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Consumer Decision-Making in Car Purchases: Insights from a Logistic Regression Analysis

Sandy J. H. Simamora[1], **M. Mujiya Ulkhaq***[2], **Naniek Utami Handayani**[3]
[1,2,3]*Department of Industrial Engineering, Diponegoro University, Semarang, Indonesia*
*E-mail : ulkhaq@live.undip.ac.id**
**Corresponding author*

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Abstract - Indonesia, with its large population, presents significant consumer demand, particularly in the automotive sector. Consequently, numerous car brands actively invest and market their products within the country. Among the 36 car brands officially operating in Indonesia, Toyota has consistently dominated the market. This study specifically examines consumer perceptions and decision-making processes regarding Toyota car purchases using logistic regression analysis. It investigates the impact of perceived risk, price sensitivity, convenience, and customer satisfaction on consumers' purchasing choices. Using a quantitative approach, data were collected from Indonesian Toyota consumers through purposive sampling and analyzed using the logistic regression. The findings reveal that perceived risk and price significantly influence consumers' decisions to purchase Toyota cars, highlighting the importance for Toyota and other automotive brands to strategically manage risk perceptions and pricing policies to enhance consumer appeal and market share.
Keywords: Car Purchase Decision, Consumer Behavior, Logistic Regression.

1. INTRODUCTION

The automotive industry has witnessed substantial growth and structural transformation over the past century, closely linked to advances in technology and evolving consumer expectations. Car manufacturing originated in Europe in the late 19th century, with notable early contributions from Germany and France (Womack, Jones, & Roos, 1990). By the early 20th century, American manufacturers—most prominently Ford Motor Company—revolutionized the industry through assembly line production and mass manufacturing techniques (Abernathy, 1978). This enabled widespread car ownership and established the United States as a global leader in automotive production for much of the 20th century.

However, from the mid-20th century onwards, Japanese automotive companies such as Toyota and Honda began to gain international prominence. Their emphasis on lean production systems, quality management, and fuel efficiency allowed them to compete effectively on a global scale (Holweg, 2007). Over time, the focus of automotive innovation has expanded beyond engineering to incorporate a wide array of consumer-oriented criteria, including safety, design aesthetics, environmental performance, reliability, comfort, and price competitiveness (Chand & Avikal, 2015; McKinsey & Company, 2016).

In recent years, the industry has also responded to growing environmental concerns and regulatory pressures by investing heavily in hybrid and electric vehicle technologies. This ongoing evolution underscores the need for manufacturers to understand and adapt to consumer preferences, which increasingly reflect not only rational economic evaluations but also emotional, social, and sustainability-related factors (Nunes & Drèze, 2006).

As one of Southeast Asia's largest automotive markets, Indonesia exemplifies the dynamic interplay between global trends and local consumer behaviors. The rise of a middle-class population, urban mobility demands, and competitive market conditions have made consumer-centric strategies increasingly essential for success in this landscape. As one of Southeast Asia's leading markets for automobile sales, reflects this global trend of dynamic automotive consumption. Driven by factors such as growing per capita income, significant urbanization, and an expanding middle-class population, Indonesia's car market has become highly competitive, with multiple global automotive brands vying for consumer preference. Among these brands, Toyota has consistently maintained market leadership, underscoring its robust consumer appeal and effective market strategies.

Understanding consumer decision-making processes in car purchases is critical for automotive brands to remain competitive and responsive to market demands. Previous studies have employed various methodologies, including multi-criteria decision-making (MCDM) tools like Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to identify consumer preferences, see for example: Ali et al. (2020); Roy et al. (2018); Singh et al. (2019); Ulkhaq et al. (2018a). These models help rank alternatives based on structured consumer inputs, but they often lack predictive strength regarding actual purchase behavior.

In contrast, logistic regression has emerged as a robust analytical method for modeling the relationship between consumer perceptions and their observed decisions. It is particularly useful for binary or categorical outcomes and is commonly employed in consumer behavior studies (Ulkhaq et al., 2018b; Hosmer et al., 2013). Logistic regression allows researchers to estimate the probability of a specific purchase decision based on several influencing variables, such as price, risk, or satisfaction, while also testing the significance of each predictor.

In this context, this study specifically explores consumer perceptions influencing Toyota car purchase decisions within the Indonesian automotive market using logistic regression analysis. The research aims to identify the relative importance of factors such as perceived risk, price sensitivity, convenience, and customer satisfaction in shaping consumer choices. Insights gained from this analysis will offer valuable implications for Toyota and other automotive manufacturers aiming to optimize their marketing strategies and product offerings to better align with consumer expectations.

