Impact of Auction Pricing Model on Customers' Willingness to Pay and Stakeholder Satisfaction in the Indian Cab Services Industry

Anukriti Sethi, Akshit Mittal, Pavithra .M, Rammyaa .M, Suresh Srinivasan & Zeeshan Akhtar
Great Lakes Institute of Management, Chennai

Abstract : The purpose of this research is to study the impact of pricing method and various factors that affect customer satisfaction and driver satisfaction in the cab service industry. Interviews were conducted from cab service aggregators such as Ola, Uber, Fast track drivers and responses was taken in the form of survey from taxi users in Delhi, Chennai and Bangalore. From the analysis of the data collected for Customer satisfaction, we have found that 'Comfort', 'Safety', 'Price Scale', 'Drivers' Behaviour and 'Auction Pricing' have a significant impact on customer satisfaction. From drivers Satisfaction data, it is found that 'Surge Pricing', 'Revenue Sharing with Cab aggregator' and 'Fixed Minimum Number of Rides per day' have a significant impact on drivers' satisfaction. In an Indian context, where the competitive rivalry is heating up among cab aggregators, using reverse auction model could be differentiator for a cab operator, provided he is able to manage the expectations of the drivers, incentivizing them through alternative models; if not it could lead to de-motivation of a key stakeholder.

Keywords : *Auction Pricing Model, Revenue Sharing*

Introduction : Over the years, technological innovation in the transport industry has been world spinning. At the same time, it is exciting and disruptive. Advent of regulated taxi services like Meru in 2007 and introduction of international players such as Ola (2011) and Uber (2014) in the Indian markets has changed the pricing strategies towards dynamic pricing models where prices upswing as demand increases in a given area. However, high surge multipliers often result in more cancellations and more unfulfilled requests.

Though surging the prices increases the supply of drivers to the areas with high demand, it depletes the supply of cabs in other areas of the city. This in turn results in price surge. To resolve this problem, we aim to propose a "surge-free" pricing strategy, as opposed to current dynamic pricing methodologies. In this study, we investigate the impact of auction pricing model on stakeholder satisfaction. We empirically compare the auction pricing strategies with fixed cost and dynamic pricing strategies, and suggest possible improvements in the pricing models currently running in the market.

2. Literature Review and Hypotheses Development

2.1. Evolution of Indian Cab Industry

Indian cab industry, till 2007, was majorly an unorganized sector and comprised of radio taxis/yellow taxis. Here the customer used to pay a fixed, pre-determined price based on 'distance to be covered' and 'time of the ride'. The price caps were essentially fixed by a regulatory body (mostly state governments) and the drivers were paid in cash for the services offered. Cab agencies ideally did not own cars. They passed on the bookings receive to the cab drivers (mostly driver-cum-owners) associated with them for a fixed commission per month. Most of the taxi bookings were done through call centres and very few through the web. Booking a cab on demand was a hassle. With general marketing strategies, i.e.; newspaper inserts and bulk SMS campaigns, customer acquisition was difficult. After 2007 Meru Cabs, Easy Cabs, Mega Cabs and TAB cab dominated the industry. The growth story started.

The cab industry has emerged as one of the fastest growing businesses in the Indian transportation sector. Rise in disposable income, changing lifestyles of passengers can be attributed to this spectacular growth. Besides this, easy hassle free booking, 24/7 access to customer queries, various payment options, easy tracking system highly supported by Global Positioning System (GPS), and investments from venture capitalists increase the huge demand for cab industries in India. Over the years, this industry has been characterized by high degree of consolidation and a few impressive mergers and acquisitions. During 2016 the Indian Radio Taxi industry stood at around $ 6.4 billion and was expected to grow by 13.7% in the next 5 years to reach $ 14.3 billion. Major players operating in the industry includes ANI technologies, Meru Cabs, Zoom car, Fast track, Uber India Technology private limited. (Techsci Research, 2017).

After 2007, Indian cab industry started transforming due to technological advances with the advent of new taxi players. Most of the regular cab users, primarily frequent airport travellers, might remember the "Meru cabs era". Regardless of high pricing, Meru was the "undisputed king of the market" mainly because of its service quality, disciplined drivers and punctuality. But passengers/customers looking for a cost-effective alternative for both within city and airport commute were at the mercy of the local cab agencies. At that point this industry was not characterized by an obvious or accepted business model that could be emulated. By refining their models over a period of time new aggregator business models emerged.

2.2 Business Model:

Internet based commerce has been one of the major contributors to evolution of cabs services in India. In an era where a consumer may purchase almost any desired service or product from stocks and bonds to pet food with just one tap on his mobile phone, cab service providers have not lagged behind and have moved to “Internet only” and eventually to “App only” platforms. They aggregate the local cab service vendors and sometimes individual owners under one brand name and serves as the entity. The aggregator companies are find ways to gain a competitive edge in the current fiercely dense markets.

Next paragraph outlines the pricing mechanism of Indian Cab industry.

2.3 Pricing Mechanism:

Introduction of international players such as Ola (2011) and Uber (that came to India in 2014) in the Indian markets has changed the pricing strategies towards dynamic pricing models where prices upsurge as demand rises in a given area.

Dynamic pricing is opposed to traditional pricing strategy. i.e., Instead of fixed charges for the product/services, here the price level adjusts according to real time demand and supply. Dynamic pricing also known as surge pricing, time based pricing, real time pricing, demand based pricing, flexible pricing, etc. This is prevalent in many industries such as travel (airlines, IRCTC, public transport), e-commerce, retail, electricity, entertainment etc.

Few dynamic pricing models are discussed below.

i. **Pricing based on time:** This pricing mechanism focused on time. For instance during holiday air ticket cost higher.

ii. **Pricing based on Competitors:** This focus on how competitor or market leader in a particular segment will charge their product and services. Based on that firm will charge their prices in order to stay competitive. For instance e-retailers charge their prices, giving discounts and promotions based on this strategy

iii. **Pricing based on Demand:** This mechanism focused on demand intensity. For instance, during peak hours/time of the day, cab companies charge higher. However, high surge multipliers often result in more can cellations and more unfulfilled requests.

