Decoding Smartphone Prices: The Evolving Value of Features Over Time

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Abstract

The mobile phone market has undergone significant transformation over the past decade, with manufacturers annually introducing models equipped with advanced features, enhanced performance, and improved designs. This study investigates the pricing dynamics of smartphones from major brands such as Apple, Samsung, and Google, focusing on the evolving importance of key features like RAM, battery capacity, camera quality, and screen size in determining prices. By employing the Least Absolute Shrinkage and Selection Operator (LASSO) regression model, this research analyzes pooled year-specific data to identify temporal trends in feature importance and their impact on pricing strategies.

The findings reveal that while features such as RAM, internal storage, and screen resolution have gained increasing significance over time, the influence of standardized attributes like 3G connectivity and battery capacity has diminished. Furthermore, operating system analysis highlights the persistent premium pricing of iOS devices compared to Android alternatives, reflecting Apple's positioning in the high-end segment. These results underscore the interplay between technological advancements, shifting consumer preferences, and competitive market forces in shaping pricing trends.

This research contributes to the growing literature on hedonic pricing models and the application of machine learning in economic analysis, addressing the limitations of traditional methods in handling high-dimensional and rapidly evolving datasets. By providing actionable insights for manufacturers to optimize pricing strategies and for consumers to better assess product value, this study enhances understanding of the dynamic relationship between smartphone features and pricing in an ever-evolving market.

1 Introduction

The mobile phone market has rapidly evolved, with manufacturers annually introducing models featuring new technologies, enhanced performance, and improved designs. These advancements not only entice consumers to upgrade but also influence the lifecycle and pricing of previous generations (Shocker et al., 2004; Bayus, 1991). Understanding how specific features impact mobile phone prices—and how these influences change over time—is crucial for optimizing pricing strategies and understanding consumer behavior.

This research investigates the pricing dynamics of mobile phones from major brands like Apple, Samsung, and Google over the past decade. By analyzing features such as RAM, battery life, camera quality, and screen size, the study examines how technological advancements and shifting consumer preferences shape the importance of different attributes in determining price. Prior studies underscore the significant role of product features in consumer valuation (Chowdhury et al., 2021; Paluch & Kraus, 2017), while competition drives manufacturers to adopt feature-based pricing strategies (Kim et al., 2016).

Traditional hedonic models effectively capture quality adjustments but often fail to scale with rapidly evolving datasets and market demands (Shapiro, 2021). Recent advancements in machine learning, particularly the use of LASSO (Least Absolute Shrinkage and Selection Operator) regression, address these challenges by enabling efficient feature selection and regularization (Shapiro, 2022). This study applies a LASSO regression model to pooled year-specific data, capturing temporal trends in pricing determinants while maintaining consistency across analyses. By identifying the most impactful features over time, this research provides actionable insights for manufacturers to refine pricing strategies and for consumers to better evaluate product value in an ever-changing market.

2 Data

This research utilizes a dataset containing specifications and prices of various mobile phone models, sourced from Kaggle (Garai, 2023). This dataset contains detailed specifications and prices for a wide range of mobile phone models, making it ideal for comparing old and new models from major brands such as Samsung, Apple, and Google. Key features include brand, storage capacity, RAM, camera resolution, battery size, processor type, and operating system, which will be used to predict and compare the prices of both newer and older models.

Additional variables include release year and other specifications that will allow for a direct comparison of how feature improvements between generations of phones affect price differences. Data cleaning and processing will involve handling missing values, standardizing feature formats, and transforming categorical variables such as brand and operating system into numerical values for machine learning models.

Complementary or more-updated data will be obtained through web-scraping major ecommerce platforms such as GSM Arena, focusing specifically on new and older models from brands like Apple, Samsung, and Google.

The dataset includes 1,350 samples with 13 primary features, capturing essential technical specifications and pricing details for each phone model. Key features in the original dataset include:

Table 1: Key Features and Descriptions

Key Features	**Descriptions**
Battery capacity (mAh)	Battery charge capacity
Screen size (inches)	Display size in inches
Total Resolution (width x height)	Screen pixel dimensions
Processor type	CPU model and make
RAM (MB)	Memory size in megabytes
Internal storage (GB)	Built-in storage capacity
Rear camera	Number of rear cameras
Front camera	Number of front cameras
Operating system	Software platform (e.g., Android, iOS)
Wi-Fi	Wireless internet capability
Bluetooth	Device connectivity feature
GPS	Location tracking support
3G	Supports 3G networks
4G/LTE	Supports 4G networks
Number of SIMs	SIM card slots available
Pixel Density	Resolution per square inch

2.1 Data Cleaning and Preprocessing

Certain features, such as Name and Model, were dropped from the dataset as they are identifiers rather than predictors. One-hot encoding is used to transform categorical variables like Operating system and Brand into binary features. Binary variables—such as Touchscreen, Wi-Fi, Bluetooth, GPS, 3G, and 4G/LTE—were encoded as 0s and 1s. To enhance the dataset and improve predictive performance, several new features, Total Resolution and Pixel Density, were engineered. Missing values were imputed using the median value of the respective feature, ensuring a balanced distribution without introducing bias from extreme values. Additionally, I applied MinMaxScaler normalization to rescale all features to a common range, which aids in improving the efficiency and accuracy of machine learning models.

2.2 Web-Scraped Data

An essential aspect missing from the dataset is the release date for each phone model. This temporal data will allow for a more accurate comparison of "new" versus "old" models across generations, providing a vital variable for assessing how feature upgrades influence price changes across successive models.

To obtain the missing release dates and historical prices for each mobile model, I wrote a web-scraping program using the BeautifulSoup and Requests libraries, targeting GSMArena. This program retrieves each phone's release date and original price by searching for the model's name on the site, extracting the details directly from the corresponding pages. The scraped prices were listed in Indian Rupees (INR), which I converted to USD based on historical exchange rates at the time of each model's release. This conversion aligns all prices to a common currency, reflecting the international market context for each phone model's launch.

Following the currency conversion, I further adjusted the prices to account for inflation. Using cumulative inflation rates for each release year, I converted all prices to 2024 USD, enabling a direct and meaningful comparison across different time periods. The inflation-adjusted prices focus on isolating the impact of feature improvements, brand, and generational differences on pricing trends over time, unaffected by currency inflation.

To analyze how specific feature importance on pricing has evolved, I pooled the dataset by calendar year from 2012 to 2020. Data from 2012 and 2020 are dropped due to small sizes. This yearly segmentation allows for a temporal comparison, where I can train separate models for each year's data to explore trends in the influence of features like camera quality, processor type, and battery size on mobile phone prices. Observing these feature importance trends over time offers insights into shifting consumer preferences and technological advancements, as well as potential changes in pricing strategies by brands.

3 Methodology

The primary goal of this research is to understand how specific features influence the price of mobile phones over time and to identify which features play a significant role in determining price across different generations of models. By examining mobile phone prices by year, this study aims to observe trends in feature importance and analyze how improvements in specifications (such as RAM, battery life, camera quality, etc.) affect mobile pricings. Shapiro (2022) emphasizes the importance of leveraging sparsity-inducing models like LASSO for feature selection in high-dimensional hedonic pricing contexts. Similarly, this study employs LASSO regression to isolate the most impactful features influencing mobile phone prices, ensuring a parsimonious yet interpretable model.

