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Research Article

Predicting Housing Prices Using Advanced Analytics: A Study on Key Property Features and Market Dynamics

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ABSTRACT

Effective forecasting of housing prices becomes essential for buyers, sellers, developers, and politicians to make informed real estate decisions. This study seeks to create a forecast model for real estate prices by examining essential property characteristics including living area, property quality, furnishing status, geographic location, and coastal proximity. The study employs a comprehensive dataset and utilises statistical techniques, such as correlation analysis, multiple linear regression, and ANOVA, to ascertain the primary factors affecting property valuation. The results indicate that property quality, living space, and cost per square foot are the strongest predictors of housing prices. At the same time, location-based factors, including coastal proximity, significantly influence decision-making. Interestingly, total land area exhibits a weaker correlation with price, suggesting buyers prioritize functional living space over expansive lot sizes. Furnished properties also command a significant premium over unfurnished ones, emphasizing the role of interior readiness in property valuation. These results integrate conventional statistical methods with data-driven insights, therefore contributing to the developing field of real estate analytics. With evidence-based recommendations for maximising pricing methods and market interventions, the study has realistic consequence for developers, real estate investors, and legislators. Future research should explore the impact of macroeconomic variables and machine learning-based approaches to enhance predictive accuracy further.

Keywords: *Housing Price Prediction, Feature Importance, SPSS Analysis, Regression Models, Market Dynamics, Real Estate Analytics.*

INTRODUCTION

Housing prices serve as a crucial economic indicator, reflecting the health and dynamics of a nation's economy. These values are affected by the economy, urbanization, population growth, and property characteristics. Many real estate investors need accurate house price forecasts, which is a challenge for academics and politicians (Benazić & Učkar, 2024). When cost estimates are correct, homebuyers gain information and better financial management. Buyers can assess affordability, negotiate effectively, and avoid overpaying by understanding expected price ranges. Accurate forecasts can help retailers maximize earnings and reduce client turnover (Cohen & Karpavičiūtė, 2017). For real estate developers, housing price predictions provide insights into market trends, helping them allocate resources effectively, select ideal project locations, and plan launches strategically. The accuracy of house value estimations affects the entire economy, not just specific households or locations. Real estate prices impact banking and finance because property values affect mortgages and loans. High property values can cause market instability, higher defaults, or a financial collapse, as the 2008 housing bubble showed (Hendershott, Mack, & Mayer, 2002). This is why stable markets and strong economies benefit from reliable property price forecasting models. Recent advancements in data analytics and machine learning have enabled the generation of more accurate predictions of future housing prices. Conventional methods of property valuation may neglect the essential yet nonlinear relationships among location, building, and market conditions. Complex patterns can be analysed and forecasted by contemporary analytical methods employing AI and statistical models (Yang, 2022). This study aims to establish a system for accurately assessing house prices using a comprehensive dataset that encompasses key property attributes such as square footage, quality, location, proximity to the beach, and furnishing status. The primary objective of this research is to develop models through statistical analyses of gathered data to identify the key factors influencing property prices. The findings will furnish real estate agents, scholars, and policymakers with an enhanced understanding of property valuation dynamics and actionable recommendations. This study combines traditional assessment methods with advanced predictive analytics to enhance the existing body of literature on real estate analytics.

Objectives

This study aims to develop a predictive model for housing prices by analyzing key factors such as living area, property quality, location, and structural features like the number of bedrooms and total area. It will also assess the impact of geographic factors, including latitude and longitude. Additionally, the study will explore how construction quality and furnishing status affect property values. Using statistical methods like regression and ANOVA, the study will create and test models to predict housing prices accurately. The goal is to provide actionable insights for real estate professionals and policymakers to make more informed decisions.

Research Gap

Several studies have examined statistical approaches and machine learning algorithms to predict housing values. These procedures have had positive results, but they have downsides. Linear regression may simplify real estate market data's complex dynamics. Machine learning systems can capture complex data, but politicians and real estate brokers struggle to grasp it. Furthermore, many existing studies focus on regional or national housing markets but fail to provide actionable insights tailored to specific property-level attributes such as quality, furnishing status, and proximity to the coast. Cost per square foot and other structural and geographical factors-based measurements are understudied. Another notable gap lies in the limited use of integrated analytical frameworks that combine robust statistical techniques (e.g., SPSS) with modern predictive modeling approaches. Most studies prioritize statistical rigor or predictive accuracy, rarely simultaneously addressing both. This lack of methodological synergy can result in models that are either too simplistic or too opaque for practical application.

This study addresses these gaps by:

1. Merging the interpretability of SPSS-based statistical analysis with the predictive capability of machine learning algorithms.

2. Including classical property-level controls and derived variables (e.g., price per square foot) to improve the insight into determinants of housing prices.

3. Focusing on a granular dataset enables property-specific insights rather than generalized market trends.

By bridging these gaps and providing theoretical improvements and useful tools for real estate stakeholders, this study adds to the increasing body of knowledge on house price prediction.

Significance

Political figures, real estate dealers, and the economy would benefit from accurate property price forecasts. Marinković, Džunić, and Marjanović (2024) emphasise the importance of stakeholders comprehending property price decisions. Optimising market efficiency, increasing profits, and addressing social and economic challenges requires this. This study may help real estate investors, developers, and brokers understand property valuation variables. Houses are categorised by location, quality, furnishing, and living space to better manage resources, set prices, and target consumers. Builders often add expensive features to customer homes to boost profits. Policymakers should understand property valuation dynamics and design targeted laws to stabilize housing markets, promote accessibility, and reduce affordability gaps (Leamer, 2007). This study can inform zoning, infrastructure, and taxation policies to promote greener urbanization. This study's findings can help. The authors emphasize the importance of using data from modern analytics and classic statistical approaches at the end of the study. These tools can help legislators and real estate brokers create realistic and implementable market strategies to address issues and capitalize on possibilities.