2.4 Surge Pricing and its effect on customers

Although surging the prices increases the supply of drivers to the areas with high demand, it depletes the supply of cabs in other areas of the city. This in turn results in price surge in these places making it a cyclical shortage pattern which subsides only post peak demand hours. Also, this strategy has earned a lot of criticism from customers as being a mean strategy of the platform to earn higher revenues by banking on the customers' helplessness and restraints in times of need. Customer complaints against Ola cabs and Uber filed by customers on Consumer Complaints (Indian consumer complaint forum) were analysed. It was found that most of the complaints posted by Indian customers are related to high price, peak period charges, excess fare charges and surge charges.

Surge pricing works based on the supply – demand of taxi in an area. All this is fed in the pricing algorithms of major cab aggregators such as Ola, Uber etc. The details of algorithms are different for different companies and are a black box of pricing structure which seems unreliable to the customers and is a major cause of customer dissatisfaction.

Surge pricing could be controlled in 3 ways:

(i) Reducing demand for cars (less people want a car for a higher price)

(ii) Creating new supply (providing an incentive for new drivers to hit the roads)

(iii) Shifting supply (drivers) to areas of higher demand.

Nicholas Diakopoulos, assistant professor in the College of Journalism at the University of Maryland, College Park conducted an analysis to understand the surge pricing model of Uber in US. He collected four week worth of Uber's dynamic pricing information from their publicly available data for five locations in Washington, DC. Every 15 seconds between March 15 and April 11, he pinged their servers and collected the surge price and estimated waiting time for an Uber car at those locations. The data collected suggest that surge pricing doesn't seem to bring more drivers out on the roads, instead it pushes drivers already on the job toward neighbourhoods with more demand and higher surge pricing. This resulted some neighbourhoods are left with higher waiting times for a car.

In conclusion, it appears that rather than getting more drivers on the road in the short-term, Ola/Uber's surge pricing strategy instead depletes drivers in adjacent areas. A price increase in one area means drivers move there, but away from another, leaving it underserved. If somebody in the newly underserved area now needs a car they wait longer, or perhaps a surge price has to come into effect to get a car over there.

2.5 Factors influencing customer preference:

In the end, dynamic pricing system appears to be more about re-allocation of existing supply. To increase the supply in an area, cause depletion in supply in an adjacent area this will create a surge in that area. This will lead to looping effect and create more revenue for cab aggregators like OLA and Uber. Apart from pricing and hidden surge charges, customers face issues with safety especially for women. Also, customers complained about driver's behaviour during ride and delay in pickup.

To resolve this issue, we aim to propose a "surge-free" pricing strategy— as opposed to current dynamic pricing methodologies. This system, made famous by Priceline.com, is currently operational in US, UK and has been a disruptive breakthrough in creating a transparent pricing method.

2.6 The Reverse Auction Pricing Model

Traditional economic, marketing and operational literature models viewed the consumer as a rational agent who makes decisions based on three factors viz current prices, income and market conditions. (Popescu, Wu 2007). The marketing literature recognized the role of price expectations to predict consumer behaviour. It also provides empirical evidence for the dependence of demand on past prices. (Yuan, Han 2011) Theoretical models have been developed and empirical evidence has been shown to prove that consumers form price expectations and use them to evaluate price information when making buying decisions.

Thanks to the Internet of things (IOT) due to which transaction costs has been lowered, Price-setting is no more static and evolved into dynamic, more interactive where price is determined by customers too. For instance, online platforms such as Priceline (Name Your Own Price (NYOP), eBay, Humble Bundle Pay-What-You-Want (PWYW) have popularized this pricing mechanism. Unlike traditional pricing methods, where the seller sets the price and consumer indicates his acceptance of price, in the Priceline style system that allows a reverse auction model where customers themselves quote a price and the seller indicates his evaluation of this price by either accepting or not accepting the customer's offer. Because the price-setting functions of the customer and the seller are reversed, this system is known as the reverse auction or bidding model. (Yuan, 2011).

The concept of reverse auction pricing model, has been referred to as an auction based pricing model continuously throughout this article.

2.7 How it works

The customer turns to the App on his/her smart phone, which automatically maps the cell phone's location for pickup. The customer inputs drop-off point and how much he/she wants to pay for the ride. App directs customer's offer to participating drivers in the area. Drivers accept in real time or a counter offer that goes right back to the consumer. Within a moment, the customer can compare prices and make a selection that works for him/her. Payment goes straight to the driver and the customer can track his/her ride as it approaches.

No surge pricing comes into play as customers and drivers decide the price mutually. Bidding helps the customer to find the best deal according to his willingness to pay. Also, drivers are free to accept, decline or provide counter offers as per their convenience. Therefore, the bidding price model helps in achieving an equilibrium in Consumer and Supplier surplus. As for the revenues of the cab aggregator company, a monthly subscription can be charged by the participating drivers linked with the app. This will allow drivers to keep the revenue they earn and will in turn motivate them to earn more. There will be no restriction on drivers to take a minimum fixed number of deals every day to achieve the targets set by cab aggregators.

Since reverse auction system serves as an opaque selling mechanism, it attracts price-conscious consumers. Sellers also benefit because they can price into multiple market segments without worrying that they might be diluting revenues they could have received from customers who are willing to use conventional selling channels and pay more. (Chernev 2003).

Typically, these cab service companies rely on two streams of revenue generation - Fares and Advertisements (commonly referred to as "cabvertising"). Both, drivers and customers, pay the intermediary company for the services provided and received respectively. (Joshi, Mehta 2015). Thus the present cab service aggregator business model revolves around two important stakeholders namely 'customers' and 'drivers'.

