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Research Article

Optimizing Dynamic Pricing Strategies for Ride-Hailing Services in Competitive Tourist Markets: A Case Study of Bolt in Málaga, Spain

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Abstract

This study presents an innovative approach to optimizing dynamic pricing strategies for ride-hailing services, focusing on Bolt's operations in Málaga, Spain. Leveraging mathematical modeling and real-time data analysis, the research evaluates Bolt's pricing strategies to enhance competitiveness, especially in tourist-dense regions. The proposed model integrates demand-supply dynamics, temporal factors, and location-based considerations to ensure balance between affordability for customers and profitability for drivers. Additionally, the study emphasizes the importance of accessible and reliable pricing, tailored to the expectations of international tourists accustomed to using ride-hailing platforms in their home countries. The findings highlight the interplay between pricing strategies and customer retention, highlighting how Bolt can leverage adaptive pricing models to outperform traditional taxis and competitors like Uber. The research underscores the significance of aligning pricing strategies with market conditions, tourist demands, and operational challenges unique to Málaga's seasonal fluctuations. By implementing these strategies, Bolt can optimize its market performance, ensure sustainable growth, and reinforce customer loyalty in competitive urban mobility landscapes.

Keywords: Dynamic pricing; Ride-hailing services; Mathematical modeling; Demand–supply optimization; Urban mobility.

INTRODUCTION

In recent years, ride-hailing services have increasingly focused on dynamic pricing strategies to account for fluctuations in supply and demand [1]. Surge pricing has become a hallmark of the ride-hailing industry, utilized by platforms like Uber, Lyft, DiDi and Bolt to dynamically adjust fares in response to real-time fluctuations in supply and demand. By temporarily raising prices during periods of high demand, such as rush hours, large events, or inclement weather, ride-hailing platforms aim to incentivize more drivers to enter the market, ensuring ride availability for passengers [2,3]. While surge pricing has been praised for its ability to optimize market efficiency, it has also sparked debates about fairness and accessibility, especially for economically disadvantaged passengers who may be priced out of service during peak times [4,5]. Additionally, several studies have explored the welfare effects of surge pricing, highlighting both its benefits and drawbacks. On one hand, surge pricing can lead to more efficient allocation of resources, as noted by [6], who argue that dynamic pricing enhances overall market welfare by matching supply more closely with demand. On the other hand, concerns have been raised about the potential for surge pricing to exacerbate inequalities within the driver community and among passengers. For example, some drivers may be unable or unwilling to work during surge periods, missing out on the potential for higher earnings [7,8]. Although secondary data shows that, due to ride hailing price dumping, taxi unions are not satisfied with platforms pricing strategy, and traditional city taxis are not able to compete with them.

Juan Camilo Castillo's study [7] on surge pricing in ride-hailing platforms, particularly using data from Uber, explores the welfare effects of surge pricing and its impact on various market participants. The study builds a comprehensive empirical model that takes into account demand, supply, and matching technology, allowing for variations in time and location as well as random fluctuations in both supply and demand. This profound analysis sheds light on the complexities of surge pricing, highlighting its benefits for riders while also acknowledging the downsides for specific groups of drivers. The study suggests that while surge pricing improves overall efficiency and welfare, it can also exacerbate inequality within the driver community, particularly affecting those who are unable or unwilling to work during peak surge hours. Additionally, surge pricing can disproportionately influence low-income passengers who may struggle to afford the higher fares during peak times [4]. The rise of ride-hailing platforms in cities around the world has also had significant implications for traditional taxi services, leading to increased competition and sometimes tension between new entrants and established players [9]. In tourist-heavy regions, particularly in Europe, ride-hailing apps have become a popular choice for visitors due to their convenience and transparency, further intensifying competition with local taxi operators [10]. As a result, understanding the dynamics of surge pricing is crucial for policymakers and businesses alike as they navigate the evolving landscape of urban mobility. Therefore, Schaller, (2021) [11] examines the impact of ride-hailing services on urban sustainability, focusing on their effects on traffic congestion, emissions, and public transit use. The study highlights the need for integrated regulatory policies to maximize environmental and social benefits while minimizing negative externalities.

Málaga, a key tourist destination on Spain's Costa del Sol, is renowned for its picturesque beaches, historical landmarks, and vibrant cultural offerings. Tourism forms the backbone of the city's economy, attracting millions of visitors annually, which in turn drives significant demand for local services, particularly transportation. Urban mobility is crucial in facilitating the flow of tourists throughout Málaga and its surrounding regions. Ride-hailing platforms, which have revolutionized transportation in many urban centers worldwide, have emerged as a convenient option for tourists who are familiar with these services from their home countries [12]. However, the maturity of these platforms, particularly Bolt, remains underdeveloped in Málaga, presenting unique challenges. Unlike other European cities where these services have been optimized to meet both local and tourist demand, Málaga's ride-hailing ecosystem still struggles with issues such as inconsistent availability and pricing, which affect tourists' experiences.

The inconsistent quality of ride-hailing services in Málaga is compounded by pricing difficulties, making the service less reliable and potentially more expensive compared to traditional taxis during peak times. This unpredictability in pricing is particularly problematic in a city where demand fluctuates heavily with the tourist seasons [9]. Tourists often face challenges in accessing affordable and convenient (Taxi or car sharing) transportation, which diminishes the appeal of ride-hailing apps that are typically valued for their transparency and ease of use [13]. Moreover, the competition with traditional taxi services adds another layer of complexity, as local taxi operators often offer more predictable pricing and better availability in key tourist areas [14]. For ride-hailing services like Bolt to become a viable option for tourists mostly from EU countries in Málaga, significant improvements in service reliability and pricing optimization are necessary to ensure competitiveness and user satisfaction. Providing timely and efficient access to competitively priced transportation services at the right time is essential to ensure customer and tourist satisfaction. Achieving the highest levels of optimization in pricing and service delivery is critical to meeting these expectations. Simultaneously, maintaining a competitive edge against other market players is vital to sustaining growth and market relevance in the dynamic ride-hailing sector.

