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RESEARCH ARTICLE

AI-enabled valuation and information asymmetry in Dubai's residential market: an exploratory case study

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ABSTRACT

This paper examines how AI-powered valuation and search products are designed to address information problems in Dubai's residential market and what market conditions make them commercially viable. The study uses a qualitative exploratory single-case design with two embedded ventures. The primary evidence is a single 55-minute semi-structured interview with the founder of both ventures, supplemented by a live product demonstration, the ventures' public materials and archival market data. Because the demonstration and venture materials are controlled by the same informant, claims were classified by type and checked against Dubai Land Department data and independent reporting where possible. The case suggests that AI creates value less through abstract automation than through evidence-referenced valuation, natural-language search, lead conversion and trusted market reports. Credible transaction data and explainable comparable evidence appear to function as commercial trust mechanisms. In the founder's account, Dubai became a viable base for AI-native valuation products once digitised transaction data, transaction volume and investor sophistication were jointly sufficient. The evidence is based on a single founder-informant with a commercial interest in the ventures studied; some quantitative claims could not be independently verified. Findings are presented as propositions for testing in other ventures and markets. Valuation products may gain user adoption when predictive outputs are accompanied by reliable, source-referenced evidence and when they support rather than replace brokers. For policymakers, the terms on which authoritative transaction data can be accessed may shape both market transparency and which firms benefit from AI-enabled valuation. The paper connects AI-enabled valuation, information asymmetry and market-readiness conditions in an emerging global housing market and develops six propositions for future research.

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1. Introduction

The housing market in Dubai has become one of the most visible housing markets in the Middle East, drawing in domestic residents, local buyers and investors from overseas. The rapid growth has intensified the need for accurate valuation, quick market access and evidence that real estate prices reflect market value. In such a market, both buyers and investors are not simply deciding between properties; they are assessing information about locations, developers, building quality, transaction histories, off-plan premiums, resale comparables, rental yields and future appreciation. This information environment poses a real housing-market problem: buyers and investors need to make high-value decisions in a space of data fragmentation and lack of information access.

The problem is particularly acute in Dubai, where many buyers are not local or internationally mobile and do not have the neighbourhood knowledge, broker networks or transaction-level data required to assess property claims independently. Listing portals, developer brochures and brokerage advice can reduce search friction, but they can also reproduce information asymmetry when customers lack the ability to verify asking prices, compare units across market segments or distinguish short-term sales narratives from evidence-based valuation. AI-enabled valuation and search systems are not just the tools of digital communication; they are potential market-information infrastructures that could alter how housing users assess price, risk and opportunity. Because the credibility of market information affects both price discovery and the durability of the firms that supply it, the question also concerns sustainable business: whether AI-native information businesses can build lasting value by improving transparency, rather than by capturing short-term transaction fees.

Recent research into real estate digitalisation shows that artificial intelligence, machine learning, digital platforms and data-driven decision systems are transforming property search, valuation and customer interaction (Al-haimi et al., 2025; Naeem et al., 2023). Existing research approaches this change from three directions, each of which stops short of the question addressed here. Technical studies develop and test valuation models, evaluating predictive accuracy and explainability (Kok et al., 2017; Teoh et al., 2022; Rodriguez-Serrano, 2025), but stop at the model rather than at the business that deploys it. Reviews of digital real estate catalogue technologies and their benefits (Al-haimi et al., 2025; Naeem et al., 2023) without examining how specific firms turn them into products. Economic studies explain why information is unevenly distributed between buyers, sellers and agents (Garmaise and Moskowitz, 2004; Levitt and Syverson, 2008; Kurlat and Stroebel, 2015), and work on algorithmic intermediaries has examined iBuyers that trade homes on their own balance sheet (Buchak et al., 2020), but neither examines ventures that sell valuation evidence and search to buyers and brokers. As a result, little is known about how AI-based businesses turn valuation models, institutional transaction records and conversational interfaces into operational decision support for buyers, investors, brokers and lenders. This gap is particularly urgent in new and emerging markets, where digitised transaction data is scarce, market participants are heterogeneous and price discovery is affected by strong promotional narratives.

A perspective on the Dubai case also allows the paper to move beyond a generic discussion of the United Arab Emirates as a digital hub. The question is not just whether the UAE is strategically attractive for PropTech. The more precise question about the housing market is what combination of market scale, data availability and participant sophistication makes an AI-native valuation product viable. The case we investigated here is useful because the founder first built valuation systems in Russian banking, considered Saudi Arabia, and then based the ventures in Dubai after he concluded that the local market had crossed a workable threshold in transaction volume, digitised records and investor demand.

Therefore, the objective of this paper is to investigate how AI-enabled valuation and search products are designed to address information problems in Dubai's residential sector and how market conditions impact the commercial viability of these products. The study examines these questions from the provider's perspective: the evidence comes from the founder of two ventures and from the products themselves, not from the buyers, brokers, investors or lenders who use them. To do so, three research questions are set:

RQ1. How do AI-enabled valuation and search systems turn housing-market

information into decision support for Dubai residential market participants?

RQ2. Which AI applications does an AI-native provider develop for buyers, investors, brokers, developers and lenders, and how are they intended to address information problems?

RQ3. What combination of data accessibility, transaction volume, and participant sophistication makes a market for AI-native valuation and search products viable?

In Section 2, we set out the theoretical foundation, review the literature on AI-enabled decision support, automated valuation, information asymmetry, platform governance and the Dubai market, and present the conceptual framework. Section 3 provides the qualitative exploratory case methodology and in Section 4 we present our findings. Section 5 discusses the findings and elaborates on the propositions, Section 6 presents the study's contributions, Section 7 addresses the limitations, and Section 8 outlines the implications and directions for future research. Section 9 concludes.

2. Theoretical foundation and literature review

2.1 Theoretical foundation: information asymmetry, search and intermediation

Information asymmetry arises when one party to a transaction knows more about the quality or value of what is traded than the other. Akerlof (1970) showed that when buyers cannot distinguish good from poor quality, prices reflect average quality, sellers of high-quality goods withdraw and the market can unravel. Two responses to this problem are central to this paper. Stigler (1961) treated information as costly to acquire: buyers search only while the expected gain from further search exceeds its cost, so price dispersion persists where search is expensive. Spence (1973) showed that the better-informed party can send signals that separate high from low quality, provided the signals are credible.

Housing markets combine these problems. Properties are heterogeneous and traded infrequently, search is costly, and sellers and agents usually know more about a property and local prices than buyers do. Empirical work shows that these asymmetries matter. In commercial real estate, market participants resolve information asymmetries by purchasing nearby properties, trading properties with long income histories and avoiding transactions with informed professional brokers (Garmaise and Moskowitz, 2004). In residential markets, homeowners appear to have superior information about neighbourhood characteristics, and when sellers are better informed, prices tend to fall and the neighbourhoods' composition subsequently changes (Kurlat and Stroebel, 2015), and homes owned by real estate agents sell for about 3.7 per cent more and stay on the market about 9.5 days longer than comparable homes the agents sell for clients (Levitt and Syverson, 2008).

Intermediation theory explains why such markets rely on middlemen. Rubinstein and Wolinsky (1987) model intermediaries who shorten the time needed to match buyers and sellers and earn a return from that service. Transaction cost economics adds that the choice between direct exchange, intermediated exchange and internal organisation depends on the costs of searching, negotiating and enforcing agreements under bounded rationality and opportunism (Williamson, 1985). In housing, brokers, portals and valuers lower search and verification costs, but because they are typically paid per transaction, their incentives need not match the client's (Levitt and Syverson, 2008).