1. Customers: With technological advances, insufficiency of public transport, tourist influx, surge in corporate demands and emerging needs of urban customers, the industry has evolved at a fast pace. There has been a growing importance towards safety, comfort, quicker response times and driver credentials along with budgeted conveyance.

Based on the analysis of customer complaints filed against OLA and Uber, Customer satisfaction (Dependent Variable) while opting for a cab ride is impacted by following independent variables (Independent Variables):

1. Comfort
2. Pickup Delay
3. Safety
4. Price Scale
5. Driver's Behaviour
6. Availability
7. Auction Pricing

Null Hypothesis based on identified Independent Variables and Dependent Variables:

H1: There is no significant relationship between Customer satisfaction and Comfort.

H2: There is no significant relationship between Customer satisfaction and Pickup Delay.

H3: There is no significant relationship between Customer satisfaction and Safety standards maintained by the cab company.

H4: There is no significant relationship between Customer satisfaction and Price.

H5: There is no significant relationship between Customer satisfaction and Driver's good behaviour.

H6: There is no significant relationship between Customer satisfaction and Availability.

H7: There is no significant relationship between Customer satisfaction and Auction Pricing.

2. Drivers: With growing aggregation, satisfaction factors for drivers have also evolved from just getting enough number of rides and decent fares to ones that give them higher job satisfaction.

Dependent Variable: Cab service aggregator drivers Job satisfaction

Independent Variables:

1. Surge Pricing
2. Revenue Sharing with Cab aggregator
3. Cancellations
4. Fixed Minimum Number of Rides per day
5. Auction Pricing

Null Hypothesis based on identified Independent Variables and Dependent Variables:

H1: There is no significant relationship between Drivers' Job satisfaction and surge pricing.

H2: There is no significant relationship between Drivers' Job satisfaction and Revenue sharing with the aggregator company.

H3: There is no significant relationship between Drivers' Job satisfaction and Cancellations.

H4: There is no significant relationship between Drivers' Job satisfaction and fixed minimum number of rides per day.

H5: There is no significant relationship between Drivers' Job satisfaction and Auction Pricing.

3. Data and Methodology

Data for the research analysis was collected from both drivers and customers through surveys and interviews.

3.1 Data Collection Process

The customers were contacted primarily through social media and responses were collected through a google form. The form carried an explanation of the proposed system in layman language along with a picture depicting the app functionality for reverse auction pricing model which made it easier for customers to understand the proposed model.

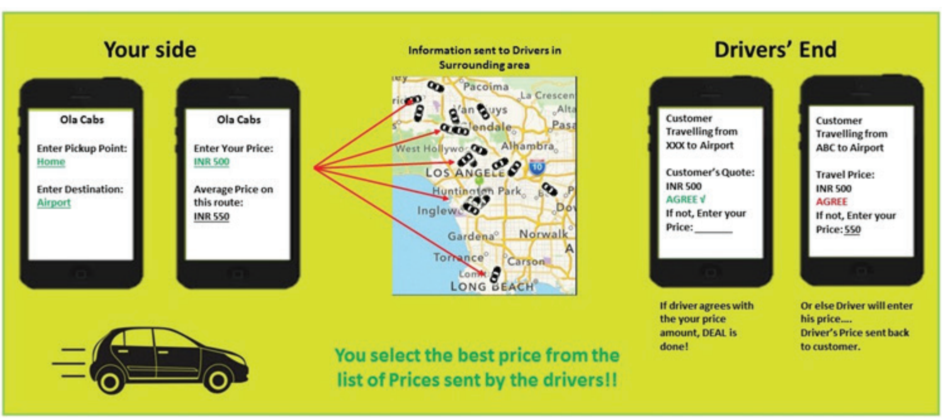

Figure.1 The suggested app functionality for the customers for the reverse auction pricing model

Data for drivers was obtained by reaching out to Ola, Uber and Fast track drivers in Bangalore, Delhi and Chennai. The drivers were contacted while waiting in queue at CNG filling stations in Delhi, outside shopping malls waiting to pick customers up and outside GLIM campus in Chennai. The questions were verbally asked to the drivers and responses were recorded accordingly. The proposed reverse auction pricing model along with subscription based payment to the cab aggregator was explained and insights were noted.

The data comprised of two parts each for customers and drivers:

1. The first part being a survey on factors that drive satisfaction in both the stakeholders

2. The second part was an interview explaining the reverse auction pricing model to the stakeholders and taking note of their acceptance or rejection of the model, asking them the reasons behind their acceptance or rejection

3.2 Measurement

The method of data collection was chosen as "Survey" since survey data is quantifiable and has high level of external validity which is needed for generalization of the proposed model. The proposed model needs to be generalizable so that it can be applied to the entire population. The survey instruments were based on market research papers for customer and driver satisfaction in taxi industry done in Australia. The questions have been modified to fit the Indian market and Likert scale data will be collected. Responses to the questions were collected on a Likert Scale ranging from Strongly Disagree to Strongly Agree:

The questionnaire for the Customers and the Drivers are mentioned in Annexure 1 & Annexure 2 respectively. Reverse coded questions are marked with and '*'.

3.3 Population and Sample

All urban taxi users who live in metro cities in India were considered as customer population. Driver population was taken as Ola, Uber & FastTrack cab drivers in India. The Sample primarily comprised of respondents from Bangalore, Chennai & Delhi. The minimum sample size proposed for the study was taken as a product of Independent variables with 15 (Kraemer, Thiemann 1987) which comes out to 105 for Customers (7 Independent Variables) and 75 for Drivers (5 Independent Variables). Actual Sample of 160 Customers and 101 Drivers completed responses used for the study.

