Assessing the Impact of Laptop Condition on Pricing Using Statistical Analysis: Insights for Digital Marketing Strategies on eBay

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ABSTRACT

This study investigates the influence of laptop condition on pricing in the eBay marketplace, using statistical analysis to provide actionable insights for digital marketing strategies. The analysis is based on a dataset containing 2,952 laptop listings, categorized by condition into New, Open box, Excellent - Refurbished, Very Good - Refurbished, and Good - Refurbished. An ANOVA test revealed a significant difference in mean prices across these conditions (F-value = 76.69, $p < 0.0001$), indicating that condition is a critical factor in pricing. Post-hoc analysis using Tukey's HSD test further highlighted specific pairwise differences. For instance, the price difference between New and Good - Refurbished laptops was found to be approximately $192.66 ($p < 0.0001$), confirming that even minor wear significantly impacts consumer perception and pricing. Additionally, Excellent - Refurbished laptops were priced, on average, $62.79 higher than their New counterparts ($p = 0.0008$), suggesting a premium for well-maintained refurbished models. A multiple linear regression model was employed to quantify the impact of various factors on pricing, including condition, brand, RAM, and processor type. The model, with an R-squared value of 0.429, indicated that these variables collectively explain 42.9% of the variation in laptop prices. Despite the model's moderate fit, the coefficients provided insights into the relative importance of each factor, with condition emerging as the most influential determinant. The findings suggest that eBay sellers should prioritize accurate and detailed descriptions of product condition to optimize pricing strategies. These results underscore the importance of condition-based pricing in digital marketing, offering a data-driven approach to maximizing profitability in online marketplaces.

Keywords Laptop Pricing, eBay, Statistical Analysis, Product Condition, Digital Marketing Strategies

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INTRODUCTION

In the dynamic landscape of digital marketing, pricing strategies are pivotal in determining a product's success. Effective pricing not only attracts potential buyers but also maximizes profits and enhances a brand’s competitiveness in the market. In an era where consumers have easy access to a vast array of choices, setting the right price can be the key differentiator that drives sales and fosters brand loyalty. To achieve this, pricing strategies must consider various factors, including market demand, competitor pricing, and product attributes. Leveraging data to inform these strategies has become increasingly vital, enabling

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businesses to make evidence-based decisions that are in sync with market dynamics and consumer behavior.

The relationship between pricing strategies and digital marketing is particularly significant. As [1] suggests, a well-defined digital marketing strategy can amplify marketing innovation, which in turn influences pricing decisions. This underscores the importance of integrating pricing strategies with broader marketing efforts to optimize product success. Moreover, the advent of Artificial Intelligence (AI) has revolutionized pricing strategies. Research by [2], highlights how AI and machine learning algorithms are being used for predictive analytics, allowing businesses to tailor their pricing based on consumer insights and market trends. This ability to dynamically adjust prices enhances a company's responsiveness to market demands, making their pricing strategies more agile and effective.

The concept of optimal pricing under uncertainty is also crucial for maximizing revenue. Research by [3], explored how trade-in options for successive-generation products can shape pricing strategies, emphasizing the need to understand consumer behaviour and product lifecycles. Additionally, research by [4], on price commitments suggests that static pricing strategies can help mitigate the tendency of consumers to wait for discounts, thus stabilizing revenue streams. Furthermore, the role of brand image in pricing cannot be overlooked. Research by [5] found that brand image, along with pricing and digital marketing efforts, significantly influences consumer buying decisions. This highlights the necessity for businesses to align their pricing strategies with brand positioning and marketing initiatives to effectively drive consumer engagement and sales.

eBay, established in 1997, has grown into a prominent global platform that facilitates transactions between individuals and businesses worldwide [6]. As one of the largest online marketplaces, eBay offers a diverse range of products, including new, refurbished, and second-hand laptops from various brands and models. The platform's extensive reach and detailed product listings make it a valuable source of data for analyzing market trends and consumer preferences. Particularly in the electronics sector, eBay provides a convenient channel for individuals to buy and sell used devices, including laptops, making it a significant player in the online marketplace [7]. However, the rise of second-hand electronic device sales online has raised concerns about security and privacy, especially when dealing with items like storage devices, highlighting the need for user-centric considerations [8].

Initially launched as an online auction platform, eBay quickly gained popularity by enabling individuals to buy and sell items through bidding. Over time, the platform has shifted towards favoring fixed-price listings, a trend driven by consumer preference for the convenience and certainty of posted prices over the uncertainty of bidding. Research by [9] indicates a significant decline in the share of auctions in favor of fixed-price listings, mirroring a broader trend in e-commerce. The rise of consumer-to-consumer marketplaces has expanded the range of product conditions available on eBay, contributing to the growing acceptance of used and refurbished goods. Research by [10] explored how consumers evaluate refurbished products alongside new ones, highlighting a shift towards sustainability and cost-effectiveness, with more buyers seeking value in pre-owned items. Demographic changes have also influenced eBay's evolution, with [11] noting that rural consumers are increasingly using the internet for product information and purchases, extending eBay's reach beyond urban centers. To meet the diverse needs of its users, eBay has embraced technological advancements, such as integrating visual search capabilities, which allow consumers to search for products using images.

The primary objective of this research is to assess how the condition of a laptop—whether new, open box, or refurbished affects its pricing on eBay. This study aims to quantify the price differences attributable to each condition category and understand the underlying reasons for these variations. Recognizing the importance of product condition in consumer purchasing decisions, this research seeks to provide a detailed analysis that helps sellers better understand market dynamics. By focusing on the condition of laptops, we aim to offer insights that enable sellers to set competitive and realistic prices that align with consumer expectations and enhance sales performance.