Automated valuation models (AVMs) can be read through this lens. In real estate research they have mainly been treated as a substitute for, or complement to, manual appraisal and assessed on accuracy and cost (Kok et al., 2017). From an information

perspective, an AVM can do three further things: lower the buyer's cost of search and price comparison (Stigler, 1961); act as a verifiable signal of value when its outputs are explained and referenced to recorded transactions (Spence, 1973); and take over part of the information function of human intermediaries (Rubinstein and Wolinsky, 1987; Williamson, 1985). Whether an AVM reduces information asymmetry or relocates the information advantage to whoever controls the model and the data is an open question. This paper examines it from the provider's side.

2.2 AI-enabled predictive analytics and housing-market decision support

AI is increasingly being used in data-intensive industries for predictive analytics, decision making and transforming large data sets into actionable recommendations. In this study, the most relevant AI capabilities are not general automation or broad digital transformation, but the ability to detect patterns in market data, predict future or hidden value, rank alternative options and provide decision support to people who are uncertain. In business research, AI is considered as a means for improving decision quality when organisations can combine analytical models with data governance, human management and domain-specific interpretation (Charles et al., 2025; Enholm et al., 2022; Kitsios and Kamariotou, 2021; Raina et al., 2026). These types of decision support systems are especially applicable to housing markets where decisions are based on uneven and spatially related information. The property market is where buyers, investors, lenders and other players need to compare properties that are in different places, build quality, legal status, amenities and market timing, rental opportunities and transaction history. Predictive analytics can therefore facilitate price estimation, investment screening, risk assessment and customer matching. But the housing-market value of AI relies on whether the output can be trusted, explained and translated into decisions that players can make as well as whether the model can make a difference in terms of the decisions they have and not just how well the model performs.

2.3 AI-enabled valuation, property search and broker augmentation

Automated valuation is one of the most developed AI applications in real estate because valuation depends on large quantities of property, location and transaction data. Traditional valuation methods remain important because they incorporate professional judgement and local market knowledge, but they may be constrained by limited comparables, subjective interpretation and slow updating. AI-based valuation models can process wider sets of variables and detect relationships that are difficult to capture manually, including spatial characteristics, building attributes, neighbourhood effects and market signals (Alsawan and Alshurideh, 2023; Huang et al., 2025; Jafary et al., 2025; Su et al., 2021). Toprakli (2025) similarly argues that AI-driven valuation is reshaping professional appraisal practice by supplementing, rather than simply replacing, appraiser judgement.

Housing-market research is particularly relevant to this paper where it links modelling techniques to housing-market decision-making. Ozhegov (2022) shows that price modelling can benefit from considering distance in both geographic space and property-characteristics space, an insight that aligns with AI valuation systems that compare properties through multiple similarity dimensions. Teoh et al. (2022) demonstrate the value of explainable machine learning for housing price prediction, using determinant analysis to make model outputs more interpretable for buyers and sellers. These studies indicate that

predictive accuracy is not sufficient; valuation tools must also reveal which features matter and why.

Recent valuation literature also emphasises multimodal and explainable models. Multimodal valuation can combine numerical attributes, text descriptions, images, spatial data and building information, while explainable models clarify how individual variables contribute to a predicted value (Huang et al., 2025; Karanikolas et al., 2025; Yazdani and Raissi, 2023). Explainability is especially important because housing valuations shape financing, negotiation, investment screening and buyer trust. A valuation report that cites comparable transactions and exposes relevant predictors can function as a market document, not merely a prediction score (Rodriguez-Serrano, 2025; Teikari et al., 2025).

AI is also increasingly relevant to property search and brokerage workflows. Digital real estate research shows that AI, customer relationship management systems, recommendation tools and digital platforms can reshape how firms acquire customers, match them to properties and maintain relationships (Al-haimi et al., 2025; Naeem et al., 2023). In growth markets, this may make transaction-facing tools more commercially salient than asset-management applications such as predictive maintenance. Property management remains an important AI application, but the present study focuses on valuation, search and brokerage augmentation because the empirical case is concentrated on the front end of the transaction value chain.

2.4 Information asymmetry, transparency and trust in housing markets

Information asymmetry is one of the defining characteristics of housing markets. Sellers, developers, brokers and platforms are usually more knowledgeable about the quality of a property, its pricing strategy, comparable transactions, expected yields and market liquidity than buyers. Buyers, especially non-local or first-time buyers, may incur high search costs and can be heavily reliant on intermediaries. This can result in unequal access to value-relevant information and create a greater risk that customers will interpret asking prices or scarcity stories as signs of market value.

Transparency in housing markets can change pricing behaviour and price discovery over time. Lo et al. (2022), in a study of the Scottish housing market, analyse how the policy of information disclosure was associated with asking and residential price discovery. Kandlbinder (2019) also finds that out-of-town buyers can face search-cost and information disadvantages even when online platforms are more transparent about the available housing information. Recently, Nguyen and Truong (2025) have shown that ambiguous price signals in an opaque housing market can lead to different behavioural responses for different groups of buyers. Gupta and Moodley (2026) showed that housing search itself is predictive of future price movements, and that search behaviour and price discovery are inextricably connected. Taken together, these studies reveal that information doesn’t always mean equal decision-making capacity; information needs to be credible, interpretable and usable.

This distinction lies at the heart of AI-enabled valuation. A platform that just displays more data may overwhelm buyers, while a system that translates data into a justified valuation, ranked alternatives and source-referenced comparisons can reduce search costs and information asymmetry more effectively. Trust therefore becomes a functional necessity. We explore trust in this paper through three related mechanisms: authoritative transaction data, explainable valuation outputs and user interfaces that ease the cognitive burden of interpreting market information.

2.5 Platform governance, business-model durability and PropTech failure

A second body of work concerns the firms that supply market information. Platform governance research examines the layers of rules and relationships that structure interactions between platform companies, users, advertisers and governments (Gorwa, 2019). In housing, this matters because listing portals, data providers and AI valuation services decide what information buyers see, in what order and on what terms. Revenue models shape those choices: a portal paid per lead or click faces different incentives from a service paid per subscription or per valuation report.

The durability of these businesses cannot be assumed. The most visible example is algorithmic home buying (iBuying), in which firms use valuation models to make fast offers on homes and resell them. Buchak et al. (2020) identify the central trade-off: providing liquidity requires fast transactions, which leads to less accurate valuations and exposes the intermediary to adverse selection, so iBuyers operate mainly in liquid, easy-to-value segments. Zillow closed its iBuying business, Zillow Offers, in November 2021 after its chief executive said the company could not forecast home prices accurately enough and after large inventory write-downs (Inman, 2021). The episode shows that valuation accuracy becomes a business risk, not only a technical metric, when a firm's balance sheet depends on it.

Research on corporate sustainability argues that firms create durable value when they maintain their economic, social and environmental capital rather than maximising short-term returns (Dyllick and Hockerts, 2002), and recent work links AI-driven management to sustainable business practices (Raina et al., 2026). Applied to market-information businesses, this raises the question of whether AI-enabled transparency builds lasting value for users and the market or mainly makes commission-based selling more efficient while concentrating data in a few firms. The PropTech literature reviewed above says little about this question.

