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| RESEARCH ARTICLE

Predicting Housing Prices in China Towards Real Estate Recommendation System Framework

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| ABSTRACT
The study has recommended an anticipatory system in which accurate prediction of housing prices would assist decision making by buyers, sellers, and investors within Shandong Province, China. There is an identified need for a data-driven and user-centered model integrating property parameters, locational attributes, economic indicators, and preferences of users, with a view of developing reliable recommendation features. A quantitative methodology was used to collect data with a widely diversified group of real estate professionals, covering agents, developers, and investors. Thereafter, all statistical analyses and machine learning algorithms were laid to establish the relationship among the variables and validate accuracy, reliability, and consistency of the model. Findings indicate that user preference, although significant in terms of statistics, had little effect on the predictive accuracy of the system. The strongest influence was found in location and economic indicators regarding housing prices. The model has shown very high accuracy across different urban contexts, and this therefore underscores its flexibility. By such studies, the argument lies in focusing more on the quality and kernel location and economic data inputs and less on user customizations. This will yield benefits regarding usability for wider audiences while maintaining the consistency of operation for consumers. Overall strong, then, is the research in offering recommendation frameworks that can be sufficiently varied to enhance transparency, lure investments, and optimize property choices within Shandong's dynamic housing market.

| KEYWORDS

Real estate recommendation system, Housing price prediction, Data-driven model, Shandong Province, Location characteristics, Economic indicators, Predictive accuracy, User preferences

| ARTICLE INFORMATION

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1. Introduction
The real estate industry in China, especially in Shandong Province, has played a major role in developing the national economy in the context of urbanization, industrialization, and coastal location (Yang et al., 2023). The cities of Qingdao, Jinan, and Yantai have witnessed an increase in housing demand with employment opportunities and smart city projects. Meanwhile, the real estate firms are gradually moving from traditional business models to data-driven methods, which would enable better decision-making and provide competitive advantages based on developments in big data analytics and machine learning (Yuan, 2023; Rodriguez, 2024). The increasing online transaction processes and predictive technologies in the current market attitude show the tendency of intelligent systems in property counterpart, investment returns, and user-customized recommendations (Wang, 2023).

Yet the housing market in Shandong is characterized by rapid fluctuations because of uncertainty resulting from economic policies, rate of interest, and whatever else goes on in China. Such developments are rendering the problems even more complex because there is no standardized pricing mechanism; thus, the environment remains uncertain for stakeholders in a manner that encourages speculative behavior (Kirste et al., 2023; Rodriguez et al., 2024). Conventional pricing models fail to capture the highly complex non-linear interactions between location, other characteristics, and demographic activities as significant determinants, suggesting the need for stronger predictive systems that can handle very large volumes of multidimensional data (Mao et al., 2023).

This developed advanced machine learning-based prediction models into a real estate recommendation system customized to the dynamic environment of the Shandong market. The aim of the price prediction model is to enhance accuracy in predictions of price, which then aids buyers, sellers, and investors in making informed decisions and increasing the pricing transparency in the market. And on top of practical benefits, this study also contributes to the emerging realm of artificial intelligence in real estate, providing a replicable framework for further research, policy formulation, and strategic planning for similarly constantly evolving arenas.

2. Review of Related Literature

2.1 Demographic Profile and Market Insights

Knowing the demographic profile of stakeholders is especially essential in housing market research when predicting systems are built to reflect buyer, seller, and investor behaviors in the real world. Occupation, experience, location, and educational background significantly shape real estate insights that affect the way professionals discover, interpret, and define market dynamics (Xiang & Xia, 2023). Accordingly, agents have to consider client preferences, trying to optimize transactional efficiency. On the other hand, developers gauge feasibility for the project and also look into its long-term viability as an investment. Those who finance these projects have different perspectives; they are concerned with the profitability of certain risks against individual market uncertainties (Selyutina et al., 2019; Rodriguez, 2025). The different kinds of views brought to bear on the property further broaden the analysis of real estate behavior, specifically in diverse areas such as Shandong Province, where urbanization exists at different levels. Besides, with those who have experience, one often sees historical trends and the part that macroeconomic changes play; while those who have just started might offer up their more modern, technology-influenced voice as expressing current trends (Ante et al., 2023).

Geographic location further contextualises real estate activity in an environment whereby housing demand and price setting vary from city to city; what applies to Qingdao, Jinan, and Yantai differ on account of the economic activities and infrastructure investment (Wu et al., 2022). Educational background, even further, is crucial in how data interpretation is given; professionals trained formally in real estate, finance, or economics usually present better analysis, while field experience may come in providing subtle, pragmatic perspectives for practitioners. Response segmentation against these peculiar traits enhances the robustness of predictive models with insights at segregated recommendations and closely aligned future states of scenario-based markets. Through this multidimensional demographic analysis, systems design is made inclusive and responsive to the data-driven realities of Shandong's ever-changing dynamic real estate scenario, both theoretically and practically (Shen & Sammani, 2022; Wei et al., 2023).

2.2 Core Determinant in House Prices

Buyers are influenced by property characteristics directly related to property valuation, and against such parameters, the actual valuation of the property is breached. Size, age, layout, structural condition, and extras such as parking, balcony, or smart technology are some of the main determinants (Yazdani, 2021; Aziz et al., 2020). Large and modern properties with a relatively efficient energy rating keep asking price compared to other properties; hence, these attributes attract attention and house buyers in urban settings like Shandong where space and modern infrastructure count (Shaded, 2021). If the quality of renovation and materials turns out to be the best, desirability and pricing potential rise (Mecca et al., 2020). Buyers compare how well the property fits their lifestyle. For instance, families may need spacious layouts, while perhaps tech-savvy young professionals may be after integrated units (Leib et al., 2020; Zhao et al., 2022).