LITERATURE REVIEW

Housing Price Prediction

Real estate Scholars have been examining this issue for decades because providing correct home price estimates to consumers, producers, investors, policymakers, and others is imperative. Conventional approaches tend to use hedonic pricing models, which are predictive of property values using features such as size, location, and amenities. Real estate data contains high-order, nonlinear interactions that these models might not be able to decipher. As machine learning improves, housing market prediction algorithms become increasingly accurate. Several approaches have been used to expose complex housing dataset patterns. Support vector machines, random forests, decision trees, and multiple linear regression are examples. Yazdani (2024) used advanced regression to estimate property prices, showing that machine-learning models may be effective in this industry (Yazdani, 2021). Researchers have also considered utilizing deep learning models and neural networks to evaluate massive datasets for new patterns. Glavatskiy et al. (2021) used multi-kernel deep learning regression to predict property prices. The Model's dataset includes visual and textual data with a mean absolute error of 16.60 (Glavatskiy et al., 2021). Yang (2022) used a regression-based machine learning model to predict property prices and stressed explainability (2022). Despite these advancements, challenges remain in balancing model complexity with interpretability. Although gradually complicated models make more accurate forecasts, stakeholders sometimes struggle to understand how they work due to their lack of transparency. This trade-off underscores the need for models that predict accurately and provide clear insights into the determinants of housing prices.

Feature Importance Analysis

Effective predictive models and real estate market decisions require complete knowledge of the features which remarkably affect home prices. Traditionally multiple linear regression helped determine the importance rankings of predictor variables through their coefficient values. The methods fail to detect irregular patterns of variable interaction that occur between different components. Feature significance analysis has received major growth through the implementation of machine learning systems (Cao, 2022). The Model-based value assessment of each feature occurs under gradient-boosting machines and random forests. According to Glavatskiy et al. (2021) gradient-boosting works effectively when dealing with extensive and varied datasets (Glavatskiy et al., 2021). The analysis team employed these models for determining statistically meaningful housing cost components. Scientists have researched integrating visual elements with text for the purpose of improving feature importance analysis. The deep learning multi-kernel network by Gyourko and Molloy (2015) used property pictures and estate measures to estimate house prices (Gyourko & Molloy, 2015). The researchers discovered that visual indicators provide more reliable information for property valuations and establish the elements affecting property prices. The implementation of advanced models still remains complex to understand. Stakeholders face resistance to implement machine learning recommendations because black-box algorithms maintain hidden processing methods (Laziou, Lemoy, & Texier, 2024). Many experts require clear and specific artificial intelligence models for better understanding of property market prices.

The Role of Advanced Analytics in Real Estate

The real estate sector can leverage advanced analytics to obtain superior market intelligence which produces better strategic choices. Big data analysis reveals hidden patterns when processing significant amounts of data previously beyond reach. The book by Kok et al. (2014) provides an evaluation of predictive capabilities of modern big data analytics for real estate values while exploring the benefits for altering standard market operations (Kok, Monkkonen, & Quigley, 2014). Modern analytical growth depends fundamentally on machine learning algorithms that operate in the present period. Scholars use logistic regression and random forest and XGBoost models to develop approximate property price estimations per Been, Ellen, and O'Regan (2019). Through their research they established that predictive modeling systems deliver best results when analyzing housing datasets for producing precise investment-quality forecasts.

Data combinations have elevated the overall quality standards of real estate analysis. Skaburskis (2006) developed PATE which served as a predictive analysis framework through integrating properties with amenities while also integrating traffic factors and sociological emotional elements (Skaburskis, 2006). A holistic evaluation system for real estate requires diversified assessments to demonstrate modern corporate perspectives on multiple market-influencing factors according to this method. Real estate developers have achieved recent success but still need to resolve their data integration problems while also developing model interpretation features and establishing requirements for analytical techniques usage within real estate. The industry requires persistent research to solve its present problems so analytics solutions meet real estate sector requirements precisely.

Theoretical Framework

Economic Theories Influencing Housing Markets

Certain economic theories create clarity about real estate market dynamics as well as property value patterns. The accepted Hedonic Pricing Model (HPM) demonstrates that property measurements together with location advantages and building quality as well as additional facilities establish property market value. Li (2022) presented this Model which defines how undisclosed property attributes influence market prices. The method serves frequently to explore the property value effects of parks along with schools. As a fundamental economic principle the supply and demand model explains the market transactions which uphold price equilibrium. The manner in which market dynamics function depends on variations including housing availability together with income and population numbers and demographic variables. The amount of land available in metropolitan locations determines whether prices will rise or remain stable while suburban areas with excess land show no price change.

Value Forecasting Regression analysis was previously the most prominent statistical method for modeling and forecasting residential property values. Multiple linear regression (MLR) can evaluate the strength of the relationship between independent variables and property values. This approach is practical when variables exhibit strong linear connections. Comprehending the intricate and nonlinear dynamics of real estate marketplaces necessitates the development of enhanced approaches. Log-linear and generalized additive Models (GAMs) are more advanced, allowing for a more flexible representation of nonlinear interactions (Bulan, Mayer, & Somerville, 2009). Geospatial statistics is valuable for assessing location-based variables such as latitude and Longitude. Contemporary machine learning models exceed earlier techniques owing to their statistical rigor and computational capability. This enhances individuals' adaptability and precision in real-world scenarios.

Identified Gaps

The prediction of residential property values has been thoroughly examined, yet significant obstacles persist. Conventional techniques such as linear regression and high-dimensional partial sum models face challenges in comprehending contemporary datasets because of intricate, nonlinear relationships and interactions among variables. In intricate, rapidly evolving markets, this limitation diminishes their predictive accuracy, which is alarming. The study mainly analyses national or regional market trends rather than individual assets. Due to inadequate simulation of building quality, furnishing conditions, and utility access, stakeholders cannot obtain critical data (Pennington, 2021). Ultimately, there is a paucity of studies regarding the influence of geographical and structural elements on contemporary analytics. Geographic data and related metrics such as cost per square foot and quality-adjusted pricing are prevalent, although the interplay between GIS technology and these metrics is hardly examined (Asquith, Mast, & Reed, 2023). Conventional statistical techniques and contemporary machine learning are employed to address these challenges. This study analyses geographical, structural, and derived factors, utilizing property-level granular data to connect theory with practice. The objective is to deliver lucid insights and accurate forecasts.