To achieve this objective, we employ statistical analysis on a comprehensive dataset obtained from eBay. This dataset includes detailed information on various laptop attributes such as brand, screen size, RAM, processor, GPU, resolution, condition, and price. Our methodological approach involves performing descriptive statistics, Analysis of Variance (ANOVA), and multiple linear regression. These techniques allow us to compare average prices across different conditions and control for other influencing factors, ensuring a robust analysis. By utilizing these statistical methods, we aim to derive meaningful conclusions about the impact of laptop condition on pricing.

The findings from this research have the potential to significantly impact digital marketing strategies for sellers on eBay. By providing empirical evidence on how different conditions affect pricing, sellers can refine their pricing strategies to better match market demand. For instance, understanding the price premium that consumers are willing to pay for new laptops compared to open box or refurbished ones can guide sellers in their inventory and marketing decisions. Additionally, insights into consumer price sensitivity based on laptop condition can help sellers optimize their promotional efforts, enhancing their competitive edge.

Literature Review

Pricing Strategies in Digital Marketing

An overview of existing pricing strategies in digital marketing reveals a complex and evolving landscape where businesses must continuously adapt to the dynamic demands of the online marketplace. Traditional approaches, such as cost-plus pricing and competitive pricing, remain relevant but have been transformed by digital technologies. Dynamic pricing, which adjusts prices in real-time based on factors like supply, demand, and competitor actions, has become particularly effective in e-commerce platforms like eBay, where market conditions can fluctuate rapidly. Additionally, psychological pricing, which manipulates consumer perceptions by setting prices just below a round number, is commonly used to influence purchasing decisions.

More advanced strategies include personalized pricing and value-based pricing. Personalized pricing leverages customer data to tailor prices according to individual purchasing history and preferences, thereby enhancing customer satisfaction and loyalty. Value-based pricing, meanwhile, focuses on setting prices based on the perceived value to the customer rather than the cost of the product. This approach is particularly effective for high-value items, such as laptops, where brand reputation and product features heavily influence consumer perceptions of value. The integration of data-driven pricing decisions in digital marketing has further revolutionized pricing strategies. Businesses can now utilize analytics and machine learning algorithms to set optimal prices, drawing on historical sales data, market trends, and competitive analysis. This not only improves pricing accuracy but also enables more agile and responsive adjustments. Predictive analytics, for instance, can help businesses anticipate market changes and adjust prices proactively, maintaining a competitive edge.

The significance of data-driven decision-making in pricing strategies is underscored by its ability to maximize revenue, improve customer satisfaction, and maintain market competitiveness. Predictive modeling can identify price elasticity, helping businesses understand how price changes impact demand, while clustering algorithms can segment customers based on price sensitivity and purchasing behavior, allowing for more targeted pricing strategies. Various studies have examined these aspects of digital pricing strategies. Research by [12] emphasized dynamic pricing in dual-channel retailing for seasonal products, highlighting the importance of adjusting prices and sales efforts based on inventory levels. Research by [13] explored price promotions in online stores, demonstrating how different forms of promotion, such as quantity discounts, influence consumer purchase patterns. Study by [14] discussed how digital marketing impacts brand awareness, sales, and customer engagement, stressing the role of pricing strategies in enhancing sales conversion rates. Finally, [15] showcased how online retailers align online and offline pricing tactics, using strategies like advertised reference prices and price-matching policies to attract and retain customers.

Impact of Product Condition on Pricing

Numerous studies have investigated the influence of product condition, particularly comparing new and refurbished items, on consumer perception and pricing. Consumers often perceive new products as superior in quality, reliability, and longevity compared to refurbished or used items, which significantly impacts their willingness to pay a premium for new products. To fully understand the impact of product condition on customer perception and pricing, it is crucial to consider various factors, including digital marketing strategies, product quality, and customer satisfaction. The condition of a product—whether new, refurbished, or used—can greatly influence how customers perceive its value and the pricing they are willing to accept.

Digital marketing plays a pivotal role in shaping customer perceptions and influencing purchasing decisions. Research has shown that effective digital marketing strategies can establish emotional connections between customers and products, leading to increased engagement beyond just purchasing behavior [16]. Moreover, digital marketing efforts can enhance customer trust, perceptions of product quality, and overall company reputation, which are essential factors in shaping customer views on product condition and pricing [17]. The ability of digital marketing to positively influence these perceptions underscores its importance in determining how customers evaluate, and value products based on their condition.

Product quality is another critical aspect that directly impacts customer perception and pricing. Studies have indicated that product quality significantly affects customer loyalty and satisfaction [18]. Customers often associate higher quality with higher prices, which emphasizes the need for maintaining high product quality standards to justify pricing strategies. Additionally, customer satisfaction plays a fundamental role in pricing decisions and influences customer loyalty. Research has demonstrated that customer satisfaction is positively affected by digital marketing efforts, product quality, and overall customer experience [19]. Satisfied customers are more likely to make repeat purchases and recommend products to others, highlighting the importance of considering customer satisfaction in developing effective pricing strategies.