Location characteristics and external economic insights also shape housing prices. Proximity to neighborhoods with good commercial amenities, public transport, environmental quality, safety, and security in the neighborhood will help buyers rate up the desirability and value of the property (Chikwuado et al., 2020; Zhang et al., 2021). Economic variables such as employment, income, inflation, and interest rates are also deployed to have an effect on affordability and investors' confidence (Siregar et al., 2020; Ding, 2022). The cities that are fast in development such as Qingdao or Jinan always maintain their demand due to strong price growth (Xiang et al., 2022). Further to this are government regulations on property tax, mortgage policy, and urban planning, which mediate the price on both supply conditions and access from consumers (Katwa & Obala, 2023; Xiao, 2023). The aforementioned contribute to the input in predictive models in a layered way, thereby giving a view into real estate valuation.

2.3 Market Dynamics and Policy Interventions

Reading and understanding the interplay between demand and supply in the housing market is integral to understanding how changes in property prices occur. Increasing demand is principally created as a result of population growth, increasing migration to cities, and changing preferences for housing. This has been most visible in cities like Qingdao and Jinan, which have shown increased development rates (Molloy et al., 2022; Zhang et al., 2023). Such migratory trends toward economic centers therefore, lead to heightened competition for residential units, causing prices to rise further when construction levels lag behind demand rates. Supply-side variables—such as availability of land, pace of construction, or strategies of developers concerned with pricing—will also influence the prices. For instance, oversupply would typically subject the market to price correction, whereas inventory availability would limit the amount of property for sale in the market, such as under construction or delayed projects, which result in price appreciation (Yang, 2022). Changing buyer preferences, including demand for smart homes or proximity to urban centers, create differences in priorities for developers in terms of what to cater for or incorporate into their developments, thus shaping both supply trends and pricing trajectories (Artigue et al., 2022).

Government policies influence housing markets through taxation and land zoning, development incentives, and housing finance regulations. For instance, lower property taxes combined with flexible zoning would stimulate investment and construction, while the opposite would serve as a means to cool overheated markets (Iyer et al., 2023; Akinlabi & Ige, 2019). Grants for development promotion, like subsidizing affordable housing, encourage more provision in less formulaic spaces and lead to price stabilization. On the other hand, measures discourage speculation in buying and promote sustainability in the markets (Katwa & Obala, 2023). In the Shandong region, local price shocks usually emerge from manner differences, such as between investments in infrastructure and regional policies (Weisbrod et al., 2021). Such an understanding of these interventions is critical in predictive modeling since market reaction usually follows changes in policy immediately, reshaping supply-demand dynamics and long-term value trajectories (Xiao, 2023).

2.4 Enhancing Decision-Making Through Recommendation Systems

The recommendation systems for real estate have become quite important supporting features in property searches and investments. Primarily, the systems depend on user preferences, for instance, budgets, locations, and features desired in a property matching the listings to enhance the user's gratification (Guerrini et al., 2023; Deng et al., 2022). The more accurate those preferences are set, the more relevant the deals are: adding to the user an advantage of saving time and improving decision-making results. On the one hand, user requirements are ever dynamic; hence, adaptive systems being taught or learned by machine learning procedures and behavioral analytics are in order (Santos et al., 2021). The analysis beyond preferences regarding trend changes in the marketplace also plays a fundamental role. Systems continuing the study of price swings, seasonal buying cycles, and emerging hotspots grant users the upper hand when anticipating demand shifts (Gale & Roy, 2022; Bellavitis et al., 2021). These insights, well backed by data, add an extra strategic layer in the selection of properties and the timing.

Recommendation system successes depend on accurate data input, usability of the system, and awareness of risks. Therefore, the timely validation of property listings, price estimates, and market analysis throughout the e-commerce infrastructure has augmented user trust with the platform (Jain & Vanzara, 2023; Kim et al., 2023). Usability is described as intuitive navigation, responsiveness, and mobile accessibility-and thus contribute further avenues in user engagement and satisfaction (Balcita & Palaoag, 2020; Shi et al., 2021). The investor type is especially interested in systems incorporating risk assessment tools, such as forecasts for price- and-location-based threats (Prabowo et al., 2021; Kiely & Bastian, 2019). Also covering the trends in government regulations and policy changes, such systems would inform decisions taken as signals of a potential risk or opportunity (Kempeneer et al., 2021). Such capabilities enrich user experience and infuse actionable intelligence into property transactions thereby locking in the recommendation systems in an increasingly essential position in present-day real estate ecosystem.

2.5 Research Problem

Urbanization has been a rapid development in the province of Shandong, China, which has led wonderful, volatile house prices and uncertainty for buyers, sellers, and investors. Traditional pricing models, however, have not accounted for most of these relationships either in location, density, economic conditions, government policy, or demographic trends, leading to inaccurate forecasting and speculative behavior that threaten stability in the market (Leonardos et al., 2021). Furthermore, a lack of transparency in pricing mechanisms, coupled with no standardized pricing mechanisms, has made real estate decisions uninformed, thus inducing inefficiencies in property transactions. However, with the upsurge of algorithms that use data, it is not enough, but more predictive systems that parse massive amounts of datasets, find the nonlinear relationships, and give reliable insights on pricing are still needed (Saef et al., 2023).