2.6 Dubai as a valuation and market-information context

Dubai’s residential market is a strong context for AI-enabled valuation as it combines international demand, high volumes of transactions, off-plan and resale segments, and an expanding institutional data infrastructure. The price drivers of property in Dubai have been shown to be nonlinear and vary across submarkets and price quantiles (Worku, 2017). Recent international research in housing markets and analysis also indicates that Dubai is still relevant as a housing market case in the context of monetary conditions and real estate performance (Rashad and Farghally, 2024) and environmental stigma in property valuation (Abou-Gad et al., 2025).

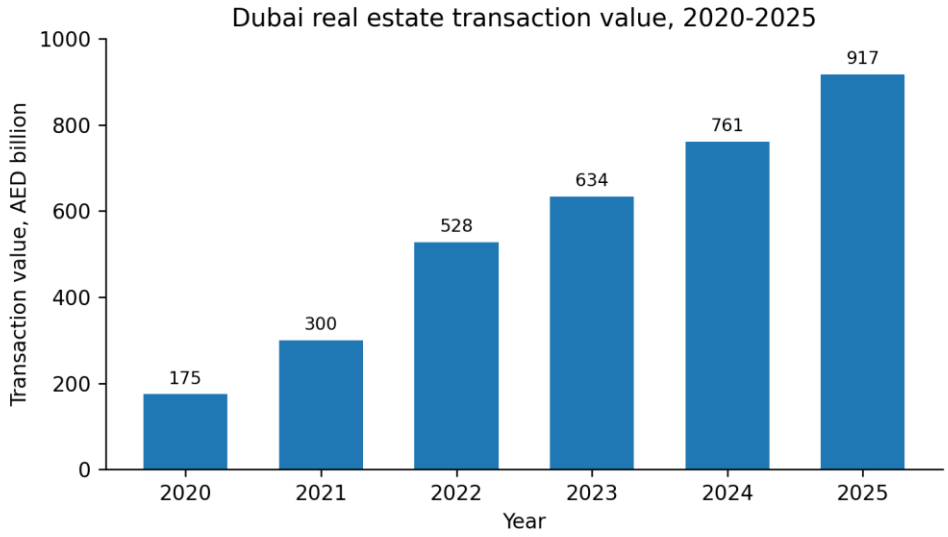
Policy and institutional context are also important. UAE's Strategy for Artificial Intelligence 2031 provides a high-level policy framework for AI adoption in the real estate sector (UAE AI Office, n.d.; UAE Government, n.d.). This does not mean that all market participants have equal access to transaction-level knowledge, but it creates the possibility that AI-native companies can build products around digitised records, market analytics, and valuation evidence.

The legal framework for digital trust is also relevant. At federal level, Federal Decree-Law No. 45 of 2021 regulates the protection of personal data, Federal Decree-Law No. 46 of 2021 governs electronic transactions and trust services, and Federal Law No. 15

of 2020 sets consumer protection rules (UAE Government, 2020, 2021a, 2021b). In Dubai's off-plan segment, Law No. 8 of 2007 requires payments made by off-plan purchasers to be deposited in a project-specific escrow account (Government of Dubai, 2007). These rules shape what data AI-enabled ventures can collect and use, how automated client communication should be handled and how far buyers are protected, so they form part of the institutional conditions under which such ventures operate.

This is an opportunity on Dubai's market scale. Dubai Land Department (2025) reported real estate transactions reaching AED 761 billion in 2024, with 2.78 million total procedures including transactions and rental agreements. Dubai Media Office (2026) and DXB Analytics (2026) reported that the market surpassed AED 917 billion in transactions in 2025 with more than 270,000 transactions of this type. These figures indicate a high-volume environment in which valuation, screening, and search tools can be useful for investors, buyers, lenders, and intermediaries (see Figure 1).

Figure 1. Dubai real estate transaction value, 2020-2025 (AED billion; total registered sales, mortgage and gift transactions). Source: authors, based on DLD-derived market data compiled from DXB Analytics (2026) and official DLD/media reporting (Dubai Land Department, 2025; Dubai Media Office, 2026).



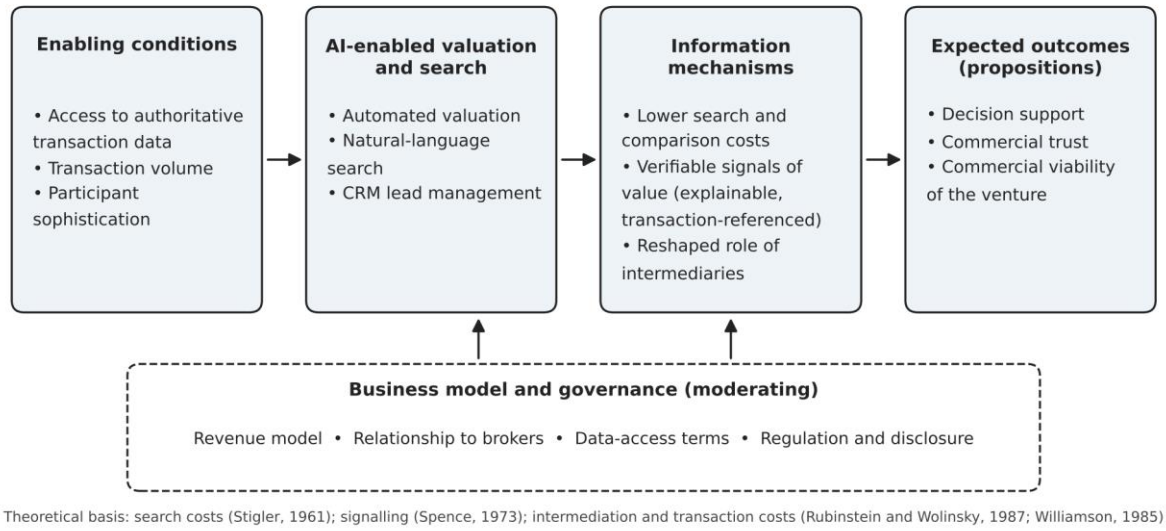
2.7 Research gap and conceptual framework

Literature therefore leaves a specific gap. Valuation studies test models but stop at predictive accuracy and explainability (Kok et al., 2017; Teoh et al., 2022; Rodriguez-Serrano, 2025). Economic studies explain why information is unevenly distributed between buyers, sellers and agents (Garmaise and Moskowitz, 2004; Levitt and Syverson, 2008; Kurlat and Stroebel, 2015) but do not examine AI-native intermediaries. Work on algorithmic intermediaries has focused on iBuyers that trade on their own balance sheet (Buchak et al., 2020) rather than on ventures that supply valuation evidence and search to buyers and brokers. Little is known about how an AI-native venture integrates valuation models, local transaction data and conversational interfaces into a commercially viable housing-market information product. The research questions address this gap by connecting valuation and information asymmetry literature to a qualitative case study of AI-enabled real estate ventures operating from Dubai.

Figure 2 summarises the conceptual framework. It makes explicit the expectations

that informed the initial coding framework (Section 3.4). Drawing on Section 2.1, we expected AI-enabled valuation and search to address information problems through three mechanisms: lowering search and comparison costs (Stigler, 1961); providing verifiable signals of value through explainable, transaction-referenced outputs (Spence, 1973); and reshaping the information role of intermediaries (Rubinstein and Wolinsky, 1987; Williamson, 1985). We expected these mechanisms to depend on enabling conditions, namely access to authoritative transaction data, transaction volume and participant sophistication (Section 2.6), and to be moderated by the venture's business model and governance, including its revenue model, its relationship to brokers, data-access terms and regulation (Section 2.5). Section 5 returns to the framework in light of the case evidence.