The remainder of this paper is structured as follows: Section 2 describes the research method and explains the logistic regression model used in the analysis. Section 3 presents the empirical results along with the interpretation of key findings as well as a detailed discussion of the implications for theory and practice. Finally, Section 4 concludes the paper with a summary of findings, limitations, and suggestions for future research.

2. RESEARCH METHOD

This study employs logistic regression analysis to explore the determinants influencing consumer decisions in purchasing Toyota cars. Logistic regression is an appropriate analytical method when the dependent variable is categorical, especially binary, making it suitable for modeling purchase decisions (purchase vs. non-purchase). The primary goal of logistic regression in this context is to identify the relationship between independent variables (consumer perceptions and demographic factors) and the dependent variable (the decision to purchase a Toyota car).

Logistic regression is particularly suitable for understanding consumer behavior because it allows for estimating probabilities and identifying influential predictors in decision-making (Hosmer et al., 2013). Several researchers have employed logistic regression to analyze

consumer decision-making in various contexts. For instance, Ulkhaq et al. (2018b) used logistic regression to analyze factors influencing consumer adoption of renewable energy, emphasizing perceptual drivers in binary decisions. In the automotive domain, Ulkhaq et al. (2018a) applied AHP and TOPSIS to explore consumer vehicle preferences, while other works integrated logistic regression with behavioral transition models (Susanty et al., 2022) and machine learning frameworks (Ulkhaq et al., 2021) to predict customer churn and segment consumer types. These studies collectively demonstrate the versatility and robustness of logistic regression in modeling both product selection and broader decision-making behavior, affirming its relevance to this study on Toyota car purchases.

Unlike linear regression, logistic regression models the probability of a binary outcome using the logistic function, which transforms the linear combination of predictors to values between 0 and 1 (Peng et al., 2002). The model estimates the log odds of the dependent event occurring as a linear combination of the independent variables:

$$Logit(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon, \quad (1)$$

where β_0 is the intercept, β_1 to β_4 are coefficients representing the influence of independent variables, and ε is the error term. The coefficients (βs) are estimated using the method of maximum likelihood estimation, which identifies the parameter values that maximize the likelihood of observing the given data. The significance of each coefficient is tested using the Wald test, and model fit is evaluated using indicators such as Nagelkerke R^2, the Hosmer-Lemeshow test, and classification accuracy (Hosmer et al., 2013; Hair et al., 2018).

Logistic regression has been widely recommended over discriminant analysis due to its flexibility in handling both metric and non-metric independent variables, and because it does not assume multivariate normality or equal variance-covariance matrices (Menard, 2010; Peng et al., 2002). These features make it particularly well-suited for modeling consumer decision-making scenarios.

The dependent variable (Y) represents the consumer's decision to purchase a Toyota car, coded as '1' for purchase and '0' for non-purchase. The independent variables included satisfaction (X_1), convenience (X_2), price (X_3), and perceived risk (X_4), each measured using a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Satisfaction refers to the consumer's overall contentment with the car's performance, features, and brand image. Satisfaction is a critical psychological factor that contributes to brand loyalty and post-purchase behavior (Oliver, 1999). It has been widely recognized in consumer research as a determinant of repurchase intention and word-of-mouth influence (Cronin et al., 2000).

Convenience represents the perceived ease of access and use of the car, including factors such as dealership proximity, ease of maintenance, and availability of service centers. Convenience plays an essential role in consumer value perception and is known to enhance user satisfaction in service and product usage contexts (Berry et al., 2002).

Price sensitivity indicates the degree to which the price of the car influences the purchasing decision. Consumers who are more price-sensitive tend to be more cautious about costs and are likely to compare alternatives before making a purchase (Lichtenstein et al., 1993). In automotive markets, price sensitivity often affects brand preference and financing choices.

Perceived risk reflects the consumer's perception of uncertainty and potential negative outcomes associated with the purchase. This can include financial risk, performance risk, and social risk. Perceived risk has been shown to negatively influence consumer decision-making and reduce purchase likelihood when high (Mitchell, 1999; Stone & Grønhaug, 1993).

Data were collected through structured questionnaires distributed to consumers across various cities in Indonesia. Respondents were selected using purposive sampling techniques,

targeting Indonesian citizens aged 17 years or older who could independently make car purchasing decisions. A total of 74 respondents participated, providing demographic data alongside their perceptions and attitudes towards Toyota car purchases.

Data analysis was conducted using SPSS software, focusing on the significance and magnitude of regression coefficients, odds ratios, and model fit indicators including Nagelkerke R^2, the Hosmer-Lemeshow test, and Parallel Lines test to assess model adequacy. Significant variables were identified to provide insights into the factors most strongly influencing consumer purchasing decisions for Toyota cars.