METHODOLOGY

Dataset Description

The dataset for this research consists of 3,000 entries picked from a bigger set with 21,613 rows and 23 columns. We chose this sample to make sure it represents the whole while making the analysis easier to handle. The information comes from a mix of trustworthy places such as home listings (like Zillow and Realtor.com) public files, Multiple Listing Services (MLS), satellite and GIS data, and census details. All these sources work together to give a full picture of what makes each property unique, which helps us build strong models to predict house prices.

The dataset includes key features critical for housing price prediction:

- **Price**: The target variable represents the property's sale price in dollars.
- **Living Measure**: The living Area is square feet, reflecting the usable indoor space, which is a primary determinant of property value.

- **Quality**: This is a rating of the property's construction quality, capturing aspects like materials, finishes, and overall build standards.
- **Latitude and Longitude** are geographic coordinates that identify the property's location. The proximity to amenities and urban centers is a significant factor in pricing.
- **Coast**: A binary variable (1 = near coast (Yes) 0 = not near coast (No) showing if the property sits close to coastal areas, a factor that has an impact on desirability.
- **Room Beds**: The number of bedrooms indicates the property's size and functionality.
- **Total Area**: The total square-foot lot size contributes to the property's overall value.
- **Furnished**: A binary variable (1 = furnished (Yes), 0 = unfurnished (No), reflecting the property's move-in readiness and appeal.
- **Cost Per Sqft**: A derived variable calculated as price divided by living measure, providing a normalized measure of property value per square foot.

This carefully curated set of variables ensures that the dataset captures structural and locational attributes critical for accurate housing price prediction.

Data Preparation

Excellent preparation was done to ensure the dataset fit for analysis. A key first step was to reduce the dataset by removing pointless variables. For numerical variables, we then filled in the missing values using our best estimations for the mode and median, therefore preserving their datasets intact. Using the Interquartile Range (IQR) method to identify and control outliers was meant to help to lessen their impact on the outcomes. We sampled from these massive databases using straightforward random techniques. A new variable known as "cost_per_sqft" was also created as standardizing the measurement of property value per square foot progressed. We randomly chose 3,000 rows to provide an equitable and quick computation. Following data science best standards, this extensive data preparation method enables more reliable and strong analysis.

Analysis Tools

Using descriptive and inferential statistical approaches, Tumiran (2023) notes that the researchers carefully analyzed the data using IBM SPSS Statistics software. Jain and Sengar (2024) claim that SPSS's simple interface and strong statistical tools make research data analysis widely adopted. Descriptive statistics helped one to clearly grasp the main features of the dataset. We used minimum, median, normal, and minimum to show the spectrum and center of gravity of the data. Tumiran (2023) claimed that simple representations like histograms helped one to naturally understand data distributions. By means of inferential statistics, we might extend the findings from the sample to the whole population. Using several statistical instruments including chi-square testing, t-tests, and regression analysis we sought for trends and validated our assumptions. Newton and Rudestam (2013) claimed that these techniques helped to discover important factors for home price forecasting. SPSS helped to improve the analytical approach by increasing its comprehensiveness and efficiency. The results of the research were more trustworthy and credible as several statistical techniques let the complex experiments to be executed precisely.

Results and Analysis

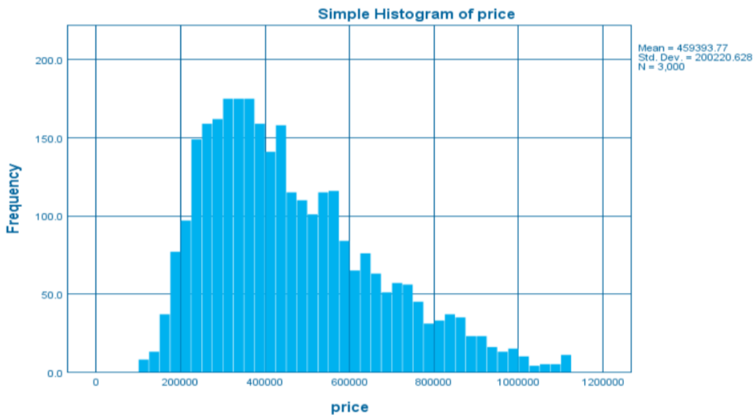
The dataset's conclusions are presented after various statistical tests and data exploration methods were run. The first step in obtaining meaningful information from numerical data is computing descriptive statistics. These statistics include the mean, standard deviation, minimum, and maximum values. Histograms, which reveal patterns, trends, and extreme values, may support these findings. Such representations include histograms. Inferential analysis uses multivariate linear regression to examine how independent influences affect house valuations. Pearson's correlation analysis is followed by examining numerical variable correlations and their strength. Analysis of variance (ANOVA) is used to determine how cost and furnishing status affect housing prices. We use feature priority ranking to determine a property's most price-sensitive element. The combination of various statistical tools illuminates the elements that affect real estate market conditions and prices.