3.4 Demographics of the Sample

Of 160 respondents, 53% are Females and 47% are Males. Majority of them are Service Professionals (58%) followed by Students (24%). 55% of the respondents are aged between 16 to 30 years. The drivers are mostly aged between 31 to 45 years (50%). About 55% of the drivers have been driving cabs for more than a year.

64% of the drivers said that they drive for 12 to 16 hours per days. 61 respondent drivers drive for Ola and 35 for Uber. Of these, 6 drive for both Ola and Uber. 11 drivers in the sample drive for FastTrack.

4. Analysis & Results Discussion

In the first section of our analysis, we show the factors that impact customer satisfaction and driver satisfaction in the present-day cab market in India and the importance of pricing methods in determining satisfaction levels in the two stakeholders. The results were derived through two separate regression analyses with Customer Satisfaction and Driver Satisfaction as dependent variables along with the respective independent variables. All analyses were carried out using IBM SPSS Statistics, Version 20.0. For the reliability test of the survey instrument, the Cronbach Alpha for each Construct was calculated. Constructs with Cronbach Alpha below the value of 0.6 were rejected.

The data has been collected as two sets.

One for the study of Customer Satisfaction and the other for the study of Driver Satisfaction. Analysis part is explained below.

1. CUSTOMER SATISFACTION ANALYSIS

Table 1.1: Summary of Reliability Test: - Cronbach's Alpha

Variable	Variable Name	Cronbach's Alpha
1	Customer Satisfaction	0.801
2	Comfort	0.849
3	Pickup Delay	0.465
4	Safety	0.864
5	Price Scale	0.754
6	Driver's Behaviour	0.633
7	Availability	0.689
8	Auction Pricing	0.708

An alpha coefficient which is low could be due to less number of questions, low inter-relatedness between items or non-homogeneous constructs. For instance, if a low alpha coefficient is due to poor correlation between the items then few need to be revised or rejected. The simplest way to find them is to compute the correlation of each test item with the total score test. Variables with low correlations (tending to zero) should be deleted.

On the other hand, if alpha coefficient is too high then redundancy might exist. A maximum alpha coefficient of 0.90 can be recommended.

The Cronbach's alpha coefficient for the five items namely Customer Satisfaction, Comfort, Safety, Price Scale, Driver's Behaviour, Availability and Auction Pricing is greater than 0.60, suggesting that the items have relatively high internal consistency. Generally, a reliability coefficient of .60 or higher is considered as "ACCEPTABLE" in most of the research situations. The variable Pickup Delay has a reliability coefficient less than 0.6. Hence Pickup Delay was not considered for further analysis.

Table 1.2: Kendal's Tau-b Correlation

Correlations

			Customer Satisfaction	Comfort	Safety	Price Scale	Driver's Behaviour	Availability	Auction Pricing
Kendall's tau_b	**Customer Satisfaction**	Correlation Coefficient	1.000	.381**	.404**	.356**	.484**	.426**	.034
		Sig. (2-tailed)	.	.000	.000	.000	.000	.000	.564
		N	160	160	160	160	160	160	160
	Comfort	Correlation Coefficient	.381**	1.000	.455**	.341**	.483**	.189**	.111
		Sig. (2-tailed)	.000	.	.000	.000	.000	.001	.061
		N	160	160	160	160	160	160	160
	Safety	Correlation Coefficient	.404**	.455**	1.000	.278**	.450**	.210**	.063
		Sig. (2-tailed)	.000	.000	.	.000	.000	.000	.289
		N	160	160	160	160	160	160	160
	Price Scale	Correlation Coefficient	.356**	.341**	.278**	1.000	.342**	.352**	-.096
		Sig. (2-tailed)	.000	.000	.000	.	.000	.000	.101
		N	160	160	160	160	160	160	160
	Driver's Behaviour	Correlation Coefficient	.484**	.483**	.450**	.342**	1.000	.365**	-.026
		Sig. (2-tailed)	.000	.000	.000	.000	.	.000	.660
		N	160	160	160	160	160	160	160
	Availability	Correlation Coefficient	.426**	.189**	.210**	.352**	.365**	1.000	-.067
		Sig. (2-tailed)	.000	.001	.000	.000	.000	.	.256
		N	160	160	160	160	160	160	160
	Auction Pricing	Correlation Coefficient	.034	.111	.063	-.096	-.026	-.067	1.000
		Sig. (2-tailed)	.564	.061	.289	.101	.660	.256	.
		N	160	160	160	160	160	160	160

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation matrix in **Table 1.2** helps us to understand the relationship between the variables. Observing the r values of all variables above, the existence of a positive relationship between some of the common attributes found in this research. Hence, to further identify the relationship between these variables and to identify the critical factors, a factor rotation test under Factor Analysis is performed upon these variables.

Factor Analysis

Before any test of factor analysis is performed, the samples have to be tested for their association with the variables identified. In order to test this, a measure of sampling adequacy is performed using KMO Test of Measuring Sampling Adequacy. The results of the tests are provided in ***Table 1.3.***

Table 1.3: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.719
Bartlett's Test of Sphericity	Approx. Chi-Square	279.395
	Df	15
	Sig.	0.000

The factor analysis test processes the samples and segregates the variables under different components to build a component matrix. The variables that have a higher factor loading (greater than 0.65) are grouped commonly as factors that influence the purpose of the study.

The results of the Factor Analysis Test are provided in the below.