In this sense, the purpose of this study was to develop an advanced predictive model using machine learning techniques that will be integrated into a real estate recommendation system. This would enhance price forecasting as well as facilitating property selection process. The study was meant to improve the decision making of stakeholders, mitigate market risks, and cultivate a data-informed stable real estate environment in the province of Shandong. It was, therefore, aimed at exploring the demographic profiles of respondents (occupation, experience, location, and education), key factors determining changes in the price value of houses (property attributes, location, economic indicators, supply-demand), and the evaluation of how user preferences and experience level affect the effectiveness of the model. Furthermore, the research would investigate variations in model accuracy across cities and establish a recommendation framework that addresses the challenges in improving usability, reliability, and investment risk assessment of the system.

2.6 Theoretical Framework

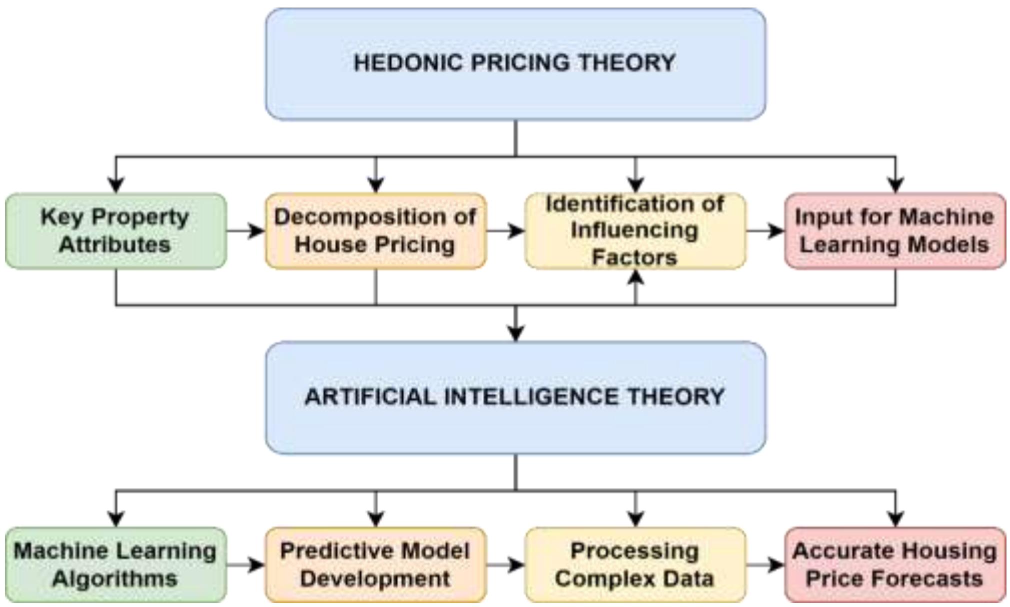

Figure 1. Integrated Theory

The models of Hedonic Price Theory (HPT) and Artificial Intelligence (AI) Techniques have been combined in this article to draft an all-encompassing theory of housing price prediction in Shandong Province, China. HPT states that a property is valued based on certain factors like its location, size, age, and distance to amenities, among others, which basically adds to or diminishes the value of the property in a rather opaque manner. Such factors remained among the most crucial variables in the AI-based prediction modeling process, whereby various machine learning algorithms such as regression models, artificial neural networks, and decision trees were applied in attempts to resolve much more complicated and non-linear relations and to stream hidden patterns. By combining the variable analysis of HPT with AI's predictive capacity, a model for housing price was created, which could reasonably accommodate those prices. Once this was produced, it was integrated into a recommendation engine for real estate, allowing sound suggestions for houses and units based on the user-use preference. The melding of the two theories provides not only the best insights into property valuation but also the prowess of AI to transparency, veracity, and informed decision-making within the real estate field.