In line with that in Figure 1, the bibliometric network analysis illustrates the interconnectedness and relevance of key research topics within the domain of e-hailing services, emphasizing the crucial role of this study. The network visually represents relationships among significant terms such as cost, traffic congestion, dynamic pricing, transportation system, and optimization. These keywords are frequently co-cited and co-occurring within the literature, highlighting their importance in addressing complex challenges in ride-hailing markets, particularly in high-demand, competitive areas.

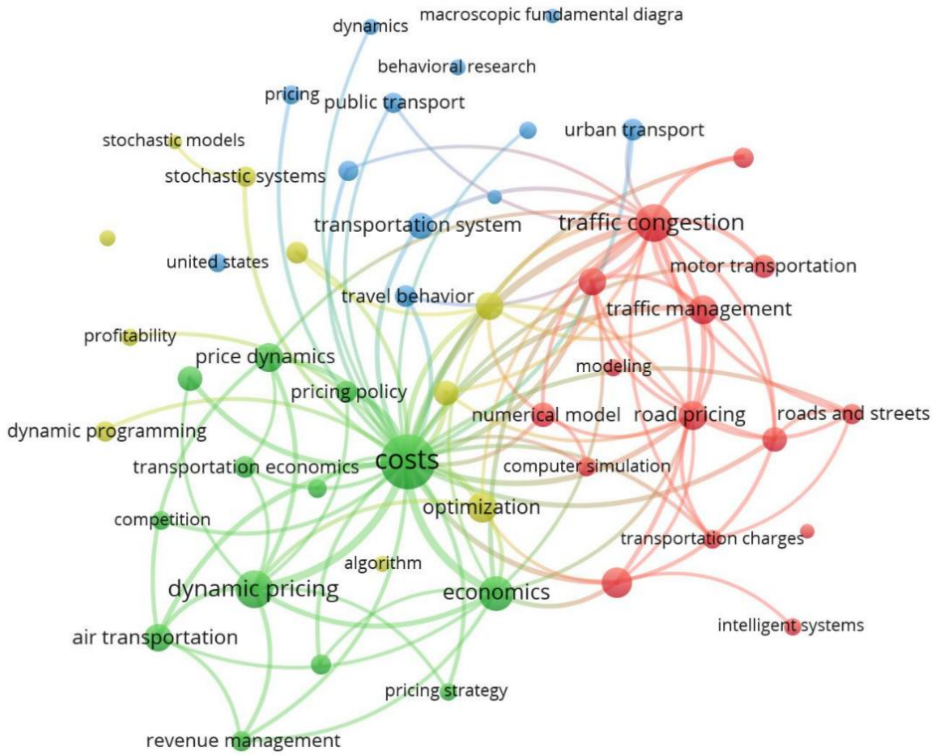

Figure 1. Bibliometrics analysis in the field

The prominence of cost and dynamic pricing reflects the industry's need to balance customer affordability with driver compensation, essential for sustainable market growth. Meanwhile, traffic congestion and optimization denote a focus on reducing urban traffic through efficient fleet management and routing algorithms. The connections between these terms illustrate how integrated pricing strategies can mitigate congestion and improve service efficiency, ultimately contributing to a more resilient transportation ecosystem. This network underscores the relevance of this study, which aims to address these interlinked topics by exploring effective dynamic pricing strategies within competitive tourist markets, thus advancing the field and providing actionable insights for urban mobility solutions.

LITERATURE REVIEW

Upon reviewing the existing literature, we identified that the domain of surge pricing and price dynamics is bifurcated into two principal subcategories. The first study addresses the comprehensive analysis of pricing and its overall influence on the driver labor market, while the second investigates its effects on passengers and customer behavior. A substantial amount of research has been conducted on pricing rationality, its correlation with consumer behavior, and pricing optimization. Research, analysis, and optimization have always been a difficult path for researchers. This may be because researchers do not have access to real historical data from major ride-hailing companies like Bolt or Uber. Therefore, our study takes on a conceptual dimension.

The rise of real-time pricing technologies, particularly surge pricing in ride-hailing services like Uber, has sparked extensive research on its welfare implications for riders, drivers, and platforms. Empirical models, demonstrate that while surge pricing enhances overall market efficiency, its benefits and drawbacks are distributed unevenly across different market participants [2,7]. The core aim and goal of surge pricing is to dynamically adjust prices to balance supply and demand during high-demand periods. Surge pricing algorithms, as demonstrated in Uber's implementation, play a crucial role in achieving this by incentivizing drivers to operate during peak times, thus increasing ride availability. Additionally, these algorithms ensure allocative efficiency by prioritizing riders who place a higher value on the service, optimizing resource allocation in real-time [4].

In light of these findings, the relationship between surge pricing and customer satisfaction emerges as multifaceted, with satisfaction levels varying based on customer loyalty and contextual factors. Loyal customers demonstrate greater tolerance for surge pricing, while non-loyal customers exhibit heightened sensitivity, affecting their retention rates. This complexity underscores the need for ride-hailing platforms to balance pricing strategies with customer satisfaction to enhance long-term retention [15]. From the driver and customer relationship in ride hailing Gao et al. [16] findings further emphasize the importance of designing adaptive pricing mechanisms that consider customer behavior, driver acceptance and market dynamics. Personalized approaches, such as the proposed models, can optimize driver incentives while maintaining customer satisfaction, ultimately enhancing the efficiency and profitability of ride-hailing platforms.

Building on the multifaceted interplay of customer satisfaction and surge pricing, Wang and Yang (2019) [17] provide a comprehensive framework for understanding ride sourcing systems, emphasizing the intricate dynamics of demand, supply, and platform operations. Their findings highlight the necessity for adaptive pricing strategies that align passenger and driver incentives to optimize market equilibrium and enhance platform efficiency. Expanding on this, Henao and Marshall (2019) [18] analyze the economic realities for ride-hailing drivers, revealing that net hourly earnings often fall below minimum wage when accounting for expenses such as vehicle maintenance and fuel. Their findings stress the importance of minimizing "deadheading" driving without passengers to improve driver profitability and reduce urban congestion. Remarking deadheading is huge challenge that ride hailing drivers faced, Henao and Marshall (2019) [18] use a quasi-natural experiment to quantify ride-hailing's impact on vehicle miles traveled (VMT), finding that deadheading contributes to a significant increase in VMT, with ride-hailing adding approximately 83.5% more miles than would have been driven without it. Their study highlights the potential environmental and congestion implications of this trend, emphasizing the need for data-driven policy interventions to mitigate these effects.