Figure 2. Conceptual framework: enabling conditions, AI-enabled valuation and search, information mechanisms and expected outcomes.



3. Methodology

3.1 Research design

The study is a qualitative exploratory single-case study and comprises two units of analysis. This design is appropriate for three reasons. First, AI-enabled valuation and property search in Gulf housing markets has been relatively new and understudied, so theory development is more suitable than theory testing (Eisenhardt, 1989). Second, the technical architecture, data sources and commercial strategies behind AI-enabled ventures are private and only partially reported publicly, so secondary data alone are insufficient. Third, the case study design allows a direct link between empirical evidence and conceptual explanation in a complex and rapidly changing market setting (Yin, 1984).

The study aims to identify and describe a mechanism rather than measure its prevalence. A single information-rich case is appropriate when the objective is to reveal a theoretically relevant process and develop propositions to be tested in future research (Siggelkow, 2007). But we are looking for how AI-based valuation is turned into services for housing market participants, and not statistical generalisation of this data. Therefore, we presented results as propositions for further research and market testing of other firms and

markets.

The research design has a serious limitation: the evidence is based on a single founder-informant who has a business interest in the types of businesses described. Section 3.5 explains how claims were classified and verified where possible, and Section 7 explains the implications in relation to this restriction.

3.2 Case selection and sampling

The case was chosen purposively and not randomly. Three criteria guided the selection. First, AI needed to be at the core of the venture and not a small part of the value proposition. Second, the venture had to be working with real-world users rather than being in a conceptual phase. Third, the main informant had to know the technical architecture and business model in advance. Since the phenomenon is most concentrated in a few specialist organisations, random sampling would have missed key cases.

The case comprises two AI-based ventures, founded and run by the same entrepreneur in the United Arab Emirates and Saudi Arabia. The first venture is a data-driven investment and property search platform that combines market, spatial and transactional information about Dubai to identify undervalued assets and estimate appreciation potential. The second venture is a conversational AI system integrated into brokerage workflows; it generates valuation and comparison reports, interacts with customer relationship management systems and messaging channels, and focuses on client leads.

The ventures are embedded within a single case. This allows us to study the way in which a common capability (automated valuation of the market using aggregated market data) is translated into two different service propositions for different market participants while the founder, technological infrastructure and market context are held constant. The founder was selected as the main informant because, in early-stage ventures, strategic, technical and commercial decisions are usually made by the founder, and because he had more than nine years of experience in machine learning for property valuation, first with banks in Russia and more recently in the UAE and Saudi Arabia.

3.3 Data collection

Data were gathered from three sources between December 2025 and September 2026 that were triangulated to enhance reliability (Jick, 1979). The main source was a semi-structured interview with the founder of the two ventures in December 2025. The founder was contacted through the professional network of one of the authors and invited to an interview about the ventures and the PropTech market. The interview lasted 55 minutes, was conducted in English by three researchers and recorded with the informant's consent and transcribed using the transcript feature of the Recorder app (version 7.05.0), and the transcript was checked against the recording by the researchers. Like Spradley (1979), the interview was structured (following open-ended questions) so that the participant could focus on what he felt was important and there were follow-up questions revolving around the study's objectives.

The interview also looked at the origins of the ventures and the market problems they seek to address, the valuation model (data sources and predictive variables), the products and services offered and the housing market participants that they were serving, and the conditions for the existence of a viable AI-enabled housing market in terms of data availability, customer behaviour and market competition.

The second source was direct observation of the product being used. During the interview, the founder shared his screen and demonstrated how the AI product works within a customer relationship management system. The demonstration showed that the system assesses individual records, recommends next steps and can send messages or initiate calls automatically when autonomous operation is on. This allowed the researchers to see functions and outputs directly as opposed to only interview descriptions.

The third source was public digital materials and archival data. Venture websites and feature descriptions were examined to compare public claims with demonstrated product functions. Market and contextual materials included DLD transaction data, official policy documents, regional press articles, market analytics reports and academic studies related to automated valuation, recommendation systems and property search. Notes were made during and after the interview, demonstration and document review. The second and third sources are not fully independent of the informant, because the demonstration and the venture websites are controlled by the founder. They were therefore used to corroborate what the products do, not claims about market conditions, competitors or performance, which were checked against DLD data and independent reporting where possible and otherwise attributed to the founder.

3.4 Data analysis techniques

The transcript was analysed in thematic fashion, and the coding categories were refined by reviewing data and literature in detail (Strauss and Corbin, 1998). The initial coding framework was based on the literature review and the conceptual framework (Section 2.7) to identify automated and multimodal valuation, recommendation and property matching, search optimisation, predictive market intelligence, lead management and conversational customer service.

Coding is organised into three steps. First, each application described or shown was identified and assigned a category in the coding framework. Applications were marked as documented when they aligned with existing research or market-specific when they focused on Dubai market conditions and were not widely cited in the literature. Second, each application was linked to the market participants it served (e.g., buyers, investors, brokers, lenders and developers) and the value it offered (efficiency, transparency, personalisation and decision support). Third, contextual information was coded into categories on data availability, institutional and regulatory issues, market size and the information environment.

Coding was carried out manually, without qualitative data analysis software. Each of the three researchers coded the transcript independently using the codebook in Appendix 1, and the coded interpretations were then compared and discussed, with additional documents reviewed where necessary. Differences were resolved through discussion until the researchers agreed on a final coding; because coding was consensus-based, a statistical inter-coder agreement coefficient was not calculated. The categories were then divided into a coding matrix to guide interpretation and develop the propositions mentioned in this discussion. Table I (Section 4.8) summarises the themes that emerged from this coding, the codes from which each was built, the documented or market-specific status of each application and the evidential basis of each theme.

3.5 Research quality and ethical considerations

Several measures were taken to strengthen credibility. The claims in the transcript were divided into three classes and treated differently. Descriptive claims about how the ventures operate were evaluated against the product demonstration and published venture materials. Where possible, factual claims about market conditions were checked against DLD transaction data and independent reporting. Statements about the behaviour or motives of other market participants were reported as the informant's perspective, not as fact.

This distinction is important because the informant is competing with intermediaries and listing platforms whose incentives he describes. This is still useful because of the way the AI-native entrant can understand the value chain as well as market-entry opportunities, and we do not take them as objective facts. Similarly, performance and standing claims that cannot be independently verified are attributed to the informant and not presented as objective facts.

Informed consent was obtained from the participant, who was informed about the purpose of the research, data storage and use, and confidentiality policies.

4. Findings

In this section we present our case findings, organised around the coding categories outlined in Section 3.4. As in Section 3.5, descriptive statements about how the ventures function are reported as fact if the product demonstration (or published material) verified them. Factual claims about the market conditions are reported as facts only where they are reported in agreement with DLD data or according to independent reporting. The evaluation of the conduct or incentives of other market participants is explicitly attributed to the founder. Direct quotations are taken from the interview transcript. Filler words and repetitions have been removed and marked […], and words added for clarity or to replace the names of firms are given in square brackets.