Table 1.4: Total Variance Explained

Total Variance Explained					
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	2.811	46.843	46.843	2.811	46.843
2	1.161	19.354	66.197	1.161	19.354
3	.761	12.675	78.873		
4	.549	9.153	88.025		
5	.440	7.327	95.352		
6	.279	4.648	100.000		

Table 1.5: Component Matrix[a]

Component Matrix[a]		
	Component	
	1	2
Comfort	.789	
Safety	.735	
Price Scale	.737	
Driver's Behaviour	.849	
Availability		
Auction Pricing		.886

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Table 1.6: Rotated Component Matrix[a]

Rotated Component Matrix[a]		
	Component	
	1	2
Comfort	.835	
Safety	.764	
Price Scale	.680	
Driver's Behaviour	.838	
Availability		
Auction Pricing		.879

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Variables are grouped under different factors (Based on Rotated Component Matrix):

Factor 1: Comfort, Safety, Price Scale and Driver's Behaviour

Factor 2: Auction Pricing

Table 1.7: Component Transformation Matrix

Component	Comfort, Safety, Price Scale and Driver's Behaviour	Auction Pricing
Comfort, Safety, Price Scale and Driver's Behaviour	0.986	-0.164
Auction Pricing	0.164	0.986

The results from the above tests indicate variables identified have been segregated into two factors or components wherein, the first component consists of Comfort, Safety, Price Scale and Driver's Behaviour and the second one Auction Pricing. Thus Availability do not seem to emerge as significant independent variable.

These components are collectively utilized as independent variables and tested for their significance in relationship with Customer Satisfaction by carrying out a regression.

Table 1.8: Regression Statistics

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.722[a]	.522	.516	.55245

a. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

b. Dependent Variable: Customer Satisfaction

The Model obtained above has a **R square of 52.2%** which indicates that when other variables remain constant, 52.2% of the variance is explained by this model. The variables used in the model are also significant as predicted by the ANOVA Table presented below.

Table 1.9: ANOVA[a]

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	52.308	2	26.154	85.694	.000
	Residual	47.916	157	.305		
	Total	100.224	159			

a. Dependent Variable: Customer Satisfaction

b. Predictors: (Constant), REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1

The resultant variables obtained through the Rotated Component Matrix of the Factor Analysis was further utilized by creating a "Factor Score" through SPSS for performing a regression statistic to identify whether these variables are significant or not. The Regression Statistic and the significance of its coefficients are produced below. Here, it is observed that Factor 1 and 2 are significant at the confidence level of 95 percent for predicting the outcome variable (Sig. <0.05) with the dependent (predictor) variable - Customer Satisfaction.

Table 1.10: Regression Coefficients[a]

RegressionCoefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.710	.044		84.946	.000
	REGR factor score 1 for analysis 1	.561	.044	.706	12.801	.000
	REGR factor score 2 for analysis 1	-.120	.044	-.151	-2.740	.007

a. Dependent Variable: Customer Satisfaction

The above table indicates that for every one percent increase in Factor 1, there is an increase of 0.561 (56 Percent) in the Customer Satisfaction when other factors remains constant. Likewise, when there is a one percent increase in Factor 2, there is a decrease of 0.120 (12 percent) in the Customer Satisfaction when other factors remain constant.

Thus, Factors assessed for Factor 1 and 2 are summarized in Table 11 below:

Table 1.11: Variables identified

Factors	**Variables identified**
Factor 1	Comfort, Safety, Price Scale and Driver's Behaviour
Factor 2	Auction Pricing

However, these variables and factors have also to be tested for its collinearity, a test that checks for multi-collinearity among variables. The results of the Collinearity tests for the factors chosen for our study are presented below. The VIF value of 1 indicates the factors and variables are unrelated.

Table 1.12: Collinearity Statistics

Collinearity Statistics								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.710	.044		84.946	.000		
	REGR factor score 1 for analysis 1	.561	.044	.706	12.801	.000	1.000	1.000
	REGR factor score 2 for analysis 1	-.120	.044	-.151	-2.740	.007	1.000	1.000

a. Dependent Variable: Customer Satisfaction

Hypotheses Supported

Table 1.13 below summarises the hypotheses that were supported by this study from amongst testing of 8 hypotheses that were formulated at the commencement of this study.

Table 1.13: Hypotheses Supported Summary

Hypothesis	Hypothesis Statement	Factor	Significance Value	R square	Result
H1	There is no significant relationship between Customer satisfaction and Comfort.	1	**0. 000**	**0.522**	Supported
H3	There is no significant relationship between Customer satisfaction and Safety standards maintained by the cab company.	1	**0. 000**		Supported
H4	There is no significant relationship between Customer satisfaction and Price.	1	**0. 000**		Supported
H5	There is no significant relationship between Customer satisfaction and Driver's good behaviour.	1	**0. 000**		Supported
H7	There is no significant relationship between Customer satisfaction and Auction Pricing.	2	**0. 007**		Supported

Table 1.13 above summarizes basis the results of various statistical tools that were used to test the Hypotheses crafted on Impact of auction pricing model on stakeholder satisfaction in the Indian cab services industry. Only 5 of the 7 hypotheses viz. Comfort, Safety, Price Scale, Driver's Behaviour and Auction Pricing seem to be supported. The other hypotheses viz. Pickup Delay and Availability do not lend themselves to be supported statistically.

Model

From the Regression analysis, the unstandardized equation will be

Customer Satisfaction = 3.710 + 0.561 * Factor1 - 0.120 * Factor2

2. Driver Satisfaction Analysis

Table 2.1: Summary of Reliability Test: - Cronbach's Alpha

Variable Name	Cronbach's Alpha
Driver Satisfaction	0.818
Surge Pricing	0.616
Revenue Sharing with Cab aggregator	0.609
Cancellations	0.133
Fixed Minimum Number of Rides per day	0.821
Auction Pricing	0.770

An alpha coefficient which is low could be due to less number of questions, low inter-relatedness between items or non-homogeneous constructs. For instance, if a low alpha coefficient is due to poor correlation between the items then few need to be revised or rejected. The simplest way to find them is to compute the correlation of each test item with the total score test. Variables with low correlations (tending to zero) should be deleted. On the other hand, if alpha coefficient is too high then redundancy might exist. A maximum alpha coefficient of 0.90 can be recommended.