For this reason, there are many gaps in ride-hailing apps that need to be optimized, in this thesis, our focus is on competitiveness and availability in tourist spots. Within this scope Shi et al, 2024 in their study focus on study on dynamic region-division-based pricing strategy that uses adaptive algorithms such as Deep Q Networks and K-Means clustering to maximize platform profits by adjusting prices according to real-time conditions in different city regions. Alternatively, Cao et al. (2021) [19] developed a comprehensive ride-sharing route optimization model that leverages a Genetic Algorithm to address these challenges. The model incorporates constraints such as rated passenger capacity, route rationality, and time windows, aiming to reduce both empty-loaded rates and travel costs. At the same time, Lan et al. (2023) [20] utilized Bayesian networks to analyze the performance of online car-hailing systems, considering factors such as service, price, safety, and travel time to improve user experience and operational efficiency. They introduced a model that identifies key influence paths affecting passenger choices and proposes investment allocation strategies to optimize system performance while minimizing costs.

The new model developed by Qureshi and Lazem (2024) [21] proposes a hybrid-pricing algorithm using a Classification and Regression Tree (CART) supervised learning model to optimize e-hailing prices, offering a more balanced pricing strategy compared to traditional reinforcement learning-based dynamic pricing models. This model addresses price surging issues and provides a foundation for further research in industries utilizing dynamic pricing. To support the optimization of ride-sharing routes in ride-hailing services, Lin et al. (2012) [22] developed a ride-sharing system model and formulated the route optimization problem. They explored the optimization of the vehicle routing problem for ride-sharing taxis. Their study formulated a comprehensive model that minimizes travel distance and improves vehicle utilization, offering practical solutions to enhance efficiency in urban ride-sharing systems.

CASE STUDY

Spain consistently ranks among the top global tourist destinations, drawing millions of visitors each year thanks to its rich history, diverse culture, stunning landscapes, and world-class infrastructure. The country's tourist infrastructure is among the best in the world, encompassing high-standard airports, efficient high-speed trains, and a wide array of accommodation options ranging from affordable hotels to luxurious resorts. This infrastructure supports the thriving tourism sector, which is a crucial pillar of Spain’s economy.

Figure 2. The geographical location of the city of Malaga in Spain

In recent years, with the rise of digital platforms, shared taxi services like Bolt, Uber, and other ride-hailing apps have become increasingly popular among tourists in Spain. These platforms provide convenience, transparency, and ease of use, particularly for international tourists who are already familiar with these apps from their home countries. However, the emergence of these ride-sharing services has introduced significant competition for traditional taxi services in Spain. Local taxi operators, who have long been a mainstay in Spanish cities, now face stiff competition from these technology-driven companies.

The ride-hailing market in Spain is projected to experience substantial growth, with revenues expected to reach approximately €716 million in 2024, expanding at a Compound Annual Growth Rate (CAGR) of 2.90% from 2024 to 2029. By 2029, the market volume is forecasted to hit approximately €827 million, driven by an estimated 13.17 million users. User penetration is projected to grow from 24.8% in 2024 to 27.9% in 2029, indicating a steady increase in adoption. Furthermore, the Average Revenue Per User (ARPU) is anticipated to reach approximately €61.12 by 2029 [23].

Since this sector operates exclusively online, with Uber and Cabify leading the market and Bolt emerging in most of the EU countries. However, recent regulatory changes, such as mandatory pre-booking, have disrupted the competitive landscape, however it ease the use of such platforms [24]. Pricing is at the heart of this competition. For tourists arriving in Spain, especially in high-traffic areas like Málaga (Figure 2), which saw over 19 million passengers in 2023, with approximately 75% being international visitors cost is often a deciding factor when choosing between a traditional taxi and a ride-sharing service. Many of these tourists are from European countries where they already use services like Bolt, so naturally, they might prefer to use these familiar platforms in Spain. The question that arises, however, is whether Bolt's pricing in Spain is truly competitive and optimized for these tourists.

In Málaga, where three major shared taxi apps compete not only with each other but also with local taxis, pricing strategies become critical. Ride-sharing companies must balance their fares to remain attractive to cost-conscious tourists while still ensuring profitability. This requires a more in-depth approach to pricing, especially in a competitive market like Málaga, where tourist demand fluctuates with the seasons, events, and other variables. Therefore, this research focuses on evaluating Bolt's pricing strategy in Málaga, particularly in comparison to its competitors in both other ride-sharing apps and traditional taxis. The goal is to determine whether Bolt offers the best price for tourists and to explore whether there is room for optimization. By analyzing current pricing models, this research will use mathematical modeling to assess and potentially improve Bolt's pricing structure.

MATHEMATICAL MODELING

The e-hailing process is initiated when a customer submits a service request. Upon specifying the departure and destination points within the app, the customer is provided with a price estimate. In practice, platforms like Didi Chuxing calculate this estimated price based on route navigation algorithms and traffic forecasts. The final transaction price, however, depends on the actual ride distance and real-time traffic conditions. Our model does not account for any discrepancies between the estimated and actual prices. Once the price is communicated, the platform selects a driver using one of two methods. In the first method, termed the "first-to-respond," the details of the customer's request (departure and destination) are broadcast to nearby drivers via their devices, typically mobile phones. The first driver to accept the request has their details (location, vehicle plate, and contact information) shared with the customer. The alternative method involves the platform directly selecting the nearest available driver, which requires centralized knowledge of all drivers' locations and availability. Notably, Didi Chuxing has gradually shifted from the first to the latter method.