4.1 Automated valuation and the ranking of predictive variables

The core valuation tool, built and deployed in Russian banks and subsequently adapted for Dubai, estimates property value from more than 200 variables per location. The founder said that the most influential variables are identified using a random-forest algorithm applied to large volumes of listing and transaction data. For residential apartments, he identified the most influential variables as location, building quality and size. Building quality is described by a 16-tier classification: A-plus to F-grade for buildings that are not worth renovating. In the founder's words, “[a] one bedroom apartment in a luxury building, in the same location will be more valuable than [a] three bedroom apartment in a disaster building.” For land, the relevant set is permitted use, since the same plot can be worth several times more if it can legally support a villa or multi-family building.

The founder reported that about 98 percent of the variables used are numerical instead of image and text-based and claimed that developer or brand reputation is not one of the top predictors for users and buyers. This observation supports and qualifies the literature reviewed in Section 2.3. It further confirms that AI-based valuation can use a wider number of variables in comparison to conventional comparable-sales methods and it is possible to rank predictors empirically (Huang et al., 2025; Jafary et al., 2025). It also

qualifies the literature on multimodal inputs by showing that the structured numerical data dominated the system deployed as the founder was attracted to speed, scalability and explainability that were needed.

The founder also distinguished between price and value. Price was presented as the observed, time-bound liquidity outcome whereas value was the modelled estimate against which observed or requested prices could be evaluated. As he put it, “The key thing in real estate is just identifying the right combination of value and the price.” This is in line with the view that automated valuation serves as a market-coordination mechanism and not just a predictive exercise (Rodriguez-Serrano, 2025; Teikari et al., 2025). It also supported the founder's perspective of how the model finds properties priced below their modelled value for investment.

4.2 Proprietary and institutional data as a basis for differentiation

According to the founder, valuation and search systems are based on open web sources, licensed or purchased data from platforms that already have market data, and closed institutional records, such as DLD transaction data, in more mature markets like the UAE. He claimed that general-purpose AI assistants can't answer questions about DLD-registered transactions because these databases do not appear in public search engines. “If you ask GPT what transactions happen, it has no idea […] because DLD is not the database that you can easily find in Google.” He said access to closed authoritative data is a key difference from generic AI tools, as opposed to modelling. In his words, “it has access, GPT doesn't have access […] this is a differentiator.”

We do not treat this claim as verified, because it is the founder's position rather than a technical fact that this study could test. It is, however, consistent with the founder's description of how the product is presented to customers, namely that the system's outputs are based on DLD-sourced transactions. Thus, the competitive value of AI was not only algorithmic modelling but also access to relevant local records to substantiate evidence-referenced reports.

4.3 Predictive market intelligence and perceived market transparency

The founder described Dubai as a market where primary off-plan and secondary resale prices of similar units in the same building may differ greatly. He attributed this to the higher commission structure he associated with primary sales (roughly 5-6 per cent compared with 2 per cent for resale transactions), and scarcity stories of new-launch units selling out very quickly. In his account, agents “are more motivated to sell primary real estate market to get paid 5-6% […] commission than to offer them secondary market”, and “you can convince all buyers around the world that it's going to sold out in a day.” He also said the model would flag prices that are too high or too low from the model's own market value estimate, and that these flags were supported by similar transactions from DLD records. Asked whether the output shows if a property is under- or overpriced, he replied: “Yeah, and it shows evidence, like transactions in, let's say, DLD.”

The magnitude of the primary-secondary price gap and the nature of broker incentives are the founder's perceptions, not the market statistics, since they were not tested independently for transaction-level DLD data. The general picture they outline of a fast-growing, high-volume market where asking prices vary from the model value is in line with the growth of transaction volume in Section 2.6 and the literature that treats real estate markets as subject to information asymmetry (Lo et al., 2022; Nguyen and Truong,

2025).

4.4 From data dashboards to natural-language search

The first venture was a data-intensive platform that processed more than 100 layers of Dubai market information, such as amenities, green space and rental yields, and made this information available to potential buyers. The founder said only a small percentage of users would be capable of interpreting this data independently; most users preferred a trusted intermediary (human or automated) to make the decision. As he explained, users "would like to have a lot of data, but they don't want to invest their time and efforts to all this stuff." This supports the view that it is more important to reduce the cost of searching and interpreting the data than it is to increase the amount of data.

During the interview, the founder presented a new product that was ready for market launch and that replaced the dashboard interface with a natural language query system. A user can write a question in simple language like asking for the best-return apartments within a budget from a reputable developer and the system searches its own database, public sites and licensed data sources at the same time. The outputs are a map, comparison table and evidence-based valuation with similar transactions cited within 10 to 15 minutes.

The system can work for any property type in any location, beyond the original UAE-only scope of the first venture, said the founder. It can also accept unstructured input such as a PDF brochure or spreadsheet of a multi-property portfolio and return valuation reports for each property. The founder said it was the switch from a data dashboard to a conversational interface that was the most influential change in adoption, rather than a single algorithmic change. Of the earlier platform, he said that "the complexity of the platform and technology […] it's a deal breaker for a lot of people to jump in."

4.5 Lead management and conversational customer service

The second venture, integrated into brokerage CRM systems, was demonstrated live during the interview. The system reviews each client record in the CRM, assesses the client's history and stage in the sales process and generates a recommended next action (e.g., message or call script) to be taken. Users can operate the system in supervised mode (where each recommended action is reviewed and approved) or autonomous mode (where the system sends messages and initiates calls without human input). The founder said that the system can be switched between these modes as needed. "If you switch on, it acts automatically […] And if you want to stop, you switch off and you take the control."

The system is also available in multiple languages and presents itself to clients under a named, human voice persona and a social media profile. The founder said that people sometimes take the persona for a real person ("Sometimes people think that she's a real person") and that "we created this to compete with agents." This practice warrants critical attention. If clients are not told that they are communicating with an automated system, the persona raises consumer-protection and ethical concerns about deception, informed consent and the handling of client data, and these concerns are sharper in autonomous mode, where messages and calls are initiated without human review. It also sits in tension with the venture's own trust strategy: the evidence-referenced reports discussed in Section 4.2 are designed to make output verifiable, while an undisclosed persona depends on clients not knowing how the service is produced. The study did not examine whether or how the system's automated nature is disclosed to clients, or how the consumer-protection and data-

protection rules outlined in Section 2.6 apply to it, so the evidence on this point is limited to the founder's account.

The founder estimated that agents spend at least part of their working day doing research, comparing and reporting, and that AI-based reporting would minimise that time considerably over an agent's career. He put this at about two hours a day: “usually 15% of their time they spend on researching, marketing reports, selecting, estimating”. This time-saving estimate is the founder's own estimate, not a measurement independently verified in this study.

4.6 Business model: subscription access and B2B integration

The natural-language search product is a freemium subscription system which has a free entry tier and a paid consumer subscription which the founder estimates to be about US$25 to US$40 per month. In his words, “you start for free but then you subscribe for 25 or 40 bucks per month.” The product is also a business-to-business integration model in which the system is directly integrated into a brokerage's existing CRM software and the agent is able to access it on a per-client basis. This is different from the first venture, which paired the data platform with lower-cost, remote, non-expert consultants to reduce the reliance on commission-based agents. The new product is also a tool that is built around the agent and brokerage workflow and does not replace them.

