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Determinants of Smartphone Prices using Backward Elimination Technique in Multiple Linear Regression

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ABSTRACT

The rapidly evolving market for smart gadgets causes smartphone prices to vary widely, frequently posing challenges to what consumers expect and can afford. Therefore, understanding the complex interrelationship of factors that determine smartphone prices has emerged as an important subject for study in an era defined by technological developments. This study seeks to identify the factors that influence the pricing of smartphones. The study focused on various factors, including the battery capacity, camera quality, screen size, charging speed, device weight, and age in months. The primary data for the research came from the Global System for Mobile Communication (GSM) online marketplace, comprising sixty smartphones selected through a simple random sampling technique. We initially developed a multiple linear regression model with SPSS and then refined it using backward elimination. The results highlight the strong influence of several characteristics on smartphone pricing, namely battery capacity, charging speed, weight, and model age. Interestingly, the examination of six variables revealed that camera and screen size had no effect on price. The knowledge acquired from this quantitative analysis not only advances our comprehension of the interplay between technology and consumer demand but also has implications for manufacturers, policymakers, and consumers who desire to navigate the ever-changing sphere of smartphone pricing.

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1. Introduction

In an era of fast technological development, it is critical to understand the factors driving smartphone prices. As consumers increasingly rely on these universal devices, manufacturers face the challenge of balancing innovation, cost, and market demand. The main issue this study attempts to solve is figuring out what factors affect smartphone prices. Our goal is to identify the complex relationship between technology and consumer preferences by conducting a thorough analysis of a wide range of factors, from battery capacity to model age. The primary objective is to present empirical findings that improve our understanding of this dynamic environment and have beneficial effects for manufacturers, lawmakers, and educated consumers negotiating the constantly changing market for smartphone pricing.

This study applied multiple linear regression approaches to analyse the pricing dynamics of smartphones on the Malaysian market. This study attempts to identify the major factors that influence smartphone prices by emphasising many different factors, such as battery capacity, camera quality, screen size, charging speed, weight, and device age in months. The results of this study could potentially add to the body of knowledge already available about smartphone buying decisions, and they will be helpful to future researchers who have similar interests in the same area of study.

The decision to include battery capacity, camera quality, screen size, charging speed, weight, and model age as dependent variables in this analysis was made with the understanding that these technical characteristics are well known to have a significant impact on smartphone prices. While camera quality affects the smartphone's multimedia capabilities, battery capacity determines how long the gadget can run on a single charge. Usability and convenience are directly impacted by screen size and charging speed, whereas opinions of device portability and build quality are influenced by weight. In the smartphone industry, the model age acknowledges the significance of technical obsolescence and reflects consumer demand for newer devices. Together, these elements offer a thorough framework for examining the complex aspects that influence the pricing dynamics of smartphones in the Malaysian market.

New smartphone prices are influenced by several variables, including the smartphone's primary features, historical data, and consumer preferences. Various methodologies, such as logistic regression, support vector machines, and random forest classifiers, can be employed to construct this price prediction model [1]. In this study, we have exclusively focused on quantitative variables and have opted to utilize multiple linear regression.

In multiple linear regression, the backward elimination method is a useful tool for simplifying the model, particularly in studies like smartphone price prediction where multiple variables could be included [1]. Using a model that contains every potential predictor at first, the predictor with the highest p-value is removed iteratively until no more predictors remain statistically significant [2]. This procedure improves the interpretability of the model and helps prevent overfitting.

The employment of inefficient algorithms, the addition of extra variables that set off the analysis, and a lower forecast accuracy were among the limitations of previous studies on smartphone pricing prediction [1], [3]. Mostly, logistic regression, decision trees, support vector machines, and other machine learning approaches have been applied in these studies [1], [3]. These drawbacks, however, can be overcome by the backward elimination strategy, which increases the accuracy and interpretability of the model by methodically removing unimportant predictors [2]. Hence, it is beneficial and possibly advantageous to employ the backward elimination strategy in this study.