In either case, after receiving the driver's information, the customer either waits for the driver to arrive or cancels the request, potentially opting for a traditional taxi service. Our model does not account for the possibility of a customer cancellation after receiving the initial price estimate, as this price is typically familiar to regular users of the service. The key variable that influences the customer's decision to accept or reject the ride is the extended waiting time of the car. We do not first predefine the geographical area under consideration or the number of available drivers. Instead, our analysis demonstrates that the dynamic pricing strategy effectively determines the area in which drivers are willing to operate. For the purposes of this study, we assume that for any given customer request, a match can always be made—i.e., that there exists a price at which at least one driver finds the request acceptable, and that driver is also acceptable to the customer.

The basic model for price increases in transportation services takes into account several key factors such as demand, supply, time, and location. Surge pricing is implemented to balance supply and demand by dynamically adjusting prices based on real-time conditions. Below is a basic formula for price increases, along with explanations of all relevant variables:

$$\text{Surge Price} = \text{Base Fare} \times \left(1 + \alpha \cdot \frac{\text{Demand} - \text{Supply}}{\text{Supply}}\right) \quad (1)$$

The surge pricing model considers several factors, including base fare, demand, supply, time, location, weather conditions, and event-based demand. The base fare is the standard fare, while demand is the number of ride requests or potential customers in a particular area and timeframe. The surge price factor is adjusted based on the level of demand and supply, with a scaling factor adjusting the surge pricing response. Time, location, weather conditions, and event-based demand are also considered. To incorporate additional influencing variables, the model can be extended to include additional coefficients or weights, allowing for fine-tuning of how each factor affects surge pricing.

Base Model with Additional Influencing Variables

To incorporate these additional variables, the model can be extended as follows:

$$\text{Surge Price} = \text{Base Fare} \times \left(1 + \alpha \cdot \frac{\text{Demand} - \text{Supply}}{\text{Supply}}\right) \cdot \beta \cdot \gamma \cdot \delta \cdot \epsilon \quad (2)$$

The surge-pricing model considers various factors such as demand-supply ratio, time factor, location factor, weather factor, and event factor. It allows ride-hailing services to adjust prices based on demand, supply, time, location, weather, and event factors. This flexible approach allows ride-hailing services to balance driver availability and customer satisfaction, ensuring pricing is adjusted based on historical data and real-time feedback.

The surge pricing model takes into account multiple aspects, including demand-supply ratio, temporal variables, geographical considerations, meteorological conditions, and event-related influences. It enables ride-hailing services to modify pricing according to demand, supply, temporal parameters, geographical location, meteorological conditions, and event-related influences. This adaptable strategy enables ride-hailing services to equilibrate driver availability and consumer contentment, guaranteeing that price is modified according to historical data and real-time input. Therefore we will have

$$\rho = f(D, S, T, L) \quad (3)$$

Partial Derivative with Respect to Demand $\frac{\partial P}{\partial D}$, this partial derivative indicates how a small change in demand affects the surge price while keeping supply, time, and location constant. If $\frac{\partial P}{\partial D}$ large, it suggests that the surge price is highly sensitive to changes in demand.

Partial Derivative with Respect to Time $\frac{\partial P}{\partial T}$,

Therefore, for all variable and partial derivative considering the function we will have following gradient vector:

$$\nabla P = \left(\frac{\partial P}{\partial D}, \frac{\partial P}{\partial S}, \frac{\partial P}{\partial T}, \frac{\partial P}{\partial L}\right) \tag{4}$$

At the same time we can reflects the overall rate of change of price over time, it can be noted alongside as:

$$(\nabla P, \frac{dP}{dt}) = (\frac{\partial P}{\partial D}, \frac{\partial P}{\partial S}, \frac{\partial P}{\partial T}, \frac{\partial P}{\partial L}, \frac{dP}{dL}) \tag{5}$$

In this case, lowering the price regularly is not enough for competitiveness, because the drivers should have enough income considering the car and fuel costs. Therefore, we show the daily income of the driver as follows:

$$\mathrm{I}=\int_0^{\mathrm{T}} \mathrm{R(t)} \cdot \mathrm{N(t)dt} \quad (6)$$

The integral for calculating a driver's total income over a period of time is calculated using the following assumptions: a constant rate of R(t) per ride, and a constant number of rides per hour. The integral can be simplified to a more accurate estimate of income over time, accommodating for dynamic changes in ride frequency and fare per ride. If rates and demand fluctuate, integration allows for summing up income across changing values, providing a more accurate picture of earnings under dynamic conditions. This method can be used for fixed rate and ride counts or for variable rates and rides.

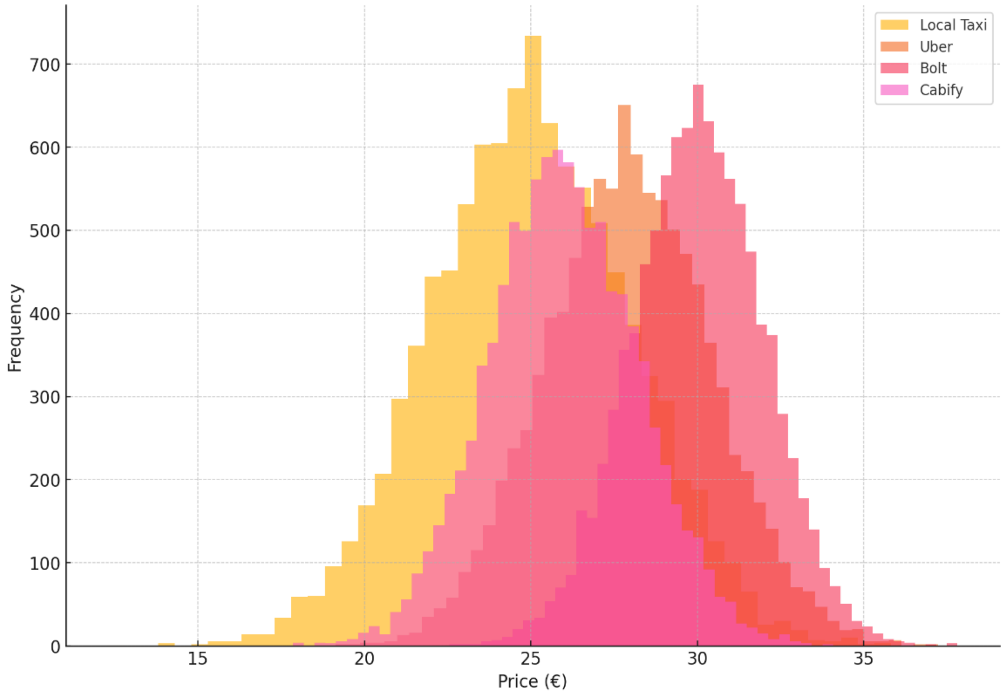

Figure 3. Price Distributions (MCMC) for Rides from Málaga Airport to Central Train Station