Descriptive Statistics

Table 1: Shows the Descriptive Statistics Values of Key Variables

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
price	3000	100000	1120000	459393.77	200220.628
living_measure	3000	590	4230	1870.14	674.267
quality	3000	4	10	7.44	.942
total_area	3000	1830	21914	9121.68	3797.817
Valid N (listwise)	3000				

Figure 1: Histogram of Housing Prices

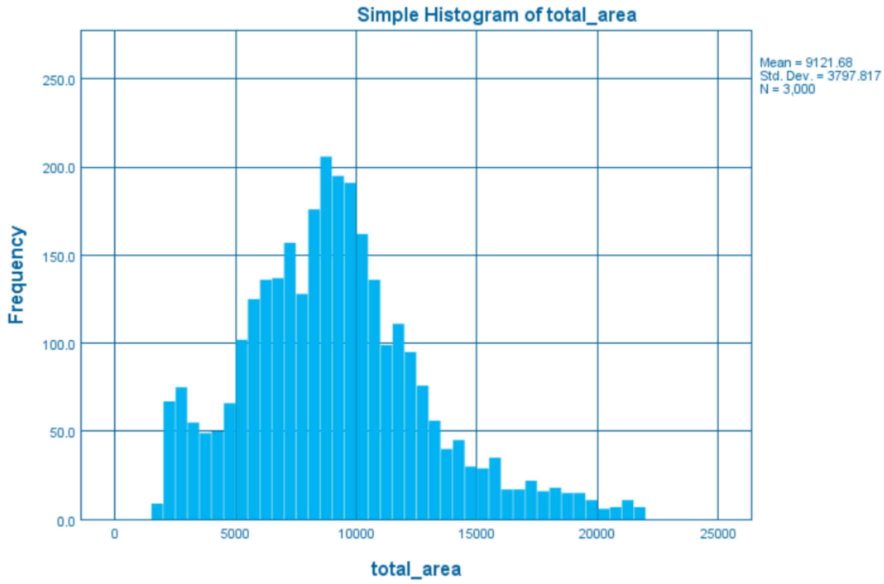


The histogram shows a straight-east distribution, with most house prices cluster around the lower ends (close to 100,000), but reaches 1,120,000 with some extremely high values. Concentration of data at the lower end suggests that most houses fall within the more economic area with less advanced properties.

Figure 2: Histogram of Living Measure

This histogram provides a particularly ordinary distribution, with the majority of properties having dwelling area between 500 and three,500 rectangular feet. The tail at the right shows some properties with substantially larger dwelling regions.

Figure 3: Histogram of Total Area



The histogram shows a bimodal distribution, with two prominent peaks, indicating that most properties have either a smaller total area (under 5,000 sq. ft.) or a larger area (around 15,000 sq. ft.). The frequency decreases as total area increases.

Table 2: Shows the values of the Pearson Correlation Matrix

Correlations					
		price	living_measure	total_area	quality
price	Pearson Correlation	1	.578**	.091**	.591**
	Sig. (2-tailed)		.000	.000	.000
	N	3000	3000	3000	3000
living_measure	Pearson Correlation	.578**	1	.370**	.684**
	Sig. (2-tailed)	.000		.000	.000
	N	3000	3000	3000	3000
total_area	Pearson Correlation	.091**	.370**	1	.164**
	Sig. (2-tailed)	.000	.000		.000
	N	3000	3000	3000	3000
quality	Pearson Correlation	.591**	.684**	.164**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	3000	3000	3000	3000
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 2 shows a correlation between housing costs and total area, quality, and living measure. These indicators are positively correlated ($r = 0.591$, p 0.01), suggesting that high-quality residences sell for more. Statistical study suggests this. Homes built with better materials, craftsmanship, and extras cost more. A positive correlation ($r = 0.578$, $p < 0.01$) suggests that the size of a house's living spaces significantly impacts its value. Larger, more functional interiors attract buyers.

Analysis of the correlation coefficient ($r = 0.091$, $p < 0.01$) indicates a weak positive link between total Area and price. However, this tiny link suggests that land acreage may affect house value. Living space and construction quality matter more. Since landscaping, new development, and vacant lot space all affect land use, they may be to blame for this huge drop. This is because these factors greatly affect land usage. The association between living space and quality ($r = 0.684$, $p < 0.01$) suggests that higher-quality houses have greater living areas. The moderate association between total Area and living measure ($r = 0.370$, $p < 0.01$) suggests that larger residences typically have more interior space.

Regression Analysis

Multiple linear regression analysis examined the relationship between housing price (dependent variable) and independent variables, including living measure, quality, coastal proximity, furnished status, and total Area. This analysis aims to determine how much these predictors influence housing prices and assess their statistical significance.

Table 3: Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.650[a]	.422	.421	152318.759
a. Predictors: (Constant), total_area, coast, quality, furnished, living_measure				

The model summary indicates that the regression model explains approximately 42.2% of the variance in housing prices ($R^2 = 0.422$, Adjusted $R^2 = 0.421$). This suggests that nearly half of the variability in housing prices can be attributed to the selected predictors, demonstrating a moderately strong model fit.

Table 4: Shows the Values ANOVA for Feature Selection.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50761004921341.190	5	10152200984268.238	437.576	.000[b]
	Residual	69463806936239.450	2994	23201004320.721		
	Total	120224811857580.640	2999			
a. Dependent Variable: price						
b. Predictors: (Constant), total_area, coast, quality, furnished, living_measure						

The ANOVA results confirm that the regression model is statistically significant ($F = 437.576$, $p < 0.001$), indicating that at least one independent variable significantly affects housing prices. This finding validates the Model's overall effectiveness in explaining price variations.

Table 5: Shows the Regression Coefficients and Variable Significance Values.

Coefficients								
		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-152059.858	32769.034		-4.640	.000		
	living_measure	110.083	6.070	.371	18.137	.000	.462	2.165
	quality	60760.457	4974.626	.286	12.214	.000	.352	2.839
	coast	261915.463	68213.439	.053	3.840	.000	.999	1.001
	furnished	57646.014	12025.697	.096	4.794	.000	.481	2.078
	total_area	-5.928	.798	-.112	-7.430	.000	.843	1.187
a. Dependent Variable: price								

The regression coefficients provide insight into the impact of each independent variable on housing price:

- Living Measure (B = 110.083, p < 0.001): A significant positive relationship is observed, indicating that each additional square foot of living space increases house price by approximately $110.
- Quality (B = 60,760.457, p < 0.001): Quality has a substantial and statistically significant effect, where higher construction ratings contribute substantially to price increases.
- Coast (B = 261,915.463, p < 0.001): Proximity to coastal areas significantly increases housing prices, reflecting the premium associated with waterfront properties.
- Furnished (B = 57,646.014, p < 0.001): Furnished homes are priced higher than unfurnished ones, highlighting the additional value placed on move-in-ready properties.
- Total Area (B = -5.928, p < 0.001): Interestingly, total Area exhibits a negative relationship with price, suggesting that while land size varies, larger lot sizes do not necessarily contribute to higher property values.