2. Literature Review

Factors affecting consumer buying decisions towards choosing a smartphone include product attributes, price, brand image, and product quality [4]. Demographic factors such as age, gender, occupation, and location also play a role in influencing consumer behaviour [5]. For example, females tend to replace their smartphones less frequently than males and are influenced by family decisions [6]. Youngsters are influenced by advertisements, accessories, and product features [7]. Additionally, customer satisfaction and reasons to change smartphones have a positive and significant effect on repurchases [8]. Quantitative variables like display, processor, memory, camera, thickness, battery, connectivity, RAM, internal storage, NFC, screen size, weight, brand, internet access, and 4G availability are frequently used in smartphone price prediction models [1], [3], [9], and [10].The key features of smartphones and how they affect cost are examined using these factors. The datasets are trained, and smartphone price predictions are made using machine learning algorithms such as logistic regression, support vector machine, decision tree, random forest regression, XGBoost regression, and naive Bayes. Accurate pricing forecasts can be generated by taking all these variables and using the proper algorithms, benefiting businesses in setting fair prices for their products while assisting consumers in making well-informed decisions. A multiple linear regression model was used by [11] to investigate the purchase decision of Universiti Kuala Lumpur Business School students and its association with brand, price, features, and social influence.

Consumer decision-making is also influenced by the availability of an internet connection on smartphones and the capacity to communicate with firms through mobile advertising [12]. A person's intention to buy a smartphone is also influenced by other significant aspects, such as how dependent they are on their phones and how much they enjoy using them [13]. To effectively target and influence consumers in their purchasing decisions, smartphone manufacturers, advertisers, and decision-makers must have a thorough understanding of these aspects. Table 1 compiles findings from various studies that explore the factors that influence consumer decisions when buying smartphones. Each row corresponds to a separate study, with details as follows:

Table 1. Summary of Factors Influencing Consumer Smartphone Purchasing Decisions

Main Findings	References
• Social groups and product features have a significant impact on buying decisions. • Price and brand name do not significantly influence buying decisions.	[14]
• Brand, features, and social influence significantly influence the purchasing decisions of smartphones among university students. • Price does not have a significant impact on the selection of smartphones among university students.	[11]
• Variables such as RAM, internal storage, NFC, screen size, and weight have a significant positive effect on smartphone prices.	[9]
• Product features have a significant effect on the purchase intention of a smartphone. • Brand image and product price have a significant effect on the purchase intention for smartphones. • Social influences do not have a significant impact on young customers' purchase intention of a smartphone.	[15]
• Younger people consider performance to be the most critical factor influencing their smartphone purchases. • Older respondents view performance as a benefit in their smartphone purchases. • Both hardware and software performance are considered the most critical factors.	[16]
• Sellers' credibility has a significant positive effect on students' smartphone purchase behaviour. • Product quality significantly influences students' smartphone purchase behaviour. • Product price is a significant factor in students' smartphone purchase decisions. • Brand attributes positively affect students' smartphone purchase behaviour. • Consumers' socio-economic status has a significant positive impact on students' smartphone purchase behaviour.	[17]

3. Methodology

3.1 Data Collection and Sampling

The sources of data in this study were primary data collected from the online shopping website, Global System for Mobile Communication (GSM). Sixty samples were chosen in this study, which included a variety of brands and were collected by adopting a simple random sampling approach. A total of 60 advertisements spanning from 2018 to 2022 were used to ensure a comprehensive snapshot of market dynamics. GSM is a digital mobile network that is widely used by mobile phone users in Malaysia. When trying to search for a new smartphone, the user showed some mobile phone specifications like brand, year, price range, type of SIM, body specifications, platform, memory, size, resolution display, camera, and battery capacity. This study selected several specifications when choosing a mobile phone. The chosen variables provide a diverse range of smartphone brands and specification attributes that were suited to regression analysis in identifying key factors affecting smartphone prices. Table 2 provides the specifications in detail.

Table 2**.** Key factors affecting smartphone prices.

Specifications	**Description**
Smartphone Price (RM)	The expectation of new smartphone prices can vary significantly depending on several factors.
Battery Capacity (mAh)	Larger smartphone batteries provide longer usage times and convenience.
Camera (Megapixels)	Higher camera quality drives smartphone pricing, as consumers value improved photography and video features.
Screen Size (Inches)	Larger screens impact user experience and pricing, particularly when paired with enhanced display technologies.
Charging Speed (watt)	Charging speed impacts user convenience and efficiency, adding a unique dimension to your analysis.
Weight (gram)	Heavier devices may be perceived as sturdier due to their weight, potentially affecting price expectations.
Model Age (months)	Model age accounts for technological obsolescence and consumer preferences. As models age, prices tend to decrease due to market dynamics.

