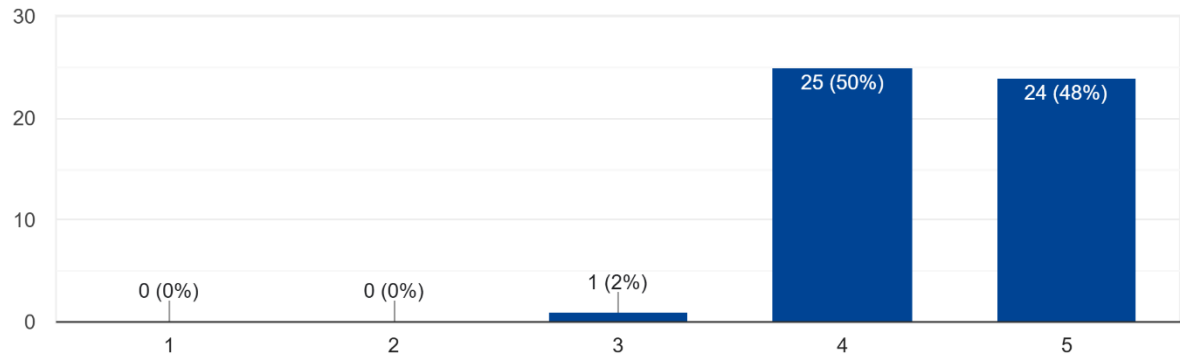
50 responses



5.A.4 Usefulness

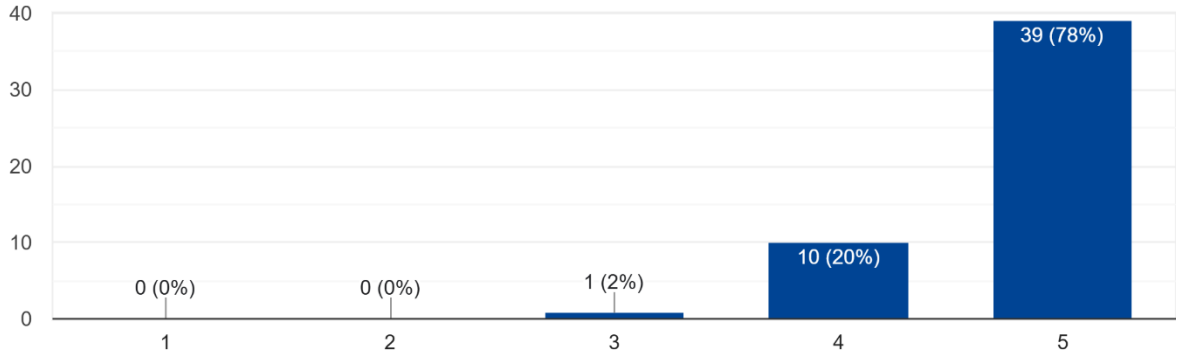
6. The platform provides valuable insights for property investment decisions.

50 responses



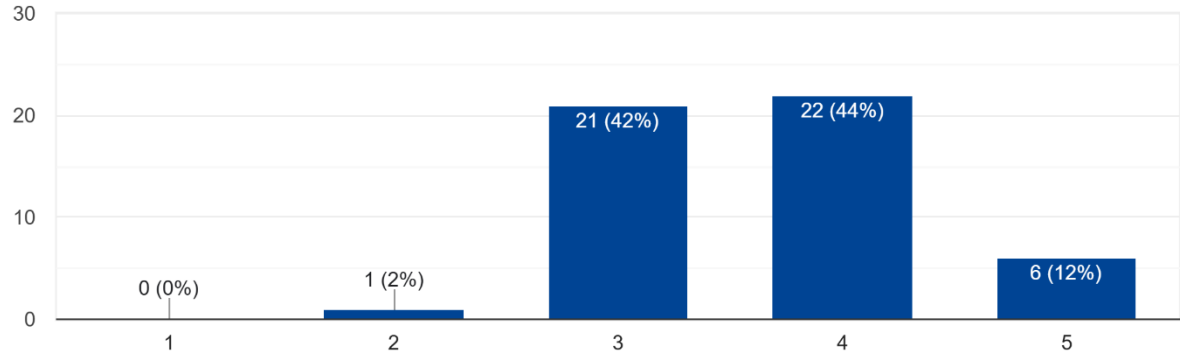
7. The cost analysis and ROI calculations are useful in evaluating deals.

