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ARTIFICIAL INTELLIGENCE (AI) DRIVEN DYNAMIC PRICING: IMPACT ON CUSTOMER LOYALTY IN INDIAN RIDE HAILING PLATFORMS

Ms. Samriddhi Batra[1]* and Dr. Nitika Aggarwal[2]

[1]PGP (MBA) Scholar, IIM Bangalore, Bengaluru, India
*Corresponding Author

[2]Assistant Professor, Department of Commerce, Ramjas College, University of Delhi, Delhi, India.

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ABSTRACT

This study examines customer behaviour toward AI-driven dynamic pricing in Indian ride-hailing services, with a focus on customer perceptions of price fairness. The research further investigates the mediating role of perceived price fairness and customer satisfaction in shaping customer loyalty. A quantitative research design was adopted, and primary data were collected from 150 respondents using a structured questionnaire and analysed through "Just Another Method of a Viable Interface" (JAMOVI) statistical software. Statistical techniques, including correlation, regression, mediation, and group comparison analyses, were employed to test the hypotheses. The findings reveal that AI-driven surge pricing has a significant negative impact on perceived price fairness, customer satisfaction, and customer loyalty. In contrast, pricing transparency exerts a significant positive influence on customer perceptions of price fairness. These results highlight that perceived price fairness and customer satisfaction serve as significant mediators in strengthening the relationships among the variables. The study concludes that transparency and fairness in pricing strategies play a crucial role in enhancing customer satisfaction and loyalty within the Indian ride-hailing industry.

KEYWORDS: AI-Driven Dynamic Pricing, Pricing Transparency, Ride-Hailing Services, Perceived Fairness, Customer Satisfaction and Customer Loyalty

INTRODUCTION

The advancement of artificial intelligence (AI) has significantly transformed pricing mechanisms across digital platforms, particularly through the adoption of dynamic pricing in ride-hailing services. Platforms such as Ola, Uber, and Rapido increasingly utilize AI-driven algorithms to adjust fares in real time in response to fluctuations in demand and supply, with the objective of optimizing operational efficiency and maximizing revenue. These systems continuously modify fares based on multiple factors, including demand intensity, supply availability, time, location, and customer behaviour, thereby enabling firms to respond to market dynamics more effectively (Spann, 2025).

Despite these advantages, however, the influence of dynamic pricing on customer perceptions remains complex. Surge pricing, in particular, often generates adverse reactions, as it affects perceived price fairness and raises concerns regarding transparency and trust. Such perceptions play a crucial role in shaping customer satisfaction and may ultimately diminish loyalty and retention.

Against this backdrop, the present study explores how customers interpret and respond to AI-driven dynamic pricing. It specifically examines the role of pricing transparency and perceived price fairness in shaping customer satisfaction and loyalty. Existing research identifies perceived fairness as a key determinant of customer loyalty on digital platforms (Song, Chen, & Lin, 2025); however, much of the literature focuses on economic outcomes while giving limited attention to behavioural responses. Accordingly, this study investigates the effects of AI-driven dynamic pricing and pricing transparency on perceived price fairness, customer satisfaction, and customer loyalty among ride-hailing customers in India.

REVIEW OF LITERATURE

Dynamic pricing refers to a pricing strategy that enables firms to adjust prices in real time in response to changing market conditions such as demand, supply, competition, and consumer characteristics (Elmaghraby & Keskinocak, 2003). With the integration of artificial intelligence (AI), these systems have become increasingly sophisticated, utilizing machine learning algorithms, data analytics, and predictive modelling to optimize pricing decisions and improve operational efficiency (Chen et al., 2021; Ferreira et al., 2016).

In the context of ride-hailing services, dynamic pricing, commonly referred to as surge pricing, is employed to balance demand and supply by incentivizing drivers and regulating customer demand during periods of market imbalance (Castillo et al., 2017; Cohen et al., 2016). Although this approach is considered economically efficient, it often gives rise to perceptions of price volatility and opportunistic behaviour among customers, thereby influencing their overall evaluation of the service (Bolton et al., 2003; Xia et al., 2004).

Previous studies have consistently highlighted that customer satisfaction, trust, and perceived fairness are key determinants of customer loyalty (Oliver, 1999; Reichheld & Sasser, 1990). This becomes particularly important in highly competitive markets such as ride-hailing services, where even minor dissatisfaction can encourage customers to switch to alternative platforms (Clemes et al., 2014).

Furthermore, research suggests that consumers are more likely to accept dynamically changing prices when such pricing practices are perceived as justified, transparent, and fair. Conversely, a lack of

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clarity regarding pricing mechanisms often leads to negative perceptions, reducing customer trust and acceptance of dynamic pricing strategies (Haws & Bearden, 2006; Kahneman et al., 1986).