The Least Absolute Shrinkage and Selection Operator (LASSO) is a regression model commonly used in machine learning for feature selection and regularization. LASSO regression is particularly valuable in contexts where there are numerous features, as it imposes an L1 penalty on the magnitude of the regression coefficients. This penalty encourages the model to shrink the coefficients of less important features to zero, effectively selecting only the most relevant features for prediction. The LASSO model is especially suitable for high-dimensional data or when interpretability is important, as it provides a more parsimonious model by reducing the number of predictors.

The LASSO regression formula is expressed as:

$$\mathbf{Price}_t = \beta_0^{(t)} + \sum_{i=1}^{p} \beta_i^{(t)} X_i + \lambda \sum_{i=1}^{p} |\beta_i^{(t)}|$$

where:

- $\mathbf{Price}_t$ represents the price of mobile phones in year t,
- $\mathbf{X}_i$ represents each feature i,
- $\beta_0^{(t)}$ is the intercept for year t,
- $\beta_i^{(t)}$ are the coefficients for feature i in year t,
- λ (or α in some implementations) is the regularization hyperparameter that controls the strength of the penalty term.

The L1 penalty term, $\lambda \sum_{i=1}^{p} |\beta_i^{(t)}|$, ensures that less significant coefficients are shrunk toward zero, promoting sparsity in the model and allowing only the most impactful features to remain. This characteristic of LASSO makes it a suitable choice for identifying the features that are most predictive of mobile phone prices.

3.1 Application in this Paper

LASSO regression is applied in this research to isolate the most influential features for each year in the dataset, thereby capturing how the importance of specific features evolves over time. Pooling the mobile phone data by year enables the model to estimate year-specific coefficients for each feature, helping to identify trends in feature valuation from year to year. By running a separate LASSO regression for each year, the study can assess whether certain features (e.g., RAM or battery size) become more or less critical to price determination over time.

To identify the optimal regularization strength, a range of potential λ values are assigned to each year's LASSO model. The performance of each model is evaluated across these values, and the best λ for each year is recorded based on model performance metrics (e.g., Mean

Absolute Error, RMSE). The average of the best λ values across all years is then selected as the single hyperparameter for all LASSO regressions in the study, ensuring a consistent level of regularization while reflecting the general importance of features across the entire timeline.

This pooled approach with year-specific regressions and a single λ for all models allows the analysis to capture both the overall influence of features on price and the nuances of year-to-year shifts in feature importance.

The models will be trained to predict price differences between older and newer models, focusing on identifying the attributes that contribute most to price changes. For example, how much does an improvement in camera quality or battery life impact the price of the newer model compared to the older one? Model evaluation will be done using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to determine prediction accuracy. Feature importance analysis will also be conducted to understand which phone attributes drive the most significant price changes between generations.

3.2 Hyperparameter Choice

Here's the list of the best hyperparameter for each year's data.

Table 2: Best Hyperparameter for Each Year

Year	2013	2014	2015	2016	2017	2018	2019
Best λ	10	1	1	1	10	0.01	1

Therefore, we set the L1 regularization term of the updated model to 1 for all regressions. The performance metrics of each regression model are as follows:

Table 3: Performance Metrics of Regression Models

Year/Metrics	**MAE**	**RMSE**	$\mathbf{R}^2$
2013	116.4191	138.3795	0.5603
2014	82.2017	106.7192	0.7234
2015	70.6622	94.3853	0.7812
2016	62.8692	92.2611	0.7834
2017	63.575	85.1083	0.7640
2018	88.8110	151.9727	0.6358
2019	124.3006	156.2476	0.7353

4 Results

4.1 Regression Tables

Table 4: 2013 Regression Results

Feature	Mean Coefficient	Lower Bound (2.5%)	Upper Bound (97.5%)	P-Value	Standard Error
Battery capacity (mAh)	-53.761	-218.632	0.000	0.442	72.660
Screen size (inches)	-18.314	-136.822	40.539	0.323	50.099
Touchscreen	0.000	0.000	0.000	0.000	0.000
Processor	0.092	-169.771	121.689	0.452	63.850
RAM (MB)	125.889	0.000	351.140	0.711	113.700
Internal storage (GB)	72.769	0.000	263.515	0.634	85.874
Rear camera	36.701	0.000	335.858	0.150	94.861
Front camera	-134.753	-286.986	0.000	0.830	81.073
Wi-Fi	0.000	0.000	0.000	0.000	0.000
Bluetooth	0.000	0.000	0.000	0.000	0.000
GPS	-22.565	-78.750	9.094	0.776	24.189
Number of SIMs	-19.394	-127.982	67.093	0.681	45.481
3G	-20.074	-78.659	8.292	0.702	24.011
4G/ LTE	32.034	-18.294	114.380	0.936	34.122
Log Price	753.226	609.870	942.054	1.000	85.605
Operating system_Android	6.415	-44.545	77.683	0.456	27.722
Operating system_BlackBerry	-9.105	-86.447	56.828	0.459	32.180
Operating system_Cyanogen	68.803	0.000	144.231	0.840	40.065
Operating system_Windows	-51.444	-151.229	15.649	0.921	43.207
Operating system_iOS	5.203	0.000	69.837	0.143	20.607
Total Resolution	15.269	-39.207	145.466	0.376	43.354
Pixel Density	-3.946	-102.008	70.989	0.152	34.882

Table 5: 2014 Regression Results

Feature	Mean Coefficient	Lower Bound (2.5%)	Upper Bound (97.5%)	P-Value	Standard Error
Battery capacity (mAh)	-53.761	-218.632	0.000	0.442	72.660
Screen size (inches)	-18.314	-136.822	40.539	0.323	50.099
Touchscreen	0.000	0.000	0.000	0.000	0.000
Processor	0.092	-169.771	121.689	0.452	63.850
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Front camera	-134.753	-286.986	0.000	0.830	81.073
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Bluetooth	0.000	0.000	0.000	0.000	0.000
GPS	-22.565	-78.750	9.094	0.776	24.189
Number of SIMs	-19.394	-127.982	67.093	0.681	45.481
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4G/ LTE	32.034	-18.294	114.380	0.936	34.122
Log Price	753.226	609.870	942.054	1.000	85.605
Operating system_Android	6.415	-44.545	77.683	0.456	27.722
Operating system_BlackBerry	-9.105	-86.447	56.828	0.459	32.180
Operating system_Cyanogen	68.803	0.000	144.231	0.840	40.065
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Pixel Density	-3.946	-102.008	70.989	0.152	34.882