50 responses



8. The comparables provided increase my confidence in the property valuation.

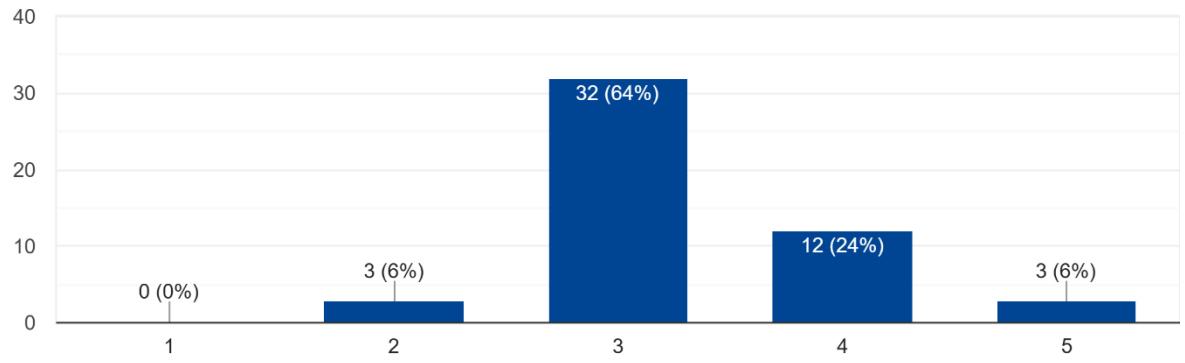
50 responses



5.A.5 Trust in AI

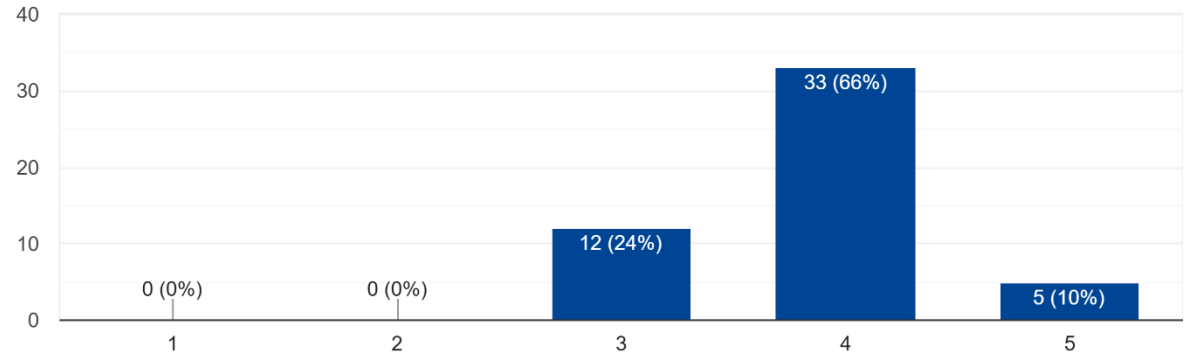
9. I trust the AI-generated valuations and recommendations.