4.7 The founder's account of incumbent platform incentives

The founder argued that classified and listing portals that generate revenue from advertising, calls and click volume are structurally disincentivised from investing in AI systems that can match buyers with properties more quickly because they will not see the benefits in delaying user search at the expense of speed. He compared it to a dating site losing a paying user when a match is made. In his view, the goal of such portals is “to keep you searching as much as possible.” He also argued that once an AI assistant rather than a human user is responsible for search, portals would be able to sell placement to the AI system but the visual and psychological cues that lead to human engagement and advertising value would not be as relevant. “AI doesn't care, it's on the top or in the bottom. For human eyes, it's important whether it's in the top or it's in the bottom.”

This view of existing platform incentives is taken in the context of the founder as a competitor rather than as the outcome of any platform’s strategy. It is of analytic value in showing how an AI-native entrant frames its opportunity for market entry: not only for better prediction, but also for a different incentive structure for search duration and matching efficiency.

4.8 Contextual validation: why Dubai, and why now

The founder’s trajectory provides a sense of why Dubai was the base of the businesses. He first built and then deployed the valuation algorithm in big Russian banks. That business came to a halt when the banking contracts were lost in 2022, following the outbreak of the war in Ukraine. In his words, “we lost all contracts with all banks in a week.” The founder then explored Saudi Arabia but judged it too early to launch an AI-based business there. (“We understood that Saudi Arabia is too early for AI.”) He moved to Dubai, where he built the first venture, which he reported was later sold.

The founder said the decision to set up the company in Dubai was based on the

volume of the market, digitised market and transaction data and international investor base. He also said the new product is now being extended back to Saudi Arabia as more data is becoming available. This account is consistent with the market-scale evidence in Section 2.6 and adds one point: in the founder's telling, Dubai was not chosen as part of a regional hub strategy, but because data availability, transaction volume and investor sophistication made an AI-based valuation and search service feasible there. Institutional factors that the founder did not discuss, such as the regulation of off-plan sales and escrow (Government of Dubai, 2007), tax policy and government digitalisation programmes, may also have contributed; these were outside the scope of the interview and are considered in Section 5.5.

Table I. Analysed themes: codes, status of applications and evidential basis

Theme (sections)	Codes applied (Appendix 1)	Status of application (Section 3.4)	Claim type and evidential basis (Section 3.5)
Valuation as verifiable evidence rather than a bare estimate (4.1, 4.2; 5.3)	Automated and multimodal valuation. Participants: buyers, investors, brokers, lenders. Value: transparency; decision support.	Documented: consistent with research on automated and explainable valuation (Section 2.3). The dominance of structured numerical variables qualifies the multimodal literature.	Descriptive: variable ranking and comparable-referenced reports corroborated by the interview and product demonstration. The share of numerical variables (about 98 per cent) is the founder's figure.
Authoritative transaction data as the basis of differentiation (4.2; 5.4)	Context: data availability; institutional and regulatory issues. Participants: investors, lenders. Value: transparency.	Contextual theme (coding step 3); not classified.	Descriptive: use of DLD-sourced records. Informant perspective: the claim that general-purpose AI tools cannot access these records was not tested.
Price–value divergence in a promotion-driven market (4.3, 4.7)	Predictive market intelligence. Context: information environment. Participants: investors, buyers. Value: transparency; decision support.	Market-specific: reflects the gap between off-plan and resale prices and new-launch scarcity narratives in Dubai, which are not widely discussed in the reviewed literature.	Descriptive: the flagging of prices above or below modelled value. Informant perspective: the size of the price gap, commission rates and portal incentives were not verified.
Reducing interpretive burden through natural-language search (4.4; 5.1)	Search optimisation; recommendation and property matching. Participants: retail buyers, international investors. Value: efficiency; personalisation; decision support.	Documented as an application (search costs and digital platforms, Sections 2.3–2.4). That the interface, rather than the model, drove adoption is not widely discussed.	Descriptive: the interface and its outputs, as presented during the interview. Informant perspective: the effect of the interface on adoption.
Augmenting brokers in the sales workflow (4.5, 4.6; 5.2)	Lead management; conversational customer service. Participants: brokers and agents. Value: efficiency.	Documented: AI and CRM tools in brokerage workflows (Section 2.3).	Descriptive: supervised and autonomous modes directly observed in the demonstration. Informant perspective: time savings and pricing of the subscription.

Theme (sections)	Codes applied (Appendix 1)	Status of application (Section 3.4)	Claim type and evidential basis (Section 3.5)
Automated client communication and trust (4.5; 5.6)	Conversational customer service. Context: institutional and regulatory issues. Participants: prospective clients.	Emergent: not anticipated in the initial coding framework or in the reviewed PropTech literature.	Informant perspective: the human-presenting persona and clients' perception of it. Disclosure practice and legal compliance were not examined.
Market-readiness conditions (4.8; 5.5)	Context: data availability; market size; institutional and regulatory issues.	Contextual theme (coding step 3); not classified.	Market factual: transaction volume checked against DLD data (Section 2.6). Informant perspective: the reasons for choosing Dubai over Saudi Arabia.

Source: Authors' research

4.9 Comparison of the two embedded ventures

The two ventures that make up the embedded case are compared in Table II. Both draw on the same valuation capability and data sources but translate them into different propositions. The first venture gave buyers and investors direct access to market data and sought to reduce reliance on commission-based agents. The second presents the same kind of evidence through a conversational interface and is built around brokers' workflows. In the founder's account, the shift followed from demand: most users did not want to interpret data themselves and preferred a trusted intermediary (Section 4.4). The comparison therefore suggests that the interface, and the channel through which evidence reaches users, distinguished the two propositions more than the underlying model did. This informs P1 and P3 in Section 5.

Table II. Comparison of the two embedded ventures

Dimension	Venture 1: investment and property search platform	Venture 2: conversational AI system for brokerage workflows
Core offer	Combines market, spatial and transaction information (more than 100 data layers) to identify undervalued assets and estimate appreciation potential.	Answers natural-language property queries with maps, comparison tables and evidence-referenced valuation reports; integrates with brokerage CRM systems to recommend and automate client communication.
Interface	Data dashboard that users interpret themselves.	Natural-language queries and CRM-embedded recommendations.
Primary users	Potential buyers and investors.	Retail buyers, international investors, brokerages and agents.
Role of human intermediaries	Paired with lower-cost, remote, non-expert consultants to reduce reliance on commission-based agents.	Built around agent and brokerage workflows; positioned as broker augmentation.
Revenue model	Not reported in the case data.	Freemium consumer subscription (founder's estimate US$25–40 per month) and business-to-business CRM integration.

Dimension	Venture 1: investment and property search platform	Venture 2: conversational AI system for brokerage workflows
Status at time of study	Reported by the founder to have been sold.	Ready for market launch; being extended to Saudi Arabia.
Evidence base	Founder interview.	Founder interview and live demonstration of CRM functions.

Source: Authors' research

5. Discussion

In this section, we interpret the findings in terms of the three research questions and literature review. As the study is based on a single information-rich case, the interpretations are presented as propositions rather than generalisable results. They are intended to describe possible mechanisms and to guide future testing of other AI-enabled PropTech projects and housing markets (Siggelkow, 2007; Yin, 1984).

5.1 AI as a housing-market information transformation mechanism (RQ1)

The case shows that AI can operate across the housing transaction value chain rather than as a single tool. In one venture family, the same basic data and modelling capability enabled valuation, investment screening, search, lead conversion and post-lead communication. This is consistent with the literature, which considers AI as a combination of predictive analytics and decision support in addition to process automation (Charles et al., 2025; Enholm et al., 2022).