RESEARCH GAP

Existing literature indicates that research on dynamic pricing in ride-hailing platforms has primarily focused on revenue optimization, demand–supply balancing, and operational efficiency. Although several studies have examined the role of pricing transparency and perceived fairness in shaping customer behaviour, these factors have often been investigated independently rather than within an integrated framework.

Consequently, a significant gap remains in understanding the overall relationship among AI-driven pricing, perceived price fairness, customer satisfaction, and customer loyalty. Furthermore, empirical evidence from emerging markets such as India remains limited, particularly within the ride-hailing industry, where customers tend to be highly sensitive to price fluctuations.

In addition, existing studies have devoted relatively less attention to customer experiences and behavioural responses associated with AI-driven pricing mechanisms. To address these gaps, the present study adopts a customer-centric perspective and examines how AI-driven dynamic pricing and pricing transparency influence perceived price fairness, customer satisfaction, and customer loyalty among ride-hailing customers in India through a structured, data-driven approach.

OBJECTIVES

1. To examine the effect of AI-driven dynamic pricing on perceptions of price fairness among ride-hailing customers.
2. To analyse the impact of pricing transparency on perceived price fairness.
3. To evaluate the influence of perceived price fairness on customer satisfaction.
4. To assess the impact of pricing transparency on customer satisfaction.
5. To determine the effect of dynamic pricing on customer satisfaction.
6. To examine the influence of customer satisfaction on customer loyalty.

HYPOTHESIS

H1: AI-driven dynamic pricing significantly influences perceived price fairness.

H2: Pricing transparency significantly influences perceived price fairness.

H3: Perceived price fairness significantly influences customer satisfaction.

H4: Pricing transparency significantly influences customer satisfaction.

H5: AI-driven dynamic pricing significantly influences customer satisfaction.

H6: Customer satisfaction significantly influences customer loyalty.

RESEARCH METHODOLOGY

The present study adopts an empirical research design and relies on primary data collection methods to examine the relationships among the selected variables. Data were collected through a structured questionnaire developed using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was administered through Google Forms and distributed via various digital platforms. A total of 150 respondents participated in the study. The sample was selected using a non-probability purposive sampling technique, targeting individuals who actively use ride-hailing platforms such as Ola, Uber, and Rapido.

For data analysis, a combination of descriptive and inferential statistical techniques was employed. Descriptive measures, including percentage analysis and weighted mean, were used to summarize and interpret the data. Furthermore, inferential statistical methods, such as correlation and regression analysis, were applied to examine the relationships among the variables. In addition, mediation analysis was conducted to assess the indirect effects between the constructs and provide a deeper understanding of their interrelationships.

All statistical analyses were performed using “Just Another Method of a Viable Interface” (JAMOVI) statistical software, which facilitated reliable, accurate, and efficient data processing and analysis.

RESULTS AND DISCUSSIONS

The demographic profile of the respondents was analysed using frequency and percentage distributions. The variables considered included age, gender, monthly income, frequency of ride-hailing usage, type of city, preferred platform, and purpose of usage. As presented in Table 1, the findings indicate that a substantial proportion of respondents belonged to the 18–35 age group (74.7%). In terms of gender distribution, 55.3% were female and 44.7% were male. Most participants were concentrated within the monthly income range of ₹20,000–₹70,000 (53.3%).

With regard to ride-hailing usage patterns, the data reveal a relatively high level of engagement, with 60.7% of respondents using such services at least 1–2 times per week (34.7%: 1–2 times; 26.0%: 3–5 times). Furthermore, a significant share of the sample resided in Tier-1 (56.7%) and Tier-2 (30.7%) cities. Platform preferences were evenly distributed between Ola (37.3%) and Uber (37.3%), while the predominant purpose of usage was work-related travel, accounting for 66.0% of the responses
Table 2 presents the overall weighted mean and standard deviation of the study variables. The results indicate a moderate level of agreement toward AI-driven dynamic pricing (Mean = 3.755, SD = 0.729),

suggesting a reasonable degree of awareness accompanied by relatively consistent responses among the participants. Similarly, pricing transparency (Mean = 3.117, SD = 0.875) and perceived price fairness (Mean = 3.139, SD = 0.818) reflect neutral to slightly positive perceptions, although some variation in respondents' opinions is evident.

