Impact of Big Data on Platform Pricing- Case Studies of Uber, Alibaba, Amazon, and Walmart

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Abstract: As the digital era progresses, big data has propelled real-time pricing strategies into global e-commerce and service platforms' core competitiveness. This study employs case studies to demonstrate how platforms establish reasonable pricing policies by utilizing big data to dive deep into user activity data that service as critical inputs for price adjustments, such as click-through rates and browsing history, and integrating the influence of variable factors like inventory levels, supply chain costs, and environmental conditions. Mathematical modeling reveals that big data directly impacts real-time pricing through price sensitivity and regional variables like logistics and tariffs. Dynamic pricing models and analysis of marginal costs and revenue are also used to quantify contributing factors. The study shows that Uber considers factors during peak hours and dynamically adjusts prices via its DRS function. Alibaba and Amazon modify 62.3% of their products' prices based on regional price sensitivity and price elasticity of demand. Walmart employs big data to quickly collect product prices in different regions and allows AI to autonomously decide the price of over 90% of products. This cross-industry research validates how big data shapes real-time pricing and concludes with methods of leveraging big data in real-time pricing strategies and relevant improvement proposals.

1 Introduction

In today's digital era, big data has emerged as a transformative force across all sectors. All industries are gradually embarking on digital transformation, and the rapid acquisition of valid data constitutes the core engine of development. In brief, big data refers to massive, complex, and rapidly expanding data sets that traditional data processing tools (e.g., databases or software) cannot capture, store, manage, and analyze within reasonable timeframes [1]. This technology enables the precise extraction of critical data from massive data sets and thus facilitates sustainable business development.

Politically, building a great modern socialist country with Chinese characteristics represents a monumental achievement that the Chinese people of all ethnic groups have attained through persistent exploration and practice. The digital economy has permeated socioeconomic and cultural domains and evolved into the pivotal force for fostering new quality productive forces, driving high-quality economic development, and constructing a modern economic framework [2]. Economically, big data can process massive heterogeneous

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data to analyze market conditions, user browsing history, corporate supply chains, and public sentiment. It integrates data and enables multidimensional analysis that transcends traditional single-dimensional approaches. Furthermore, big data can synthesize previous cases and generate predictive insights into future economic trajectories [1].

The digital economy, driven by big data, aligns with China's socio-economic development demands and strategic needs. Through digital innovation, transformation, and industrialization within economic sectors and technological platforms, it has amplified big data's pivotal role in socio-economic advancement, thereby providing robust support for the country's high-quality economic growth [2]. At a granular level, big data can be used for financial risk management, business intelligence decision-making, industrial restructuring, and facilitation of emerging industries, and it can also be used to perform analyses to propose optimization strategies. For example, e-commerce platforms like Alibaba and Amazon can predict trending products based on user activity data and adjust inventory levels in time, financial institutions can track transactional data and detect anomalies, and service sectors use big data to calculate prices rapidly and maximize profits.

This study focuses on how big data influences platforms' real-time pricing from various perspectives. Commonalities have been identified through a comparative analysis of cases in different sectors (e.g., Uber, Amazon, Alibaba), and mathematical models like DRS are utilized to deconstruct pricing, costs, and profits, and reveal how big data impacts real-time pricing. The findings will transcend traditional pricing models that only consider demand elasticity, costs, and profits, enhance platform operational performance, and raise consumers' willingness to purchase to maximize profits for platforms. Last but not least, the integrated findings across sectors will convincingly demonstrate big data's impact on dynamic pricing.

2 Uber's surge pricing

2.1 Surge pricing

As a leading ride-hailing platform, Uber adjusts pricing based on real-time rider-to-driver demand and even triggers surcharge multipliers during peak hours in specific regions[3]. Meanwhile, it leverages big data to gauge users' price sensitivity and filter out a proportion of ride requests when raising prices.

