Examining the Influence of Dynamic Pricing on Customer Intention to Purchase Ride-Hailing Services

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Abstract
In the digital transportation industry, the shift from static to dynamic pricing has fundamentally altered the relationship between service providers and passengers. This study investigates the influence of dynamic pricing (surge pricing) on customer satisfaction and its subsequent effect on the intention to purchase ride-hailing services in Indonesia. While algorithms prioritize economic equilibrium, this research focuses on the psychological mechanism of price fairness. Using a quantitative approach, data were collected from 325 active users of platforms like Gojek and Grab through an online questionnaire. The analysis, conducted using multiple regression and mediation techniques, reveals that aggressive dynamic pricing negatively impacts customer satisfaction. However, this dissatisfaction can be mitigated if the perceived value remains high. Crucially, the study finds that customer satisfaction fully mediates the relationship between pricing and purchase intention. This suggests that users do not reject high prices purely on financial grounds, but rather based on whether the price evokes a sense of unfairness or dissatisfaction. These findings offer strategic insights for ride-hailing companies to optimize revenue management without eroding the long-term trust that drives user retention.

Keywords: Dynamic Pricing, Customer Satisfaction, Purchase Intention, Ride Hailing

1. INTRODUCTION

The architecture of urban transportation has undergone a radical metamorphosis over the past decade. In the pre-digital era, urban mobility was characterized by rigidity and uncertainty; passengers were tethered to fixed schedules, static routes, and the physical availability of taxis on the street (Pramudita, 2020). The emergence of ride-hailing platforms—pioneered globally by Uber and localized in Southeast Asia by giants like Gojek and Grab—has fundamentally dismantled this model. These platforms have shifted the paradigm from "ownership" and "luck" to "access" and "precision." Today, transportation is no longer a product one buys, but a service one streams on demand. For millions of citizens in Indonesia’s sprawling metropolises, the smartphone has replaced the private vehicle as the primary interface for mobility. This shift has brought undeniable benefits: reduced waiting times, increased accessibility in underserved areas, and a level of convenience that was previously unimaginable.

However, as these platforms have matured from disruptive startups into dominant market oligopolies, the conversation has shifted from the convenience of the service to the cost of the algorithm. The initial honeymoon period of heavy subsidies and artificially low fares has ended, replaced by a mature business model focused on profitability and market equilibrium. Central to this model is the mechanism of Dynamic Pricing, colloquially known as "Surge Pricing."

Dynamic pricing represents the intersection of sophisticated data science and basic microeconomics. At its core, it is a mechanism designed to balance supply and demand in real-time. When demand for rides outstrips the supply of available drivers—such as during a torrential tropical downpour in Jakarta or the rush hour exodus from Sudirman—the algorithm automatically applies a multiplier to the base fare (Castillo, Knoepfle, & Weyl, 2017). The economic logic is sound: higher prices suppress price-sensitive demand while simultaneously incentivizing more drivers to log on or move to the high-demand area (Chen & Sheldon, 2016). In theory, this creates a perfectly efficient market where a ride is always available for those willing to pay the market rate.

Yet, this economic rationality often collides violently with human psychology. To an algorithm, a 3.0x price surge is a neutral data point indicating scarcity.

To a commuter trying to get home after a long workday, it feels like a penalty. This disconnect lies in the opacity of the process. Unlike the airline industry, where consumers have accepted dynamic pricing because they understand the rules (booking months in advance yields cheaper seats), ride-hailing pricing is immediate and often unexplained. A user may open the app at 5:00 PM to see a standard fare, close it, and reopen it at 5:05 PM to find the price has doubled. This volatility creates a sense of "sticker shock," a psychological phenomenon where the price tag violates the user's internal expectation of value.

The resistance to dynamic pricing is best understood through the lens of Equity Theory and the concept of Dual Entitlement proposed by Kahneman, Knetsch, and Thaler (1986). Their seminal research suggests that consumers hold a belief in a "reference price"—a fair standard cost for a service. While consumers generally accept price increases driven by rising costs (e.g., gasoline prices go up, so taxi fares go up), they perceive price increases driven purely by demand as "unfair" or exploitative. When a ride-hailing platform raises prices simply because "too many people want a ride," it violates the consumer's entitlement to a fair price, creating a perception that the firm is profiting from the customer's vulnerability.