Table 6: 2015 Regression Result

Feature	Mean Coefficient	Lower Bound (2.5%)	Upper Bound (97.5%)	P-Value	Standard Error
Battery capacity (mAh)	-45.333	-106.204	0.000	0.701	34.077
Screen size (inches)	-90.461	-183.990	0.000	0.914	45.373
Touchscreen	0.000	0.000	0.000	0.000	0.000
Processor	-30.446	-77.722	0.000	0.612	27.393
RAM (MB)	1.187	0.000	29.448	0.053	11.346
Internal storage (GB)	42.670	0.000	145.741	0.655	45.662
Rear camera	19.762	0.000	158.717	0.181	46.645
Front camera	-126.459	-189.357	-74.468	0.999	29.927
Wi-Fi	0.000	0.000	0.000	0.000	0.000
Bluetooth	0.000	0.000	0.000	0.000	0.000
GPS	5.824	-20.855	50.379	0.247	17.273
Number of SIMs	-53.635	-112.061	-8.419	1.000	26.858
3G	0.000	0.000	0.000	0.000	0.000
4G/ LTE	-44.395	-66.442	-24.633	1.000	10.519
Log Price	815.106	643.853	971.400	1.000	85.214
Operating system_Android	16.844	0.000	80.633	0.359	27.930
Operating system_BlackBerry	-18.614	-142.139	0.000	0.174	43.055
Operating system_Cyanogen	-2.747	-61.783	0.000	0.039	14.009
Operating system_Tizen	0.014	0.000	0.000	0.001	0.431
Operating system_Windows	-0.960	-76.401	52.250	0.119	23.639
Operating system_iOS	47.002	0.000	219.567	0.297	76.264
Total Resolution	388.333	0.000	590.167	0.949	156.942
Pixel Density	-8.141	0.000	0.000	0.044	83.053

Table 7: 2016 Regression Results

Feature	Mean Coefficient	Lower Bound (2.5%)	Upper Bound (97.5%)	P-Value	Standard Error
Battery capacity (mAh)	-5.374	-39.072	0.000	0.232	11.507
Screen size (inches)	-151.045	-222.838	-90.665	0.989	36.238
Touchscreen	2.735	0.000	55.531	0.046	12.846
Processor	-118.832	-176.358	-62.034	0.998	30.470
RAM (MB)	2.320	0.000	0.000	0.023	15.591
Internal storage (GB)	0.000	0.000	0.000	0.000	0.000
Rear camera	-115.545	-229.087	0.000	0.768	72.274
Front camera	-7.414	-86.929	0.000	0.100	23.453
Wi-Fi	0.000	0.000	0.000	0.000	0.000
Bluetooth	8.767	0.000	66.043	0.172	19.992
GPS	-3.143	-26.867	0.000	0.153	7.922
Number of SIMs	-1.966	-29.878	4.299	0.180	11.563
3G	4.545	-10.434	37.833	0.205	12.588
4G/ LTE	-45.809	-66.719	-27.349	1.000	10.154
Log Price	788.979	679.544	886.056	1.000	52.214
Operating system_Android	-31.382	-142.109	4.574	0.551	44.751
Operating system_Sailfish	0.000	0.000	0.000	0.000	0.000
Operating system_Tizen	0.000	0.000	0.000	0.000	0.000
Operating system_Windows	4.843	0.000	107.555	0.051	25.053
Operating system_iOS	83.271	0.000	295.181	0.352	115.901
Total Resolution	205.618	117.344	281.417	0.999	41.613
Pixel Density	0.000	0.000	0.000	0.000	0.000

Table 8: 2017 Regression Results

Feature	Mean Coefficient	Lower Bound (2.5%)	Upper Bound (97.5%)	P-Value	Standard Error
Battery capacity (mAh)	-95.191	-143.748	-45.430	1.000	26.024
Screen size (inches)	-111.005	-310.929	0.000	0.496	118.186
Touchscreen	-5.588	-71.652	0.000	0.121	19.576
Processor	-85.388	-142.580	0.000	0.934	32.462
RAM (MB)	-0.356	0.000	0.000	0.005	9.037
Internal storage (GB)	42.836	0.000	144.683	0.618	46.627
Rear camera	-183.659	-268.074	-83.242	0.991	49.177
Front camera	-52.614	-117.230	0.000	0.856	33.488
Wi-Fi	0.000	0.000	0.000	0.000	0.000
Bluetooth	-2.760	-49.306	0.000	0.058	11.820
GPS	8.459	-13.047	42.327	0.382	14.797
Number of SIMs	-37.945	-74.567	-3.632	0.995	18.295
3G	-13.456	-43.881	0.000	0.693	13.541
4G/ LTE	9.346	0.000	61.893	0.200	19.829
Log Price	1226.518	1048.678	1392.273	1.000	86.155
Operating system_Android	-85.342	-270.885	0.056	0.707	85.397
Operating system_Cyanogen	10.632	0.000	163.646	0.068	42.877
Operating system_Tizen	-4.385	-120.198	0.000	0.026	27.372
Operating system_iOS	92.646	0.000	325.373	0.529	105.306
Total Resolution	441.257	307.160	622.578	0.995	101.507
Pixel Density	-2.287	0.000	0.000	0.008	48.266

Table 9: 2018 Regression Results

Feature	Mean Coefficient	Lower Bound (2.5%)	Upper Bound (97.5%)	P-Value	Standard Error
Battery capacity (mAh)	0.000	0.000	0.000	0.000	0.000
Screen size (inches)	0.000	0.000	0.000	0.000	0.000
Touchscreen	0.000	0.000	0.000	0.000	0.000
Processor	0.000	0.000	0.000	0.000	0.000
RAM (MB)	0.100	0.000	0.000	0.001	3.174
Internal storage (GB)	0.000	0.000	0.000	0.000	0.000
Rear camera	0.000	0.000	0.000	0.000	0.000
Front camera	-2.666	0.000	0.000	0.011	25.434
Wi-Fi	0.000	0.000	0.000	0.000	0.000
Bluetooth	0.000	0.000	0.000	0.000	0.000
GPS	0.000	0.000	0.000	0.000	0.000
Number of SIMs	-0.118	0.000	0.000	0.002	2.659
3G	2.001	0.000	52.733	0.031	11.467
4G/ LTE	3.534	0.000	73.604	0.047	16.220
Log Price	1057.611	872.470	1200.776	1.000	85.916
Operating system_Android	-13.911	-193.229	0.000	0.089	59.335
Operating system_Cyanogen	0.000	0.000	0.000	0.000	0.000
Operating system_iOS	25.382	0.000	381.105	0.076	91.188
Total Resolution	63.197	0.000	264.923	0.321	95.587
Pixel Density	0.000	0.000	0.000	0.000	0.000