2.2 Factors that influence pricing

Uber's real-time pricing mechanism harnesses big data to collect user locations, travel demand intensity, and the number of available drivers. It implements a 'surge pricing' strategy that dynamically applies premium multipliers based on real-time conditions considering key determinants: (1) demand to supply dynamics: density of ride requests (e.g., requests surge when concerts let out), user cancellation rates (pricing elevates when demand outstrips supply), number and distribution of available drivers (e.g., shortage of drivers at night time), and driver response time (delays may trigger price surges); (2) external factors: weather (demand increases during rain/snow), and traffic congestion (prolonged trip durations). In this way, Uber can meet users' needs and simultaneously maximize drivers' earnings and platforms' profits [4].

2.3 DRS pricing model

Research indicates that surging ride-hailing requests during peak hours will disrupt the Demand-to-Supply Ratio (DSR) equilibrium [5]. Platforms leverage real-time big data to

raise prices accordingly and motivate drivers to take orders. The DSR multiplier is dynamically adjusted based on an exponential function. DSR = real-time demand/cars on the road. Multiplier = 1 + α * (DSR_current/DSR_threshold) ^ β. α is the Gini index (0.3-0.6), and β is an elastic index (typical value: 1.5-2.2) [6]. As shown in table 1 that when DSR = 1.5 * threshold value, the multiplier is 1.5 to 2.1. For example, if DSR > 1.2, the multiplier will be 1.5. Table 1 lists trip fares in different regions and at different times. If α = 0.5 and β = 2.0, the DSR function will show a reasonable price rise during peak hours.

Table 1. Case Study on Surge Pricing with the DRS Function Model

Case	Location	Time	Vehicle model	Original price	Adjusted price	Multiplier	Postulated α, β	DSR_threshold	DSR_current
1	Hong Kong	Rush hours	Taxi	HK$120	HK$286.96	2.39	α=0.5, β=2.0	1.2	≈ 2.0
2	Hong Kong	08:12 - 08:15	UberX	HK$120	HK$302.45	2.52	α=0.5, β=2.0	1.2	≈ 2.1
3	Hong Kong	8:14	UberXL	HK$120	HK$190.96	1.59	α=0.5, β=2.0	1.2	≈ 1.4
4	Sydney/ Eastern Suburbs	10:20	UberX	AU$15	AU$34.78	2.32	α=0.4, β=1.8	1.2	≈ 1.9
5	Washington DC	4:40 a.m.	UberX	US$10	US$32.42	3.24	α=0.6, β=2.0	1.2	≈ 2.3

3 Alibaba's pricing strategies

3.1 Alibaba platforms

As China's largest digital commerce ecosystem, Alibaba operates across diverse sectors with multiple business patterns. Its B2B e-commerce platform integrates varied transaction models like B2B, B2C, and C2C, while its consumer platforms like Taobao and Tmall play an indispensable role in people's daily life [7]. In particular, Alibaba has utilized big data as a core operational strategy for a long time. This analysis examines how its e-commerce platforms leverage big data to adjust prices in time, dive deep into the market, understand target consumers' preferences, always prioritize consumers' needs, and maximize platforms and users' interests via differential pricing.

3.2 Factors that influence differential pricing

Alibaba builds personalized pricing models based on user browsing history, add-to-cart rates, and historical consumption data, and analyzes metrics like daily transaction volumes and user traffic. For instance, users with average dwell time exceeding 2.5 minutes show a 30% increase in conversion rates, click on heatmap products and then add-to-cart accounts for 45% of clicks, and searches for high-frequency terms like 'discount' and 'promotion' trigger a 25%

higher probability of dynamic price adjustments. Meanwhile, it closely monitors the market to understand user preferences and purchasing power. Examples are that users in first-tier cities exhibit 5-8% lower price sensitivity compared to other regions, and iOS users are 12% more willing to pay than Android users. These insights enable Alibaba to offer accurate product recommendations to consumers so that they can find suitable products and purchase them. Alibaba also uses price elasticity models to analyze different products. Fast-moving consumer goods have an elasticity of -1.2 (a 10% drop in price boosts sales by 12%), and luxury goods have an elasticity of -0.6. Dynamic discount ranges are offered to attract new users and reactivate existing ones [8]. These strategies help Alibaba to find favor with more consumers, start its big data era, and establish a commercial ecosystem.