50 responses



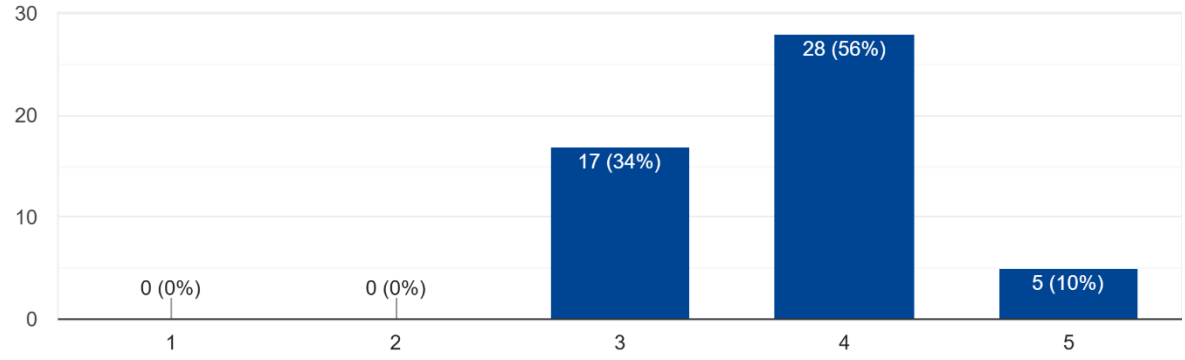
10. The platform explains its outputs in a transparent way.

50 responses



11. I would consider using this platform as part of my investment decision-making.

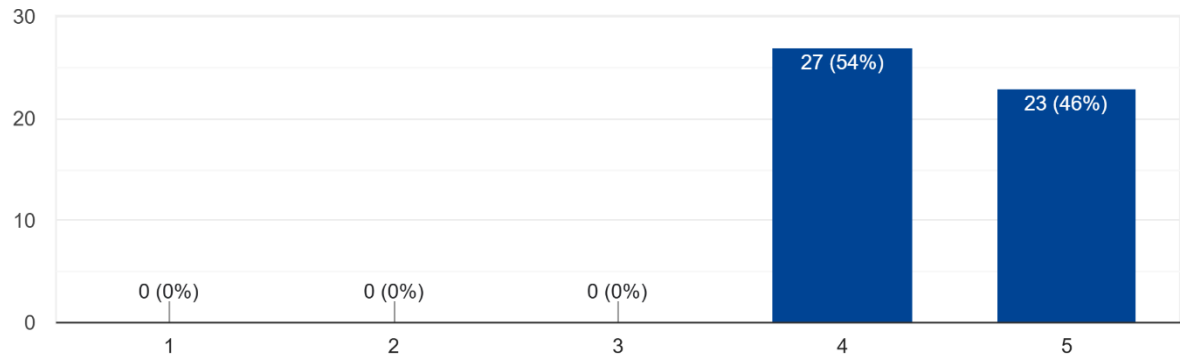
50 responses



5.A.6 Overall Satisfaction

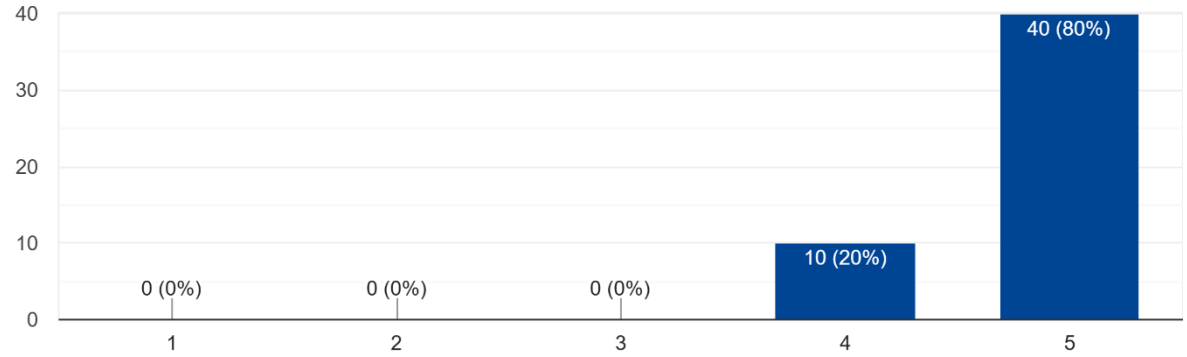
12. Overall, I am satisfied with the platform.