This histogram as Figure 3, compares the price distributions of various transportation options, including local taxis, Uber, Bolt, and Cabify, for rides from Málaga Airport to the Central Train Station. Using data modeled with Markov Chain Monte Carlo (MCMC) simulations, it highlights the variability and frequency of pricing across these services. Local taxis demonstrate the most consistent pricing range, while Uber, Bolt, and Cabify present overlapping yet distinct price clusters, reflecting competitive dynamics in the ride-hailing market. However, this visualization represents the current state without incorporating an in-depth analysis or an optimized pricing strategy, leaving significant room for improvement in pricing models to enhance competitiveness and efficiency.

Model for Optimizing Dynamic Pricing in Ride-Hailing Services

The model for optimizing dynamic pricing in Ride-Hailing Service involves six steps as shown in Figure 4.

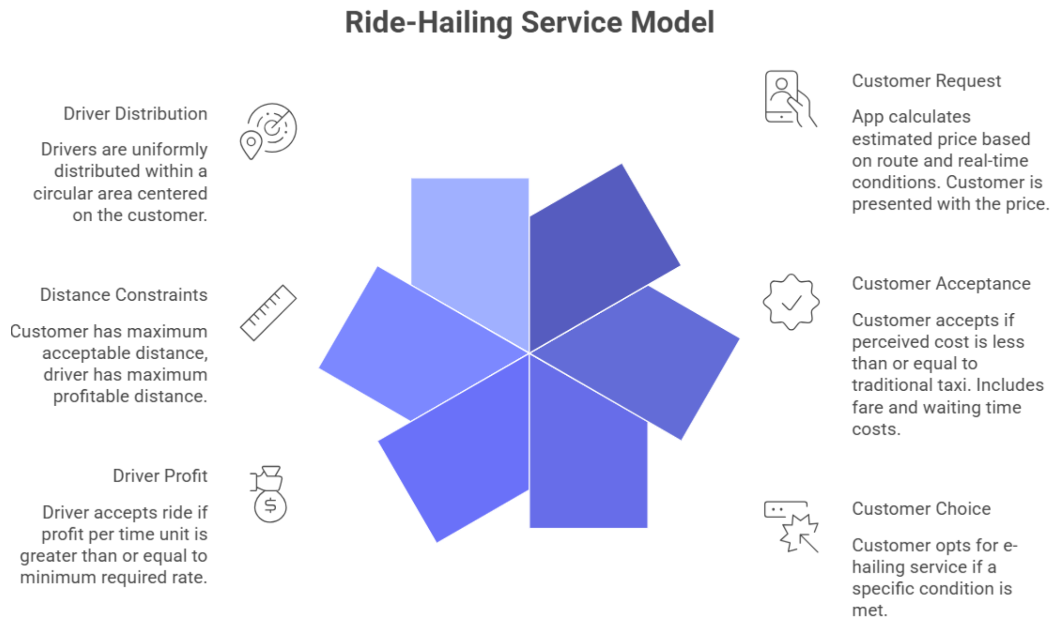

Figure 4. Model for optimizing dynamic pricing in Ride-Hailing Service

1. Customer Request and Pricing

- When a customer submits a ride request, the app calculates an estimated price based on:

  - Route navigation (distance and expected traffic).

  - Real-time conditions (final price may vary).

- The customer is presented with the price, F, and then waits for the driver to accept the request. We focus on two modes:

  - First-to-respond: The request is sent to nearby drivers, and the first one to accept is matched.

  - Centralized selection: The platform directly assigns the closest available driver.

2. Customer Acceptance and Waiting Time

- Customer decision rule: A customer will accept an e-hailing service only if the total perceived cost is less than or equal to that of a traditional offline taxi. This includes both fare and waiting time costs.

- Waiting time(T_w): This depends on the distance from the driver to the customer, (r_i), divided by the driver's average speed, (v):

$$T_w = \frac{r_i}{v} \quad (8)$$

- Total e-hailing cost(C_E): This includes the ride fare F and the waiting cost, which depends on the waiting time T_w and a time-dependent cost parameter(τ):

$$C_E = F + \tau \cdot T_w = F + \tau \cdot \frac{r_i}{v} \quad (9)$$

- Offline taxi cost(C_O): This cost consists of:

- A base fare (a).

- An additional cost k per kilometer after an initial minimum distance m.

- A waiting cost based on average offline waiting time (αT):

$$C_O = a + k \cdot (l - m)^+ + \tau \cdot \alpha T \quad (10)$$

- Where ($(l - m)^+$) denotes the distance beyond the base fare threshold, if any.

3. Customer Choice Condition

- The customer will opt for the e-hailing service if($C_E \leq C_O$), which simplifies to:

$$F \leq a + k \cdot (l - m)^+ + \tau \cdot \alpha T - \tau \cdot \frac{r_i}{v} \quad (11)$$

4. Driver Profit Condition

- A driver will accept a ride if the profit per time unit is greater than or equal to the minimum required rate p.

- Driver profit calculation:

- Assuming the platform takes a fraction f of the fare F, the driver earns $(1 - f)F$.

- The time taken for the ride, based on distance to the customer r_i and the destination l, is ($\frac{r_i + l}{v}$).