The Cronbach's alpha coefficient for the five items namely Driver Satisfaction, Surge Pricing, Revenue Sharing with Cab aggregator, Fixed Minimum Number of Rides per day and Auction Pricing is greater than 0.60, suggesting that the items have relatively high internal consistency. Generally, a reliability coefficient of .60 or higher is considered as "ACCEPTABLE" in most of the research situations. The variable Cancellations has a reliability coefficient less than 0.6. Hence Cancellations was not considered for further analysis.

Table 2.2: Kendal's Tau-b Correlation

Correlations			Driver Satisfaction	Surge Pricing	Revenue Sharing with Cab aggregator	Fixed Minimum Number of Rides per day	Auction Pricing
Kendall's tau_b	Driver Satisfaction	Correlation Coefficient	1.000	.311**	.361**	.343**	-.151*
		Sig. (2-tailed)	.	.000	.000	.000	.042
		N	101	101	101	101	101
	Surge Pricing	Correlation Coefficient	.311**	1.000	.339**	.378**	-.202**
		Sig. (2-tailed)	.000	.	.000	.000	.007
		N	101	101	101	101	101
	Revenue Sharing with Cab aggregator	Correlation Coefficient	.361**	.339**	1.000	.385**	-.328**
		Sig. (2-tailed)	.000	.000	.	.000	.000
		N	101	101	101	101	101
	Fixed Minimum Number of Rides per day	Correlation Coefficient	.343**	.378**	.385**	1.000	-.374**
		Sig. (2-tailed)	.000	.000	.000	.	.000
		N	101	101	101	101	101
	Auction Pricing	Correlation Coefficient	-.151*	-.202**	-.328**	-.374**	1.000
		Sig. (2-tailed)	.042	.007	.000	.000	.
		N	101	101	101	101	101

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The correlation matrix helps us to understand the relationship between the variables. Observing the r values of all variables above, the existence of a positive relationship between some of the common attributes found in this research. Hence, to further identify the relationship between these variables and to identify the critical factors, a factor rotation test under Factor Analysis is performed upon these variables.

Factor Analysis

Before any test of factor analysis is performed, the samples have to be tested for their association with the variables identified. In order to test this, a measure of sampling adequacy is performed using KMO Test of Measuring Sampling Adequacy. The results of the tests are provided in Table 2.3.

Table 2.3: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.708
Bartlett's Test of Sphericity	Approx. Chi-Square	81.806
	Df	6
	Sig.	0.000

The factor analysis test processes the samples and segregates the variables under different components to build a component matrix. The variables that have a higher factor loading (greater than 0.65) are grouped commonly as factors that influence the purpose of the study.

The results of the Factor Analysis Test are provided in the below.

Table 2.4: Total Variance Explained

Total Variance Explained					
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	2.190	54.743	54.743	2.190	54.743
2	.825	20.621	75.364		
3	.546	13.649	89.013		
4	.439	10.987	100.000		

Table 2.5: Component Matrix[a]

Component Matrix[a]	
	Component
	1
Surge Pricing	.714
Revenue Sharing with Cab aggregator	.768
Fixed Minimum Number of Rides per day	.832

Extraction Method: Principal Component Analysis.

b. 1 components extracted.

Table 2.6: Rotated Component Matrix[a]

Rotated Component Matrix[a]

a. Only one component was extracted. The solution cannot be rotated.

Variables are grouped under single factor (Based on Rotated Component Matrix):

Factor 1: Surge Pricing, Revenue Sharing with Cab aggregator and Fixed Minimum Number of Rides per day

The results from the above tests indicate variables identified have been segregated into a single factor or components wherein, the component consists of Surge Pricing, Revenue Sharing with Cab aggregator and Fixed Minimum Number of Rides per day. These components are collectively utilized as independent variables and tested for their significance in relationship with Driver Satisfaction by carrying out a regression.

Table 2.7: Regression Statistics

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.536[a]	.288	.280	.75299

a. Predictors: (Constant), REGR factor score 1 for analysis 1

b. Dependent Variable: Driver Satisfaction

The Model obtained above has a **R square of 28.8%** which indicates that when other variables remain constant, 28.8% of the variance is explained by this model. The variables used in the model are also significant as predicted by the ANOVA Table presented below.

Table 2.8: **ANOVA**[a]

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22.660	1	22.660	39.965	.000b
	Residual	56.132	99	.567		
	Total	78.792	100			

a. Dependent Variable: Driver Satisfaction

b. Predictors: (Constant), REGR factor score 1 for analysis 1

The resultant variables obtained through the Rotated Component Matrix of the Factor Analysis was further utilized by creating a "Factor Score" through SPSS for performing a regression statistic to identify whether these variables are significant or not. The Regression Statistic and the significance of its coefficients are produced below. Here, it is observed that Factor 1 is significant at the confidence level of 95 percent for predicting the outcome variable (Sig. <0.05) with the dependent (predictor) variable - Driver Satisfaction.

Table 2.9: Regression Coefficients[a]

RegressionCoefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.428	.075		45.755	.000
	REGR factor score 1 for analysis 1	.476	.075	.536	6.322	.000

a. Dependent Variable: Driver Satisfaction

The above table indicates that for every one percent increase in Factor 1, there is an increase of 0.476 (47.6 Percent) in the Driver Satisfaction when other factors remains constant.

Thus, Factors assessed for Factor 1 are summarized in Table 2.10 below:

Table 2.10: Variables identified

Factors assessed for Factor 1 are presented below:

Factors	Variables identified
Factor 1	Surge Pricing, Revenue Sharing with Cab aggregator and Fixed Minimum Number of Rides per day

However, these variables and factors have also to be tested for its collinearity, a test that checks for multi-collinearity among variables. The results of the Collinearity tests for the factors chosen for our study are presented below. The VIF value of 1 indicates the factors and variables are unrelated.