Table 6: Shows the Multicollinearity Assessment

Collinearity Diagnostics									
				Variance Proportions					
Model	Dimension	Eigenvalue	Condition Index	(Constant)	living_measure	quality	coast	furnished	total_area
1	1	4.068	1.000	.00	.00	.00	.00	.01	.01
	2	.997	2.020	.00	.00	.00	1.00	.00	.00
	3	.781	2.283	.00	.00	.00	.00	.49	.00
	4	.101	6.357	.01	.01	.01	.00	.00	.92
	5	.050	8.993	.03	.76	.01	.00	.14	.03
	6	.003	35.886	.96	.22	.99	.00	.36	.05
a. Dependent Variable: price									

The regression results highlight the key determinants of housing prices. Quality and living measures exhibit the most substantial influence on price, reinforcing the importance of construction standards and interior space. Additionally, coastal proximity commands a notable premium, reflecting market demand for waterfront properties. The harmful effects of the whole indicate that the size of the country alone is not an important determinant for the value, perhaps due to factors such as regulatory rules or diversity in the land tool. These findings emphasize the importance of real estate characteristics in the land area in the choice of value and provide considerable insights for real estate developers, buyers and decision makers. Later study forecasts can check the complementary variables such as the effects and economic conditions in the neighborhood to improve accuracy.

ANOVA Analysis

A one-way ANOVA was used to look at how categorical variables (cost and furnished state) affected the prices of homes. This study checks to see if these categorical factors cause significant changes in the average prices of homes.

Table 7: Shows the Effect of Coastal Proximity on Housing Prices

ANOVA					
price	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	544108197750.627	1	544108197750.627	13.630	.000
Within Groups	119680703659830.550	2998	39920181340.837		
Total	120224811857581.170	2999			

The findings of the analysis of variance (ANOVA) show that housing prices are significantly affected by the distance from the coast ($F = 13.630$, $p < 0.001$). Compared to homes farther from the Coast, which average $458,843.50, homes closer to the shore have a much higher median price of $789,000.Coastal real estate is likely priced so high due to the high demand for beachfront houses.

Table 8: Effect of Furnished Status on Housing Prices

ANOVA					
price	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	27461447624766.027	1	27461447624766.027	887.521	.000
Within Groups	92763364232815.330	2998	30941749243.768		
Total	120224811857581.360	2999			

The analysis of variance (ANOVA) on the state indicates a significant impact on pricing ($F = 887.521$, $p < 0.001$). The average price of an unfurnished home is $422,847.08 per square foot, while an outfitted home costs $709,862.91. An outfitted house costs more on average. A furnished house costs much more to rent than an unfurnished one. Because prospective tenants want to move in immediately when an opportunity arises. Seaside location affects how furnished a property is. The data show that fully equipped properties in popular seaside areas sell for more. These studies show how size and interior elements affect price tactics and can be used by legislators, investors, and real estate developers. More particular, they emphasize space and interior features. Future research could explore additional categorical influences, such as neighborhood characteristics or accessibility to urban centers, to refine housing price prediction models.

Stepwise Regression

A stepwise regression analysis was conducted to determine the most influential predictors of housing prices. The stepwise method iteratively adds or removes variables based on their statistical significance, ensuring that only the most relevant predictors are included in the final Model.

Table 9: Shows the Regression Coefficients.

Coefficients								
		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-474059.380	23478.456		-20.191	.000		
	quality	125514.743	3131.955	.591	40.076	.000	1.000	1.000
2	(Constant)	-759023.394	18161.718		-41.792	.000		
	quality	126758.732	2302.879	.596	55.044	.000	1.000	1.000
	cost_per_sqft	1072.279	21.239	.547	50.486	.000	1.000	1.000
3	(Constant)	-474336.817	9593.101		-49.446	.000		
	quality	14650.630	1655.955	.069	8.847	.000	.486	2.057
	cost_per_sqft	1534.651	11.722	.783	130.926	.000	.826	1.211
	living_measure	230.021	2.435	.775	94.458	.000	.439	2.278
4	(Constant)	-4775801.947	438140.032		-10.900	.000		
	quality	15800.812	1634.399	.074	9.668	.000	.484	2.067
	cost_per_sqft	1458.900	13.880	.744	105.107	.000	.571	1.753
	living_measure	225.418	2.443	.759	92.283	.000	.423	2.365