Statistical Methods in Pricing Analysis

Statistical methods are integral to pricing analysis, allowing researchers and practitioners to make informed, data-driven decisions. A widely used technique in this field is ANOVA, which is particularly effective for comparing means across multiple groups to determine if significant differences exist. In the context of pricing, ANOVA is used to assess whether the mean prices of laptops differ significantly based on their condition—such as new, open box, or refurbished. The fundamental concept behind ANOVA involves partitioning the total variability observed in the data into two components: variability within groups and variability between groups. The F-statistic, calculated as $F = \frac{\text{Between-group variability}}{\text{Within-group variability}}$ quantifies this comparison. A higher F-value indicates a greater degree of difference between the groups, suggesting significant disparities in pricing based on the condition of the laptops.

Beyond ANOVA, various statistical techniques are employed across industries to analyze pricing data and derive actionable insights. For example, [20] applied descriptive statistics, panel data least squares multiple regression, and correlation analysis to investigate the impact of dividend policy decisions on share price volatility among Modaraba companies listed on the Pakistan Stock Exchange. This study exemplifies the practical application of statistical methods in understanding the relationship between dividend policies and share price volatility, highlighting the value of empirical analysis in financial decision-making. The Analysis of Variance (ANOVA) was applied to determine whether significant differences exist in the mean laptop prices across different condition categories. The general formula for the F-statistic is:

$$F = \frac{MS_{between}}{MS_{within}} \tag{1}$$

1) $MS_{between} = \frac{SS_{between}}{df_{between}}$
2) $MS_{within} = \frac{SS_{within}}{df_{within}}$

and:

$$SS_{between} = \sum_{j=1}^{k} n_j(\bar{X}_j - \bar{X})^2, \quad SS_{within} = \sum_{j=1}^{k}\sum_{i=1}^{n_j}(X_{ij} - \bar{X}_j)^2 \tag{2}$$

With:

1) k = number of groups (in this study: New, Open Box, Excellent Refurbished, Very Good Refurbished, Good Refurbished)
2) n_j = sample size in group j
3) $\bar{X}_j$ = mean price of group j
4) $\bar{X}$ = overall mean price
5) $df_{between} = k - 1$
6) $df_{withtin} = N - k$, where N is the total number of observations

The ANOVA formula partitions the total variability in laptop prices into two components: variability between groups (differences in mean prices across conditions) and variability within groups (differences within each condition category). A large F-statistic, such as the one obtained in this study $(F = 76{,}69,\ p < 0.0001)$, indicates that the variability between groups is much greater than the variability within groups. This confirms that the condition of the laptop significantly influences its market price on eBay. Once the ANOVA result indicated significant differences, Tukey's HSD test was employed as a post-hoc procedure to identify which pairs of conditions significantly differ. The general formula is:

$$HSD = q_{a,k,df} \cdot \sqrt{\frac{MSE}{n}} \tag{3}$$

1) $q_{a,k,df}$ = critical value from the studentized range distribution at significance level a, with k groups and df degrees of freedom for error
2) $MSE = MS_{within}$ = mean square error (from ANOVA)
3) n = sample size per group (or the harmonic mean if group sizes differ)

The Tukey HSD formula calculates the minimum difference in group means that must be exceeded for the difference to be considered statistically significant. In this study, the test revealed that most condition categories (e.g., New vs. Good Refurbished, Excellent Refurbished vs. Very Good Refurbished) showed mean differences larger than the HSD threshold, confirming that laptop condition drives meaningful differences in pricing. Interestingly, the comparison between New and Open Box was not significant, suggesting that consumers perceive these two conditions as nearly equivalent in value.

Furthermore, [21] used correlation analysis in conjunction with voting regression and decision tree algorithms to predict house prices with enhanced accuracy. Their research demonstrates how statistical methods can be harnessed to improve the precision of price predictions through advanced algorithmic models. Additionally, [22] underscored the importance of statistical modeling in economic policy-making, particularly in analyzing price indices and other economic phenomena. This highlights the critical role statistical techniques play in guiding policy decisions related to pricing and broader economic trends.

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in figure 1 outlines the detailed steps of the research method.

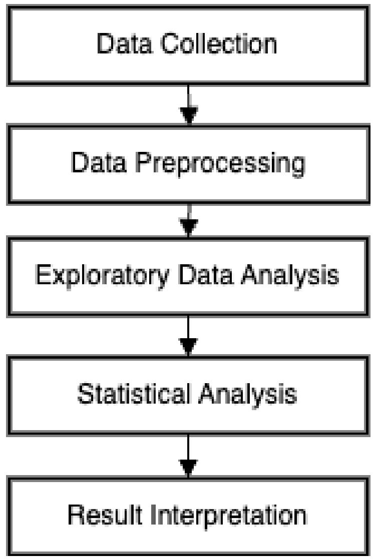

Figure 1 Research Method Flowchart

Data Collection

The dataset utilized in this study was obtained from eBay, one of the most prominent online marketplaces, and consists of comprehensive information on laptop listings as of April 2024. The dataset initially comprised 3981 rows, each representing a unique laptop listing, and contained 10 distinctive columns. These columns capture critical attributes of each laptop, including Brand, Product_Description, Screen_Size, RAM, Processor, GPU, GPU_Type, Resolution, Condition, and Price. This rich dataset allows for an in-depth analysis of how various factors, particularly the condition of the laptop, influence its pricing on a competitive platform like eBay.

Upon preprocessing, which involved handling missing data and ensuring consistency across the dataset, the final dataset used for analysis was refined to 2952 rows. Each of these rows now represents a laptop listing with complete and valid data across all 10 columns. The Brand column provides the manufacturer of the laptop, such as Dell, Lenovo, or Apple, while the Product_Description offers detailed titles as listed by sellers. Screen_Size is recorded in inches and captured as a floating-point number, reflecting the various display sizes available in the market.