Table 10: 2019 Regression Results

Feature	**Mean Coefficient**	**Lower Bound (2.5%)**	**Upper Bound (97.5%)**	**P-Value**	**Standard Error**
Battery capacity (mAh)	-27.172	-108.186	7.775	0.680	33.823
Screen size (inches)	-187.876	-423.299	0.000	0.806	125.247
Touchscreen	3.457	0.000	28.656	0.030	22.378
Processor	-101.119	-169.799	-43.855	0.999	31.733
RAM (MB)	-20.073	-299.576	70.372	0.136	80.663
Internal storage (GB)	300.871	0.000	521.444	0.931	121.040
Rear camera	7.693	-461.047	272.902	0.311	150.101
Front camera	-122.077	-186.515	-50.037	0.998	34.874
Wi-Fi	0.000	0.000	0.000	0.000	0.000
Bluetooth	0.000	0.000	0.000	0.000	0.000
GPS	-12.453	-50.065	18.422	0.554	18.532
Number of SIMs	-44.111	-122.494	0.000	0.712	38.306
3G	-19.504	-190.122	46.148	0.532	59.816
4G/ LTE	85.383	0.000	263.922	0.925	68.365
Log Price	1013.363	850.770	1177.575	1.000	82.169
Operating system_Android	-43.740	-366.327	0.000	0.341	90.149
Operating system_Cyanogen	-3.541	-81.031	0.000	0.030	20.760
Operating system_iOS	242.835	0.000	424.151	0.790	138.237
Total Resolution	203.770	82.342	314.125	0.991	103.068
Pixel Density	-6.187	0.000	0.000	0.006	82.023

4.2 Coefficient Trend Interpretation

In the following section, a few noticeable trends in coefficients are further analyzed.

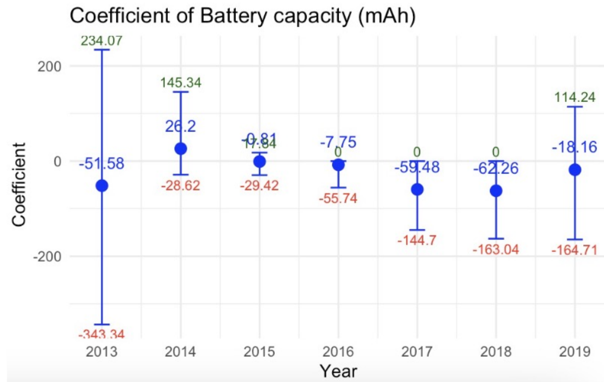

Figure 1: Battery Capacity Trend

The influence of battery capacity (mAh) on mobile phone prices exhibited significant variability over the years, as shown by the changing coefficients from 2013 to 2019. In 2013, the coefficient was negative (-51.58) with a wide confidence interval, indicating uncertainty in its role during this period. By 2014, the relationship shifted to a strong positive value (26.2), suggesting that battery capacity became a more important determinant of price. However, in the subsequent years, the coefficient gradually decreased, turning negative from 2016 onward (-7.75 in 2016 and -59.48 in 2017). This trend indicates that higher battery capacities were associated with lower prices during these years, possibly reflecting changes in market dynamics as battery technology became more standardized. In the later years (2018–2019), the negative relationship persisted but weakened (-62.26 in 2018 and -18.16 in 2019), suggesting that while battery capacity continued to influence prices, its importance diminished relative to other features. The large confidence intervals in earlier years further highlight the evolving valuation of battery capacity in the mobile phone market.

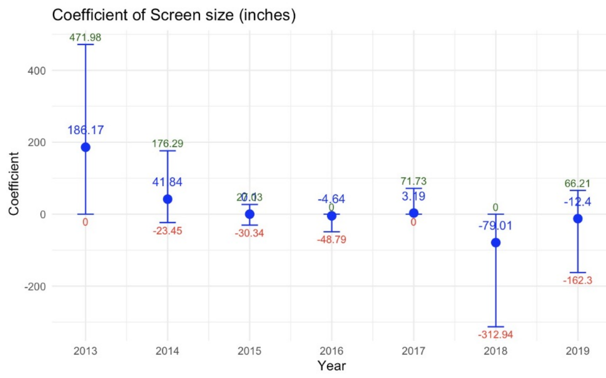

Figure 2: Screen Size Trend

The relationship between screen size (inches) and mobile phone prices varied significantly from 2013 to 2019. In 2013, the coefficient was positive (186.17) with a wide confidence interval, indicating some uncertainty about its importance during this period. By 2014, the coefficient remained positive (41.84) but had decreased substantially, suggesting a reduced impact of screen size on pricing. From 2015 to 2016, the coefficient shifted further, becoming negative (-30.34 in 2015 and -4.64 in 2016), which implies that larger screens began to have a weak or negligible association with higher prices. In 2017, the coefficient returned to a small positive value (3.19), indicating a slight resurgence in the importance of screen size for pricing. However, by 2018, the relationship again turned negative (-79.01) with a large confidence interval, signifying variability in its influence. In 2019, the coefficient was slightly negative (-12.4), suggesting that screen size became less critical as a pricing determinant by the end of the observed period. These fluctuations highlight the evolving role of screen size as a feature. While screen size initially had a positive influence on price, its impact diminished over time, likely due to the standardization of larger screens across models and the increasing importance of other features such as resolution and design quality.

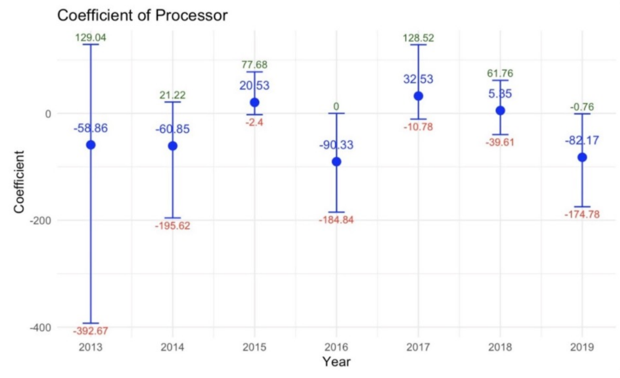

Figure 3: Processor Trend

The influence of processor type on mobile phone prices fluctuated significantly over the years, as indicated by the changing coefficients between 2013 and 2019. In 2013, the coefficient was negative (-58.86) with a wide confidence interval, suggesting some uncertainty in its role during this period. The negative trend continued into 2014 (-60.85) but with a reduced magnitude, indicating a consistent yet modest association between processor type and lower prices during these years.

By 2015, the coefficient turned slightly positive (20.53) and remained positive in 2016 (32.53), indicating a growing premium associated with certain processors. This shift might reflect advancements in mobile processors during this time and their increasing importance in driving consumer preferences. However, by 2017, the coefficient began to decline (5.85 in 2018 and -82.17 in 2019), suggesting a reduced impact of processor type on price as other features, such as cameras and storage, gained importance.

These variations highlight the evolving role of processor type in determining price, with periods of both positive and negative associations. The large confidence intervals in earlier years suggest greater variability in how processors influenced price, which stabilized in later years as the technology became more standardized across models.