The algorithm is decribed as follows:

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BEGIN

  Step 1: Import dataset into SPSS

  Step 2: Preprocess data
    - Check for missing values and address them
    - Confirm variable types and recode if necessary

  Step 3: Define variables
    - Set dependent variable (Purchase Decision: 1 = purchase, 0
      = no purchase)
    - Select independent variables (Satisfaction, Convenience,
      Price Sensitivity, Perceived Risk)

  Step 4: Conduct descriptive statistics
    - Generate frequency tables and descriptive summaries

  Step 5: Perform logistic regression
    - Navigate to Analyze > Regression > Binary Logistic
    - Assign dependent and independent variables
    - Specify categorical variables if any
    - Enable Hosmer-Lemeshow test, classification plots, and odds
      ratios

  Step 6: Evaluate output
    - Review model fit statistics (e.g., -2 Log Likelihood,
      Nagelkerke R²)
    - Check significance of predictors (Wald test, p-values)
    - Interpret odds ratios (Exp(B))
    - Check classification accuracy

  Step 7: Interpret results and implications

  Step 8: Document and save outputs

END
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3. RESULTS AND DISCUSSION

3.1. Logistic Regression Result

The logistic regression analysis provided valuable insights into the determinants influencing consumer decisions to purchase Toyota cars. The results from the logistic regression

analysis offer empirical insights into the determinants of consumer decisions in purchasing Toyota cars. A total of 74 valid responses were analyzed using SPSS, with four independent variables entered into the model: satisfaction, convenience, price sensitivity, and perceived risk.

Perceived risk (X_4) emerged as the most significant predictor ($p < 0.05$), negatively correlated with the purchase decision. This finding underscores the importance of managing consumer perceptions of risk associated with Toyota cars. Consumers who perceived lower risks associated with Toyota vehicles demonstrated a significantly higher likelihood of making a purchase.

Price sensitivity (X_3) also showed a significant relationship with consumer purchase decisions ($p < 0.05$), suggesting that competitive pricing strategies significantly impact consumer willingness to purchase Toyota vehicles. Respondents who expressed sensitivity to price were significantly influenced in their buying decisions, highlighting the necessity for Toyota to maintain competitive pricing.

However, satisfaction (X_1) and convenience (X_2) did not show statistically significant effects on purchasing decisions. While these factors likely contribute to overall consumer experiences, they were less influential in determining the specific decision to purchase Toyota cars within this sample.

In summary, the logistic regression analysis identified perceived risk and price sensitivity as the most influential factors in determining whether consumers would purchase a Toyota vehicle. These findings suggest that consumer trust and pricing strategies are critical levers for influencing automotive purchase behavior in the Indonesian context.

3.2. Model Fit

The model fit for the multinomial logistic regression was evaluated using several diagnostic tests. The test of parallel lines yielded a chi-square value of 26.919 with a significance level of 0.863, indicating that the assumption of proportional odds holds true. This confirms that the estimated slopes do not significantly differ across response categories, allowing the model to be interpreted using a cumulative logit approach.

Next, the model fitting information compared the intercept-only model (-2LL = 142.717) and the final model (-2LL = 79.856), resulting in a chi-square value of 62.861 ($df = 12$, $p < 0.001$). This significant improvement confirms that the inclusion of the independent variables substantially enhances the model's explanatory power.

To assess the overall goodness-of-fit, two tests were applied. The Pearson chi-square test indicated a large value (2330.151, $p < 0.001$), which might suggest poor fit if interpreted alone. However, the Deviance test, showing a value of 59.628 with a p-value of 1.000, demonstrated excellent model fit and is considered more reliable in multinomial logistic regression contexts. Thus, the Deviance test result supports that the model fits the observed data well.

Lastly, three pseudo R-square measures were computed to assess the explanatory strength of the model. The Cox and Snell R^2 was 0.544, the Nagelkerke R^2 was 0.603, and the McFadden R^2 was 0.338. Among them, the Nagelkerke R^2 is considered the most interpretable and adjusts for the maximum value that the Cox and Snell R^2 can reach, thus providing a more realistic estimation of model strength. A Nagelkerke R^2 of 0.603 suggests that 60.3% of the variation in consumers' purchase decisions can be explained by the predictors included in the model. Although pseudo R-squares do not have a direct interpretation equivalent to R^2 in linear regression, these values collectively indicate a moderately strong model fit and support the reliability of the logistic regression analysis.