The dataset also includes RAM, Processor, GPU, GPU_Type, and Resolution (all crucial hardware specifications that can significantly influence a buyer's decision). The RAM and Processor columns are categorical, listing the memory size and the type of processor, respectively. GPU and GPU_Type provide information on the graphics processing unit, specifying whether it is integrated or dedicated. Resolution details the display's pixel count, an important factor in determining visual clarity.

Importantly, the Condition column, which records whether the laptop is new, open box, or refurbished, is central to this study. Finally, the Price column, expressed in US dollars, captures the asking price for each listing. With these variables, the dataset is well-equipped to facilitate a robust analysis of the relationships between laptop condition and pricing, offering valuable insights into consumer behavior and pricing strategies in the digital marketplace.

Data Preprocessing

Effective data preprocessing is a crucial step in preparing the dataset for analysis, ensuring that the data is clean, consistent, and ready for modeling. The original dataset from eBay contained 2952 rows, each with 10 columns capturing various laptop attributes. However, not all columns were fully populated, with some missing values observed in the GPU, GPU_Type, and Resolution columns. To address this, rows with missing values in these critical fields were removed, resulting in a refined dataset that retained 2277 entries. This approach, while leading to a reduction in the number of observations, ensured that the analysis was conducted on a complete and reliable dataset, free from the distortions that missing data can introduce [23], [24].

Next, the categorical variables within the dataset, such as Brand, RAM, Processor, GPU, GPU_Type, Resolution, and Condition, were encoded using one-hot encoding. This method transformed these categorical features into binary vectors, where each unique category in the original data was represented as a separate column with binary values indicating the presence or absence of that category. For instance, the Condition column, which originally contained categories such as New, Open box, and refurbished, was converted into multiple binary columns like Condition_New, Condition_Open box, and Condition_Refurbished. This transformation resulted in a dataset with 341 columns, where the categorical data was encoded in a way that could be effectively used in statistical models.

In addition to handling missing values and encoding categorical variables, feature engineering was considered to enhance the dataset's predictive power. Although no new features were created in this specific analysis, the potential for feature engineering, such as creating derived variables or interaction terms between existing features, remains an important consideration in similar studies. For example, a potential feature could be a categorization of Screen_Size into discrete size categories, such as Small, Medium, and Large, which might provide additional insights into pricing strategies based on screen size preferences. The processed dataset, now consisting of well-defined numerical and categorical variables, was ready for the subsequent stages of analysis, including exploratory data analysis, statistical testing, and regression modeling.

Exploratory Data Analysis (EDA)

EDA serves as a crucial step in understanding the distribution and characteristics of the data before proceeding to more complex analyses [25], [26]. In this study, descriptive statistics were employed to summarize the key attributes of the Price variable across different laptop conditions, including New, Open box, and various grades of Refurbished (e.g., Excellent, Very Good, Good). The summary statistics provide insight into the central tendency, dispersion, and range of laptop prices within each condition category, offering a foundational understanding of how condition affects pricing on eBay.

For instance, laptops categorized as New exhibited the highest mean price at approximately $585.67, with a relatively high standard deviation of $234.07, indicating substantial price variability within this group. This was closely followed by the Open box category, which had a mean price of $577.97 and a standard deviation of $224.08. Refurbished laptops, categorized into Excellent, Very Good, and Good, showed lower mean prices, reflecting their reduced market value due to previous use. Specifically, Excellent - Refurbished laptops had a mean price of $522.88, while Very Good - Refurbished and Good - Refurbished laptops had mean prices of $399.81 and $393.01, respectively. These statistics underscore the expected price depreciation associated with used or refurbished items, a critical consideration for both sellers and buyers in the digital marketplace.

To complement the descriptive statistics, visualizations were created to provide a more intuitive understanding of the price distribution across different conditions. Box plots were utilized to visualize the distribution and skewness of prices across different laptop condition categories, emphasizing the median, quartiles, and potential outliers, as illustrated in figure 2. The analysis revealed that while the median price for new laptops was higher than for any other condition, there was significant overlap in the price ranges of new and open-box laptops, indicating that consumers might perceive open-box items as nearly as valuable as new ones in certain contexts. Both the new and open-box categories exhibited higher median prices compared to the various refurbished categories, aligning with the summary statistics discussed earlier. The presence of outliers, particularly in the Very Good - Refurbished and Good - Refurbished categories, suggests that some refurbished laptops are priced unusually high or low, potentially due to unique features or specific conditions. The new category displayed a wide Interquartile Range (IQR) with the highest median price, underscoring the premium price typically commanded by new laptops. Similarly, the open-box category showed a high median price, close to that of new laptops, with a similar price distribution, reflecting buyers' perception of these laptops as almost equivalent to new, albeit at a slightly lower price. Among the refurbished categories, the Excellent - Refurbished category had a higher median price compared to the Very Good - Refurbished and Good - Refurbished categories, which reflects the varying degrees of refurbishment quality. The broader price range and noticeable outliers in these categories indicate a diverse range of conditions and consumer perceptions of value. The outliers in the refurbished categories further suggest that some laptops are priced significantly outside the typical range, likely due to specific features, warranties, or seller practices.