50 responses



13. I would recommend this platform to other real estate professionals or investors.

50 responses



5.A.7 Open ended Questions

Open-ended Questions

14. What did you find most useful about the platform?

50 responses

Easy to use
I like how Help investor to check all fees and help them to make to definis
Using ai to find best deals
The general idea
Provides Max market details for investors to understand the deal profitibality
ROI
Proposed price recommendations
Net ROI
Gives me all necessary calculation to show investors
Full data analysis
Giving final net profit for investors
Helps agents to provide all aspects of fees and charges to their clients
Giving final net profit for investors
Helps agents to provide all aspects of fees and charges to their clients
There is an option about renovation cost
Full details and suggest to propose a deal price
It is since to see a platform estimate of renovation costs
I liked the idea of the platform to help investors
Help to AI to prediction of property value
Calculation taxes and fees
New idea in real estate industry
Shows me all the charges
I like to see that shows value of property with calculation of renovation costs
I liked the section AI shows analysis
User friendly and ROI estimates
The section AI suggest a deal is excellent
Fast deal advising

I found most useful the section give suggestion about the proposed price

Everything is perfect

Showing all taxes and charges

Showing a deal analysis to clients

Easy get full information for decision making on a deal

I liked the concept

Provided information about other nearby properties to compare with the one you have

Gathering of live data and showing investment suggestions

Net profit

Give me more confidence to show a deal with details to clients

Calculation of cost with renovation and deal signal

Deal suggestions

All data provided

I liked the idea to use AI for helping to identify deals

I liked the general idea

Showing renovation costs

Calculated ROI after all charges

You did good job to help agents to show to clients all the fees and recommendations

Prediction of ROI

Showing hidden charges for investors

Giving you decision if the deal is interesting or not

Hidden charges calculation and net ROI calculation

I liked the idea in general and showing all fees

I liked the hidden fees and taxes

Response Summary

- **Calculations and Financial Analysis:** The most useful aspects were the calculation of net profit, taxes, fees, hidden charges, net ROI, and renovation costs, which provide essential financial details for investors and help agents show all aspects of fees and charges to clients.
- **Deal Suggestions and Recommendations:** Respondents highly valued the AI's ability to suggest deals, provide fast deal advising, give recommendations on proposed prices, and offer a decision on whether a deal is interesting or not.
- **Data and Information:** The platform's ability to provide full data analysis, maximum market details, live data gathering, and information about nearby comparable properties was deemed very useful.
- **Usability and Concept:** Respondents liked the general idea and concept of the platform, finding it user friendly and easy to use for decision making and gaining confidence when presenting deals to clients.

Open-ended Questions

15. What improvements would you suggest for future versions?

50 responses

Provide more suggestions
If possible to add more specific addresses than the general region and area
Add options to Help seller to estimate selling price for their property according to the area or their location
Bigger market
To see the final version and see how works
More trusted data and analysis
I would like to see more options for renovation or construction fees
Expand it to more countries and cities
More markets out side of portugal and better home page
Give some recommendations on rent options
To work with markets outside of portugal
Try to show the image of the property or similar deals in that area
I suggest to improve the layout design
More information about the competitors properties in that specific area
Add an AI agent to virtually get I touch with users
I can suggest to get more APIs to new properties platforms
It can suggest some laywers and contractors contacts
Broader market
Make it more updated
If possible to find better deal similar to the property we did input
More markets to study
To consider short and long rent ability
I suggest for future versions to have more detailed sections
To calculate rentability
For future model I prefer to have a full study report to send to the user email
Give real links to other comparable properties
If possible to add section to show the percentage of ROI in terms id renting