TABLE 1: Demographic Profile

Age (years)	18–25 years	64	42.7%
	26–35 years	48	32.0%
	36–45 years	23	15.3%
	Above 45 years	15	10.0%
Gender	Female	83	55.3%
	Male	67	44.7%
Monthly Income (₹)	Below ₹20,000	31	20.7%
	₹20,001 – ₹40,000	39	26.0%
	₹40,001 – ₹70,000	41	27.3%
	₹70,001 – ₹1,00,000	20	13.3%
	Above ₹1,00,000	19	12.7%
Frequency Of Usage	Daily	13	8.7%
	3–5 times per week	39	26.0%
	1–2 times per week	52	34.7%
	A few times a month	33	22.0%
	Rarely (less than once a month)	13	8.7%
Type of City	Tier-1 city	85	56.7%
	Tier-2 city	46	30.7%
	Tier-3 city or small town	19	12.7%
Preferred Ride-Hailing Platform	Ola	56	37.3%
	Uber	56	37.3%
	Rapido	38	25.3%
Primary Purpose	Work	99	66.0%

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	Leisure	51	34.0%

In contrast, customer satisfaction (Mean = 2.766, SD = 0.707) indicates a slight level of dissatisfaction, with a comparatively high degree of agreement among respondents. Furthermore, customer loyalty (Mean = 1.880, SD = 0.673) records the lowest mean score, suggesting a strong consensus regarding weak loyalty toward ride-hailing platforms.

TABLE 2: Weighted mean scores and Standard deviation of the variables

Constructs	Items	Weighted Mean Score	Standard deviation	Interpretation
Dynamic Pricing	B1-B5	3.755	0.729	Moderate Agreement
Pricing Transparency	C1-C4	3.117	0.875	Neutral to Slight Agreement
Perceived Price Fairness	D1-D5	3.139	0.818	Neutral to Slight Agreement
Customer Satisfaction	E1-E6	2.766	0.707	Slight Disagreement
Customer Loyalty	F1-F5	1.880	0.673	Strong Disagreement

Taken together, these findings imply that relatively lower levels of perceived transparency and price fairness may adversely affect customer satisfaction, which, in turn, could contribute to reduced customer loyalty.

As presented in Table 3, the reliability analysis indicates satisfactory internal consistency across the study constructs, with all variables exceeding the recommended threshold of 0.70. The only exception is Pricing Transparency ($\alpha = 0.679$), which has been retained due to its theoretical significance and its proximity to the acceptable reliability level.

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Table 3: Reliability Analysis

Construct	Items	Cronbach's Alpha (α)	Status
Dynamic Pricing Awareness	5	0.7770	**Acceptable**
Pricing Transparency	4	0.6789	**Marginally Acceptable**
Perceived Price Fairness	5	0.8919	**Acceptable**
Customer Satisfaction	6	0.9006	**Acceptable**
Customer Loyalty	5	0.7856	**Acceptable**

As shown in Table 4 and the eigenvalue scree plot presented in Figure 1, most items exhibit adequate factor loadings above the recommended threshold of 0.40, indicating a well-defined factor structure. The eigenvalue results further reveal that Factor 1 (7.5525), Factor 2 (1.6549), and Factor 3 (1.4624) account for a substantial proportion of the total variance.

Table 4: Exploratory Factor Analysis (EFA)

Item	Factor	Loading	Uniqueness
B1	3	0.729	0.452
B2	3	0.540	0.566
B3	3	0.741	0.462
B4	3	0.618	0.537
B5	3	0.451	0.720
C1	5	0.508	0.660
C2	5	0.447	0.734
C3	5	0.668	0.528
C4	5	0.718	0.440
D1	2	0.764	0.415
D2	2	0.763	0.329
D3	2	0.730	0.352
D4	2	0.794	0.333

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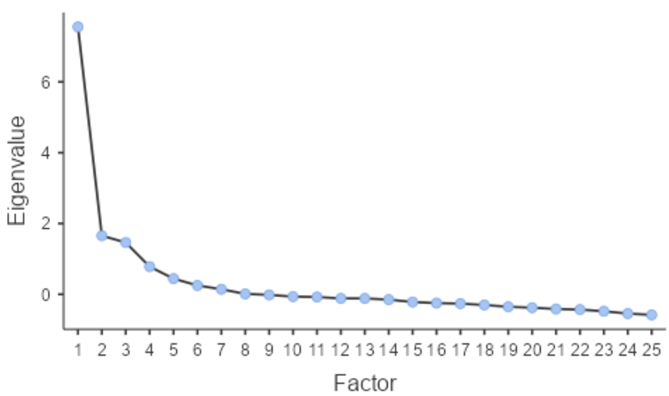
D5	2	0.756	0.353
E1	1	0.658	0.345
E2	1	0.757	0.291
E3	1	0.693	0.383
E4	1	0.673	0.384
E5	1	0.808	0.347
E6	1	0.678	0.524
F1	4	0.583	0.470
F2	4	0.422	0.544
F3	4	0.628	—
F4	4	0.471	0.609
F5	4	0.581	0.448

Correspondingly, the scree plot displays a distinct "elbow" at Factor 3, suggesting the suitability of a three-factor solution.