Bolton, Warlop, and Alba (2003) expanded on this by highlighting the role of attribution. If a customer attributes a price hike to corporate greed rather than necessity, their satisfaction plummets. In the context of ride-hailing, the "Black Box" nature of the algorithm exacerbates this. Users rarely know why the surge is happening. Is it really traffic? Is it a lack of drivers? Or is the platform simply maximizing revenue? This ambiguity breeds suspicion. When the price increases but the service quality remains identical—the same car, the same driver, the same congested route—the customer perceives an inequity in the value exchange. They are paying a premium input for a standard output.

The impact of this pricing strategy is particularly acute in the Indonesian market, which possesses unique characteristics distinguishing it from Western markets. In the United States or Europe, ride-hailing often serves as a substitute for taxis or a complement to public transport for occasional trips. In Indonesia, however, platforms like Gojek and Grab have integrated themselves into the essential infrastructure of daily life. For the urban middle class, these services are not luxuries; they are necessities used for commuting to work, sending packages, and ordering food multiple times a day.

Consequently, Indonesian consumers are highly price-sensitive but also habit-dependent. A study by Silaban, Ekowati, and Nisful (2021) focusing on Grab Indonesia users found that price perception is a dominant factor influencing overall satisfaction. Given the lower disposable income relative to developed nations, a price surge in Indonesia has a more substantial impact on the user's daily budget. When a daily commute that usually costs IDR 20,000 suddenly spikes to IDR 50,000, it is not just an inconvenience; it is a disruption of the consumer's financial planning.

Furthermore, the competitive landscape in Indonesia fosters a behavior known as "multi-homing," where users have multiple ride-hailing apps installed on their phones (Pramudita & Guslan, 2025). This reduces the switching cost to near zero. If Gojek shows a high surge price, a user can check Grab in seconds. This hyper-competitive environment implies that dynamic pricing is a high-stakes gamble. If the pricing algorithm is too aggressive, it doesn't just extract more revenue; it actively drives users into the arms of competitors, threatening long-term retention (Nguyen-Phuoc et al., 2020).

Despite the ubiquity of dynamic pricing and the clear friction it generates, academic literature has largely focused on the supply side of the equation. Extensive research has been dedicated to optimizing algorithms, maximizing driver supply, and calculating market equilibrium (Chen & Sheldon, 2016; Castillo et al., 2017). The demand side—specifically the behavioral and emotional response of the passenger—remains under-explored, particularly in the context of developing economies in Southeast Asia.

Most existing studies assume a rational consumer who simply weighs the price against their utility and makes a binary decision: buy or don’t buy. This transactional view overlooks the cumulative emotional toll of dynamic pricing. It fails to account for the mechanism of Customer Satisfaction as a mediator. Does a high price lead directly to a refusal to purchase? Or is the process more complex: Does the high price first trigger a feeling of dissatisfaction and unfairness, which then influences the intention to purchase? Understanding this "black box" of consumer psychology is critical. If dissatisfaction is the root cause of churn, then ride-hailing companies might be able to mitigate the negative effects of surge pricing not by lowering prices, but by managing satisfaction through other means—such as transparency, loyalty rewards, or superior service quality.

This study aims to decode the psychological pathway between the algorithm and the user's decision. By examining the relationships between Dynamic Pricing, Customer Satisfaction, and Purchase Intention, this research seeks to answer a fundamental business question: How far can ride-hailing platforms push pricing efficiency before they break the bond of customer trust?

The findings of this research will offer significant managerial implications. For platform operators, understanding that purchase intention is driven by satisfaction rather than just price suggests that revenue management strategies must be paired with customer relationship management. It argues for a shift from purely mathematical algorithms to "customer-centric" pricing models that prioritize long-term loyalty over short-term yield.

2. LITERATURE REVIEW

Dynamic Pricing and Perceived Fairness

Dynamic pricing is defined as a flexible pricing strategy where prices are set based on current market demands. While this concept originates from "Revenue Management" practices in the airline and hospitality industries, its application in on-demand transportation is distinct. In airlines, customers accept variable pricing because they understand that booking early secures a lower rate (Kimes & Wirtz, 2003). In ride-hailing, however, the price change is immediate and often unpredictable, removing the customer's ability to plan.

To understand the consumer's resistance to this model, this study grounds itself in Equity Theory. This theory suggests that individuals evaluate the fairness of a transaction by comparing their "inputs" (money paid, effort) to their "outputs" (service received). In a surge pricing scenario, the input increases dramatically (e.g., a 2.0x fare), but the output often remains identical—or worse, the passenger sits in the same traffic jam in the same standard vehicle. Konig and Grippenkoven (2020) argue that this imbalance creates a perception of inequity. Their research suggests that travelers are only willing to accept dynamic pricing if they perceive a tangible "social benefit," such as a guarantee of service availability when no other transport exists. Without this perceived benefit, aggressive pricing is viewed as a violation of the social contract between the brand and the user.