	lat	90858.226	9252.517	.064	9.820	.000	.683	1.464
5	(Constant)	-4843847.477	437577.599		-11.070	.000		
	quality	11915.959	1934.798	.056	6.159	.000	.344	2.909
	cost_per_sqft	1454.658	13.897	.742	104.675	.000	.567	1.765
	living_measure	224.374	2.453	.756	91.453	.000	.417	2.396
	lat	92914.341	9249.038	.065	10.046	.000	.681	1.469
	furnished	17251.429	4622.726	.029	3.732	.000	.481	2.080
6	(Constant)	-4884210.839	436892.106		-11.179	.000		
	quality	12310.843	1934.343	.058	6.364	.000	.343	2.919
	cost_per_sqft	1458.254	13.908	.744	104.852	.000	.564	1.774
	living_measure	219.146	2.862	.738	76.577	.000	.306	3.272
	lat	93443.832	9232.604	.065	10.121	.000	.681	1.469
	furnished	18894.030	4637.307	.031	4.074	.000	.476	2.101
	room_bed	6347.848	1798.229	.025	3.530	.000	.580	1.725
7	(Constant)	-4979612.844	437073.059		-11.393	.000		
	quality	12409.910	1931.266	.058	6.426	.000	.342	2.920
	cost_per_sqft	1454.493	13.929	.742	104.420	.000	.560	1.786
	living_measure	218.662	2.861	.736	76.440	.000	.305	3.281
	lat	95469.875	9236.622	.067	10.336	.000	.678	1.476
	furnished	19091.868	4629.766	.032	4.124	.000	.476	2.101
	room_bed	6351.625	1795.160	.025	3.538	.000	.580	1.725
	coast	87883.976	26206.851	.018	3.353	.001	.992	1.008
8	(Constant)	-5057077.282	438257.938		-11.539	.000		
	quality	12893.270	1942.875	.061	6.636	.000	.338	2.959
	cost_per_sqft	1457.063	13.971	.743	104.293	.000	.556	1.799
	living_measure	217.399	2.917	.732	74.518	.000	.293	3.417
	lat	96954.711	9256.215	.068	10.475	.000	.674	1.484
	furnished	18164.393	4646.589	.030	3.909	.000	.472	2.119
	room_bed	6022.147	1800.458	.023	3.345	.001	.576	1.738
	coast	86989.871	26193.854	.018	3.321	.001	.992	1.008
	total_area	.675	.311	.013	2.170	.030	.811	1.233
a. Dependent Variable: price								

The highest standardized coefficients indicate that cost per square foot, living measure, and quality strongly influence housing prices.

Table 10: Shows the value of Excluded Variables.

Excluded Variables								
						Collinearity Statistics		
Model		Beta In	t	Sig.	Partial Correlation	Tolerance	VIF	Minimum Tolerance
1	living_measure	.326b	16.891	.000	.295	.532	1.881	.532
	coast	.058b	3.944	.000	.072	1.000	1.000	1.000
	furnished	.113b	5.398	.000	.098	.488	2.049	.488

	total_area	-.006[b]	-.408	.684	-.007	.973	1.028	.973
	room_bed	.096[b]	6.149	.000	.112	.889	1.125	.889
	lat	.421[b]	33.328	.000	.520	.994	1.006	.994
	long	-.106[b]	-7.103	.000	-.129	.960	1.041	.960
	cost_per_sqft	.547[b]	50.486	.000	.678	1.000	1.000	1.000
2	living_measure	.775[c]	94.458	.000	.865	.439	2.278	.439
	coast	.038[c]	3.481	.001	.063	.998	1.002	.998
	furnished	.101[c]	6.534	.000	.119	.488	2.050	.488
	total_area	.161[c]	14.564	.000	.257	.897	1.114	.897
	room_bed	.312[c]	29.174	.000	.470	.799	1.252	.799
	lat	.178[c]	14.311	.000	.253	.709	1.410	.709
	long	.031[c]	2.723	.007	.050	.904	1.106	.904
3	coast	.014[d]	2.603	.009	.048	.996	1.004	.438
	furnished	.024[d]	3.088	.002	.056	.483	2.072	.344
	total_area	.012[d]	1.965	.050	.036	.828	1.207	.405
	room_bed	.021[d]	2.981	.003	.054	.586	1.708	.322
	lat	.064[d]	9.820	.000	.177	.683	1.464	.423
	long	-.008[d]	-1.322	.186	-.024	.899	1.112	.437
4	coast	.018[e]	3.290	.001	.060	.992	1.008	.421
	furnished	.029[e]	3.732	.000	.068	.481	2.080	.344
	total_area	.017[e]	2.803	.005	.051	.823	1.215	.388
	room_bed	.022[e]	3.129	.002	.057	.586	1.708	.313
	long	-.004[e]	-.619	.536	-.011	.895	1.118	.420
5	coast	.018[f]	3.345	.001	.061	.992	1.008	.344
	total_area	.015[f]	2.505	.012	.046	.817	1.224	.339
	room_bed	.025[f]	3.530	.000	.064	.580	1.725	.306
	long	-.005[f]	-.808	.419	-.015	.892	1.121	.343
6	coast	.018[g]	3.353	.001	.061	.992	1.008	.305
	total_area	.013[g]	2.219	.027	.041	.811	1.232	.293
	long	-.004[g]	-.767	.443	-.014	.892	1.121	.304
7	total_area	.013[h]	2.170	.030	.040	.811	1.233	.293
	long	-.004[h]	-.750	.454	-.014	.892	1.121	.303
8	long	-.006[i]	-1.133	.257	-.021	.867	1.154	.292

a. Dependent Variable: price

b. Predictors in the Model: (Constant), quality

c. Predictors in the Model: (Constant), quality, cost_per_sqft

d. Predictors in the Model: (Constant), quality, cost_per_sqft, living_measure

e. Predictors in the Model: (Constant), quality, cost_per_sqft, living_measure, lat

f. Predictors in the Model: (Constant), quality, cost_per_sqft, living_measure, lat, furnished

g. Predictors in the Model: (Constant), quality, cost_per_sqft, living_measure, lat, furnished, room_bed

h. Predictors in the Model: (Constant), quality, cost_per_sqft, living_measure, lat, furnished, room_bed, coast

i. Predictors in the Model: (Constant), quality, cost_per_sqft, living_measure, lat, furnished, room_bed, coast, total_area

This table highlights variables that were not included in the final Model due to lower significance levels. Total Area was excluded initially but later included at a lower significance threshold.