Nevertheless, five factors were retained in accordance with the underlying theoretical framework. This decision supports the conceptual structure of the study and provides evidence of acceptable construct validity.

Figure 1: Eigen Value Scree Plot



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As presented in Table 5, AI-driven dynamic pricing (experience) exhibits a negative relationship with perceived fairness ($r = –0.294$), customer satisfaction ($r = –0.369$), and customer loyalty ($r = –0.269$). These results suggest that greater exposure to dynamic pricing is associated with less favourable customer evaluations and experiences. In contrast, pricing transparency demonstrates positive associations with perceived fairness ($r = 0.269$), customer satisfaction ($r = 0.363$), and customer loyalty ($r = 0.317$), highlighting its importance in enhancing the overall customer experience.

Table 5: Correlation Analysis

Variables	Experience	Transparency	Fairness	Satisfaction	Loyalty
Experience	—	-0.091	-0.294***	-0.369***	-0.269***
Transparency	-0.091	—	0.269***	0.363***	0.317***
Fairness	-0.294***	0.269***	—	0.482***	0.431***
Satisfaction	-0.369***	0.363***	0.482***	—	0.693***
Loyalty	-0.269***	0.317***	0.431***	0.693***	—

***$p < 0.001$

Furthermore, perceived fairness is positively related to both customer satisfaction ($r = 0.482$) and customer loyalty ($r = 0.431$), indicating that fair pricing perceptions contribute to more favourable customer outcomes. Among all the relationships examined, customer satisfaction shows the strongest association with customer loyalty ($r = 0.693$), underscoring its critical role in fostering long-term customer commitment.

Overall, the findings suggest that pricing transparency and perceived fairness play a vital role in strengthening customer satisfaction and loyalty, whereas unfavourable perceptions of dynamic pricing may adversely affect these outcomes.

REGRESSION ANALYSIS

According to Table 6, the regression results demonstrate that surge pricing exerts a significant negative effect on perceived price fairness ($\beta = –0.272$, $p < .001$) and customer satisfaction ($\beta = –0.338$, $p < .001$). Conversely, pricing transparency has a significant positive influence on both perceived fairness ($\beta = 0.245$, $p = .002$) and customer satisfaction ($\beta = 0.332$, $p < .001$). A similar pattern is observed with respect to customer loyalty, where surge pricing negatively affects loyalty, whereas pricing transparency contributes positively to it. Collectively, these findings indicate that although dynamic pricing may adversely shape customer perceptions and experiences, greater transparency can enhance perceptions of fairness, strengthen satisfaction, and foster loyalty.

Table 6: Regression and Mediation Analysis

Model	Dependent Variable	Predictor	β	t	p	R^2
M1	Perceived Price Fairness	Surge Pricing	-0.272	-3.56	<.001	0.146
		Transparency	0.245	3.20	.002	
M2	Customer Satisfaction (Direct)	Surge Pricing	-0.338	-4.70	<.001	0.245
		Transparency	0.332	4.62	<.001	
M3	Customer Satisfaction (Mediation)	Surge Pricing	-0.245	-3.50	<.001	0.346
		Transparency	0.248	3.57	<.001	
		Price Fairness	0.344	4.74	<.001	
M4	Customer Loyalty (Direct)	Surge Pricing	-0.243	-3.19	.002	0.159
		Transparency	0.296	3.89	<.001	
M5	Customer Loyalty (Mediation)	Surge Pricing	-0.153	-2.04	.043	0.251
		Transparency	0.215	2.89	.004	
		Price Fairness	0.328	4.23	<.001	
M6	Customer Loyalty	Customer Satisfaction	0.693	11.70	<.001	0.481

MEDIATION ANALYSIS

The mediation analysis reveals that perceived price fairness has a significant positive influence on customer satisfaction ($\beta = 0.344$, $p < .001$) and simultaneously reduces the direct effects of surge pricing and pricing transparency, thereby indicating partial mediation. A comparable mediating role is evident in relation to customer loyalty, where perceived fairness diminishes the direct impact of the independent variables on loyalty outcomes. Furthermore, customer satisfaction emerges as a strong predictor of customer loyalty ($\beta = 0.693$, $p < .001$), accounting for the highest proportion of explained variance ($R^2 = 0.481$).