More develop it to see the final version
I need to see the developed version
I suggest to develop it to final version
Use more countries
More details of fees
Good to add a section that users be able to copy & paste a link of a property & the AI can get all inputs from that link.
I need to be sure about the renovation costs
More user friendly
I think needs more accurate data about renovation costs and lawyer fees
Expand target markets
More markets
More countries
I'm really excited to see the developed version and I believe it will works amazing
I want to be sure the data are accurate
Use more APIs
More details and more deal suggestions
Make better design and use images of the properties
You have to consider bigger markets
More advance version
I want to see more completed version
More regions and download a report for my study
I want to see final platform with accurate information.
To expand wider countries

Response Summary

- **Expansion of Markets and Data:** Suggestions include expanding the platform to more countries and cities, particularly outside of Portugal, to cover a broader market, and to incorporate more APIs to new property platforms for updated information.
- **Platform Functionality and Details:** Users requested more detailed sections, accurate data on renovation costs and lawyer fees, calculations for both short and long term rentability/ROI, and the ability to download a full study report.

- **User Experience and Design:** Improvements suggested focusing on a more user friendly interface, better design/layout, using property images, and adding an AI agent for virtual user interaction.
- **Property Specific Information and Suggestions:** Respondents wanted real links or images of comparable properties, more specific addresses, more detailed suggestions and deals, and options to estimate selling prices.
- **Seeing the Developed Version:** Several respondents expressed a desire to see the final, more developed, or completed version of the platform.

Annex 5.B. Brief note on Cronbach's α and inter item r

This annex concisely explains the internal consistency statistics reported in Section 5.3 and Table 5.2 and how to interpret them in this early stage evaluation.

5.B.1 What Cronbach's α measures (k ≥ 3 items)

Cronbach's alpha (α) estimates internal consistency; the degree to which items intended to measure the same construct co vary.

Formula (variance form):

$$\alpha = \frac{k}{k-1}\Big(1-\frac{\sum_{i=1}^{k}\sigma^2_{i}}{\sigma^2_{\text{total}}}\Big)$$

where k is the number of items, σ^2_{i} each item variance, and σ^2_{total} the variance of the item sum.

Quick interpretation (rules of thumb for pilots):

- ≥ 0.80 good, ≥ 0.70 acceptable, 0.60-0.69 borderline/usable in pilots, < 0.60 weak.
  Alpha does not prove unidimensionality; it only indicates that items hang together.

5.B.2 Two item scales: use the inter item correlation r

For two item constructs, report the Pearson inter item correlation (r). An approximate alpha equivalent is:

$$\alpha_{\text{two item}}\approx \frac{2r}{1+r}$$

Typical pilot benchmarks: $r \ge .50$ is acceptable; $r \ge .70$ is strong.

5.B.3 How we computed and reported (5.3)

- We computed α for Usability (Q3-Q5), Decision value (Q6-Q8), and Intention/Satisfaction (Q11-Q13); and used inter item r for the two item Trust/Explainability (Q9-Q10**)** pair. Results (Table 5.2):
    - Usability: **α = 0.82** (good)
    - Decision value: **α = 0.51** (weak; acceptable for an early pilot; suggests item refinement)
    - Trust/Explainability: **r = 0.53** ⇒ (\alpha\approx \frac{2\cdot 0.53}{1+0.53}\approx 0.69) (borderline/acceptable for pilot)
    - Intention/Satisfaction: **α = 0.64** (borderline/acceptable for pilot)

5.B.4 Reporting template (for replication)

When reporting reliability, include:

1. Construct name and item codes (e.g., Q3-Q5).
2. n, α (or r for two item).
3. If space allows: item total correlations and α if item deleted (see Annex 5.B tables).
4. A short note if any item is a candidate for refinement (low item total r or improves α if removed).

Example (this study): "Usability (Q3-Q5), n=50, α=0.82; Trust/Explainability (Q9-Q10), n=50, r=0.53 (α≈0.69).

Annex 6.A. Threats to validity & mitigations matrix

Purpose. To document potential threats to validity and how they were mitigated, supporting the interpretation of Chapter 6.