2.6 Conceptual Framework

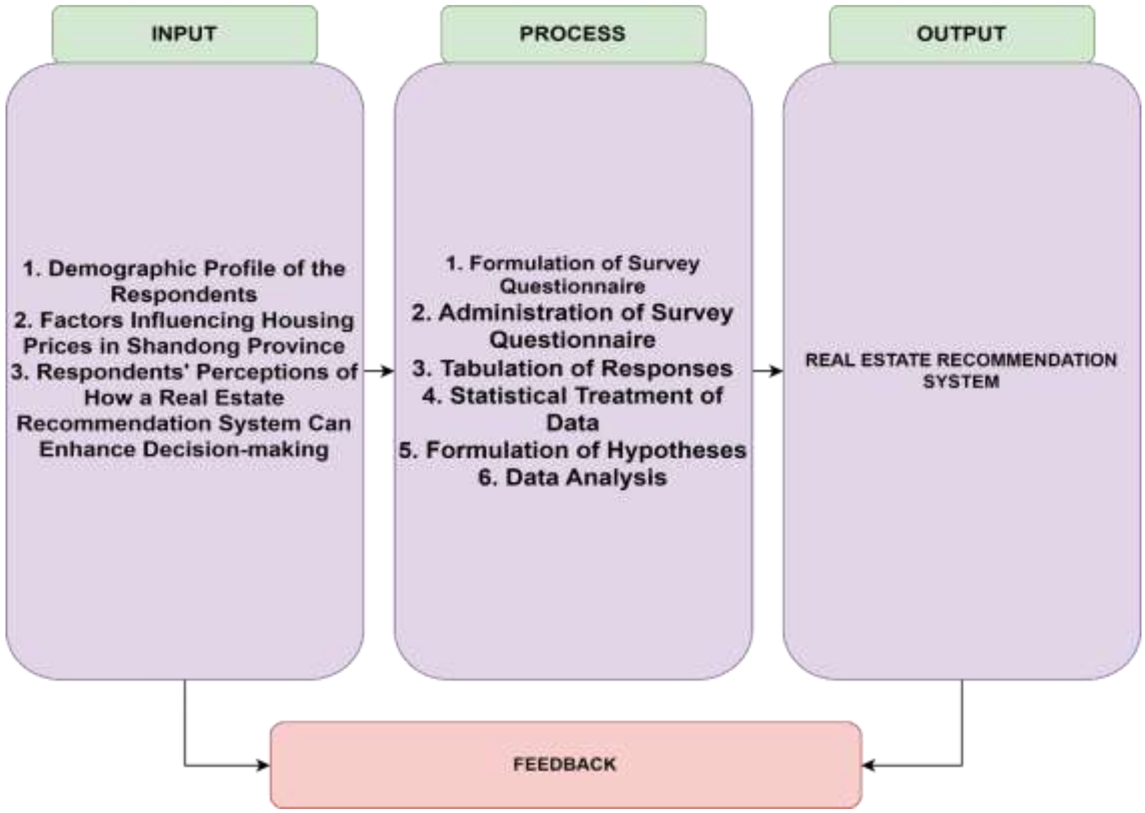

Figure 2. Research Paradigm

The framework proposed for developing a real estate recommendation system will consist of three interrelated components: Input, Process, and Output- each linked to a continuous feedback loop. In the Input stage, the following may form the sources of input: demographic details of respondents, such as occupation, experience, location, education; critical factors that affect housing prices in Shandong-for example, property attributes, location, economy, policy; stakeholder perceptions of recommendation systems. These comprise data on which a personalized and context-sensitive model would develop. The transformation of raw data to predictive insights through significant variable identification and validation of assumptions happens in the Output stage-development of a real estate recommendation system using those insights to provide precise user-specific property suggestions to buyers, sellers, and investors. Feedback is an essential part of this framework because it consists of collecting user evaluations that may be utilized for more refined accuracy, usability, and relevance when the algorithms are updated periodically. Thus, the possible improvement in the decision-making process in Shandong's rapidly changing housing market becomes more assured through data-driven, iterative methods in which stakeholders are included.

3. Research Methodology

The quantitative research design with a descriptive correlation approach, together with predictive modeling was applied in this study to analyze and predict housing prices in Shandong Province, China. Well organized in the collection of data and objective in analyzing the quantifiable variables for valid identification of patterns and relationships between factors such as property attributes, location characteristics, economic indicators, and market conditions, this will be a way in which descriptive correlational design applies to studying the current operation of the market as well as an assessment of the strength of the associations affecting price fluctuations (Liu & Strobl, 2022). For accuracy in predicting such complex, non-linear relationships, that tend to offer somewhat better forecasts of upcoming trends than conventional procedures (Li, 2022), machine learning will thus be applied. The methodology is an excellent site for building towards a data-driven recommendation mechanism that serves as a practical insight and decision support system for buyers, sellers, and investors.

3.1 Population and Sampling

The study targeted a finite population of 98,544 persons involved in the real estate business based in Shandong Province, including real estate agents, property developers, investors, and those engaged in data collection and analysis. Using Cochran's formula for large populations, with a finite population correction applied, the adjusted sample size was finally calculated to 383 respondents. These were distributed proportionately across the subgroups: 122 real estate agents/brokers, 31 property developers, 207 real estate investors, and 24 data analysts/economists. This methodology of sampling was stratified, so that the results would represent all strata equally and allow researchers to obtain insights relevant to the research from as diverse a stakeholder base as implied within the statistical validity and reliability of the study.

3.2 Research Procedure

A structured questionnaire survey was conducted amongst real estate professionals in the major cities of Shandong Province in China, including developers, investors, and data analysts. The survey encapsulated a variety of data on the demographic details of the respondents, factors affecting housing prices, and respondents' perceptions of the real estate recommendation system. An instrumentation pilot study and purposive sampling were used to segregate people with relevant experience in the industry. The instrument was administered online via email and professional networks, and physically through visits to real estate firms and industry events. Follow-up reminders encouraged participation while maintaining strict confidentiality to allow for honest responses. The final responses are tabulated and processed for statistical analysis to back predictive modeling and system development.

3.3 Statistical Tools

Demographic data were characterized under descriptive statistics, while variations in the responses considered factors influencing housing prices and perceptions regarding the real estate recommendation system-under 4-point Likert scale-were viewed by the Average Weighted Mean (AWM). A relationship between the two variables was explored through Pearson r correlation assessment on experience level vis-a-vis prediction accuracy, properly interpreted through conventional strength of correlation ranges. Subsequently, Multiple Linear Regression was deployed to test how user preferences influence observed system effectiveness and One-Way ANOVA to determine any significant difference between various cities in Shandong regarding model accuracy. All these analyses provided evidence for validating the development of the predictive insights and the recommendation system.