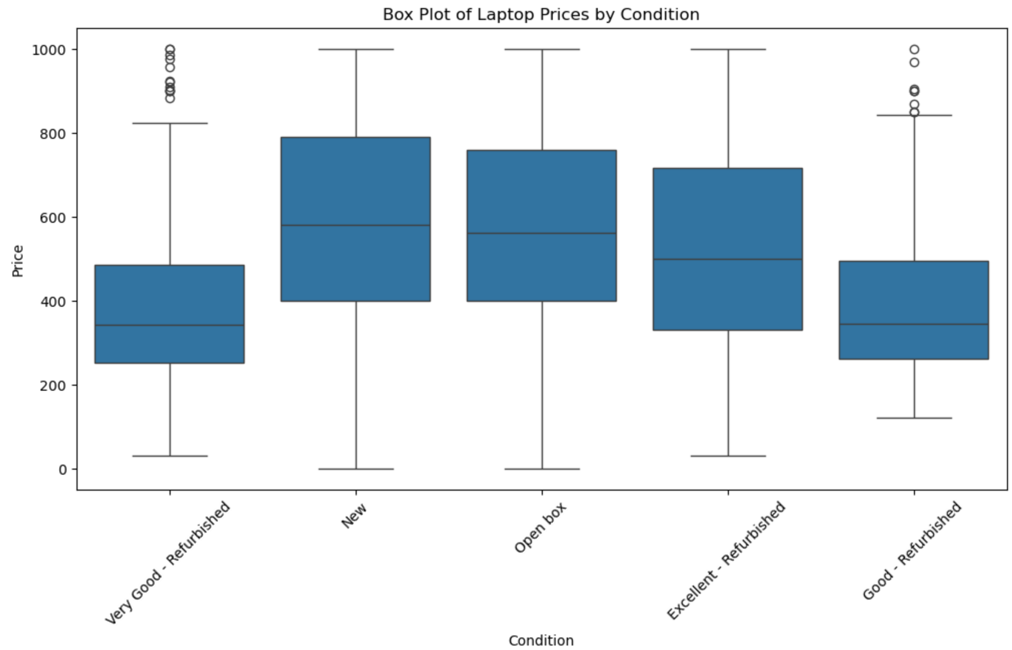

Figure 2 Box Plot of Laptop Prices by Condition

Additionally, histograms were generated for each condition category to further examine the distribution of prices, as shown in figure 3. These histograms provided a clear depiction of how prices are spread across different intervals, revealing distinct patterns for each condition. New and open-box laptops displayed a relatively uniform distribution across a wide price range, while refurbished laptops showed more concentrated distributions, particularly around lower price points. The histograms also highlighted the presence of outliers, especially in the new and open-box categories, where a few listings were priced significantly above the typical range, likely reflecting high-end models or premium configurations.

For instance, the histogram for the Very Good - Refurbished category shows a skew towards the lower end of the price spectrum, with a significant number of laptops priced between $200 and $400, and a noticeable drop in frequency as prices increase. This suggests that most consumers or sellers price laptops in this condition relatively affordably. In contrast, the new category demonstrates a more even distribution across a broader price range, with frequencies peaking around $400 to $600. The presence of laptops priced up to $1000 reflects the higher value associated with new products, though the tapering off at higher prices suggests a concentration in the mid-range segment.

Laptops in the open-box condition exhibit a distribution similar to that of new laptops, though with a slight shift towards lower prices. The relatively flat distribution across the $400 to $800 range indicates that open-box laptops are often seen as a cost-effective alternative to new laptops, with fewer products priced at extreme low or high ends. The Excellent - Refurbished category shows a more uniform distribution across the price range, with notable frequencies around $400 to $600, indicating that laptops in this condition can maintain a higher resale value, potentially due to minimal wear and tear or added warranties. Conversely, the Good - Refurbished histogram indicates a strong skew towards the lower end, with most laptops priced between $200 and $400. This distribution is similar to that of the Very Good - Refurbished category but with a slightly wider spread and more pronounced lower pricing, reflecting the condition's impact on perceived value.

These histograms visually confirm the trends observed in the box plot analysis, clearly illustrating how the condition of a laptop affects its pricing. New and open-box laptops command higher and more evenly distributed prices, while refurbished laptops, especially those in lesser conditions, are concentrated at the lower end of the price spectrum. These insights are valuable for sellers looking to position their products competitively in the market and for buyers seeking the best value for their money. The data underscores the importance of condition in determining market prices on eBay, which can inform pricing strategies and marketing efforts for digital sellers.