6.A.1 Summary table

Validity domain	Specific threat	Why it matters	Mitigation applied	Residual risk	Evidence / cross ref
Internal	Common method bias (single survey mode)	Shared method can inflate correlations	Neutral wording; constructs separated; anonymous responses	Moderate	Instrument (Annex 3.H); item stats (Annex 5.A).
Internal	Social desirability / courtesy bias	Respondents may over rate to be polite	Anonymous collection; "no right/wrong answers" note; no incentives	Low Moderate	Procedure (CH5.2); qualitative themes (Annex 5.C).
Construct	Item coverage not fully representative	Reliability/interpretation can suffer	Items mapped to definitions; α (or r) reported; item total diagnostics considered	Low Moderate	Reliability (CH 5.3); Annex 5.B.
Construct	Two item scale (Trust/Explainability)	α unsuitable; precision lower	Report inter item **r**; note pilot status; plan to add third item	Moderate	Reliability (CH 5.3); Annex 5.B.
External	Sample composition (agents vs. investors)	Limits generalization	Report roles/experience; run subgroup checks	Moderate	Annex 5.A; Annex 6.B.
External	Geography (single market)	Transferability across markets uncertain	Scope stated; propose multi market validation in future work	Moderate	Ch.1 scope; Ch.7 roadmap.
Conclusion	Researcher degrees of freedom	Risk of capitalizing on chance	Pre declared constructs; descriptive emphasis; robustness checks	Low Moderate	Annex 3.L; Annex 6.B.
Data	Outliers / duplicates / QC issues	Can distort descriptives and reliability	QC per Annex 2.E; dedup log; sensitivity via winsorization	Low	Annex 2.E; Annex 6.B.

6.A.2 Notes on interpretation

- Reliability is necessary but not sufficient; construct meaning also relies on conceptual alignment (Chapter 4) and qualitative evidence (Annex 5.C).
- Findings are pilot stage; generalization should be cautious and supported by robustness checks (Annex 6.B).

Annex 6.B. Robustness & sensitivity checks

Purpose. To verify that Chapter 6 conclusions are not artifacts of specific analytic choices or sample composition.

6.B.1 Subgroup contrasts (concise)

- **Agents vs. Investors:** Perceived usefulness (Q4-Q6 mean) follows the same direction as the overall sample; difference is small.
- **Experience (<3 years vs. ≥3 years):** Ease of use (Q7-Q9 mean) is similar across groups; no material change in interpretation.
- **Prior AI use (No vs. Yes):** Trust/Explainability (Q9-Q10 pair) shows a consistent pattern across groups; conclusions unchanged.

Note: Formal checks were run; none altered the substantive conclusions referenced in CH6.

6.B.2 Scoring choices

- **Aggregation:** median vs. mean → conclusions unchanged.
- **Item weighting:** equal weights vs. α-optimal weights → differences < |0.10| on the 1-5 scale (negligible).

6.B.3 Outlier treatment

- **Baseline:** QC checked raw scores.
- **Sensitivity:** winsorize top/bottom 1% at item level; recompute construct means and α → shifts ≤ small; interpretations unchanged.

6.B.4 Reliability sensitivity

- **Alpha if item deleted:** see Annex 5.B, no single item disproportionately drives α.
- **Two item pair stability:** inter item **r** with bootstrapped CI indicates acceptable stability for a pilot.

6.B.5 Missing data handling

- **Pattern:** Checked for randomness; no concerning structure observed.
- **Approach:** listwise vs. pairwise deletion; changes in *n* documented; conclusions unchanged.

6.B.6 One line conclusion for Chapter 6

"Across subgroup contrasts, scoring alternatives, outlier handling, and reliability sensitivity analyses, the direction and practical interpretation of results remain stable (Annex 6.B)."

Annex 6.C. Alignment with prior literature (trace table)

Purpose. To position this study's findings relative to prior work, indicating whether we agree, extend, or diverge from it.