- Driver's profit threshold condition:

$$\frac{(1-f)F}{\frac{r_i + l}{v}} \geq p \Rightarrow r_i \leq v \cdot \left(\frac{(1-f)F}{p} - l\right) \quad (12)$$

5. Maximum Distance Constraints for Acceptance

- Customer's Maximum Acceptable Distance: Based on customer acceptance, we find (M_c), the maximum acceptable driver distance (r_i), as follows:

$$M_c = v \cdot \frac{a + k \cdot (l - m)^+ + \tau \cdot \alpha T - F}{\tau} \quad (13)$$

- Driver's Maximum Acceptable Distance: Similarly, the maximum distance (M_d) for which a driver finds it profitable to accept a ride is given by:

$$M_d = v \cdot \left(\frac{(1-f)F}{p} - l\right) \quad (14)$$

6. Spatial Distribution of Drivers

- Assuming drivers are uniformly distributed within a circular area of radius (R) centered on the customer:

- Probability Density Function (PDF):

$$f_r(r) = \frac{2r}{R^2}, \quad 0 \le r \le R \ (15)$$

- Cumulative Distribution Function (CDF):

$$F_r(r) = \frac{r^2}{R^2}, \quad 0 \le r \le R \ (16)$$

The equations above allow us to analyze the expected distance of a matched driver to the customer under uniform distribution, which approximates real-world driver spread within a designated area.

Optimizing Driver's income in case of heavy competition

In the context of maximizing a driver's income or optimizing surge pricing in ride-hailing services, **gradient descent** can be used to find optimal values for variables like pricing rate R(t), ride frequency N(t), or other influencing factors. Gradient descent is an iterative optimization technique that adjusts these variables to either maximize income or balance supply and demand effectively.

In this case, the goal is to maximize the driver's income over a specified time period *T*. We can define income *I* as equation (6) which was defined.

Gradient descent is applied by breaking down continuous intervals into smaller time steps and approximating as a sum.

$$\mathrm{I} \approx \sum_{t=0}^{\mathrm{T}} \mathrm{R(t)} \cdot \mathrm{N(t)} \Delta \mathrm{t} \quad (17)$$

This involves computing the partial derivatives:

$$\frac{\partial \mathrm{I}}{\partial R(\mathrm{t})} = N(\mathrm{t})\Delta\mathrm{t} \quad (18)$$

$$\frac{\partial \mathrm{I}}{\partial N(\mathrm{t})} = R(\mathrm{t})\Delta\mathrm{t} \quad (19)$$

These would tell us how sensitive the income is to changes in the ride rate R(t) and ride frequency N(t) at each time step t.

Using the computed gradients, we update R(t) and N(t) iteratively to maximize I. For each time step t, we adjust R(t) and N(t) in the direction of the gradient, using a learning rate η:

$$R(t)=R(t)+\eta \cdot N(t)\Delta t \quad (20)$$

$$N(t)=N(t)+\eta \cdot R(t)\Delta t \quad (21)$$

Gradient descent begin to update R(t) and N(t) at each time step until minimal changes occur, resulting in an optimal set of values that maximizes income over time. However considering both sensitive variable maximizing driver income at the same time optimizing price would be challenging and complex.

To remain competitive, Bolt's objective is to minimize the difference between Bolt's price and Uber's price while adjusting for Bolt-specific conditions, such as driver supply and customer demand. To optimize Bolt's prices to compete with Uber's surge pricing, we can set up a gradient descent framework to adjust Bolt's prices dynamically based on multiple factors, including Uber's pricing. The goal is to strike a balance where Bolt's prices remain attractive to customers while ensuring profitability and driver availability.

The objective function J for Bolt could be defined as follows:

$$J = \int_0^T ((P_{Bolt}(t) - P_{Uber}(t))2 + \alpha \cdot (D_{Bolt}(t) - S_{Bolt}(t)))dt \quad (22)$$

Therefore, for adjusted prices utilizing descent gradient we will have:

$$\frac{\partial J}{\partial P_{Bolt}(t)} = 2\big(P_{Bolt}(t) - P_{Uber}(t)\big) + a.\frac{\partial(\mathrm{D_{Bolt}(t) - S_{Bolt}(t)}}{\partial P_{Bolt}(t)} \quad (23)$$

RESULTS AND DISCUSSION

First part of the results derived by modeling equations (8) to (16) in the MATLAB environment and executing the code with the sample data, are shown in the following figures. As one of the results, Figure 5 represents a contour plot illustrating the joint acceptance conditions for taxi rides, determined by two factors: the fare (in Euros) and the distance of the driver from the customer (in kilometers). The plot is designed to visualize the scenarios in which both the customer and driver find the ride acceptable. In the contour plot, the x-axis represents the fare amount, ranging from 10 to 30 Euros, while the y-axis shows the distance between the driver and the customer, extending from 0 to 20 km. The color gradient across the plot indicates regions of acceptance and rejection for both parties:

The red area represents regions where the ride is not jointly accepted by both the customer and the driver. This typically occurs when either the fare is too low or the distance between the driver and customer is too great, making the ride unattractive for one or both parties.

The blue area represents conditions under which both the customer and the driver find the ride agreeable. This suggests that the fare is sufficient to compensate for the distance, making it favorable for both parties. The boundary between the red and blue regions shows the critical threshold for mutual acceptance, indicating how increasing the fare can improve the willingness of both the driver and customer to accept a ride, even if the driver has to cover a greater distance to reach the customer. This contour plot effectively highlights the interplay between pricing and logistics in ride-hailing services, providing insights into how fare adjustments can impact the likelihood of successful matches between drivers and customers. It is useful for determining optimal fare pricing and acceptable travel distances to maximize mutual acceptance rates, ultimately improving the efficiency and satisfaction of the ride-hailing system.