Figure 1 presents a conceptual framework that influences the pricing of smartphones. An in-depth analysis of factors such as battery capacity, camera quality, and other specifications yields a more comprehensive understanding of how they directly influence a smartphone's final price. This conceptual framework is an essential tool for comprehending the dynamics of the smartphone market and guiding price decisions.

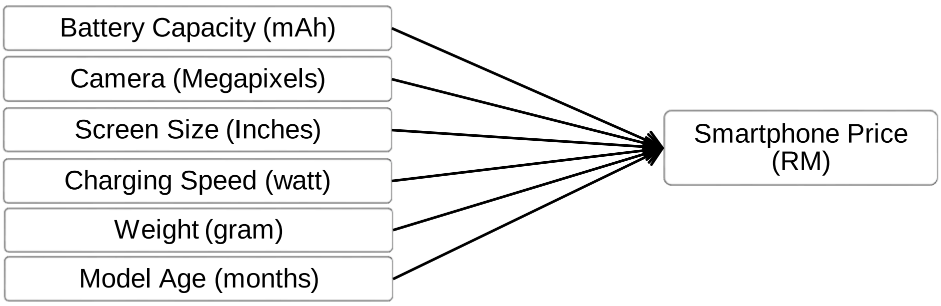

Figure 1. Conceptual Framework

3.2 Data Analysis

Initially, model adequacy checking was performed to evaluate their assumptions. Next, this study performed a correlation analysis to identify the relationship between independent and dependent variables. To identify the key factors influencing smartphone price, multiple linear regression (MLR) analysis was performed using SPSS software. The final model was refined using the backward elimination technique. Backward elimination is used to choose features in regression analysis, especially multiple linear regression. It assists in creating a predictive model by identifying the most important independent variables.

This study used 0.05 for statistical significance in backward elimination. Begin by including all potential factors in a multiple linear regression model. For each predictor, p-value will determine selection. Independent variables with p-values above 0.05 are eliminated from the model. This stage preserved statistically significant predictors. Repeat the procedure until no independent variables have a p-value above the significance level. Only statistically significant factors were used to create the final model, ensuring its smartphone price prediction accuracy.

4. Results and Discussion

4.1 Model Adequacy Checking

The regression model relies on specific assumptions. As a result, the model's applicability is dependent on the validity of these assumptions. When evaluating adequacy, all criteria should be considered, including a linear relationship between the dependent and independent variables, independent error terms, residuals exhibiting consistent variance at all levels of the independent variable, and residuals conforming to a normal distribution. If any of these assumptions are violated, the reliability and interpretability of linear regression results may be compromised.

Figure 2 shows the scatter plot of unstandardized residuals and predicted values. The residuals should be at random, with no trend or curvature. As the scattered points were not organised, the model met the linearity assumption. All predictors and the response were linear.