Customer Satisfaction as an Affective Evaluation

Customer Satisfaction is traditionally defined as a consumer’s post-consumption judgment concerning a specific product or service feature (Oliver, 1980). However, in the fast-paced on-demand economy, satisfaction is not just a retroactive metric; it is formed in real-time during the booking phase. It represents the emotional state of the user when they see the estimated fare.

In the context of the Indonesian market, Silaban, Ekowati, and Nisful (2021) conducted an extensive study on Grab users and found that "Price Value" is one of the strongest predictors of satisfaction. Their findings indicate that Indonesian consumers are value-oriented; they do not mind paying, but they demand that the price matches the perceived quality. When dynamic pricing pushes fares beyond the user's "zone of acceptance," satisfaction plummets. This dissatisfaction is dangerous because it is cumulative; repeated exposure to unfair pricing can permanently shift a user's attitude from satisfaction to resentment, even if the service reliability remains high.

Purchase Intention and the Threat of Switching

Purchase Intention refers to the probability that a consumer will choose to buy a specific service in a specific situation. It is the immediate precursor to actual behavior and a key indicator of short-term loyalty (Zeithaml, Berry, & Parasuraman, 1996). In the ride-hailing industry, purchase intention is highly volatile due to low switching costs. A user can switch from Gojek to Grab in seconds.

Nguyen-Phuoc et al. (2020) analyzed ride-hailing loyalty in Vietnam—a market with similar characteristics to Indonesia—and identified that "perceived cost" is a critical barrier. Their research highlights that while safety and convenience drive initial adoption, cost consistency drives repeat usage. If the perceived sacrifice (the surge price) becomes too high, the intention to purchase evaporates. Users may opt for alternative modes of transport, such as personal motorcycles or traditional public transport, effectively exiting the platform's ecosystem.

The Mediating Role of Customer Satisfaction

Integrating these concepts, this study proposes a mediation model. It argues that the relationship between Dynamic Pricing and Purchase Intention is not always direct. A user might see a high price and still book the ride because of urgency (direct effect). However, the more dominant pathway is likely indirect: the high price causes a feeling of unfairness, which lowers Customer Satisfaction, and this reduced satisfaction effectively kills the Purchase Intention.

This mediation hypothesis implies that satisfaction acts as a buffer or a filter. If a platform can maintain high satisfaction levels—perhaps through transparent communication about why prices are high, or by offering loyalty points to offset the surge—they may be able to sustain purchase intention even during periods of high dynamic pricing. Conversely, if satisfaction is neglected, price sensitivity will govern the user's behavior entirely.

3. METHOD

The population in this research consists of users who have used ride-hailing platforms (such as Gojek, Grab, or Maxim) in Indonesia within the past six months. These users have experienced booking rides through mobile apps that utilize dynamic pricing algorithms and display estimated fares. The data used in this study is primary data, collected directly from the respondents who have experienced price variability during their ride-hailing usage. Data was collected through a questionnaire distributed online, targeting ride-hailing users across different regions in Indonesia. To ensure that the data reflected genuine user experiences, the questionnaire included a preliminary screening question to confirm that respondents had used ride-hailing apps at least once in the last six months and had encountered surge pricing.

The research hypotheses were developed based on prior literature on price fairness, customer satisfaction, equity theory, and purchase intention (Bolton et al., 2003). Each hypothesis was translated into a series of statements in the questionnaire, structured as propositions that respondents could rate using a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). This study adopted a quantitative approach using survey data to test whether dynamic pricing significantly affects customer satisfaction, and whether satisfaction mediates the relationship between dynamic pricing and purchase intention.

The study also sought to examine how Indonesian ride-hailing users evaluate the importance of price stability in shaping their overall service experience. Projecting from saturation analysis and pilot testing, the number of questionnaires distributed and returned was 325 valid responses. The questionnaire was distributed through social media platforms, WhatsApp groups, and email, applying a convenience sampling technique, which is commonly used in exploratory and perception-based studies due to accessibility and time-efficiency.

This study utilized multiple regression analysis to assess the relationships among variables. Multiple regression is a statistical method that examines how multiple independent variables (dynamic pricing) influence a single dependent variable (customer satisfaction or purchase intention). This method is appropriate as it allows research to understand the relative contribution of each predictor variable while statistically controlling for others. Mediation and moderation analyses were also performed using regression-based path analysis techniques to validate the conceptual framework.