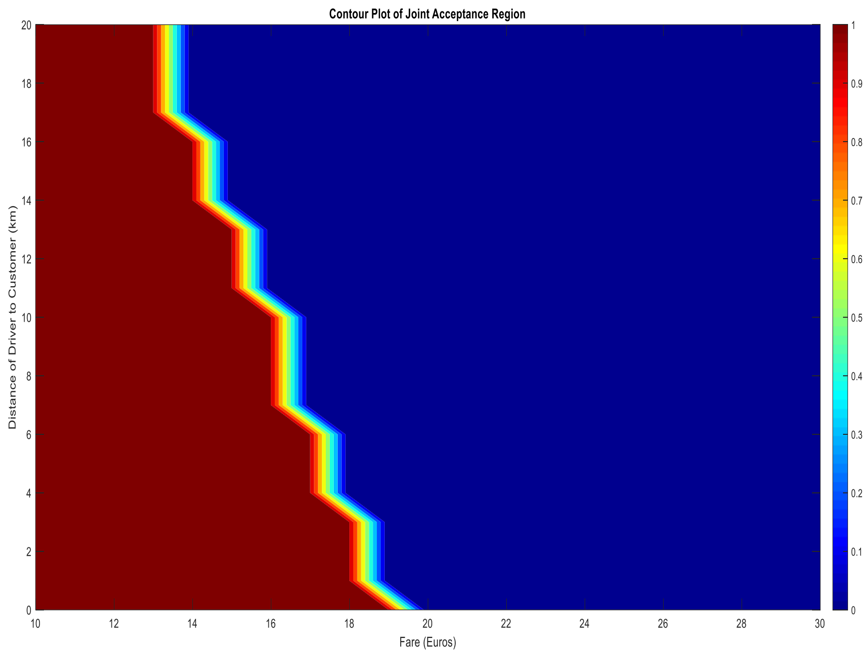

Figure 5. Contour plot depicting the mutual acceptance criteria for taxi rides

Figure 5 provides a comprehensive analysis of how fare influences acceptance decisions for both customers and drivers in a ride-hailing scenario. The three subplots highlight distinct differences in fare preferences between the two groups, emphasizing the interplay between affordability and profitability. The first subplot, a histogram on the top left, depicts the fare distribution for rides accepted by customers. Fares range from 10 to 20 Euros, with acceptance rates peaking between 10 and 12 Euros. This suggests that customers generally prioritize affordability, likely driven by budget constraints, as lower fares see significantly higher acceptance rates.

The second subplot, a histogram on the top right, presents the fare distribution for rides accepted by drivers. Covering fare amounts from 10 to 30 Euros, this visualization reveals a more evenly distributed acceptance pattern. However, a noticeable increase in acceptance occurs at higher fares, around 30 Euros, reflecting drivers' preference for fares that adequately compensate for their time, effort, and costs.

Finally, the bottom subplot, a boxplot, compares fare acceptance ranges for customers and drivers. It shows that customers accept a broader range of fares, with a median fare that is lower compared to the drivers' median. Conversely, drivers exhibit a narrower acceptance range, favoring higher fares. This contrast highlights the differing motivations: customers are primarily driven by affordability, while drivers focus on maximizing earnings per ride. These insights underscore the challenges of balancing pricing strategies to satisfy both groups effectively.

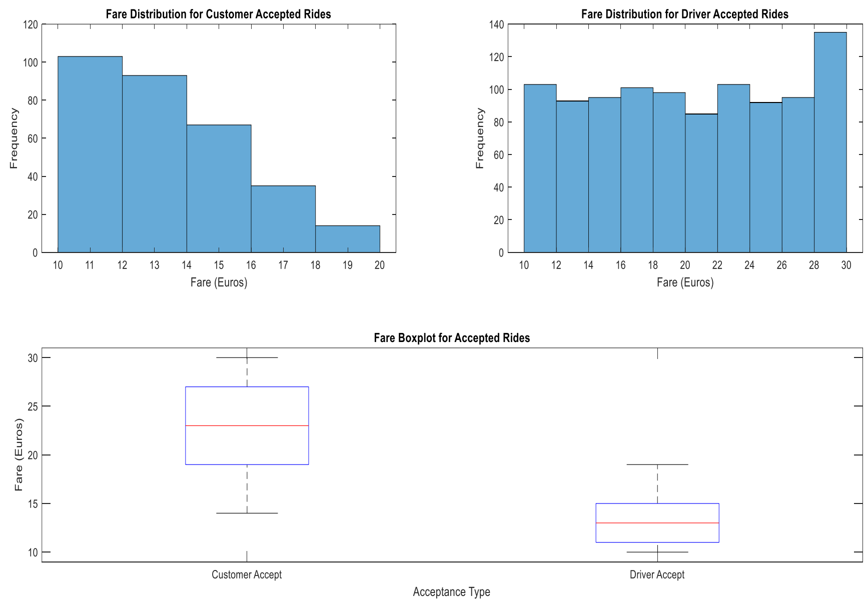

Figure 6. The impact of fare on acceptance decisions by customers and drivers in a ride-hailing context

Figure 6 highlights the differing priorities of customers and drivers in terms of fare acceptance. Customers generally seek lower fares, while drivers are more inclined to accept higher fares to justify the distance and time involved. This distinction underscores the challenge in setting optimal pricing to balance customer affordability with driver profitability, thereby achieving mutual satisfaction in the ride-hailing service.

On the other hand, maximizing the revenue in a ride-hailing app for a city like Málaga, using Bolt as a benchmark, requires another mathematical modeling approach. The model can be simplified in the equation (10) as:

$$\text{MaximizeRevenue} = \sum \ (Price\ per\ ride)i \times (Number\ of\ rides)i \quad (10)$$

This visualization showcases the updated price distributions for local taxis, Uber, Bolt, and Cabify based on the newly developed mathematical model. The model ensures Bolt's pricing remains competitive with other market players while considering factors such as customer affordability and driver income sustainability. The distributions highlight the overlap and competitiveness of Bolt's prices, demonstrating an optimized balance between market demand and drivers' daily earnings.