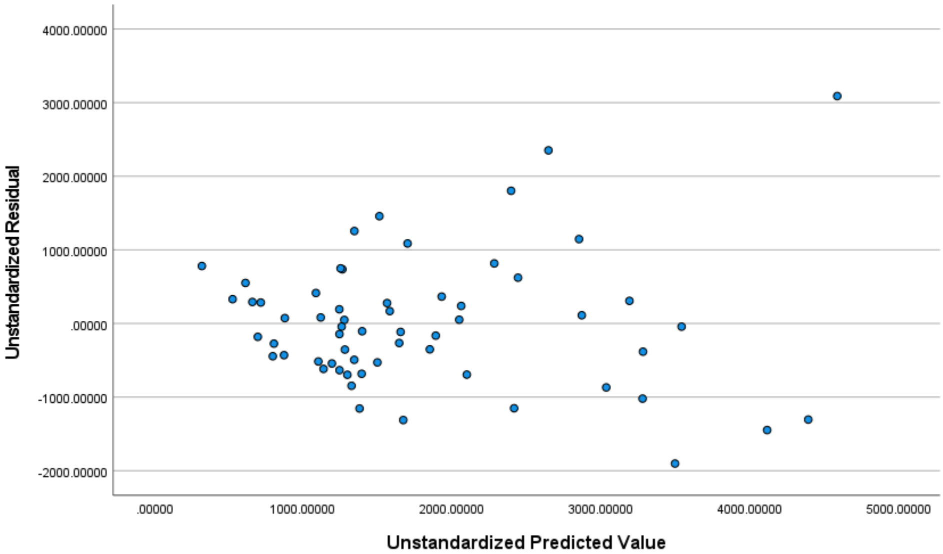

Figure 2. Linearity

Figure 3 shows a normal P-P plot of regression standardised residual to evaluate regression analysis's normality assumption. The observed cumulative residual probability is shown against the expected cumulative probability under a normal distribution. Most dots align with the diagonal line or spread out along the 45° line, signifying a normal distribution of the residuals and a normal regression model.

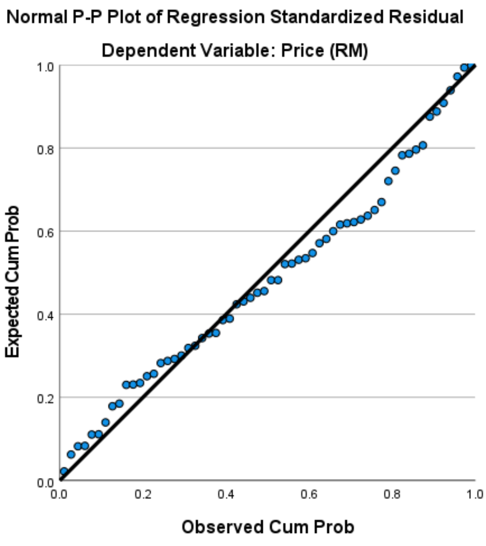

Figure 3. Normality

Figure 4 shows the scatter plot of regression standardized predicted values and residual values. Most of the plot along the x-axis of the graph standardised residual plot vs. standardised predictor values, is distributed about e = 0, as shown in Figure 4. As a result, the variance is hence constant.

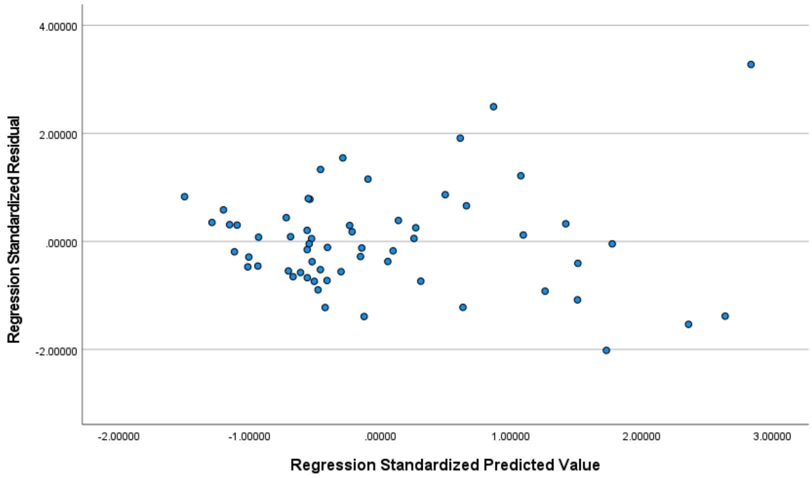

Figure 4. Homoscedasticity

Finally, the value of Durbin-Watson is 2.392, as shown in Figure 5. Durbin-Watson ranges from 0 to 4. Since 2.392 falls between 1.5 and 2.5, we may infer that the error term is independent and the model fits.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.741[a]	.549	.498	943.098	2.392

a. Predictors: (Constant), Model Age (months), Weight (gram), Camera (megapixels), Charging Speed (watt), Battery Capacity (mah), Screen Size (inches)

b. Dependent Variable: Price (RM)

Figure 5. Independent

4.2 Descriptive Statistics

The lowest and maximum values, mean, standard deviation, and skewness for all variables in each criterion are presented in Table 3. The skewness values indicate that the distributions of smartphone prices rely on these factors. In general, skewness values close to zero suggest a normal distribution. Sixty of the data in Table 3 have a right-skewed distribution. The distribution of the changing battery capacity, on the other hand, is negatively skewed.