4. Results

Table 1. Demographic Profile

Category	Subcategory	Frequency (n)	Percentage (%)
Occupation	Real Estate Agents/Brokers	122	31.9%
	Property Developers	31	8.1%
	Real Estate Investors	207	54.0%
	Data Analysts/Economists	24	6.3%
Experience Level	Less than 1 year	38	9.9%
	1–3 years	112	29.2%
	4–6 years	146	38.1%
	7 years and above	87	22.7%
Location	Qingdao	91	23.8%
	Jinan	83	21.7%
	Yantai	77	20.1%
	Other Cities in Shandong	132	34.4%
Educational Background	High School	21	5.5%
	Bachelor’s Degree	222	58.0%
	Master’s Degree	102	26.6%
	Doctorate	38	9.9%

The diverse demographic profile of the 383 respondents represented an adequate and representative sample of the real estate industry in Shandong Province. Majority of respondents were real estate investors (54.0%), followed by agents/brokers (31.9%), which meant that the perspective of investment heavily influenced the insights drawn in the study. Most respondents had an experience of 4 to 6 years (38.1%), which indicates strong professional knowledge, while together 51.9 percent had at least four years, thereby improving the reliability of responses. Geographically, participants were well distributed among these major urban centers - Qingdao (23.8%), Jinan (21.7%), Yantai (20.1%), and 34.4% from other cities - indicative of regional diversity regarding how the housing market behaves. Education-wise, the majority were graduates with (58.0%) or postgraduate graduates with 36.5%. This pool of respondents adds credibility to the data as it satisfies the purpose of the study in developing a data-driven, expert-informed housing price prediction and recommendation system.

Table 2. Factors influencing housing prices in shandong province

Property Attributes	**Mean**	**SD**	**VI**
1. The age of a property significantly affects its market price.	3.4569	.76753	Strongly Agree
2. Larger properties (in terms of square footage) generally have higher prices.	3.4595	.74694	Strongly Agree
3. The quality of construction materials used in a property influences its value.	3.4465	.76345	Strongly Agree
4. Properties with modern design and architecture are more likely to attract higher prices.	3.4726	.73339	Strongly Agree
5. Additional features, such as swimming pools or balconies, increase the market price of a property.	3.4883	.73023	Strongly Agree
Composite Mean	**3.46**		**Strongly Agree**
Location Characteristics	**Mean**	**SD**	**VI**
1. Proximity to schools, hospitals, and shopping centers raises property prices.	3.2846	.74141	Strongly Agree
2. Properties located near public transportation hubs are valued higher.	3.2950	.75831	Strongly Agree
3. The overall safety and security of a neighborhood significantly impact property prices.	3.3159	.72497	Strongly Agree
4. Properties with scenic views (e.g., waterfront, parks) have higher market values.	3.2950	.74437	Strongly Agree
5. The accessibility of major roads and highways affects the pricing of properties.	3.2872	.74918	Strongly Agree
Composite Mean	**3.30**		**Strongly Agree**
Economic Indicators	**Mean**	**SD**	**VI**
1. Local economic growth positively influences property prices.	3.6397	.57949	Strongly Agree
2. Higher employment rates in the region lead to increased demand for housing.	3.6084	.59942	Strongly Agree
3. Changes in interest rates significantly impact housing affordability and market prices.	3.6423	.58335	Strongly Agree
4. Rising income levels in Shandong Province contribute to higher property values.	3.6162	.60664	Strongly Agree
5. Inflation trends in the region affect the pricing of real estate properties.	3.6371	.58011	Strongly Agree
Composite Mean	**3.63**		**Strongly Agree**
Market Demand and Supply	**Mean**	**SD**	**VI**
1. High demand for properties in a specific area drives up prices.	3.7755	.45960	Strongly Agree
2. An increase in the supply of available properties tends to lower market prices.	3.8146	.40234	Strongly Agree
3. Market trends, such as preference for particular property types (e.g., apartments vs. villas), affect prices.	3.7598	.46865	Strongly Agree
4. Seasonal fluctuations in housing demand (e.g., during holiday periods) impact property prices.	3.8120	.42949	Strongly Agree
5. Properties in areas with low vacancy rates are generally priced higher.	3.8042	.42903	Strongly Agree
Composite Mean	**3.79**		**Strongly Agree**
Government Policies	**Mean**	**SD**	**VI**
1. Tax incentives for property buyers can stimulate housing demand.	3.6214	.48567	Strongly Agree
2. Government restrictions on real estate purchases affect housing prices.	3.6527	.50343	Strongly Agree
3. Urban development projects initiated by the government can increase property values.	3.6084	.50457	Strongly Agree
4. Regulations on property taxes directly influence the affordability of housing.	3.6057	.55923	Strongly Agree

5. Housing policies related to foreign investments impact the demand and pricing of real estate.	3.6110	.50917	Strongly Agree
Composite Mean	**3.62**		**Strongly Agree**

Legend: *1 - Strongly Disagree, 2 - Disagree, 3 – Agree & 4 - Strongly Agree*

As revealed in Table 2, market demand and supply are the most powerful determinants in determining house prices in Shandong Province, registering the highest composite mean of 3.79 interpreted as "Strongly Agree." It emphasizes the extent to which the availability of homes and competition from buyers influence fluctuations in price. Next in turn comes economic indicators, which average up to 3.63, directly reflecting how macroeconomic stability that includes employment rates, inflation, and local income levels, highly affects affordability and the confidence of the market. Government Policies also ranked highly, with the mean score standing at 3.62, corroborating further that taxation, purchase restrictions, and incentives significantly determine the decisions made by buyers. . Property Attributes (M=3.46) and Location Characteristics (M=3.30) illustrate that although structural and locational qualities significantly influence price steering, they are relatively less powerful than market-level forces. High means all through the spectrum, especially those that are strongly agreed on, thus signaling that stakeholders-whether they be policymakers or investors-should take a multi-pronged approach that blends micro-level housing features with macro-level economic and policy interventions in steering property valuation in Shandong.