4 Amazon's retail pricing

4.1 Amazon e-commerce platform

Amazon was founded in 1994 in Seattle, Washington. Originally an online bookstore, it rapidly expanded its business scope. After launching Amazon Marketplace and allowing third-party sellers to sell products on its platform, it gradually became one of the world's largest e-commerce platforms [9]. By integrating global inventory data, logistics costs, and regional consumption preferences, as shown in the table 2 below, Amazon implements real-time pricing through its database and executes differential pricing strategies [10, 11].

Table 2. Case Study on Amazon's Pricing Factors

1. Logistics costs	Cost of Transatlantic shipping: $8.5/kg Cost of last-mile delivery: €2.8/order	Cost of local transportation: $2.3/kg Cost of last-mile delivery: $1.5/order	+18% - 25% (depends on weight)
2. Tariff and VAT	TARIC: 15% for electronic products VAT: 19%-25%	United States tariff: 0%-5% for electronic products No federal VAT	+20% - 30% (includes tariff and VAT)
3. Purchasing power parity	Purchasing power index: Germany: 85% of the US Brazil: 78% of US (Non-American countries are included here, and the index is adjustable)	US: purchasing power is 100% as a benchmark	Europe: prices are 90%-110% of prices in the US
4. Market competition	Local e-commerce platforms in Europe compete fiercely (e.g., Zalando, OTTO), so Amazon shall cut prices by 5% - 10%	E-commerce is concentrated in the US (Amazon occupies 38% of the market share) Amazon has more freedom in pricing	Prices in Europe may be lower than in the US by 5% - 10%
5. Consumer preferences	European consumers prefer energy-efficient products Additional costs of eco-friendly packaging: €3-5/order	US consumers prefer fast delivery The US has a higher proportion of Prime members (71% vs. 58% in Europe)	Difference in additional costs: €2-4/order

4.2 Influencing factors

Using the agency system to balance all industries and platform operators, Amazon first lowers consumers' perceived value of products. Then, based on the pricing model $\triangle P = k * \varepsilon 1 * (Cm - Rm)$, operators manage to increase product prices that consumers can physiologically afford [12]. Variance in prices of the same product in North America and Europe reaches up to 20%.As shown in table 3, the Nintendo Switch – OLED Model cost was $349 in North America and €379 in Europe in 2023, including all regional tariffs and VAT. However, the retail price was $370 in the US and €447 in Europe, which means a 22% premium in Europe post currency conversion. The same pricing strategies were applied to other products to maximize Amazon's profits. Based on logistics costs and purchasing power disparities, Amazon convinces consumers that they have purchased goods at a lower price than in other regions, thereby boosting consumption needs. In the meantime, Amazon has harnessed price elasticity models and found that consumers in different areas exhibit varied sensitivity to product prices. Therefore, it allows a higher premium in regions where consumers are less sensitive and thus obtain more profits than expected.

Table 3. Amazon's EU vs. US Price Variations

Product	Price in Europe (Germany)	Price in America (US)	Price difference (Euro → US dollar, %)	Main driving force
Nintendo Switch – OLED Model	€447 (≈ $493)	$370	33%	Logistics cost (18%) + VAT (19%)
Kindle Paperwhite	€149 (≈ $164)	$159	3%	Market competition (European consumers have low demand for e-books
Instant Pot pressure cooker	€129 (≈ $142)	$99	43%	Tariff (15%) + logistics costs (transportation premium for heavy cargo)
Levi's 501 jeans	€89 (≈ $98)	$69	42%	Europe's VAT on clothing (19%) + the brand's regional pricing strategies
Apple AirPods Pro 2	€279 (≈ $307)	$249	23%	Europe's VAT on electronic products + the brand's regional premium strategies