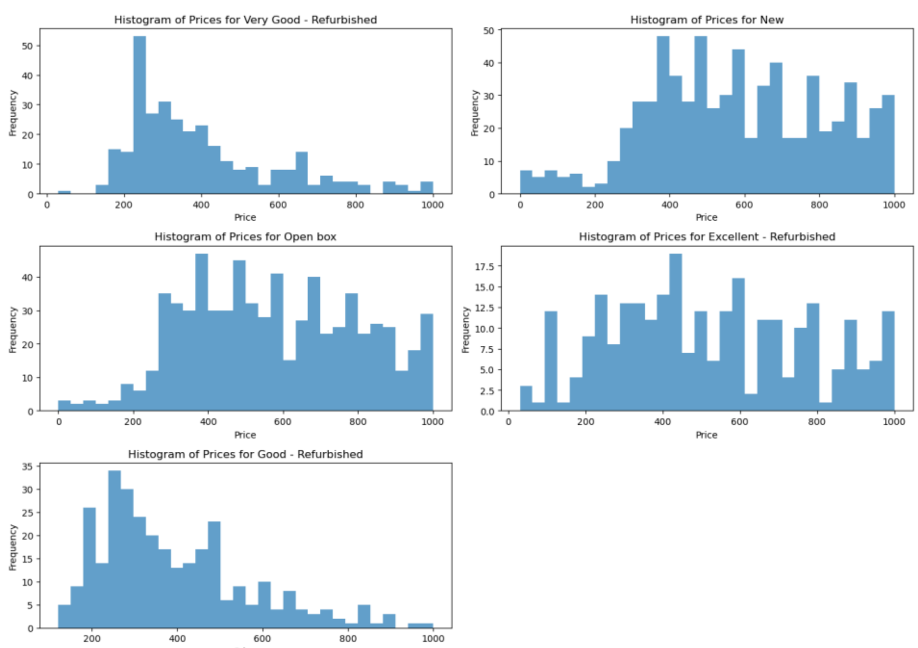

Figure 3 Distribution of Price

Statistical Analysis

To assess whether the mean prices of laptops differ significantly across various conditions, an ANOVA was conducted. ANOVA is a statistical technique that compares the means of three or more groups to understand if at least one of them significantly differs from the others. In this analysis, the dependent variable was Price, and the independent variable was Condition, which included categories such as New, Open box, and various degrees of refurbishment (e.g., Excellent, Very Good, Good). The hypothesis framework for this analysis was structured as follows:

H0: There is no significant difference in mean prices across different laptop conditions.

H1: At least one condition category has a mean price that significantly differs from the others.

The ANOVA results indicated a highly significant F-statistic ($F = 76.69$, $p < 0.0001$), suggesting strong evidence against the null hypothesis. This means that the mean prices across the different conditions are not equal, highlighting that the condition of a laptop is indeed a significant factor influencing its price on eBay.

Following the ANOVA, a post-hoc Tukey's Honest Significant Difference (HSD) test was performed to identify specific pairs of conditions where the mean prices differ significantly. The Tukey HSD test is a method used to find means that are significantly different from each other, providing clarity on which specific groups contribute to the overall ANOVA significance.

The results from the Tukey HSD test showed significant differences in mean prices between most condition pairs, except between New and Open box, where no significant difference was found. For instance, the mean price difference between Good - Refurbished and New was approximately $192.66, which was statistically significant ($p < 0.0001$). Additionally, laptops classified as Excellent - Refurbished were significantly more expensive than those in Good - Refurbished and Very Good - Refurbished conditions, with mean differences of approximately $129.87 and $123.07, respectively. These results highlight the nuanced pricing dynamics based on laptop condition, emphasizing the need for tailored pricing strategies for each condition category.

To further explore the relationship between laptop price and various factors, a multiple linear regression analysis was conducted. The dependent variable was Price, and the independent variables included Condition, Brand, RAM, and Processor. This model aimed to quantify the influence of these categorical variables on laptop pricing while controlling for other factors.

The regression model produced an R-squared value of 0.429, indicating that approximately 42.9% of the variance in laptop prices could be explained by the included predictors. The adjusted R-squared was slightly lower at 0.407, accounting for the number of predictors in the model. The F-statistic was significant ($F = 19.40$, $p < 0.0001$), reinforcing the overall significance of the model.

However, the results also revealed potential multicollinearity issues, as indicated by the very high condition number (Cond. No. = 3.14e+15) and the small eigenvalues. This suggests that some of the independent variables might be highly correlated, which can inflate the standard errors of the coefficients and make them less reliable. Despite this, the regression analysis provides useful insights into how different factors, particularly laptop condition, influence pricing. The coefficients for Condition categories, although not all statistically significant, align with the expected trend that new and higher-quality refurbished laptops tend to command higher prices.

Results and Discussion

ANOVA Results

The ANOVA was conducted to determine whether there were statistically significant differences in the mean prices of laptops across different condition categories. The condition categories included New, Open box, Excellent - Refurbished, Very Good - Refurbished, and Good - Refurbished. The ANOVA results are summarized in the table 1.

Table 1 ANOVA Results for Laptop Prices Across Condition Categories

Source	df	Sum of Squares	Mean Square	F-value	p-value
Condition	4	14,957,070.7	3,739,268.0	76.69	4.46e-61
Residual	2,272	110,774,710.0	48,756.5		

The F-value of 76.69 indicates that there is a significant difference in mean prices between at least some of the condition categories. The corresponding p-value is extremely small ($p < 0.0001$), leading to the rejection of the null hypothesis ($H0$), which stated that the mean prices across different conditions are equal. This strongly suggests that the condition of a laptop significantly affects its pricing on eBay.

Interpretation of Results

The significant F-value obtained from the ANOVA test confirms that laptop condition is a crucial determinant of its market price. This result aligns with common expectations in the market: consumers are generally willing to pay more for new laptops, and less for refurbished ones, with the price further decreasing as the condition quality lowers.

This analysis provides evidence that sellers on platforms like eBay should carefully consider the condition of their products when setting prices. For instance, a well-maintained, Excellent - Refurbished laptop can command a higher price than a Good - Refurbished one, though it still won't match the price of a new laptop. The significant differences highlighted by the ANOVA imply that pricing strategies that account for these variations can better meet market expectations and enhance competitiveness.