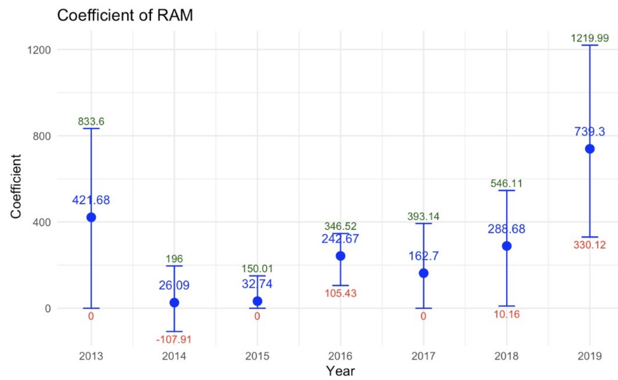

Figure 4: RAM Trend

The influence of RAM on mobile phone prices showed a consistently positive trend from 2013 to 2019, with an overall increase in its importance over the years. In 2013, the coefficient was 421.68 with a wide confidence interval, indicating that RAM had a notable but uncertain influence on price. By 2014, the coefficient dropped sharply to 26.09, reflecting a diminished impact, possibly due to varying consumer priorities during that year.

Starting in 2015, the importance of RAM began to steadily increase, with coefficients rising from 150.01 in 2015 to 242.67 in 2016 and 393.14 in 2017. This upward trend suggests that as RAM capacities increased across models, consumers placed greater value on higher memory, making it a more significant determinant of price.

In 2018 and 2019, the coefficients further increased to 546.11 and 739.3, respectively, with larger confidence intervals indicating some variability in its effect across models. By 2019, the sharp increase in the coefficient suggests that RAM had become one of the most critical features influencing mobile phone prices, likely due to the rising demands of modern applications and multitasking capabilities.

This trend highlights the growing importance of RAM in driving mobile phone prices, particularly in the later years, as smartphones evolved to meet higher performance expectations.

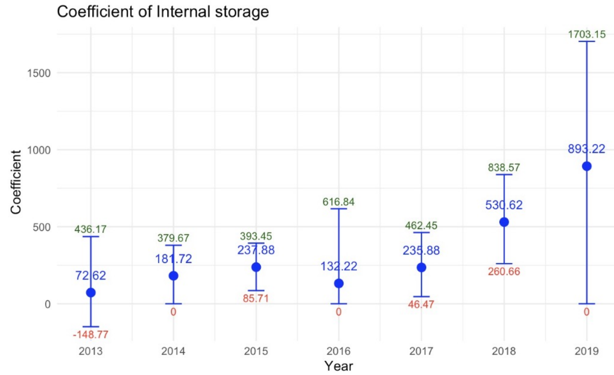

Figure 5: Internal Storage Trend

The coefficient of internal storage exhibited a consistently positive trend from 2013 to 2019, highlighting its increasing importance as a determinant of mobile phone prices. In 2013, the coefficient was modest at 72.62, with a wide confidence interval indicating some uncertainty about its influence. Over the subsequent years, the coefficient steadily increased, reaching 237.88 in 2015 and peaking at 530.62 in 2018. This trend reflects the growing consumer demand for higher storage capacities, driven by the proliferation of apps, media, and data-intensive features.

The largest jump occurred in 2019, where the coefficient surged to 893.22, with a wide confidence interval suggesting variability across phone models. This substantial increase underscores the critical role of internal storage in determining price, as larger capacities became not only desirable but essential for modern smartphones. The steady rise in the coefficient values over time demonstrates that storage size transitioned from being a supplementary feature to a core driver of value in the mobile phone market.

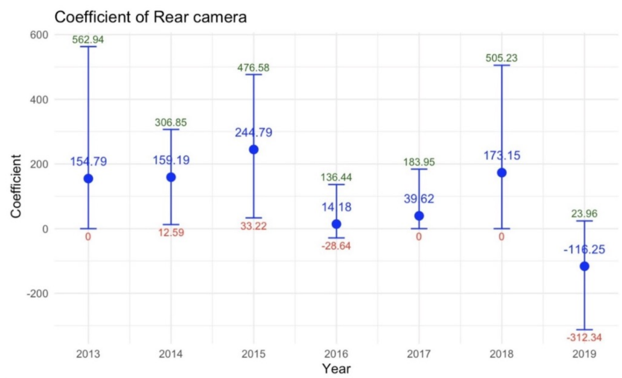

Figure 6: Rear Camera Trend

The influence of rear camera quality on mobile phone prices demonstrated notable fluctuations from 2013 to 2019. In 2013, the coefficient was 154.79 with a wide confidence interval, indicating a moderate but uncertain impact of rear camera quality on pricing. This positive relationship persisted in 2014 and 2015, with coefficients of 159.19 and 244.79, respectively, suggesting that higher camera quality became an increasingly valued feature during this period.

By 2016, the coefficient dropped to 136.44, and in 2017, it remained moderate at 39.62, reflecting a diminishing but still positive impact of rear camera quality on pricing. In 2018, the coefficient was 173.15, indicating a brief resurgence in the importance of rear cameras. However, by 2019, the coefficient declined significantly to -116.25, signaling a negative relationship between rear camera quality and price, possibly due to advancements in other features overshadowing the role of rear cameras in driving consumer preferences.

These trends highlight the evolving role of rear cameras as a differentiating factor in mobile phone pricing. While rear camera quality was an important determinant in earlier years, its influence waned in later years, potentially due to standardization of camera technology across models.

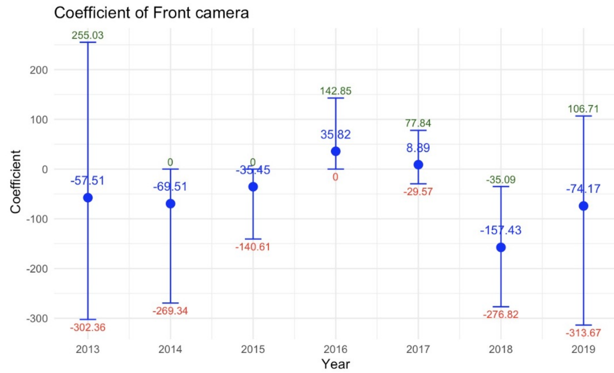

Figure 7: Front Camera Trend

The influence of front camera quality on mobile phone prices displayed significant variability and inconsistency from 2013 to 2019. In 2013, the coefficient was negative (-57.51) with a wide confidence interval, indicating a modest negative relationship with pricing, though the uncertainty suggests variability across models. This trend continued into 2014 (-69.51) and 2015 (-35.45), indicating that higher front camera quality had little to no added value to the price during these years, possibly due to its secondary importance compared to rear cameras.

By 2016, the coefficient turned slightly positive (35.82), signaling an increasing association between front camera quality and price. This positive trend persisted into 2017 (77.84), suggesting that the growing popularity of selfies and video calls led to greater consumer demand for better front-facing cameras. However, from 2018 onward, the coefficient returned to negative territory (-35.09 in 2018 and -74.17 in 2019), reflecting a diminishing role of front cameras in price determination, potentially due to their standardization across phone models.

These trends highlight the fluctuating importance of front camera quality in influencing mobile phone prices. While front cameras gained value in the mid-2010s as a differentiating feature, their impact waned in later years as advancements in other features, such as processing power and storage, took precedence.