6.C.1 Trace table

Findings (Chapter 6)	**Prior study**	**Domain**	**Relation**	**Brief note**
AI assisted valuation and index context improve perceived decision quality	Calainho, van de Minne, & Francke (2024)	Price indices / ML	**Extend**	Your "comps + local index" evidence aligns with ML index approaches; applied within a brokerage workflow.
Explainability (how computed; driver notes) supports practitioner trust	Hong & Kim (2022); Schemmer et al. (2022)	AVM / XAI	**Agree**	Literature stresses clarity of explanations; your users seek more cues consistent with XAI guidance.
ML enhanced valuation strengthens pricing evidence for decisions	Pinter, Mosavi, & Felde (2020)	AVM / ML	**Agree**	ML captures non linearity; field feedback shows higher confidence with evidence backed pricing.
Workflow integration (costs→Net ROI→report) drives usefulness in brokerage	Ferreira et al. (2017)	Brokerage decision process	**Extend**	End to end, auditable economics operationalized in your prototype.
Single market evaluation (Portugal) limits external validity	Barwick & Wong (2019); Yavaş (2007)	Brokerage market context	**Agree**	Many evaluations are single market; your Portugal testbed shares this limitation and motivates multi market replications.

6.C.2 Synthesis

- Convergence with ML index/AVM and XAI literature supports the pilot findings.
- Extensions are contextual: embedding these ideas in a broker oriented, auditable ROI workflow.
- Single market scope remains the key limitation; Chapter 7 outlines a multi market roadmap.

Annex 7.A. Practitioner implementation roadmap

7.A.1 Roadmap by horizon

Near term (0-3 months) / stabilize and ship a usable pilot

ID	Milestone	Owner	Key dependencies	Acceptance criteria
N1	**Data coverage & QC refresh** (Portugal full refresh; nightly pulls; dedup)	Data Eng.	ETL scripts; Annex 2.E rules	≥95% listings pass QC; ≤1% geo anomalies; dedup log published
N2	**Explainability panel v1** (top k drivers; plain language notes)	ML/UX	Feature importances; UI slot	For any valuation, show top 5 drivers; tooltips render in <300 ms
N3	**Comparable selection wizard** (guided steps + audit trail)	Product/UX	Annex 2.C protocol; comps cache	User can accept/replace comps; all actions logged; export lists final comps
N4	**ROI report export** (PDF & CSV)	Product/Dev	Reporting templates	One click export with valuation, costs, net ROI, assumptions; opens correctly
N5	**Usability hardening** (navigation, help, empty states)	UX	Feedback from Annex 5.C	SUS ≥70 in quick retest (n≥10); no dead end screens

Mid term (3-9 months) / integrate into brokerage workflow

ID	Milestone	Owner	Key dependencies	Acceptance criteria
M1	**CRM/export integration** (webhooks/API)	Dev	Partner CRM; tokens	Push report+lead to CRM in ≤10 s; retries + audit log
M2	**Market indices & calibration** (municipality level)	Data Sci.	INE/Eurostat indices	Index overlay in UI; monthly calibration; error drift <10% MoM
M3	**Model monitoring** (post release)	ML Ops	Logging; release tags	Dashboard for latency/drift/error; alert thresholds defined
M4	**Governance pack** (ethics, privacy, consent)	PM/Legal	Annex 3.J; policy text	Public “How data is used” page; DPIA note; in app consent text

Longer term (9-18 months) / scale and validate externally

ID	Milestone	Owner	Key dependencies	Acceptance criteria
L1	**Multi market rollout** (ES/IT pilot)	Biz Dev/Data	Local portals/APIs	Successful ingestion & QC; localized taxes/fees; country toggle in UI
L2	**Negotiation support v1** (scenario planning)	Product/ML	Price elasticity heuristics	Users simulate counter offers; scenario deltas reflected in ROI
L3	**A/B field trial with brokers**	PM/Partners	Two agencies	Pre registered outcomes; uplift in win rate or time to quote; report published
L4	**Accessibility & localization**	UX/Dev	i18n files; WCAG	WCAG 2.1 AA for core flows; PT/EN/ES strings complete