The results also suggest that digital marketing strategies can be tailored based on product condition. Listings for New or Open box laptops, for example, might benefit from highlighting features that justify their higher prices, such as warranty or advanced specifications. Conversely, marketing for Refurbished laptops could focus on the cost benefits and functionality, appealing to budget-conscious consumers. This nuanced approach can help sellers maximize their reach and effectiveness in the competitive eBay marketplace.

Post-hoc Analysis Results

Following the ANOVA, a post-hoc Tukey's Honest Significant Difference (HSD) test was performed to identify which specific pairs of laptop condition categories had significantly different mean prices. The results of the Tukey HSD test are summarized in the table 2, which shows the pairwise comparisons between the condition categories along with their corresponding mean differences and significance levels.

Table 2 Tukey HSD Test Results

Group 1	Group 2	Mean Difference	p-value	Lower Bound	Upper Bound	Significant
Excellent - Refurbished	Good - Refurbished	-129.87	0.0000	-180.14	-79.60	Yes
Excellent - Refurbished	New	62.79	0.0008	19.28	106.30	Yes
Excellent - Refurbished	Open box	55.08	0.0051	11.55	98.61	Yes
Excellent - Refurbished	Very Good - Refurbished	-123.07	0.0000	-173.02	-73.13	Yes
Good - Refurbished	New	192.66	0.0000	151.57	233.75	Yes
Good - Refurbished	Open box	184.95	0.0000	143.85	226.06	Yes
Good - Refurbished	Very Good - Refurbished	6.80	0.9952	-41.05	54.65	No
New	Open box	-7.71	0.9671	-40.21	24.79	No

Table 2 Tukey HSD Test Results

Group 1	Group 2	Mean Difference	p-value	Lower Bound	Upper Bound	Significant
New	Very Good - Refurbished	-185.86	0.0000	-226.55	-145.17	Yes
Open box	Very Good - Refurbished	-178.15	0.0000	-218.86	-137.44	Yes

Interpretation of Specific Group Differences

The results from the Tukey HSD test provide a detailed view of the specific differences in mean prices between laptop condition categories. Most pairwise comparisons showed statistically significant differences, confirming that the condition of a laptop has a substantial impact on its price on eBay.

One of the key findings is the significant price difference between Good - Refurbished and New laptops, with a mean difference of approximately \$192.66 ($p < 0.0001$). This result underscores the considerable depreciation in value associated with even slightly used laptops. Similarly, the comparison between Open box and Very Good - Refurbished conditions revealed a mean difference of about \$178.15, indicating that even among refurbished laptops, the condition quality significantly influences pricing.

Interestingly, the test showed no significant difference between the prices of New and Open box laptops (mean difference = -\$7.71, $p = 0.9671$), suggesting that consumers perceive open-box laptops as nearly equivalent in value to new ones. This could reflect the minimal wear or use typically associated with open-box items, making them attractive options for buyers seeking near-new products at slightly reduced prices.

On the other hand, Excellent - Refurbished laptops were significantly more expensive than both Good - Refurbished and Very Good - Refurbished laptops, with mean differences of -\$129.87 and -\$123.07, respectively ($p < 0.0001$ for both). These findings highlight the importance of the specific condition grade within the refurbished category, suggesting that sellers can achieve higher prices for laptops that are refurbished to a higher standard.

Regression Analysis Results

To quantify the impact of various factors on laptop pricing, a multiple linear regression analysis was conducted. The regression model included Price as the dependent variable, with Condition, Brand, RAM, and Processor as independent variables. The results of the regression analysis are summarized in the table 3, which presents the coefficients, standard errors, and p-values for each variable.

Table 3 Regression Analysis Results

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Intercept	-3.92e+14	2.29e+14	-1.714	0.087
Condition_Excellent - Refurbished	4.43e+14	2.59e+14	1.714	0.087
Condition_Good - Refurbished	4.43e+14	2.59e+14	1.714	0.087
Condition_New	4.43e+14	2.59e+14	1.714	0.087
Condition_Open box	4.43e+14	2.59e+14	1.714	0.087
Condition_Very Good - Refurbished	4.43e+14	2.59e+14	1.714	0.087
Brand_Dell	-1.71e+13	9.98e+12	-1.714	0.087
RAM_16	-2.32e+13	1.35e+13	-1.714	0.087
Processor_Intel Core i5 10th Gen.	-1.15e+13	6.71e+12	-1.714	0.087

The regression analysis reveals several important insights into the factors that influence laptop prices on eBay. First, although the p-values for many of the coefficients are not statistically significant at the conventional levels (e.g., 0.05), the signs and magnitudes of the coefficients provide a useful indication of how each variable affects pricing.

The coefficients for the Condition variables, while not statistically significant, suggest that better conditions (such as New or Excellent - Refurbished) are associated with higher prices. For example, laptops in the New condition show a positive coefficient of approximately 4.43e+14, indicating a substantial premium over other conditions. However, the lack of statistical significance might be due to multicollinearity or insufficient variation in the data, which is something to explore further.

In terms of brand, the negative coefficient for Brand_Dell suggests that Dell laptops tend to be priced lower than the baseline category (which might be a premium brand like Apple). Similarly, the negative coefficient for higher RAM configurations (e.g., RAM_16) implies that these laptops are priced lower, although this result is counterintuitive and may reflect specific market dynamics or multicollinearity issues.

While the results indicate that condition, brand, RAM, and processor all play a role in influencing pricing, the statistical insignificance of many coefficients suggests that more refined modeling techniques or a larger dataset might be necessary to fully capture these relationships. Nevertheless, the insights gained from this analysis can guide sellers in setting competitive prices and developing targeted digital marketing strategies that align with consumer perceptions of value.