Table 2.11: Collinearity Statistics

Collinearity Statistics								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.428	.075		45.755	.000		
	REGR factor score 1 for analysis 1	.476	.075	.536	6.322	.000	1.000	1.000

a. Dependent Variable: Driver Satisfaction

Hypotheses Supported

Table 12 below summarises the hypotheses that were supported by this study from amongst testing of 8 hypotheses that were formulated at the commencement of this study.

Table 2.12: Hypotheses Supported Summary

Hypothesis	Hypothesis Statement	Factor	Significance Value	R square	Result
H1	There is no significant relationship between Drivers' Job satisfaction and surge pricing.	1	**0. 000**	**0.288**	Supported
H2	There is no significant relationship between Drivers' Job satisfaction and Revenue sharing with the aggregator company.	1	**0. 000**		Supported
H4	There is no significant relationship between Drivers' Job satisfaction and fixed minimum number of rides per day.	1	**0. 000**		Supported

Table 12 above summarizes basis the results of various statistical tools that were used to test the Hypotheses crafted on Impact of auction pricing model on stakeholder satisfaction in the Indian cab services industry. Only 3 of the 5 hypotheses *viz. Surge pricing, Revenue sharing with the Aggregator Company and fixed minimum number of rides per day* seem to be supported. The other hypotheses viz. *Cancellations andAuction Pricing* do not lend themselves to be supported statistically.

Model

From the Regression analysis, the unstandardized equation will be

Driver Satisfaction = 3.428 + 0.476 * Factor1

Summary Results: From the analysis of the data collected for customer satisfaction, we have found that comfort, safety, price Scale, drivers' behaviour and auction Pricing have a significant impact on customer satisfaction. From drivers Satisfaction data, it is found that surge pricing, revenue Sharing with cab aggregator and fixed minimum number of rides per day have a significant impact on drivers' satisfaction.

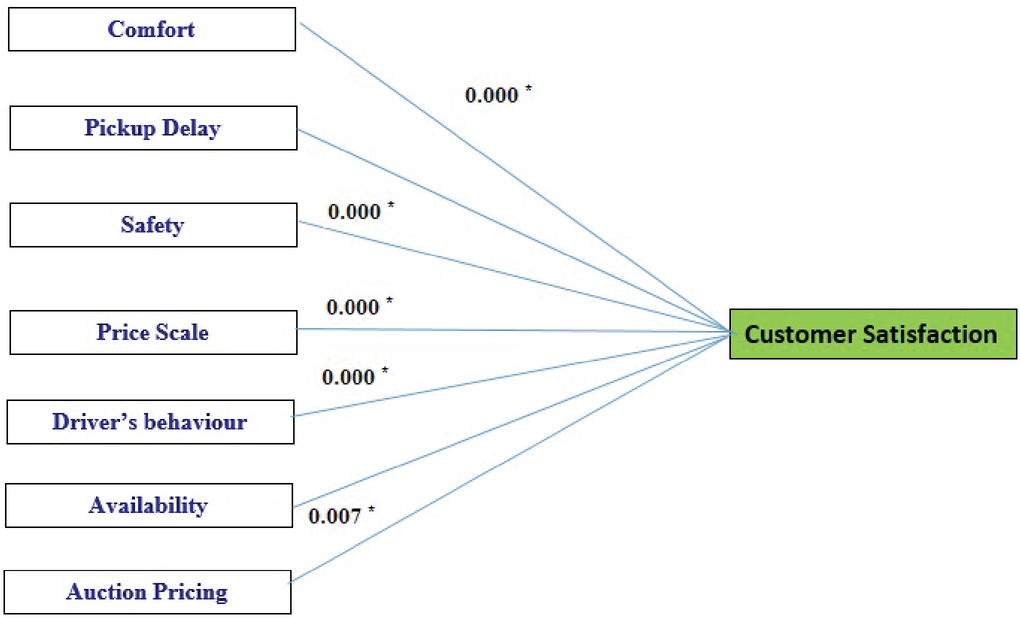

Figure 2: Customer Satisfaction

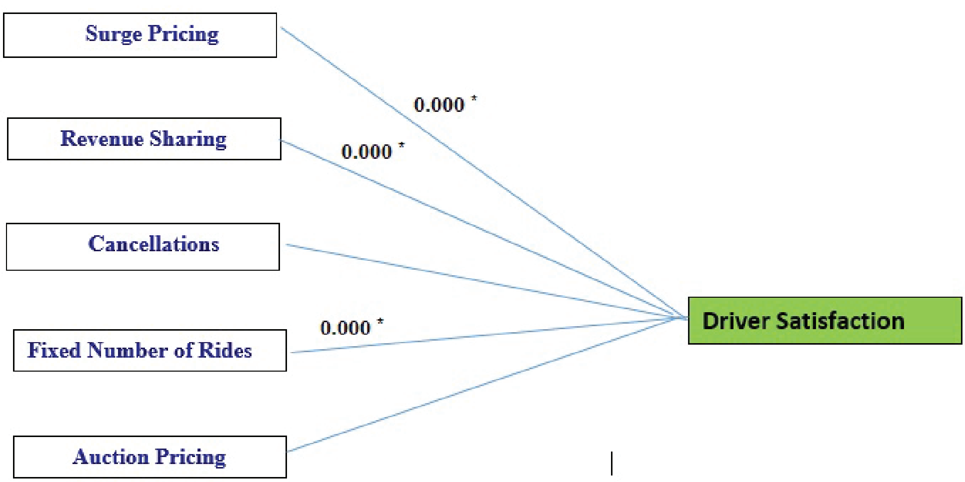

Figure 3: Driver Satisfaction

5. Conclusion & Managerial Implications:

Considering the current working modelof the Indian cab industry, it is clear that there is a scope for improvement in both the customers and drivers (key stakeholders) satisfaction levels. Customers are not happy with the varying prices during peak hours whereas drivers are unhappy about the revenue sharing and minimum rides criteria set by cab aggregators. Drivers seem to be happy with the 'surge pricing' mode, which however may not be positively viewed by the customer who is more comfortable with the reverse auction pricing model.