Table 3. Descriptive Statistics

Variables	Min	Max	Mean	Standard Deviation	Skewness
Price (RM)	223	7677	1792.03	1330.45	1.86
Battery Capacity (mAh)	2510	6000	4440.9	692.209	-0.452
Camera (megapixels)	12	200	43.353	29.8298	2.457
Screen Size (inches)	5.5	8	6.5077	0.3633	1.023
Charging Speed (watt)	10	200	41.27	35.428	2.321
Weight (gram)	159	295	196.597	27.0745	1.633
Model Age (months)	0	58	23.92	18.606	0.325

4.3 Correlation Analysis

A correlation coefficient reflects the degree of association and the presence of a link between two variables. Less than 0.49 is regarded as a weak connection, 0.5 to 0.69 as moderate, and greater than 0.69 as high. The correlation values between six (6) predictor variables are displayed in Table 4. The connection between BC (R = 0.174), C (R = 0.245), SS (R = 0.474), CS (R = 0.499), and MA (R = 0.258) is weakly positive. In contrast, W (R = 0.597) indicates a somewhat favourable correlation. The six predictor variables move in the same direction; as one variable rises, the others will also rise. When the price of smartphones grows, so do the six predictor factors.

Table 4. Correlation Analysis

Variable	Correlation (R)	Strength
BC - Battery Capacity (mAh)	0.174	Weak Positive
C - Camera (megapixels)	0.245	Weak Positive
SS - Screen Size (inches)	0.474*	Weak Positive
CS - Charging Speed (watt)	0.499*	Weak Positive
W - Weight (gram)	0.597*	Moderate Positive
MA - Model Age (months)	0.258*	Weak Positive
*Correlation coefficient is less than 0.05		

4.4 Multiple Linear Regression

In a multiple linear regression analysis, Table 5 depicts the association between six predictor variables, BC, C, SS, CS, W, and MA, and the price of smartphones. It demonstrates the existence of a substantial association (R = 0.741) between dependent variables (BC, C, SS, CS, W, and MA) and the price of smartphones, as measured by a coefficient of determination of 54.9%. This suggests that 54.9% of smartphone pricing variation is attributable to BC, C, SS, CS, W, and MA. In contrast, 45.1% of the variance is attributable to external variables.

Table 5. Correlation Analysis in Multiple Linear Regression

Variable	Correlation (R)	Strength	R^2
BC, C, SS, CS, W and MA	0.741	Strong Positive	0.549

Using multiple linear regression, the link between six independent variables, BC, C, SS, CS, W, and MA, and smartphone pricing was studied using multiple linear regression. The result in Table 6 indicates that the significance level (p-value 0.001) is less than the significance level of 0.05. Hence, the linear regression model is significant and reveals a substantial association between six predictor factors and smartphone pricing.

Table 6. ANOVA test in Multiple Linear Regression

Model	Sum of Squares	df	Mean Square	F	Significance
Regression	57295118.45	6	9549186.408	10.736	<.001
Residual	47139996.13	53	889433.889		
Total	104435114.6	59			

The existence of multicollinearity, which might considerably diminish the model's effectiveness, is another worry about the linear regression model. The result of the variance inflation factor (VIF) in Table 7 displays all suitable values for each predictor variable. BC (VIF = 2.598), C (VIF = 1.395), SS (VIF = 2.819), CS (VIF = 1.576), W (VIF = 2.674), and MA (VIF = 2.6) have VIFs greater than one but less than five. A VIF score of 1 is non-collinear; values between 1 and 5 are moderately collinear, and values greater than 5 indicate a severe collinearity issue. Hence, there are no multicollinearity issues with the linear regression model.

Table 7. Coefficient of regression model and variance inflation factor analysis of the relationship between six predictor variables and student effort

Variable	B estimation	Standard error	T value	Significance	VIF	TOL
Constant	-42.897	2875.381	-0.015	0.988		
Battery Capacity (mah)	-0.806	0.286	-2.821	0.007*	2.598	0.385
Camera (megapixels)	0.576	4.861	0.118	0.906	1.395	0.717
Screen Size (inches)	-140.879	567.388	-0.248	0.805	2.819	0.355
Charging Speed (watt)	10.564	4.35	2.428	0.019*	1.576	0.635
Weight (gram)	33.048	7.416	4.456	<0.001*	2.674	0.374
Model Age (months)	-26.132	10.64	-2.456	0.017*	2.6	0.385

A multiple linear regression model was performed to determine whether factors in Table 7 had a significant impact on the pricing of new smartphones. Four predictors have a considerable influence on the pricing of smartphones: battery capacity, charging speed, weight, and model age. In contrast, camera and screen size were found to have no significant impact on smartphone price. These four crucial factors, namely battery capacity, charging speed, smartphone weight, and model age, play a significant role in determining the price of a smartphone.