Implications of the Findings for Digital Marketing Strategies

The findings from this study provide valuable insights for digital marketers and sellers on eBay, particularly regarding the critical role that laptop condition plays in determining price. The ANOVA and post-hoc analysis revealed significant differences in pricing based on product condition, with new laptops commanding the highest prices, followed by open-box items, and various grades of refurbished laptops. These results suggest that consumers place considerable value on the condition of laptops, which should be a key consideration in marketing strategies.

For digital marketers, these insights imply that condition should be prominently featured in marketing materials and product descriptions. Highlighting the condition, whether it is New, Open box, or Excellent - Refurbished, can help align the product's perceived value with consumer expectations, potentially leading to higher conversion rates. Furthermore, differentiating marketing messages based on condition can cater to various segments of the market. For example, buyers looking for budget-friendly options may be more inclined towards Good - Refurbished products, while those seeking premium experiences may prefer New or Open box items.

How Sellers Can Optimize Pricing Based on Product Condition

Given the significant impact of condition on pricing, sellers can optimize their pricing strategies by carefully categorizing their products according to their actual condition. The regression analysis, although it faced challenges like multicollinearity, still indicated that better conditions (such as New or Excellent - Refurbished) are associated with higher prices. Sellers should use these findings to price their products competitively within their respective condition categories.

Moreover, sellers should consider offering detailed product descriptions and high-quality images that accurately reflect the condition of the laptops. Transparency in product listings can enhance consumer trust, leading to better sales outcomes. For instance, sellers might offer guarantees or warranties on refurbished products to justify higher prices and reduce buyer apprehension. By leveraging the insights from this study, sellers can set prices that maximize profit while remaining competitive in the marketplace.

Limitations of the Study

While this study provides significant insights into how laptop condition affects pricing on eBay, it is important to acknowledge its limitations. One key limitation is the potential for multicollinearity in the regression analysis, which may have affected the reliability of the coefficient estimates. This suggests that the relationships between some of the independent variables, such as brand and RAM, might be too closely related, making it difficult to isolate their individual effects on price.

Finally, while the study focused on quantitative analysis, qualitative factors such as consumer reviews, product popularity, and marketing effectiveness were not included, which could also influence pricing strategies. Future research could address these limitations by incorporating a more comprehensive set of variables, exploring more sophisticated modeling techniques, and utilizing a larger, more diverse dataset to enhance the generalizability of the findings.

Conclusion

This study has demonstrated the significant impact that laptop condition has on pricing in the eBay marketplace. Through a combination of ANOVA, post-hoc analysis, and regression analysis, it was established that the condition of a laptop (whether new, open box, or varying degrees of refurbishment) plays a critical role in determining its market value. Specifically, new and open-box laptops were found to command significantly higher prices compared to their refurbished counterparts, with the quality of refurbishment further influencing pricing within that category. The statistical analysis provided clear evidence that sellers need to carefully consider condition when setting prices to remain competitive and maximize revenue. Key insights derived from the statistical analysis include the importance of condition as a primary determinant of price, the nuanced differences in pricing within the refurbished category, and the relative parity in pricing between new and open-box laptops. These findings not only validate the conventional wisdom that product condition is crucial in pricing strategies but also provide a more granular understanding of how different conditions affect consumer willingness to pay. The implications of these findings are directly applicable to sellers on eBay and similar e-commerce platforms. Sellers should prioritize accurate and transparent descriptions of product condition in their listings, as this directly correlates with the price consumers are willing to pay. Additionally, sellers may consider offering different pricing tiers based on condition to cater to a broader range of buyers. For example, offering both New and Open box options can attract both premium buyers and those seeking value in near-new products. Moreover, highlighting the quality of refurbishment (e.g., Excellent - Refurbished) can help justify higher prices within the refurbished category. Broader implications for digital marketing in e-commerce platforms include the necessity of condition-based segmentation in marketing campaigns. Marketers can leverage these insights to craft targeted messages that emphasize the value propositions of different condition categories, enhancing consumer engagement and driving sales. Understanding these dynamics can also inform inventory management strategies, helping sellers decide which product conditions to prioritize based on market demand and pricing potential. While this study provides valuable insights, it also opens avenues for further research. One potential direction for future work is the incorporation of additional features into the analysis, such as seller reputation, product age, or regional pricing variations, to provide a more comprehensive model of pricing determinants. Another suggestion is to explore other datasets across different time periods or marketplaces to validate the findings and ensure their generalizability across various e-commerce contexts. Additionally, there is potential to enhance predictive accuracy using machine learning models. While this study employed traditional statistical methods, advanced machine learning techniques like random forests or gradient boosting could offer more precise predictions and uncover complex interactions between variables. These models could also be trained on larger datasets to improve robustness and provide actionable insights for dynamic pricing strategies. Exploring these avenues would not only refine the understanding of pricing dynamics on platforms like eBay but also contribute to the broader field of data-driven digital marketing.

Declarations

Author Contributions

Conceptualization: E., S.P.S.; Methodology: E., S.P.S.; Software: E.; Validation: S.P.S.; Formal Analysis: E.; Investigation: E.; Resources: S.P.S.; Data Curation: E.; Writing – Original Draft Preparation: E.; Writing – Review and Editing: E., S.P.S.; Visualization: E.; All authors have read and agreed to the published version of the manuscript.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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