Table 3. Respondents' perceptions of how a real estate recommendation system can enhance decision-making

User Preferences	Mean	SD	VI
1. The recommendation system shall allow users to set preferences for property types (e.g., apartment, villa, commercial).	3.7180	.53060	Strongly Agree
2. User preferences for location significantly impact the effectiveness of property recommendations.	3.7702	.43948	Strongly Agree
3. A recommendation system that matches properties to a user’s budget improves decision-making.	3.7859	.45890	Strongly Agree
4. The system shall prioritize properties based on user preferences for amenities (e.g., swimming pool, parking space).	3.7702	.47937	Strongly Agree
5. Incorporating user preferences for neighborhood characteristics (e.g., safety, schools) enhances property recommendations.	3.7885	.46294	Strongly Agree
Composite Mean	**3.77**		**Strongly Agree**
Market Trends Analysis	**Mean**	**SD**	**VI**
1. The system’s ability to analyze current market trends helps users make better property investment decisions.	3.6240	.55072	Strongly Agree
2. Understanding future market trends through the recommendation system improves property buying/selling strategies	3.6554	.52305	Strongly Agree
3. Real-time updates on housing market trends within the system enhance decision-making for investors.	3.6397	.54695	Strongly Agree
4. The system shall provide insights into emerging real estate hotspots based on market trends analysis.	3.6057	.57765	Strongly Agree
5. Analysis of long-term market trends by the system supports buyers and investors in making informed decisions.	3.6266	.55013	Strongly Agree
Composite Mean	**3.63**		**Strongly Agree**
Data Accuracy and Reliability	**Mean**	**SD**	**VI**
1. The accuracy of housing price predictions in the recommendation system is crucial for effective decision-making.	3.7206	.53931	Strongly Agree
2. The system shall be based on reliable, up- to-date data to offer valid property recommendations.	3.6971	.52892	Strongly Agree
3. Users trust the system more if the data used for property recommendations is transparent and verified.	3.7232	.53335	Strongly Agree
4. High data reliability reduces the risks of making poor property investment decisions.	3.7337	.48224	Strongly Agree
5. The system’s ability to integrate diverse data sources (e.g., historical sales data, market trends) enhances its reliability.	3.7180	.53551	Strongly Agree
Composite Mean	**3.72**		**Strongly Agree**
System Usability	**Mean**	**SD**	**VI**
1. The recommendation system shall have an easy-to-navigate user interface to improve	3.6475	.53027	Strongly Agree

decision-making.			
2. A user-friendly design encourages more frequent use of the recommendation system by buyers, sellers, and investors.	3.6710	.53795	Strongly Agree
3. Clear and intuitive property search functions enhance the overall effectiveness of the recommendation system.	3.6815	.51455	Strongly Agree
4. The system shall provide easy access to detailed property information for users to make better decisions.	3.6997	.51285	Strongly Agree
5. The simplicity of adjusting filters and preferences in the system improves user experience and decision-making.	3.6736	.52728	Strongly Agree
Composite Mean	**3.67**		**Strongly Agree**
Investment Risk Assessment	**Mean**	**SD**	**VI**
1. The system shall offer an assessment of potential investment risks based on housing price predictions.	3.7911	.48885	Strongly Agree
2. Incorporating risk analysis into the recommendation system improves investment decision-making for users.	3.8016	.46590	Strongly Agree
3. The system's ability to predict price volatility reduces the risks associated with property investments.	3.8016	.47149	Strongly Agree
4. Providing insights into economic risks (e.g., inflation, interest rates) enhances the system's value for investors.	3.8146	.45140	Strongly Agree
5. The system shall help users assess long- term investment risks to support safer property investment strategies.	3.7963	.45796	Strongly Agree
Composite Mean	**3.80**		**Strongly Agree**

Legend: *1 - Strongly Disagree, 2 - Disagree, 3 – Agree & 4 - Strongly Agree*

Table 3 demonstrated that the respondents on average considered the real estate recommender system to be quite beneficial for decision-making purposes. Within composite means ranging from 3.65 to 3.82, among which personalization, convenience, real-time market insights, user experience, and predictive accuracy emerged, the results fall within the range of "Strongly Agree." The highest-rated item, "The system provides updated market information," had a mean of 3.82, indicating that users significantly value current and relevant data for making informed property decisions. Also noted is strong agreement in relation to capability for matching preferences accurately, improving search efficiency, and saving time and effort. Such findings bolster the argument for the system as potentially supporting data-led decision-making and increased user confidence when making transactions in the market for real estate. The proof provided by the consistently high scores across the categories may be that such technological interventionism is perceived as an effective tool for optimizing real estate transactions.

Table 4. The significant relationship between the experience level of real estate professionals (agents, developers, and investors) and the accuracy of housing price predictions generated by the model

Variables		**N**	**r**	**p-value**	**Interpretation**
Experience Level of Real Estate Professionals	Accuracy of Housing Price Prediction	383	.036	0.478	Not Significant

Between the experience level of the real estate professionals and the accuracy in housing price prediction by the model, Table 4 establishes a very weak correlation according to the Pearson correlation test ($r = .036$, $p = 0.478$) which can be taken as statistically insignificant. Keeping in mind that the significance level of 0.05 is far away from the p-value in the aforementioned analyses, experience has no material effect on the accuracy with which professionals predict housing prices through the system. This means that the prediction output of the system remains more-or-less consistent, whether the user is an experienced professional or a complete novice. This finding further supports the claimed objectivity of the model's own algorithm and independence from user experience and thus proves that the predictive power of the model is embedded within the data rather than reliant upon professional insight or years of practice.