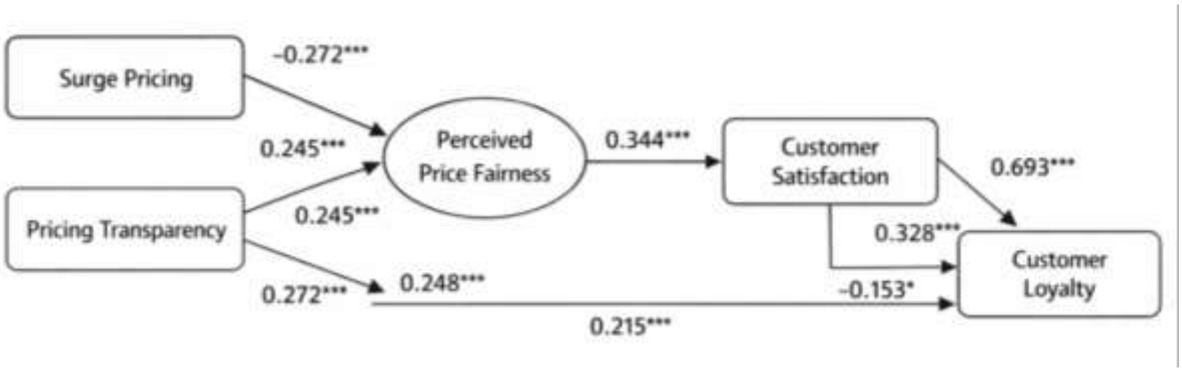
Overall, these results underscore the importance of perceived fairness and customer satisfaction as key underlying mechanisms through which pricing strategies shape customer loyalty in the ride-hailing industry.

Table 7: Hypothesis Testing Results

Hypothesis	Path	β	p-value	Result
H1	Surge Pricing → Price Fairness	-0.272	<.001	Supported
H2	Transparency → Price Fairness	0.245	.002	Supported
H3	Price Fairness → Satisfaction	0.344	<.001	Supported
H4	Transparency → Satisfaction	0.248	<.001	Supported
H5	Surge Pricing → Satisfaction	-0.245	<.001	Supported
H6	Satisfaction → Loyalty	0.693	<.001	Supported

The findings reveal that all hypothesized relationships (H1–H6) are supported and statistically significant. The results further demonstrate that surge pricing negatively affects both perceived price fairness and customer satisfaction, while pricing transparency exerts a consistently positive influence on these variables. Moreover, perceived price fairness contributes positively to customer satisfaction, which, in turn, serves as a strong driver of customer loyalty. The framework in figure 2 shows Direct and Mediated Relationships with Standardized Coefficients (β).

Figure 2: Final Conceptual Framework



SUGGESTIONS AND FUTURE IMPLICATIONS

The findings of the study suggest that ride-hailing platforms should enhance the transparency and clarity of their pricing mechanisms, as these factors play a crucial role in fostering customer loyalty. Clearly communicating the reasons behind fare increases during peak demand periods can help strengthen trust and minimize customer frustration. Moreover, maintaining a simple and easily understandable pricing structure, while prioritizing overall customer experience rather than focusing solely on revenue generation, can contribute significantly to higher levels of satisfaction and loyalty. In addition, regularly gathering and incorporating user feedback may assist platforms in making more informed and customer-oriented pricing decisions.

With regard to future research, it would be valuable to examine how customer perceptions of AI-driven pricing evolve over time through longitudinal studies. Comparative analyses across different ride-hailing platforms could also provide deeper insights into variations in customer responses. Furthermore, future investigations may explore user behaviour in smaller cities and emerging markets, where market conditions and customer expectations may differ considerably. Additional research can also focus on the roles of trust, perceived user control, and ethical considerations in shaping customer attitudes toward AI-based pricing strategies.

CONCLUSIONS

This study examined the impact of AI-driven dynamic pricing and pricing transparency on perceived price fairness, customer satisfaction, and customer loyalty within the Indian ride-hailing industry. The findings reveal that, although dynamic pricing adversely affects perceptions of fairness and customer satisfaction, pricing transparency plays a significant role in enhancing customer evaluations and experiences. Furthermore, perceived price fairness emerges as a critical mediating factor that strengthens customer satisfaction and, in turn, indirectly influences customer loyalty. Among all the variables examined, customer satisfaction is identified as the strongest predictor of loyalty.

Overall, the study highlights the importance of striking an appropriate balance between technological efficiency and transparent, fair pricing practices. Such an approach is essential for building customer trust, improving overall service experience, and fostering long-term customer relationships in an increasingly competitive digital marketplace.

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