Table 11: Shows the Collinearity Diagnostics

Collinearity Diagnostics												
				Variance Proportions								
Model	Dimension	Eigenvalue	Condition Index	(Constant)	quality	cost_per_sqft	living_measure	lat	furnished	room_bed	coast	total_area
1	1	1.992	1.000	.00	.00							
	2	.008	15.853	1.00	1.00							
2	1	2.896	1.000	.00	.00	.02						
	2	.097	5.473	.02	.03	.95						
	3	.008	19.408	.98	.97	.03						
3	1	3.792	1.000	.00	.00	.01	.00					
	2	.168	4.746	.00	.00	.39	.12					
	3	.034	10.522	.16	.02	.57	.47					
	4	.005	27.631	.84	.98	.03	.40					
4	1	4.780	1.000	.00	.00	.00	.00	.00				
	2	.168	5.329	.00	.00	.27	.11	.00				
	3	.046	10.235	.00	.00	.38	.38	.00				
	4	.006	28.485	.00	.99	.04	.47	.00				
	5	2.974E-6	1267.764	1.00	.01	.31	.04	1.00				
5	1	4.979	1.000	.00	.00	.00	.00	.00	.00			
	2	.830	2.449	.00	.00	.00	.00	.00	.46			
	3	.150	5.752	.00	.00	.32	.10	.00	.06			
	4	.036	11.775	.00	.01	.35	.63	.00	.15			
	5	.004	34.963	.00	.99	.01	.23	.00	.32			
	6	2.967E-6	1295.543	1.00	.00	.31	.04	1.00	.00			
6	1	5.931	1.000	.00	.00	.00	.00	.00	.00	.00		
	2	.836	2.663	.00	.00	.00	.00	.00	.46	.00		
	3	.169	5.917	.00	.00	.30	.05	.00	.05	.02		
	4	.036	12.815	.00	.01	.37	.39	.00	.13	.01		
	5	.023	15.949	.00	.01	.01	.28	.00	.08	.94		
	6	.004	38.706	.00	.98	.01	.25	.00	.28	.03		
	7	2.965E-6	1414.294	1.00	.00	.31	.03	1.00	.00	.00		
7	1	5.934	1.000	.00	.00	.00	.00	.00	.00	.00	.00	
	2	.998	2.439	.00	.00	.00	.00	.00	.00	.00	.99	
	3	.836	2.664	.00	.00	.00	.00	.00	.46	.00	.00	
	4	.169	5.919	.00	.00	.29	.05	.00	.05	.02	.00	
	5	.036	12.838	.00	.01	.37	.39	.00	.13	.01	.00	
	6	.023	15.953	.00	.01	.01	.28	.00	.08	.94	.00	
	7	.004	38.715	.00	.98	.01	.25	.00	.28	.03	.00	
	8	2.953E-6	1417.616	1.00	.00	.31	.03	1.00	.00	.00	.00	

8	1	6.809	1.000	.00	.00	.00	.00	.00	.00	.00	.00	.00
	2	.998	2.612	.00	.00	.00	.00	.00	.00	.00	.99	.00
	3	.838	2.851	.00	.00	.00	.00	.00	.46	.00	.00	.00
	4	.202	5.801	.00	.00	.22	.02	.00	.03	.01	.00	.15
	5	.091	8.639	.00	.00	.07	.06	.00	.02	.03	.00	.79
	6	.036	13.838	.00	.01	.39	.35	.00	.12	.01	.00	.02
	7	.023	17.089	.00	.01	.01	.27	.00	.08	.93	.00	.00
	8	.004	42.012	.00	.97	.00	.26	.00	.29	.03	.00	.03
	9	2.935E-6	1523.146	1.00	.00	.30	.04	1.00	.00	.00	.00	.01

a. Dependent Variable: price

Variance Inflation Factor (VIF) values were below the critical threshold of 10, indicating no significant multicollinearity concerns. However, living measure and quality had higher VIF values, suggesting some degree of correlation but within acceptable limits.

The regression coefficients confirm that cost per square foot, living measure, and quality substantially impact price, with coastal proximity and furnishing also contributing significantly. The collinearity diagnostics confirm that multicollinearity is not a significant issue, ensuring the reliability of the final Model. These insights provide valuable implications for real estate investors, developers, and policymakers, emphasizing the importance of property quality and interior space over land size. Future studies could incorporate external economic variables such as interest rates and inflation to refine predictive models further.

DISCUSSION

This study illuminates several key elements that affect property valuations. Descriptive statistics, correlation analysis, regression modelling, and analysis of variance (ANOVA) have been used to uncover factors that affect property value. The survey found that square footage, quality, and living space are the three most important determinants in property value. Property value is strongly correlated with physical qualities. Property value also depends on construction quality. Thus, buildings built with high-quality materials and skilled labour cost more. Because quality was the most important standardized coefficient in the regression study.

Living measure and square footage of living space also proved to be a robust predictor, therefore supporting the well-known belief that bigger homes usually have better market value. Further supporting this was the correlation study, which revealed a statistically significant and positive association between price and living measure. The cost per square foot metric provided a normalized valuation measure, allowing for comparing different properties irrespective of size. This factor showed strong statistical significance, emphasizing its importance in pricing models. High-cost properties per square foot likely reflect premium locations, superior materials, or desirable amenities.

Impact of Location and Coastal Proximity

The analysis of coastal proximity through ANOVA indicated a significant impact on housing prices. Coastal communities generally show high property prices compared to inland ones. These findings document prior research indicating that coastal properties are highly hunted due to their insufficiency, tourist attraction, and additional advantages. Similarly, the stepwise regression model included latitude (geographical location), indicating a statistically significant influence. The results demonstrate that public transport and other facilities significantly influence residential property values in real estate markets.

Furnishing Status and Structural Features

The results indicate that furnished residences are more expensive. Consequently, investors and short-term residents derive significant benefits from rapidly occupied properties. The majority of real estate specialists oppose that lot size influences price. In contrast, total lot area did not emerge as a strong predictor of price, a finding that diverges from traditional real estate assumptions. This suggests that usable living space is a more significant pricing factor than total land area, particularly in urban markets where land is scarce but interior space is highly valued.