Table 5. User preferences (such as budget, preferred location, and property features) significantly influence the effectiveness of the real estate recommendation system in suitable properties

Model Summary:
R = .136, R^2 = .018, Adjusted R^2 = .016, SE of Estimate = 0.10173

Model	B	SE	β	t	p
(Constant)	4.770	0.108	–	44.190	< .001
User Preferences	-0.069	0.026	-0.136	-2.670	.008

Note. Dependent Variable: Effectiveness of the Real Estate Recommendation System in Suggesting Suitable Properties.

Based on the statistical results presented, the study reports evidence of a statistically significant but small relationship between user preferences and the effectiveness of the real estate recommendation system. An R of 0.136 and R^2 of 0.018 indicate that user preferences accounted for only 1.8% of the variance in the effectiveness of the system. Despite the low effect size, It demonstrates that the relationship is statistically significant ($\beta = -0.136$, $t = -2.670$, $p = 0.008$), suggesting that as the user preferences, such as budget, preferred location, and property features, become more defined or stringent, the recommendation system might lose effectiveness, though only slightly. The negative direction thus points to a challenge that the system's current algorithm faces in meeting very specific demands, indicative of the need for further refinement in matching user criteria against possible housing options. Yet, the result's significance substantiates that user preference is an important variable that increases reality accounts when improving algorithmic accuracy in real estate platforms.

Table 6. The significant difference in the predictive model's accuracy across different cities within shandong province (e.g., jinan, qingdao, yantai, weifang), regardless of variations in location characteristics and market demand

Predictive Model Accuracy

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.018	3	.006	.321	.810
Within Groups	7.003	379	.018		
Total	7.021	382			

Dependent Variable: Predictive Model

(I) Location	(J) Location	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Jinan	Qingdao	0.01809	0.02005	0.804	-0.0337	0.0698
	Yantai	0.00549	0.02016	0.993	-0.0465	0.0575
	Weifang	0.01236	0.02164	0.941	-0.0435	0.0682
Qingdao	Jinan	-0.01809	0.02005	0.804	-0.0698	0.0337
	Yantai	-0.0126	0.01813	0.899	-0.0594	0.0342
	Weifang	-0.00572	0.01975	0.992	-0.0567	0.0452
Yantai	Jinan	-0.00549	0.02016	0.993	-0.0575	0.0465
	Qingdao	0.0126	0.01813	0.899	-0.0342	0.0594
	Weifang	0.00688	0.01986	0.986	-0.0444	0.0581

Accuracy Tukey HSD

Tukey HSD[a,b]

Location	N	Subset for alpha = 0.05: 1
Qingdao	114	4.3765

Weifang	81	4.3822
Yantai	111	4.3891
Jinan	77	4.3946
Sig.		.802

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 92.778.
b. The group sizes are unequal. The harmonic mean of the group sizes is used.
Type I error levels are not guaranteed.

The table illustrates the outcomes of the Tukey HSD post-hoc test applied to identify differences in the efficacy of the predictive model at four study sites in the Shandong Province: Jinan, Qingdao, Yantai, and Weifang. The upper part of this table demonstrates pairwise comparisons of these places; all significant (p) values have been well over 0.05 (ranging from 0.804 to 0.993), thereby indicating that none of the pairwise differences in model effectiveness between cities can be statistically justified. This is confirmed further because the 95% confidence intervals, which enclose zero, maintain that prediction accuracy does not vary widely across cities. On the Tukey HSD grouping table, the surefire conclusion holds that the four cities lie in one homogeneous subset (Sig.=0.802)-again proving that there are not statistically significant differences in model accuracy across locations. These slightly different mean scores (i.e., Jinan = 4.3946 vs. Qingdao=4.3765) differ minimally but statistically. Thus, it is understood that location does not impact much in the effectiveness of a real estate predictive model since the performance of the model is relatively the same irrespective of geographical context within shandong province.