4.4 Final Model using Backward Approach in Multiple Linear Regression

A multiple linear regression model using a backward approach was performed to determine whether factors in Table 8 had a significant impact on the pricing of smartphones. Four predictors have a considerable influence on the pricing of smartphones from Table 8, battery capacity, charging speed, weight, and model age.

Table 8. Coefficient of regression model using backward approach

Variable	B estimation	Standard error	T value	Significance	VIF	TOL
Constant	-658.276	1312.083	-0.502	0.618		
Battery Capacity (mAh)	-0.814	0.278	-2.934	0.005*	2.537	0.394
Charging Speed (watt)	10.688	3.951	2.705	0.009*	1.347	0.742
Weight (gram)	31.759	5.289	6.005	<0.001*	1.410	0.709
Model Age (months)	-25.863	10.233	-2.527	0.014*	2.492	0.404

Predicted Equation for Smartphone Price = -658.276 – 0.814X1 + 10.688X2 + 31.759X3 – 25.863X4

X1 = Battery Capacity (mAh)
X2 = Charging Speed (watt)
X3 = Weight (gram)
X4 = Model Age (months)

Battery Capacity reduced the price of smartphones by RM0.814 (p-value 0.01). Specifically, the price of a smartphone decreases by 0.814 (± 0.278) for every unit (mAh) increase in battery capacity. The charging speed factor also resulted in a RM10.688 price rise for smartphones (p-value 0.01). Specifically, the price of a smartphone increases by 10.688 (± 3.95) for every unit (watt) improvement in charging speed. Weight also resulted in a RM31.759 price rise for smartphones (p-value 0.01). Specifically, the price of smartphones increases by 31.759 (± 5.289) per unit for each unit (gram) of weight increase. Model age led to an RM25.863 drop in the price of smartphones (p-value 0.01). Particularly, a 25.863 (± 10.233) unit decrease in the price of a smartphone for every one-unit increase in model age.

The two factors that contribute to smartphone price rising are the device's weight and its charging speed. The weight factor supported the findings of [9], providing additional evidence for the proposed concept. Modern advancements in technology have numerous impacts, including charging speed. The study conducted by [18] on the advancements in smartphone charging technology over the last ten years can clarify the findings. The increase in charging power can be linked to larger screens, more powerful CPUs, and enhanced camera technology. Users have a prevailing expectation for fast charging to be a standard feature. Manufacturers must give priority to maintain a delicate balance between speed and safety [18].

The model age does not produce surprising outcomes. As smartphone technology evolves rapidly, it makes sense that more recent models will be more popular than outdated ones. After all, people buy phones based on demand, price, and interface. Companies should focus on product quality rather than excessive advertising, as advertisements do not significantly influence purchasing decisions [19].

5. Conclusion

The present investigation has demonstrated that smartphone prices are significantly impacted by certain factors, namely battery capacity, charging speed, weight, and model age. However, upon considering six factors, it was discovered that camera size and screen size do not serve as decisive determinants of smartphone prices. In subsequent research, it would be worthwhile to delve into additional qualitative factors such as RAM and brand reputation in relation to pricing. Moreover, examining the demographic backgrounds of users could yield further insights into the dynamics of pricing. A deeper knowledge of the factors that influence smartphone prices may also be improved by future research projects that use other analytical techniques. The knowledge acquired from this quantitative analysis not only advances our comprehension of the interplay between technology and consumer demand but also has implications for manufacturers, policymakers, and consumers who desire to navigate the ever-changing sphere of smartphone pricing. As the smartphone industry continues to progress, our research contributes to the expanding knowledge base that informs strategic decisions and stimulates discourse concerning pricing strategies and consumer behavior.

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Conflict of Interest
The authors declare no conflict of interest in the subject matter or materials discussed in this manuscript.

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