At the same time, the case qualifies this literature. For retail customers, the biggest change reported by the founder was not just the quality of valuation estimates but the usability of the interface. The founder's move from a data dashboard to natural language search indicates that AI creates housing-market value by reducing the interpretive burden of market information. In other words, the product is about translating fragmented data into a decision document that a buyer, lender or agent can understand and act upon.

P1. *In residential markets where retail customers are willing to use evidence but unwilling to interpret raw data, AI-enabled valuation creates value by reducing interface complexity as much as by improving predictive accuracy.*

5.2 Applications that matter to housing-market participants (RQ2)

Table I (Section 4.8) shows that the most developed applications in the case are at the front end of the housing value chain: valuation, search, lead conversion and evidence-based reporting. This differs from the digital real estate literature, which emphasises property management, smart buildings and predictive maintenance as the key. The difference is not a contradiction; it is the growth-market context of the case. In a fast-moving transaction market, the bottleneck identified by the founder was in connecting buyers and capital to opportunities and not optimising the operating cost of completed buildings.

The case also qualifies the assumption that AI necessarily disintermediates brokers. Although the systems automate analytical and communication work that agents would normally perform, the founder positioned the product as broker augmentation rather than immediate replacement. The reason was demand-side, not technical: most customers still

prefer a trusted intermediary over independent data interpretation. This suggests that, at least in early adoption, AI in housing markets is likely to strengthen intermediaries by making them more analytically efficient, even if the technology erodes their informational advantage over time.

P2. *In growth-phase, brokerage-intermediated housing markets, AI-enabled PropTech ventures are more likely to direct their initial AI development toward transaction-facing functions (valuation, search and lead conversion) than toward asset-operation functions such as property management and predictive maintenance.*

P3. *Where customers show low willingness to interpret data directly, AI-enabled PropTech ventures initially position products to augment human intermediaries, even when they automate much of the underlying analytical and communication work.*

5.3 Explainability and evidence as commercial trust mechanisms

Literature typically frames explainability as an ethical, regulatory or technical requirement for AI-based valuation. The case is consistent with this framing but adds a commercial dimension. The founder presented source-referenced reports, with comparable transactions and downloadable evidence, as central to his value proposition, and contrasted them with a black-box number and to general-purpose AI assistants that, in his view, do not have access to authoritative local transaction data.

In the founder's account, explainability is what turns an algorithmic estimate into a usable market document: a buyer can use it for negotiation, an agent can use it for advice for clients, and a lender might be able to use it as evidence for risk assessment. This result extends the work on explainable housing price prediction (Teoh et al., 2022) and AI-augmented valuation (Teikari et al., 2025) in showing how explainability becomes part of the product's commercial value proposition. In signalling terms (Spence, 1973), transaction-referenced reports are credible because they can be checked against recorded sales, which a bare estimate cannot.

P4. *In housing markets where AI-generated valuations must be accepted by third parties, explainable and evidence-referenced outputs function as commercial trust mechanisms and competitive differentiators, not only as ethical safeguards.*

5.4 Institutional data as a structuring input

Section 2.6 treated government digital infrastructure and DLD transaction records as part of Dubai's enabling environment. The case suggests a more specific mechanism. Access to authoritative local transaction data was not only a background condition; it was a product input that shaped differentiation. The founder framed DLD-sourced comparables as a reason the venture could provide more reliable reports than generic AI assistants or unsupported search interfaces.

This shifts institutional data infrastructure from a general macro enabler to a scarce and unevenly distributed resource. If access to closed or licensed transaction records is needed to provide trusted valuation results, the competitive advantage can belong more to those who can acquire, license, or incorporate them. The policy implication is that the design of data-access regimes can affect the structure of AI-enabled PropTech competition.

P5. *The competitive advantage created by government transaction-data infrastructure accrues disproportionately to AI-enabled PropTech ventures that can access and integrate authoritative records, rather than being distributed evenly across all AI tools in the market.*

5.5 Market viability thresholds and Dubai's role (RQ3)

In the founder's account, Dubai's position is better viewed as a market-readiness threshold than as a static hub effect. His timing illustrates this: the Russian business ended for geopolitical reasons, Saudi Arabia was judged too early for the product, and Dubai became workable when the digitisation of data, transaction volume and investor sophistication became sufficient. This interpretation refines the broad argument that the UAE is attractive because of policy support and digital infrastructure.

This interpretation rests on the founder's explanation of his own decisions and should be treated with caution. The study did not examine institutional factors that are likely to have shaped Dubai's readiness, including the regulation of off-plan sales and escrow (Government of Dubai, 2007), tax policy and government digitalisation mandates, nor whether the founder's emphasis on data and investor sophistication reflects the factors that actually mattered. Testing P6 therefore requires comparing markets on these institutional dimensions as well as on data availability and transaction volume.

For an AI-native valuation product, attractiveness is based on a more concrete mix of usable data, market liquidity and customers who understand why an evidence-based decision-making process is important. This threshold interpretation may also explain why the founder is now extending the product back to Saudi Arabia as local data sources mature. It suggests that Dubai's advantage may not be exclusive. Other GCC markets might become viable for similar AI-native products as their transaction records, regulatory systems and investor bases take shape. The theoretical argument is that market readiness for AI-enabled valuation should be treated as a dynamic condition instead of a fixed national attribute.

P6. *The commercial viability of AI-native housing valuation products in a market depends on the joint presence of digitised transaction records, sufficient transaction volume and investor sophistication; ventures will be less likely to enter, or more likely to exit, markets where any one of these conditions is absent, regardless of general policy support for AI.*

5.6 Transparency, data concentration and sustainable business value

The case also bears on whether AI-enabled transparency creates durable value for markets and firms or mainly reinforces data concentration and commission-driven intermediation. The evidence supports both readings. On the one hand, evidence-referenced valuation makes divergence between asking prices and modelled values visible to buyers and lenders (Section 4.3), which could discipline promotional pricing and support more stable price discovery. On the other hand, Section 5.4 suggests that these benefits accrue mainly to firms that can access authoritative records, and because the second venture is built around brokers' workflows, the same tools can make commission-based selling more efficient without necessarily improving outcomes for buyers. The study cannot establish which effect dominates; that requires user-side and market-level evidence.

The case also offers limited evidence on the durability of AI-native business models.

The founder's first business depended on contracts with banks in a single national market and ended when those contracts were lost in 2022 (Section 4.8). The current product combines consumer subscriptions with business-to-business integration into brokerage CRM systems (Section 4.6), which spread revenue across more than one customer type. This suggests that dependence on a single client segment, market or data source is a material risk for AI-native PropTech ventures. The study did not, however, observe either venture through a market downturn, so claims about resilience remain to be tested.

Finally, the human-presenting AI persona described in Section 4.5 shows that trust-building and trust-eroding practices can coexist within the same venture. Evidence-referenced reports are designed to make outputs verifiable, whereas an undisclosed persona relies on clients not knowing how the service is produced. If, as P4 proposes, trust is a source of commercial advantage, practices that could undermine trust once discovered are a risk to the venture's long-term legitimacy as well as an ethical and consumer-protection concern.