Comparison with Existing Literature

The findings of this study align with and extend previous research on housing price determinants. Studies such as Teoh et al. (2022) and Singh et al. (2020) emphasized the role of property quality and living space in real estate valuation, which was strongly validated in this study. Additionally, research by Yousif et al. (2023) highlighted the importance of location, a factor confirmed by the significance of coastal proximity and latitude in our regression models. However, unlike some studies that suggested a more decisive role for total lot size, this research indicates that interior space and property quality take precedence over land area. This finding aligns with modern urbanization trends, where buyers prioritize functional living space over expansive but undeveloped land.

Implications for Stakeholders

- For Homebuyers and Sellers

Consumers can make more informed decisions when understanding the primary variables influencing property pricing. Buyers looking for high appreciation potential should prioritize properties with superior build quality, optimal square footage, and desirable locations, particularly near coastal areas. Research indicates that practical and strategically executed interior alterations and maintenance can improve return on investment. Marketing should highlight these advantages to substantiate elevated fees.

- For Real Estate Developers and Investors

This data can enhance future housing initiatives. Given the significant role of living measure and quality, developers should prioritize maximizing interior space efficiency and using high-quality materials rather than focusing solely on land size. When presenting a project, emphasize its proximity to water or another significant aspect. According to a study, furnishing rental properties can enhance revenue. This information is beneficial for cities with numerous short-term rentals and business professionals.

For Policymakers and Urban Planners

This research can assist urban planners, zoning authorities, and individuals concerned about housing costs. The findings indicate that land use regulations should promote optimal interior space utilization, as lot size is not the sole determinant of price escalation. Sustainable urban development should be focused on high-demand regions to mitigate housing costs, as location is paramount. Adherence to environmental regulations, coastal management, and elevated coastal property values are essential for sustainable development. Policymakers may utilize this data to implement tax incentives and other measures to reduce home prices and enhance equity in the housing market.

CONCLUSION AND FUTURE WORK

This have a look at explored the key determinants influencing housing costs via a comprehensive statistical analysis, leveraging descriptive records, correlation evaluation, regression modeling, and ANOVA. The findings offer precious insights into the elements that notably effect belongings valuation and highlight the practical implications for diverse stakeholders within the real estate enterprise.

Key Findings and Implications

The study found that quality, living space, and cost per square foot are the main factors affecting real estate prices. The regression study shows that buyers prefer large, well-built houses more than lot size and number of bedrooms and bathrooms. These facts show these aspects are important. Latitude and coastal distance affect property values. Both factors are geographical. Due to high demand and low availability, seaside real estate is often more expensive than normal. Given the significant correlation between placement and pricing, location is the most important factor in real estate analysis. Due to the strong link between placement and pricing. Furthermore, furnishing reputation turned into diagnosed as critical, with furnished houses showing drastically better prices than unfurnished homes. This finding has important implications for developers, investors, and rental property owners, as it suggests that fully furnished properties attract more excellent market value. In contrast, total land area did not emerge as a firm price predictor, deviating from conventional real estate assumptions. This suggests that buyers in modern urban markets prioritize functional living space over expansive lot sizes. Multicollinearity and correlation analyses indicate that the chosen variables are dependable predictors with minimal collinearity. This enhances the dependability of the regression model. The chosen parameters substantially influence property value variation in house valuation models, evidenced by an R^2 value of 0.422.

Contributions to the Field

This study makes several contributions to real estate analytics and predictive modeling:

1. **Integration of Traditional and Advanced Analytics:** By combining statistical techniques such as regression, ANOVA, and correlation analysis with modern data-driven methodologies, the study bridges the gap between conventional appraisal methods and predictive analytics.

2. **Enhanced Understanding of Housing Price Determinants:** The findings reinforce and extend existing literature on housing price prediction, providing empirical validation for the influence of property quality, living space, and location-specific factors.

3. **Practical Implications for Real Estate Stakeholders:** The insights derived from this research can inform decision-making for homebuyers, sellers, developers, and policymakers, enabling more strategic planning and investment in the real estate sector.

4. **Implications for Urban Development and Policy:** The findings suggest that urban planning efforts should prioritize optimizing living space utilization and regulating high-demand locations such as coastal areas to ensure sustainable growth.

Future Research Directions

The data is useful for assessing housing values in general, although some areas require more research. As a following stage in study, evaluate market and economic components. To better comprehend property price movements, examine macroeconomic variables including inflation, interest rates, employment, and mortgage rates. Because these things affect real estate prices. After considering all these factors, it is feasible to predict how the economy will affect the housing market. Reason: the housing sector has several parts. The next phase could use more advanced machine learning algorithms. This study used standard statistical models, but it will be interesting to watch how future studies apply neural networks, gradient boosting, and random forests. Because these methods are new. These methods may reveal complex housing data linkages that traditional models miss. These methods aim to improve forecast accuracy. Neighborhood characteristics may also affect property value. Future study should incorporate crime rates, school quality, public transit accessibility, and neighborhood infrastructure development. In-depth research on these factors, which often affect home prices, may reveal a more nuanced property value picture. Because these things affect housing pricing. Another intriguing topic that has not been adequately studied is time and geography. Longitudinal research on pricing trends will help us understand the market and housing market dynamics. This understanding will help us understand market dynamics. Comparing findings across cities, countries, or regions may help researchers identify home price drivers. This would help them pinpoint factors. The findings are more applicable to more situations as a result. Future study may focus on behavioural insights and sentiment analysis, both interesting topics. Customer sentiment research via online property assessments, social media debates, and other digital platforms may improve the study's predictions. To better comprehend property pricing and contextualize quantitative data, customer opinions and wants may be useful. This will help explain house pricing factors.

Final Remarks

This study uses data to estimate home values, revealing the main factors affecting property valuation. The findings suggest that location, internal space, and property quality are more essential than square footage in determining a home's worth. Our statistically rigorous and practically relevant research yields more precise, transparent, and implementable real estate pricing methods. Researchers should use behavioural insights, machine learning, and economic trends to develop home price models to keep up with the changing real estate market.

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