With customer satisfaction lying at the forefront of any organization for retaining competitive advantage and for a sustained growth, auction pricing model definitely needs a serious look in spite of driver preference for a surge pricing model..

Globally, reverse auction pricing model has already been implemented by a few cab aggregators in UK & USA markets. Companies such as bidyourtaxifare.com, Opoli and Shipme2 are using this model successfully. In an Indian context, where the competitive rivalry is heating up among cab aggregators, using reverse auction model could be differentiator for a cab operator, provided he is able to manage the expectations of the drivers, incentivizing them through alternative models; if not it could lead to de-motivation of a key stakeholder.

6. Limitations and Future Scope of Research

The proposed the model is currently in nascent stages and needs to go through further modifications to make it viable for Indian market. Possible legal issues and corporate ethics need to be taken into account to make this idea business-ready. Customer preference levels are motivating. However, considering limited visibility of this model in real market but we need to include more ideas which can enhance the CVP (Customer Value Proposition). Also, revenue model and growth expansion plan is not considered for testing out Reverse Auction Pricing Model. Only customer satisfaction and driver satisfaction have been considered as the criteria for model acceptance.

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Annexure 1

Questionnaire -1 | For the Customer

Customer Satisfaction

1. I am satisfied with the current cab service such as Ola, Uber
2. The quality of the cab services is poor*
3. Overall experience with cab services is enjoyable
4. Overall, so far, I have had positive experiences with Ola/Uber
5. What I get from Ola/Uber falls short of what I expect for this type of Service*

Comfort

1. Ola/Uber cars are visually appealing
2. Ola/Uber cars are clean and attractive
3. Most of Ola/Uber cars are in good condition

Pickup Delay

1. Ola/Uber Cabs usually arrive on time
2. ETA given by Ola/Uber on the time of booking are accurate
3. Ola/Uber apps do not tell exactly when the cab will arrive*

Safety

1. I do not fear to travel anytime in Ola/Uber
2. I feel safe as a customer riding with Uber
3. Uber (and their policies) has done an adequate job of keeping customers safe in Uber vehicles

Price Scale

1. Most cab services I use are overpriced*
2. I believe cab providers can charge lower prices and still be profitable*
3. Most prices are reasonable given the high cost of doing business
4. Most prices are fair
5. In general, I am satisfied with the prices I pay

Driver's Behaviour

1. Cab drivers mostly serve their customer well.
2. Because of the way drivers behave, most of my traveling is unpleasant*
3. I find most drivers to be very helpful
4. I find drivers to be very polite
5. Cab drivers do not refuse or make excuse for not going to my destination

Availability

1. I find cab around me whenever I need it
2. I usually don’t have to wait for cabs for more than 10 minutes
3. When I need cab urgently, I am usually not able to get it.*
4. When asked for type of cab I need, usually I don’t get it and have to settle for other service.*
5. I would be willing to postpone my ride if the cab was temporarily unavailable.*

Auction Pricing Model - Interview

Here's how it works:

1. You log into the app
2. Enter the destination & Select the type of car you would like to take
3. Quote a price that you think is appropriate
4. This is sent to the drivers in your vicinity & The driver who agrees to the price accepts the booking
5. Else, each driver sends you back a quoted price of his choice
6. You select the lowest price from these quotes and the ride is booked!!

No surge pricing!! Select your own price!! Bargain directly with the driver!!

It’s like bidding for the best deal...

What say?!

Acceptance of Auction Pricing model:

1. Auction pricing will be advantageous to me
2. I will be happy if I get to select my price
3. I am happy with the current pricing scenario*
4. I will opt for auction pricing over current pricing

Name					
City					
Gender	Male	Female		Others	
Age	Below 16 years	16 – 30 years	31 – 45 years	46 – 60 years	Above 60 years
Profession	Student	Service Professional	Business person	Homemaker	Other

Annexure -2

Questionnaire -2 | For the Driver

Driver Satisfaction

1. I am satisfied with my job as Ola/Uber driver
2. The job of Ola/Uber driver is enjoyable
3. Given a chance, I will switch my job*
4. I recommend this job to other people who are interested in becoming a taxi driver

Surge Pricing

1. I am happy with the current pricing model
2. I am satisfied with surge pricing
3. Surge pricing is not beneficial for me*
4. I get better business when surge prices are not applicable

Revenue Sharing with Cab aggregator

1. I am comfortable sharing my revenue with the company
2. The revenue share taken by the company should be reduced*
3. Amount charged by Ola/Uber is apt

Cancellations

1. I am not bothered by the number of cancellations
2. High number of cancellations affects my earnings*
3. There are too many cancellations everyday

Fixed minimum number of rides

1. I am comfortable with the minimum rides criteria of Ola/Uber
2. It is difficult to get the minimum number of rides per day*
3. I need to stretch long working hours to fulfil the criteria*
4. It is easy to get the fixed minimum number of rides everyday

Auction Pricing Model - Interview

Features:

1. There will be no fixed minimum number of rides per day
2. There will be no revenue sharing. You will be charged on a subscription basis.
3. Drivers will have the freedom to choose their customers whose offer suits them
4. Drivers will have the freedom to drive as much/less as they want

Acceptance of Auction Pricing model

1. Auction pricing will be advantageous to me
2. I will be happy if I get to select the price
3. I am happy with the current pricing scenario*
4. I will prefer auction pricing over current pricing

Name				
City				
Gender	Male	Female	Others	
Age	16 – 30 years	31 – 45 years	46 – 60 years	Above 60 years
Which company do you drive for?	Ola	Uber	Other	
How long have you been driving for Ola / Uber?	0-3 months	3-6 months	6-12 months	12+ months
How many hours per day do you work?	4-8 hours	8-12 hours	12-16 hours	16+ hours