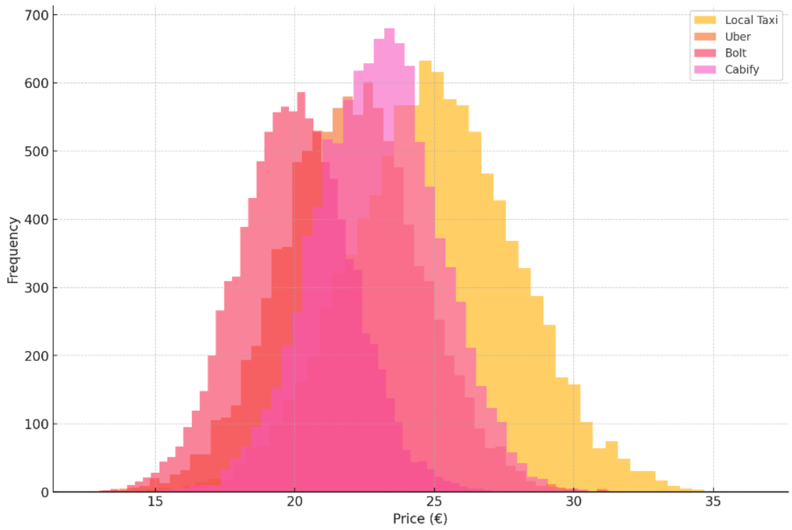

Figure 7. Projected pricing range for each service derived from our assumptions and the MCMC simulation

The distributions in Figure 7 illustrate the estimated range of prices for each service, derived from the MCMC simulation and underlying assumptions. The height of the bars reflects the frequency of various price points, providing insights into the likelihood of specific pricing scenarios for each service. This model enables Bolt to maintain a competitive edge over its primary rivals in Málaga, compared to Uber and Cabify, by optimizing pricing strategies to balance affordability for customers with profitability for drivers. The simulation demonstrates how Bolt's dynamic pricing model outperforms competitors by effectively adapting to market fluctuations, ensuring consistent demand and customer satisfaction, especially in tourist-heavy regions. The height of the bars indicates the frequency of different price points, allowing us to see the likelihood of encountering specific prices for each service.

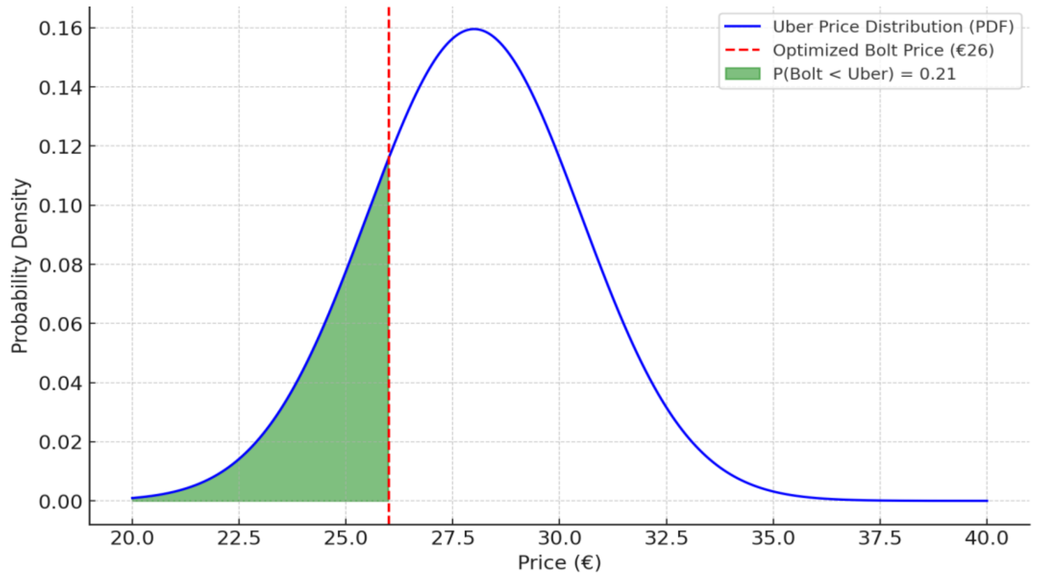

Figure 8. Comparison of Uber's price distribution with the optimal pricing of Bolt

Figure 8 visualizes the Uber price distribution (in blue) and the optimized Bolt price (marked by the red dashed line). The green shaded area represents the probability that Bolt's price is lower than Uber's price.

CONCLUSION AND FUTURE RESEARCH

This model provides Bolt with a dynamic and adaptive pricing strategy tailored to remain competitive with Uber and other competitors in real-time. By leveraging data-driven decision-making, automating price adjustments based on demand and supply, and optimizing profitability, Bolt can enhance its operational efficiency and customer satisfaction. These strategies support Bolt in achieving short-term revenue growth while developing long-term objectives such as expanding market share and strengthening brand loyalty. Our research takes a unique approach by emphasizing the critical aspects of convenience, accessibility, and pricing, particularly for tourists arriving in Málaga. This demographic often values seamless experiences and familiarity when traveling. By offering reliable services with competitive pricing, Bolt can align with tourists' expectations, ensuring an attractive and dependable option for their transportation needs. This approach not only enhances user confidence but also solidifies customer retention, further contributing to Bolt’s reputation as a globally reliable ride-hailing service.

Future research could delve into the advanced applications of dynamic pricing models in the ride-hailing sector, particularly focusing on real-time competitive markets like Málaga. The integration of machine learning, neural networks, generative AI (GEN AI), and large language models (LLMs) provides a significant opportunity to refine predictive pricing strategies. These advanced algorithms can analyze vast amounts of real-time data, enabling platforms like Bolt to dynamically adjust fares to remain competitive against traditional taxis. For instance, Bayesian networks can identify customer behavior patterns by evaluating variables such as waiting time, price sensitivity, and distance preferences. This data-driven methodology allows for dynamic pricing adjustments tailored to both market demands and customer expectations, ensuring affordability and profitability. Another promising avenue is the application of game theory to model the strategic interactions between ride-hailing platforms and local taxi services. By employing concepts such as the Nash Equilibrium, researchers could investigate how Bolt and its competitors might adjust pricing and service offerings to maximize market share while avoiding destructive price wars. Additionally, integrating behavioral economics theories, like the anchoring effect, could shed light on how tourists perceive value and make choices between Bolt and local taxis. Future studies could also explore the impact of loyalty programs, value-based pricing, and strategic partnerships with local businesses on customer retention and satisfaction. These insights would provide a robust framework for optimizing pricing strategies in highly competitive urban markets, enhancing sustainable growth for ride-hailing platforms.

CONFLICT OF INTERESTS

The authors confirms that there is no conflict of interest associated with this publication.

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