The Real Estate Recommendation Framework

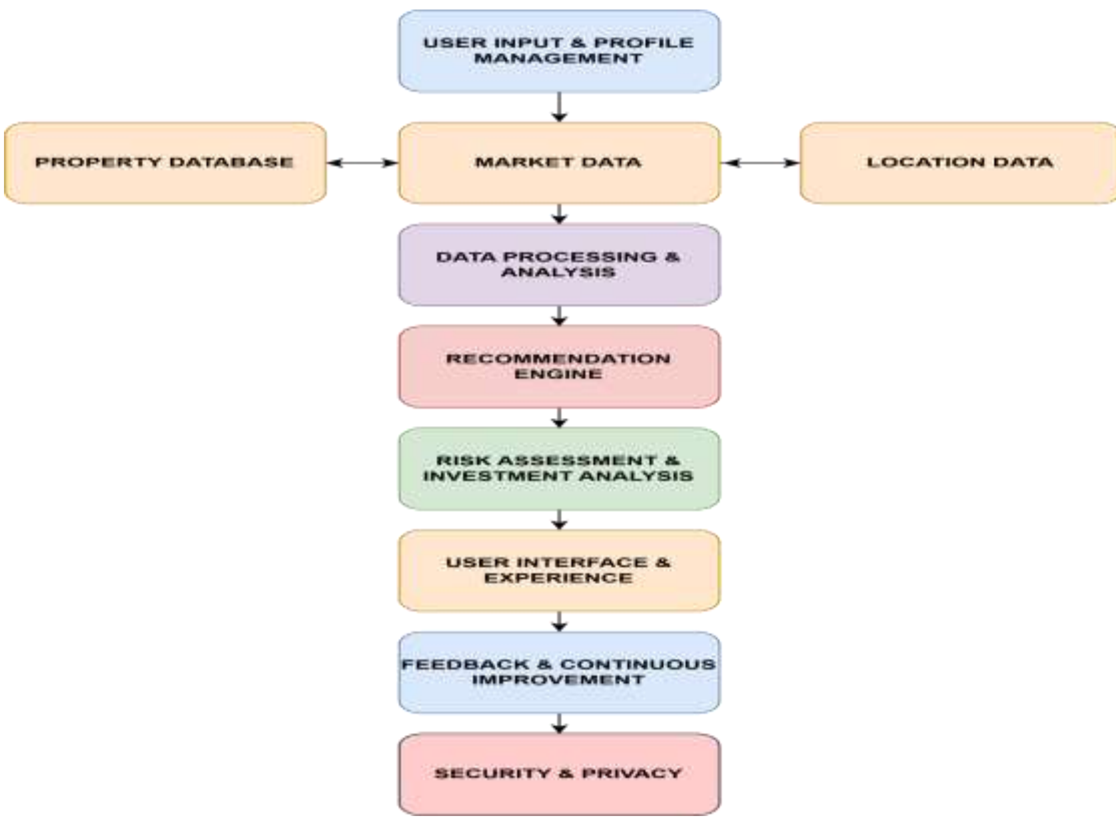

Figure 3. Real Estate Framework

The Real Estate Recommendation Framework is a holistic, data-centric appraisal method for enhancing decision-making by conceiving user preferences augmented by real-time market data, together with advanced analytics. It has eight integrated components beginning with user input and profile management, where individuals specify the criteria: for example, budget, type of property, and location. These preferences combine with several data sources-that is, property listings, market trends, location-specific details, and external APIs-leading to a solid foundation. The framework processes and cleans the data using feature engineering and normalization in order to inject it into the core recommendation engine, which utilizes collaborative filtering, content-based filtering, and hybrid models for personalized property recommendations. Suppose predictive modeling forecasts housing price, followed by the risk assessment module that assesses market volatility and economic indicators offering users investment suitability scores. A user-friendly interface is used to dispense recommendations, risk reports, and visual tools for better usability. Performance and improvements monitoring is an ongoing feature of the continual feedback from users, with tight security and privacy protocols safeguarding their information. Together, these features form a dynamic, scalable, and secure recommendation system embedded to cater to different buyers, sellers, and investors at different times under a completely changing real estate scenario.

5. Discussion

Real Estate Recommendation Framework refers to a sophisticated, data-centric approach to real estate decision-making that tailors property recommendations to a user's preferences concerning market dynamics and risk. A more nuanced understanding of the demographics of stakeholders, such as occupation, experience, and education, that goes beyond interpreting and responding to market trends by agents, developers, and investors about differing regions of Shandong Province, where real estate behavior varies with urbanization levels and economic activity (Xiang & Xia, 2023; Selyutina et al., 2019; Rodriguez, 2025). With housing attributes (such as property size, age, layout, location) as core determinants directly affecting valuation, the preferences tend to vary between families, investors, and tech-savvy professionals (Yazdani, 2021; Aziz et al., 2020; Zhao et al., 2022). These come alongside broader factors such as access to location and closeness to facilities as well as other external economic parameters like inflation and employment levels to help predict pricing trends and buyer interests (Chikwuado et al., 2020; Siregar et al., 2020; Ding, 2022). The demand-supply nexus is directly impacted by the movement patterns caused by migration, delays in construction, and government policies, which create an unstable environment in the real estate market and require developers' and buyers' constant reassessments of investment timing and property selection (Molloy et al., 2022; Artigue et al., 2022; Xiao, 2023). Adaptive recommendation systems add more value to this because they analyze user behavior, preferences, and current shifts in the market to give personalized recommendations with risk-based scoring and visual presentations of market trends (Guerrini et al., 2023; Gale & Roy, 2022; Kempeneer et al., 2021). Added with the right amount of user-friendly interface and secured data handling, these advanced tools will then be very instrumental in significantly improving decision-making and risk mitigation while giving stakeholders actionable insights (Jain & Vanzara, 2023; Balcita & Palaoag, 2020; Prabowo et al., 2021). Thus, the framework addresses layered complexity associated with markets such as real estate in Shandong but at the same time empowers its users through predictive accuracy and strategic intelligence based on demographics, economy, and technology (Shen & Sammani, 2022; Wei et al., 2023).

6. Conclusion

In short, the Real Estate Recommendation Framework provides a holistic, data-centric framework for improving decision-making in the real estate industry through integrating user preferences, predictive analytics, and market intelligence approaches. Property characteristics, supply and demand on the market, the specifics of locations, economic indicators, and state policies heavily influence hypotheses in forming prices for housing in Shandong Province. However, the results obtained indicate that the experience of real estate experts does not have a significant impact on the precision of predictions of housing prices, which suggests that data integration and system intelligence drive systems rather than individual expertise. The difference in dynamics among cities, such as Qingdao, Jinan, Yantai, and Weifang, also highlights the other geographic and socio-economic characteristics that make a difference in the housing markets. This study asserts that a properly designed recommendation system that offers personalized user inputs, adaptive learning, and risk analysis can improve both operational efficiency and precision toward property identification and investment planning.

Recommendations are persistently improving on real estate recommendation systems with periodic data upgrades, real-time economic indicators, and locality-specific urban trends for higher prediction fidelity. It has been recommended that, institutionally, training on how to understand and utilize these systems effectively be provided to real estate professionals. Policymakers and developers can also incorporate insights from this system into the improved designs of housing, zoning policies, and priorities in investments all based on sufficient data evidence according to the market needs. Future work could consider feedback loops of users integrated with AI for behavioral analytics to improve recommendation accuracy and system adaptability across various regions and cycles on the market.

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