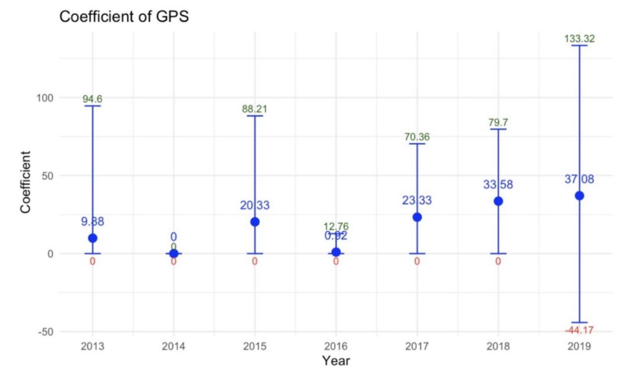

Figure 8: GPS Trend

The coefficient of GPS functionality demonstrated modest but varying importance in determining mobile phone prices from 2013 to 2019. In 2013, the coefficient was slightly positive (9.88) with a wide confidence interval, indicating some association between GPS and price, albeit with uncertainty. In 2014, the coefficient dropped to zero, highlighting its negligible influence during that year.

From 2015 onward, the coefficients showed a gradual increase, reaching 20.33 in 2015 and peaking at 70.36 in 2017, suggesting that advancements in GPS capabilities or its integration into smartphones may have contributed to slight price differentiation during this period. In 2018 and 2019, the coefficients remained positive at 33.58 and 37.08, respectively, though with considerable variability as indicated by the wide confidence intervals.

Overall, the results suggest that while GPS was not a dominant driver of mobile phone prices, it gained moderate significance in later years, potentially reflecting consumer demand for location-based services and navigation features. Despite this, its influence remained relatively minor compared to other features such as storage or RAM.

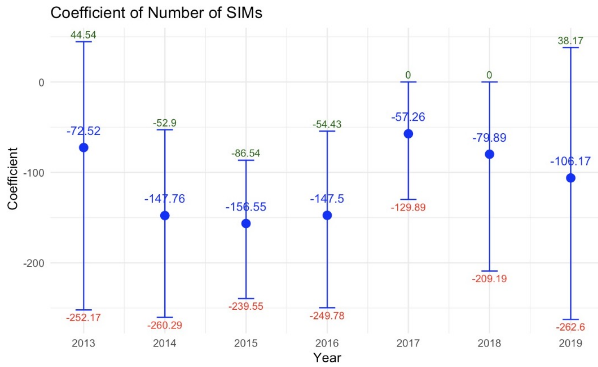

Figure 9: Number of SIMs Trend

The coefficient of the number of SIMs shows a consistently negative relationship with mobile phone prices from 2013 to 2019, suggesting that devices with dual or multiple SIM slots were generally priced lower than their single-SIM counterparts. In 2013, the coefficient was moderately negative (-72.52) with a wide confidence interval, indicating some variability in its effect across phone models. This trend continued into 2014 (-147.76) and 2015 (-156.55), with a further decline in 2016 (-147.50), emphasizing the growing association of multiple SIMs with lower-priced phones, likely due to their popularity in budget and mid-range markets.

From 2017 to 2019, the coefficients remained negative but exhibited slight fluctuations (-57.26 in 2017, -79.89 in 2018, and -106.17 in 2019). The consistently wide confidence intervals across the years suggest variability in the influence of SIM slots on price, depending on the market segment or target audience for the phones. Overall, the results reflect the positioning of multi-SIM devices as a feature typically associated with affordability and utility rather than premium pricing.

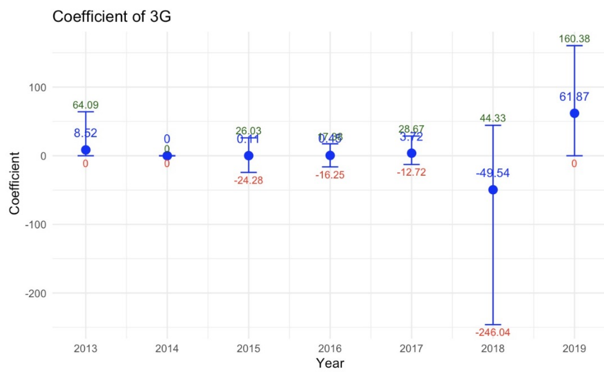

Figure 10: 3G Trend

The coefficient of 3G connectivity fluctuated significantly over the years, reflecting its changing role in determining mobile phone prices from 2013 to 2019. In 2013, the coefficient was modestly positive (8.52) with a wide confidence interval, suggesting a minor influence of 3G on price. In 2014, the coefficient dropped to zero, indicating that 3G connectivity was no longer a differentiating factor as it became standard across most devices.

From 2015 to 2017, the coefficients showed slight positive values (6.11 in 2015 and 3.72 in 2017), indicating a minor resurgence in its influence, though the effect remained small. However, in 2018, the coefficient dropped significantly to -49.54 with a large confidence interval, suggesting a diminishing role of 3G as newer connectivity technologies like 4G/LTE became more prominent.

By 2019, the coefficient rebounded to a strongly positive value (61.87), reflecting a potential increase in 3G's relevance for lower-end models in markets where 4G penetration remained limited. Overall, the variability in coefficients over time highlights the evolving role of 3G, transitioning from a premium feature in earlier years to a diminishing factor as technology advanced.

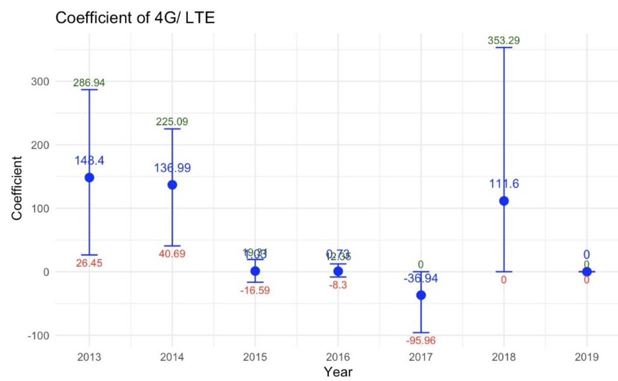

Figure 11: 4G Trend

The coefficient of 4G/LTE connectivity shows a clear evolution over time, reflecting its transition from a premium feature to a standard one in mobile phones between 2013 and 2019. In 2013, the coefficient was significantly positive (148.4), suggesting that 4G/LTE connectivity added considerable value to mobile phones during its early adoption phase. This trend persisted in 2014 (136.99), emphasizing its continued importance as a differentiating feature.

However, from 2015 to 2017, the coefficients began to decline sharply, turning slightly negative in 2017 (-36.94), as 4G became more ubiquitous and less of a distinguishing factor. By 2018, the coefficient increased again to 111.6, possibly reflecting advancements in 4G technology or its integration into higher-end models. In 2019, the coefficient returned to zero, indicating that by this time, 4G/LTE had become a standard feature across nearly all models, no longer influencing pricing decisions.

These trends highlight the lifecycle of 4G/LTE connectivity as a pricing factor, with its initial premium status diminishing over time as the technology became widely adopted and normalized in the mobile phone market.