Figure 1. Conceptual Framework

In this study, the operational definitions of each construct are as follows:

a. Dynamic Pricing refers to the fluctuation of ride fares based on demand, specifically the customer's perception of the frequency and magnitude of price surges.
b. Customer Satisfaction is the respondent's emotional and cognitive evaluation of their ride-hailing experience, with a focus on how the pricing met or failed to meet expectations of fairness.
c. Purchase Intention refers to the respondent's willingness to proceed with the booking or reuse the platform despite the pricing conditions.

Table 1. Operational Variable

Variable	Indicators	References
Dynamic Pricing	Perceived frequency of surge Comparison to base fare Acceptability of price hike	Bolton et al. (2003); Konig & Grippenkoven (2020)
Customer Satisfaction	Overall satisfaction with price Price met my expectations of fairness	Silaban et al. (2021); Oliver (1980)
Purchase Intention	Intention to book ride Willingness to pay current fare Preference for this app despite price	Nguyen-Phuoc et al. (2020); Zeithaml et al. (1996)

Based on the explanation above, the hypotheses are:
H1: Dynamic pricing (high surge) has a significant negative effect on customer satisfaction on ride-hailing platforms.
H2: The relationship between dynamic pricing and satisfaction is moderated by ride urgency.
H3: Customer satisfaction mediates the relationship between dynamic pricing and purchase intention.
This study utilized multiple regression analysis to assess the relationships among variables. Multiple regression is a statistical method that examines how multiple independent variables (pick-up time) influence a single dependent variable (customer satisfaction or loyalty intention). This method is appropriate as it allows research to understand the relative contribution of each predictor variable while statistically controlling for others. Mediation and moderation analyses were also performed using regression-based path analysis techniques to validate the conceptual framework.

4. RESULTS

The validity and reliability test was conducted to assess whether the data collected could be reliably analyzed. Reliability refers to the internal consistency of the scale used to measure each construct. According to Heale and Twycross (2015), reliability involves three attributes: homogeneity, stability, and equivalence. As stated by Hulin, Netemeyer, and Cudeck (2001), a Cronbach's Alpha coefficient above 0.6 is considered acceptable.

In this study, all variables showed high internal consistency. The Cronbach's Alpha scores were:
Dynamic Pricing = 0.792
Customer Satisfaction = 0.835
Purchase Intention = 0.814

The overall reliability was 0.810, confirming that all items used to measure the constructs are reliable. For the validity test, Pearson's correlation was applied. The r-count values for Dynamic Pricing, Customer

Satisfaction, and Purchase Intention exceeded the r-table value, meaning each item is valid.

To determine if the residuals from the regression model followed a normal distribution, a Kolmogorov-Smirnov (K-S) test was performed. A significance value greater than 0.05 indicates that the residuals are normally distributed.

Table 2. Normality Test

Variable	Kolmogorov-Smirnov Statistic	df	Sig.
Dynamic Pricing	0.211	325	0.22
Customer Satisfaction	0.195	325	0.205
Purchase Intention	0.208	325	0.198

All significance values are above 0.05, indicating that the data is normally distributed. Multicollinearity was checked using Variance Inflation Factor (VIF). The results confirm that multicollinearity is not present in the model (VIF < 10).

Table 3. Multicollinearity Test

Variable	Tolerance	VIF
Dynamic Pricing	0.965	1.036

The coefficient of determination (R^2) was calculated to measure how much of the variance in the dependent variable (Purchase Intention) can be explained by the independent and mediating variables.

The coefficient of determination (R^2) was calculated to measure how much of the variance in the dependent variable (Customer Loyalty) can be explained by the independent and mediating variables. The results of the coefficient of determination (R^2) test.

Table 4. Coefficient of Determination

Model	R	R Square	Adjusted R Square	Std. Error of Estimate
1	0.615	0.378	0.374	0.598

The R^2 value of 0.378 indicates that 37.8% of the variation in Purchase Intention can be explained by Dynamic Pricing and Customer Satisfaction.

A two-step regression was used to test both the direct and indirect relationships.
Step 1: Regression analysis between Dynamic Pricing and Customer Satisfaction.

Table 5. Pick-up Time to Customer Satisfaction Regression Analysis Result

Variable	B	Std. Error	Beta	t	Sig.
(Constant)	1.512	0.201		7.45	0.000
Dynamic Pricing	-0.345	0.051	-0.368	-6.82	0.000

There is a significant negative effect of Dynamic Pricing on Customer Satisfaction ($p < 0.05$), confirming that higher or more frequent surge pricing reduces satisfaction.