3.3. Discussion

The findings of this study provide meaningful insights into the underlying factors influencing consumer decisions in purchasing Toyota cars in Indonesia. Among the four independent variables tested—satisfaction, convenience, price sensitivity, and perceived risk—only price sensitivity and perceived risk were found to have a statistically significant impact on purchase intentions.

Perceived risk demonstrated a significant negative association with the likelihood of purchasing a Toyota car. This aligns with earlier studies by Mitchell (1999) and Stone and Grønhaug (1993), who emphasized that higher perceived risk—whether financial, social, or functional—can deter consumers from making a purchase. In the automotive context, risk can stem from doubts about product durability, safety, post-purchase service, or long-term cost implications. Therefore, managing risk perception through credible communication, after-sales guarantees, extended warranties, and third-party endorsements can play a crucial role in enhancing customer trust and driving purchase decisions.

Price sensitivity also emerged as a statistically significant predictor. Consumers with higher price consciousness were more likely to factor cost considerations into their decision-making process. This finding supports the assertions of Lichtenstein et al. (1993), who explained that price-sensitive consumers are more likely to compare alternatives and delay purchase until they perceive value or discounts. Toyota and similar automakers should focus on transparent pricing strategies, flexible financing plans, and perceived value creation to attract and retain price-conscious buyers.

On the other hand, satisfaction and convenience were not found to be significant predictors in this analysis. Although these factors are often associated with consumer loyalty and post-purchase evaluation (Oliver, 1999; Berry et al., 2002), their insignificance in this context suggests that they may influence repeat purchases or brand advocacy more than initial buying decisions. Alternatively, their influence may be mediated by other variables not captured in this model, such as brand reputation or peer recommendation.

The logistic regression model demonstrated good explanatory power with a Nagelkerke R^2 of 0.603, indicating that the selected variables accounted for approximately 60.3% of the variance in purchase decision outcomes. This level of fit is considered robust in behavioral research (Hosmer et al., 2013), reaffirming the reliability of the findings. Furthermore, the Hosmer-Lemeshow test indicated a good model fit, validating the appropriateness of the logistic regression approach for analyzing consumer behavior data.

These findings align with previous research that underscores the dual importance of minimizing consumer-perceived risk and optimizing perceived economic value (Cronin et al., 2000; Ulkhaq et al., 2018). To remain competitive in an increasingly saturated automotive market, Toyota should continue to invest in strategies that increase perceived reliability and cost-effectiveness while maintaining consistent service quality.

Overall, this study contributes to the literature by reinforcing the relevance of perceived risk and pricing in automotive purchase decisions in emerging markets and demonstrates how statistical modeling can reveal key behavioral insights for strategic decision-making in marketing and product positioning.

4. CONCLUSION

This study examined the key factors influencing consumer decisions to purchase Toyota cars in Indonesia using logistic regression analysis. Based on data from 74 respondents, the results revealed that perceived risk and price sensitivity significantly affect purchase intentions,

while satisfaction and convenience do not show a direct impact. The model demonstrated a strong explanatory power with a Nagelkerke R^2 of 0.603, affirming its validity.

These findings underline the necessity for Toyota to focus its strategic efforts on reducing perceived consumer risk and maintaining competitive pricing. Such initiatives may include strengthening warranty programs, improving after-sales service, and enhancing value-for-money perceptions. By prioritizing these factors, Toyota can better align its offerings with consumer expectations and reinforce its market leadership in the Indonesian automotive sector.

While this study provides valuable insights into consumer decision-making in the Indonesian automotive market, it is not without limitations. First, the sample size was relatively small (n = 74), which may limit the generalizability of the findings to broader populations or different geographic regions. Future research should consider increasing the sample size and including respondents from multiple provinces to enhance representativeness. Second, the study utilized cross-sectional data collected at a single point in time. This limits the ability to capture changes in consumer behavior over time or in response to market dynamics. Longitudinal studies or panel data analysis could provide a more comprehensive understanding of how consumer preferences evolve. Third, the current model focuses on only four independent variables—satisfaction, convenience, price sensitivity, and perceived risk. Although these factors are relevant, they may not fully capture the complexity of consumer behavior. Future studies could incorporate psychological constructs (e.g., brand trust, motivation), socio-demographic variables (e.g., income, education), and digital engagement (e.g., online reviews, influencer exposure) to enrich the explanatory power of the model. Lastly, while logistic regression provided robust results, integrating other analytical techniques such as decision trees, random forests, or ensemble machine learning models could enhance predictive accuracy and uncover nonlinear relationships. Comparative model performance evaluation could also offer insights into the most effective approaches for modeling consumer behavior in the automotive sector.

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