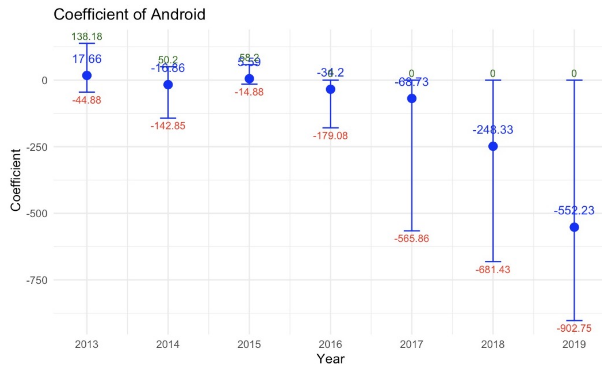

Figure 12: Android Trend

The coefficient of Android as an operating system reveals a significant and increasingly negative relationship with mobile phone prices over the years, reflecting its association with a broader range of low- and mid-tier devices compared to other operating systems. In 2013, the coefficient was slightly positive (17.66) with a wide confidence interval, indicating some variability in its influence. By 2014, the coefficient had turned negative (-16.86), and this downward trend continued into 2015 (-5.29) and 2016 (-34.2), signaling a growing association of Android with lower-priced devices.

From 2017 onward, the coefficient became strongly negative, dropping to -68.73 in 2017, -248.33 in 2018, and -552.23 in 2019, indicating that Android-powered devices were consistently priced lower than their counterparts. This pattern underscores the dominance of Android in the budget and mid-range segments of the mobile phone market, which contrasts with competing operating systems like iOS that are predominantly featured in high-end devices.

The large negative coefficients in later years suggest that while Android's flexibility and adoption across a variety of devices expanded its market share, it also solidified its position in less expensive product categories, thereby exerting downward pressure on prices.

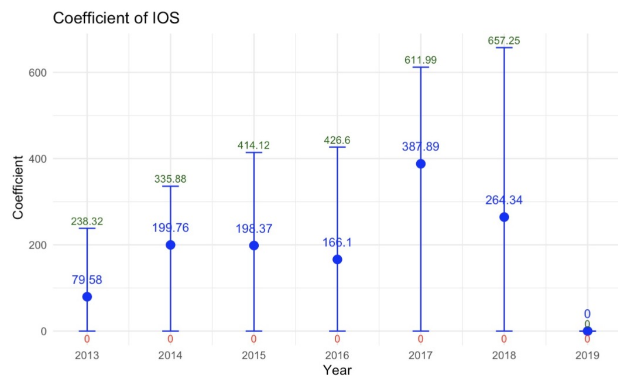

Figure 13: IOS Trend

The coefficient of iOS as an operating system exhibited a strong and consistently positive relationship with mobile phone prices from 2013 to 2018, reflecting its association with high-end devices. In 2013, the coefficient was relatively modest at 79.58, but it increased steadily in subsequent years, reaching 199.76 in 2014 and 198.37 in 2015. This positive trend highlights the premium pricing associated with iOS devices, likely driven by their brand perception, exclusive features, and ecosystem.

From 2016 to 2018, the coefficient saw a further sharp increase, peaking at 387.89 in 2017, before slightly declining to 264.34 in 2018. The large confidence intervals during these years reflect variability across models but consistently confirm the premium status of iOS devices. By 2019, the coefficient dropped to zero, suggesting that by this time, the specific influence of iOS on pricing had diminished, possibly due to the standardization of high-end features across the mobile market or saturation of the premium segment.

These results emphasize the role of iOS as a strong pricing determinant during its peak years, solidifying its position as a marker of premium devices, especially in earlier years of the observed period.

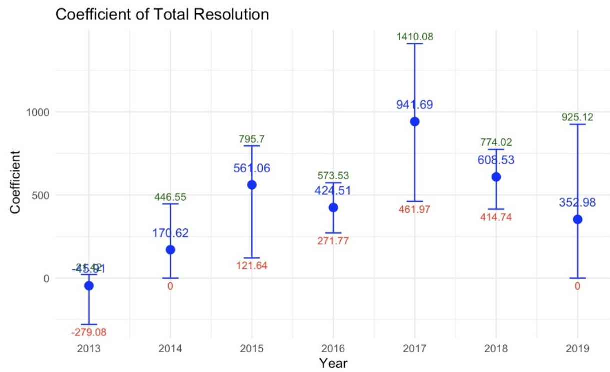

Figure 14: Total Resolution Trend

The coefficient of total resolution consistently demonstrated a strong positive relationship with mobile phone prices from 2013 to 2019, underscoring its importance as a key determinant of price. In 2013, the coefficient was slightly negative (-45.91), with a large confidence interval suggesting uncertainty about its influence during the early stages of resolution improvements. However, from 2014 onward, the coefficient increased significantly, reaching 446.55 in 2014 and peaking at 795.7 in 2015, reflecting the growing consumer demand for higher resolution displays and their association with premium devices.

From 2016 to 2018, the coefficients stabilized at elevated levels, with values of 573.53 in 2016, 941.69 in 2017, and 774.02 in 2018. This trend highlights the sustained impact of display resolution on pricing during the mid-to-late 2010s, as screen quality became a central focus in smartphone differentiation. In 2019, the coefficient remained high at 352.98, though the slight decline suggests that advancements in resolution might have become less differentiated across models by this time.

These results illustrate the critical role of total resolution in influencing mobile phone prices, particularly during the years of rapid improvement in display technology, as consumers increasingly valued sharper and more vibrant screens.

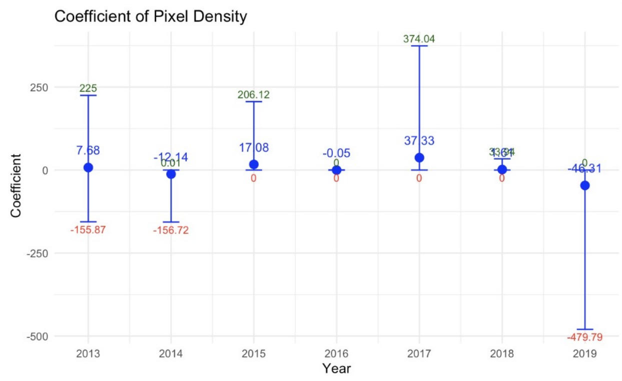

Figure 15: Pixel Density Trend

The coefficient of pixel density revealed notable variability over the years, reflecting its evolving role in determining mobile phone prices. In 2013, the coefficient was slightly positive (7.68) with a wide confidence interval, suggesting a minor influence of pixel density on price during the early years of smartphone display development. In 2014, the coefficient dropped to -12.14, indicating a negligible or even slightly negative impact on price as this feature began to standardize across devices.

From 2015 onward, the influence of pixel density became more pronounced, with the coefficient increasing to 17.08 in 2015 and peaking at 37.33 in 2017. This upward trend highlights the growing consumer preference for sharper and higher-resolution displays during this period. However, in 2018 and 2019, the coefficient declined slightly, reaching 33.61 in 2018 and turning slightly negative (-46.31) in 2019. The wide confidence interval in 2019 reflects uncertainty, likely due to the varying importance of pixel density across different market segments.