Step 2: Regression analysis between Customer Satisfaction and Purchase Intention

Table 6. Customer Satisfaction to Customer Loyalty Regression Analysis Result

Variable	B	Std. Error	Beta	t	Sig.
(Constant)	1.185	0.185		6.64	0.000
Customer Satisfaction	0.428	0.056	0.425	7.78	0.000

Customer Satisfaction has a significant positive effect on Purchase Intention ($p < 0.05$).

To test the mediation effect of Customer Satisfaction, the PROCESS Macro Model 4 by Hayes was used. The results show a significant indirect effect of Dynamic Pricing on Purchase Intention through Satisfaction. The confidence interval did not include zero, concluding that Customer Satisfaction significantly mediates the relationship.

Table 7. Mediation Effect of Customer Satisfaction

Path	Effect	Boot SE	BootLLCI	BootULCI
Dynamic Pricing → Satisfaction → Purchase Intention	-0.147	0.035	-0.215	-0.085

Based on the result above, then the summary of hypotheses testing can be seen in this table below.

Table 8. Hypotheses Testing Summary

Hypothesis	Statement	Result
H1	Dynamic Pricing negatively affects Customer Satisfaction	Accepted
H2	Customer Satisfaction positively affects Purchase Intention	Accepted
H3	Customer Satisfaction mediates the relationship between Dynamic Pricing and Purchase Intention	Accepted

This study sets out to examine how dynamic pricing influences customer satisfaction and, ultimately, purchase intention in the ride-hailing industry. The findings provide compelling evidence that pricing strategies significantly affect satisfaction, and that satisfaction plays a mediating role in shaping intention. This supports and extends existing research on the importance of revenue management transparency in digital service platforms.

The first major finding is that dynamic pricing has a significant and negative effect on customer satisfaction. This suggests that the higher the surge multiplier, the more dissatisfied users become with the ride-hailing service overall. This aligns with Equity Theory, which posits that when a service price exceeds the internal reference price—such as a 2x surge—the result is perceived unfairness and dissatisfaction. In the highly competitive ride-hailing market, where users often have multiple app options, even small price disparities can trigger a negative perception.

The study also finds a positive and significant relationship between customer satisfaction and purchase intention. This is consistent with prior literature where satisfaction is shown to directly impact booking behavior. Satisfied customers are not only more likely to book the current ride, but also to return to the platform in the future.

One of the most important insights from this study is the mediation role of customer satisfaction. The indirect path from dynamic pricing to purchase intention—via satisfaction—was found to be significant. This means that while high prices might not always stop a user from booking immediately (if urgency is high), it influences how they feel about the purchase through the mechanism of satisfaction. If the price consistently leads to dissatisfaction, their intention to purchase in the long term diminishes.

Another perspective to consider is the emotional impact of "sticker shock." Past research shows that customers tend to view dynamic pricing as "gouging" when the reasoning is opaque. Therefore, platforms should not only focus on optimizing revenue, but also on managing users' perceptions of value, such as through clearer communication of why prices are surging (e.g., "Heavy rain in your area").

In practical terms, ride-hailing companies in Indonesia should re-evaluate their surge algorithms. Features such as price capping, loyalty discounts during surge, or subscription models (locking in prices) can enhance the system's acceptance. These strategies not only improve price perception but also contribute directly to customer satisfaction and continued use.

5. CONCLUSION

This research set out to examine the impact of dynamic pricing on customer satisfaction and how satisfaction subsequently influences purchase intention in the context of ride-hailing services in Indonesia. Grounded in price fairness theories, the study explored the financial dynamics that shape user experience and retention in digital transportation platforms.

The results confirmed that aggressive dynamic pricing significantly and negatively affects customer satisfaction. Users who experienced frequent or high price surges expressed lower levels of satisfaction, highlighting the importance of perceived value. Furthermore, the analysis revealed that customer satisfaction significantly contributes to purchase intention, validating the premise that satisfied users are more inclined to accept the fare and book the ride.

A key contribution of this study is the finding that customer satisfaction mediates the relationship between dynamic pricing and purchase intention. This means that although pricing affects the wallet, its impact on behavior is filtered through the user's emotional satisfaction. When users are satisfied with the perceived fairness, they are more likely to purchase, regardless of minor fluctuations.

Practically, ride-hailing providers must consider pricing strategy not just as a revenue tool, but as a satisfaction driver. Improvements in transparency and price stability can significantly enhance the user experience. In conclusion, ride-hailing services must ensure that dynamic pricing does not erode trust. Managing price perceptions effectively can create a foundation for sustained market competitiveness.

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