6. Contributions

The paper makes three contributions. First, it contributes to housing market research by connecting AI-enabled valuation to information asymmetry, price discovery and buyer decision support. Instead of viewing AI as a general digital transformation tool, the paper studies how valuation evidence and natural-language search alter the information environment of housing transactions. Theoretically, the case suggests that an AI-enabled valuation service can act at once as a search-cost reducer, a signalling device and a new kind of intermediary (Section 2.1), and that which role dominates depends on data access and the business model. This extends the treatment of AVMs as substitutes for manual appraisal (Kok et al., 2017).

Second, the paper adds to PropTech and automated valuation research by demonstrating how structured numerical data, trustworthy transaction records and explainable reports may matter more than algorithmic novelty. In this case, differentiation depended less on the model itself than on how data access, interpretability and workflow integration worked together.

Third, the paper offers a market-readiness perspective on Dubai. It shifts the discourse from a broad narrative of the UAE hub to a threshold model in which AI-based housing products can be developed if transaction volumes, data digitisation and investor sophistication are jointly sufficient. This provides a more precise basis for future comparison across Gulf housing markets.

7. Limitations

The limitations are inherent in the structure of the research. The evidence is based on a single founder-informant who has a direct commercial interest in the ventures described and in the intermediary and platform business models he critiques. The claims made in the interview about the incentives of competitors and several quantitative estimates made at the interview, such as commission differences, primary-secondary price gaps, time savings and acquisition value, could not be verified through the scope of the study. Thus, these claims are presented as the founder's perspective and not fact. In addition, the second and third data sources are controlled by the informant and therefore offer limited independent corroboration. No buyers, brokers, investors or lenders were interviewed, so the study cannot show how these groups use AI-enabled valuation or

whether it reduces information asymmetry in practice; the findings describe how the provider designs products to address information problems, not their measured effects.

The study is limited to one entrepreneur's two ventures in a particular growth-market setting. The propositions should therefore be taken as candidate mechanisms for future testing and not as generalisable statements. Finally, the researchers did not have access to the underlying model code, the training data or any full performance measurements. Rather, the research focuses on the commercial and informational nature of AI-driven valuation and not on the technical performance of the models themselves.

8. Implications and future research

In practice, the case suggests that AI-enabled valuation products need to solve a trust problem as much as a prediction problem. Buyers and investors are more likely to act on AI-generated outputs that have comparable evidence and local transaction records and plain-language explanations. Brokers and agents might also be more likely to adopt AI since it adds to their workflow and reduces the time to prepare for a report rather than threatening to replace them.

For policymakers, the case suggests that the accessibility, quality and governance of authoritative transaction data matter as much for AI-enabled market transparency as general policy support for AI. Data-access regimes can determine whether AI-enabled valuation benefits market transparency in general or only a small group of firms. Three directions for regulators follow, each of which would need to be tested in practice. First, the terms on which private firms can access DLD transaction records (cost, eligibility and data granularity) may decide whether smaller entrants can offer evidence-referenced valuation at all, so open or tiered access could lower barriers to entry. Second, regulators could require AI valuation products marketed to consumers to disclose their data sources and the comparable transactions behind an estimate, which would make the explainability observed in this case a baseline rather than a competitive option. Third, clear disclosure rules for automated client communication would address the risks raised by synthetic personas (Section 4.5).

For PropTech firms, the case suggests two lessons for building durable business models, although the study did not observe either venture through a market downturn. First, the founder's first business depended on bank contracts in a single national market and ended when those contracts were lost; spreading revenue across client types and markets, as the current combination of consumer subscriptions and business-to-business integration attempts to do, may reduce this exposure. Second, because the venture's trust strategy rests on verifiable evidence, practices that depend on clients not knowing how the service works, such as undisclosed AI personas, are a reputational and legal risk to that strategy.

Future research should assess the propositions on a larger and more representative sample of AI-enabled PropTech companies, including firms with multiple informants and independent performance data, and should include users such as buyers, brokers, investors and lenders to establish whether AI-enabled valuation reduces information asymmetry in practice. A comparison between Dubai, Abu Dhabi, Riyadh and other Gulf markets would be important to test if the threshold pattern identified here is replicated as local data infrastructure grows. Additionally, autonomous CRM communication and synthetic customer-facing personas in AI-mediated brokerage relationships also need more research on disclosure, consent and governance.

9. Conclusion

This paper investigated how AI-enabled valuation and search solutions are addressing information challenges in Dubai's residential market. It suggests that AI creates value by converting fragmented housing-market data into evidence-based decision-making. Automated valuation, natural-language search, DLD-sourced comparables and CRM-integrated communication are designed to lower search costs and support valuation judgement; whether they do so for buyers, brokers and investors was not measured in this study and remains to be tested.

The primary argument of the study is that AI-enabled valuation is a trust-building information mechanism, not just a predictive tool. In the Dubai case, the value of AI depended on explainable results, reliable transaction data and interfaces that customers can use without becoming market analysts. The case also suggests that Dubai's role can be viewed as a market-readiness threshold where transaction volume, digitised data and investor sophistication became jointly sufficient to support AI-native valuation products.

The propositions also indicate what evidence would support or challenge them. User-side data showing that adoption rises when interfaces reduce interpretive burden and when products work through intermediaries would support P1 and P3; evidence that buyers act directly on raw-data platforms, or that brokers are bypassed, would challenge them. P2 would be challenged by growth-market ventures that invest first in asset-operation functions. P4 and P5 could be tested by comparing the adoption of explainable and black-box valuation tools, and of ventures with and without access to authoritative transaction records. P6 would be supported if comparable ventures enter Gulf markets in the order in which their data infrastructure matures and challenged if entry follows policy incentives or other institutional factors instead.

Since our study is based on a single case, the results cannot be generalised without further study. However, our six propositions can serve as a basis for further empirical testing and the theorisation of AI-powered valuation, information asymmetry and market transparency in emerging housing markets.

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Data availability

The interview transcript and product demonstration notes are not publicly available because of confidentiality and commercial sensitivity. Public market and policy sources used in the study are listed in the references.

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Appendix 1. Codebook

The codebook lists the code groups and codes used in the manual coding of the interview transcript, demonstration notes and documents (Sections 3.4 and 3.5).

Code group	Code	Definition / application rule
AI application	Automated and multimodal valuation	Estimation of property value from structured, text, image or spatial data.
AI application	Recommendation and property matching	Ranking or recommending properties against a user's stated needs.
AI application	Search optimisation	Reducing the time or effort needed to find and compare properties, including natural-language search.

Code group	Code	Definition / application rule
AI application	Predictive market intelligence	Forecasting or flagging price movements, undervalued assets or divergence between price and modelled value.
AI application	Lead management	Prioritising client records and recommending next actions in sales workflows.
AI application	Conversational customer service	Automated written or voice communication with clients.
Evidence status	Documented / Market-specific	Documented: the application aligns with existing research (Section 2). Market-specific: it reflects Dubai market conditions and is not widely discussed in the literature.
Market participant	Buyers; investors; brokers and agents; lenders; developers	The participant group that an application serves.
Value offered	Efficiency; transparency; personalisation; decision support	The type of value an application provides to the participant.
Context	Data availability; institutional and regulatory issues; market size; information environment	Conditions described as enabling or constraining the ventures.
Claim type	Descriptive; market factual; informant perspective	Descriptive claims checked against the demonstration and venture materials; market claims checked against DLD data and independent reporting; statements about others' behaviour or motives attributed to the informant (Section 3.5).