Overall, the results suggest that while pixel density was an important feature influencing prices during the mid-2010s, its impact diminished in later years as other display features, such as screen size and total resolution, gained prominence in driving consumer preferences.

5 Conclusion

This study investigated the determinants of mobile phone prices across different years, focusing on how specific features influenced pricing trends over time. By employing LASSO regression on pooled data with year-specific interactions, the analysis provided valuable insights into the evolving roles of various technical specifications in determining the value of mobile phones.

RAM and internal storage consistently emerged as key determinants of mobile phone prices across the analyzed years. The coefficients for both features exhibited significant growth, reflecting their increasing importance in consumer valuation. This aligns with findings from Chowdhury et al. (2021), who emphasize that memory and storage play a pivotal role in determining the perceived value of smartphones. As applications became more resource-intensive and consumer expectations for multitasking grew, higher RAM and storage capacities transitioned from supplementary features to primary drivers of price. This trend highlights the growing importance of performance in shaping consumer preferences and pricing strategies, particularly in the premium and mid-range segments.

Display quality, captured by screen resolution and pixel density, was another significant factor influencing mobile phone prices. The coefficients for these features peaked during the mid-to-late years of the analysis, indicating a period when display technology served as a key differentiator in the market. Shapiro (2022) notes that advancements in display technologies are among the most visible and marketable improvements, driving consumer willingness to pay premiums. However, as high-resolution screens became standardized, their pricing influence began to stabilize, suggesting a shift in market dynamics where other features, such as performance or design, gained prominence.

Camera quality demonstrated an interesting evolution, with the rear camera initially showing a strong positive impact on price, which diminished over time. The front camera, on the other hand, showed a brief period of rising importance during the "selfie boom" years before its influence waned. This aligns with Kim and Srinivasan's (2016) observation that consumer preferences for specific features are often influenced by societal trends and technological advancements. The decline in camera importance in recent years reflects the standardization of high-quality camera systems across models, making them less of a pricing differentiator.

Connectivity features exhibited a clear lifecycle pattern. The significance of 3G declined sharply as 4G/LTE became widely adopted, with 4G/LTE showing a strong positive influence on price during its early adoption phase. However, as Shocker et al. (2004) highlight, the adoption of new technologies follows a predictable curve, with early adopters driving initial premiums before features become standardized. By the later years of the analysis, 4G/LTE and other connectivity features, such as Wi-Fi and Bluetooth, exhibited negligible influence on price, reflecting their ubiquity across all device segments.

Operating systems showed a stark contrast in their influence on mobile phone prices. iOS consistently commanded a significant price premium, reflecting Apple's positioning as a high-end brand and its strong association with exclusivity and ecosystem integration (Paluch & Kraus, 2017). Conversely, Android devices were associated with lower price points, particularly in the mid-to-low-tier market segments. This divergence underscores the role of operating systems in shaping market segmentation and consumer perception, with iOS dominating the premium segment and Android offering a broader range of affordable options. The pricing dynamics of operating systems highlight their centrality in differentiating product value.

Battery capacity showed fluctuating importance, with a positive influence on price in earlier years that gradually diminished and even turned negative in later years. This trend may reflect the market's transition to prioritizing other factors, such as charging efficiency and performance optimization, over raw battery size. Multi-SIM functionality consistently showed a negative relationship with price, reflecting its association with budget and mid-tier devices. As noted by Shapiro (2021), features targeting specific consumer segments often polarize pricing dynamics, with multi-SIM phones catering primarily to cost-sensitive consumers in developing markets. This trend highlights how market segmentation influences the valuation of technical specifications.

The results demonstrate the dynamic nature of the smartphone market, where feature relevance evolves in tandem with technological advancements and consumer preferences. This evolution highlights the importance of contextualizing pricing strategies within the broader technological landscape. By identifying key price determinants and their trajectories over time, this research provides valuable insights for manufacturers and consumers alike, aiding in the understanding of pricing trends and the development of informed market strategies.

Future research could expand on this work by incorporating additional datasets, exploring global market differences, or examining the interplay between pricing strategies and consumer satisfaction. Additionally, incorporating emerging features such as AI capabilities and 5G connectivity could provide further insights into the future of smartphone pricing and the ongoing competition between Android and iOS platforms (Kim et al., 2016).

6 Discussion

There are certain limitations in this research. One significant challenge lies in the dataset itself. While the data spans multiple years, it is limited to models from certain manufacturers and specific features. This restriction may overlook other influential factors, such as regional price variations, marketing strategies, or broader economic conditions. Future studies could address this limitation by integrating more comprehensive datasets that include global market trends and emerging manufacturers.

Another key limitation is the reliance on cumulative inflation adjustments and historical exchange rates to standardize prices across years. While these adjustments are essential for comparability, they may introduce noise due to inaccuracies in economic indicators or unaccounted market-specific inflation rates. Incorporating region-specific price indices or alternative price normalization methods could refine these adjustments, ensuring a more precise analysis of temporal trends.

A technical shortcoming in this study is the failure to use the log-transformed price as the dependent variable. While log price is commonly used in hedonic pricing models to stabilize variance and interpret coefficients as elasticities, the implementation of log price caused the regression code to collapse for unknown reasons. This issue remains unresolved but highlights a clear area for improvement. Future iterations of this analysis should prioritize using log price, as it could improve model performance and offer more meaningful insights into the proportional effects of features on smartphone prices.

The use of LASSO regression, while effective for feature selection and regularization, has its limitations. By design, LASSO tends to shrink coefficients, which may underestimate the impact of certain features, especially when multicollinearity exists among predictors. Alternative methods, such as Elastic Net regression, could mitigate this bias by balancing the benefits of L1 and L2 regularization. Additionally, using post-selection inference methods could provide more robust statistical insights into feature significance.

One notable trend observed in the analysis is the declining influence of features such as 3G connectivity, Bluetooth, and battery capacity, reflecting their standardization. However, the model does not explicitly capture interactions between features, such as the synergy between processor type and battery efficiency, which may influence pricing dynamics. Future research could incorporate interaction terms or adopt non-linear models like random forests or gradient boosting to capture these complex relationships.

Finally, while this study captures temporal trends in feature importance, it does not fully address the influence of external factors like consumer sentiment, technological disruptions (e.g., the introduction of 5G), or supply chain dynamics. Incorporating sentiment analysis from social media or sales data could offer a richer context for understanding price changes and consumer behavior.

Despite these limitations, the study underscores the importance of technological evolution and market dynamics in shaping smartphone pricing strategies. By identifying key features that drive price differentiation and examining their trajectories over time, this research provides a foundation for further exploration into the interplay between innovation, consumer preferences, and pricing in the smartphone industry. Future studies could extend this work by exploring emerging technologies like artificial intelligence capabilities or environmental sustainability features, which are likely to shape the next generation of smartphones and their associated pricing models.

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