5 Walmart's consistent pricing across online and offline channels

By taking actions to accelerate the digitization of offline data, such as AI-enabled shelves and members' consumption data, Walmart is driving consistent pricing across omni-channels. It monitors real-time inventory through big data to enable real-time pricing, and its intelligent systems automatically track competitors' pricing to adjust prices dynamically and maintain the advantage of 'Everyday Low Prices' [13]. During Black Friday sales, 80% of its discounted products had identical pricing across online and offline channels, and Walmart managed to update the price of over 500,000 SKUs every hour via big-data algorithms and synchronize online promotions with 4,700 physical stores. Its self-developed SBY system enables Walmart to integrate consumer activity data, understand consumer preferences, and optimize pricing decisions based on promotion tactics and large-scale procurement to balance efficiency and responsiveness. Significant improvement can be found in (1) responding speed

and price update frequency: price of certain products (such as electronic products) updates every hour and price of fresh food updates within minutes, (2) A/B test: new prices are piloted in select stores or regions before assessment and full rollout, (3) automated decision-making: AI directly puts over 90% price adjustments into effect with human intervention only for anomalies.

6 Analysis

Based on the aforementioned real-time pricing strategies across the four sectors, the study verifies that big data helps gain insight into users' behavioral preferences by collecting click-through rates and consumption habits. Platforms use big data to analyze inventory levels and mathematical models to integrate the impact of supply chain and logistics costs and regional variations in consumption willingness to obtain real-time pricing and maximize profits quickly. However, the underlying drivers are different. Uber primarily adjusts real-time pricing based on conditions in a specific region and time, while e-commerce and Walmart retail platforms mainly alter pricing strategies and achieve differential pricing by collecting and analyzing user behavior data. Moreover, Uber's mechanism is more transparent than that of e-commerce. Big data may have enabled price discrimination against existing consumers on e-commerce retail platforms, which is data misuse and may even lead to abnormally low or surging prices. Considering all these issues, platforms could disclose their pricing calculation mechanisms. Uber may reference Walmart's A/B testing mechanism to validate the price adjustments based on the DRS premium function and avoid price discrimination. Platforms across all sectors should strengthen supervision over differential pricing and involve government regulation when necessary to enhance the transparency of pricing strategies and users' trust in platforms.

7 Conclusion

The comparative case analysis in this article verifies how big data influences platforms' real-time pricing. Uber uses big data to collect the demand-to-supply ratio and DRS function to dynamically adjust pricing, revealing that during peak hours in regions like Hong Kong, DSR is about 2.1, and premium reaches 2.52 times ($\alpha = 0.5$, $\beta = 2.0$). E-commerce platforms like Alibaba and Amazon primarily leverage big data to collect and integrate global user behavioral preferences for rational price adjustments. For instance, Amazon increased the prices of Switch OLED in Europe by 33% (logistics 18% + VAT 19%), and iOS users exhibit 12% higher willingness-to-pay than Android users. Walmart's special computational mechanisms enable autonomous real-time pricing via big data and consistent pricing across online and offline channels. It has also automated 90% of price adjustments through AI and facilitated rapid price updates with big data during Black Friday, reaching up to 500,000 SKU price modifications per hour.

Based on the four case studies, this article can provide theoretical recommendations for using big data in dynamic pricing across platforms. For platforms like Uber that match user supply and demand, Uber's DRS function model can serve as a pricing reference, combined with Walmart's A/B testing mechanism to validate price adjustments and avoid price discrimination. E-commerce platforms can decode user activities and implement differential pricing strategies. Furthermore, platforms can learn from the limitations observed in these four cases to prevent low pricing transparency and potential data misuse that may undermine users' trust, such as price discrimination based on big data. These findings provide an essential theoretical foundation for platforms to implement real-time pricing and promote sustainable development.

Due to incomplete data and limited details of platforms' differential pricing algorithms, this study contains particular uncertainty. Furthermore, as a significant portion of the data originates from user-generated online sources, it may carry some subjective biases. Future research could employ quantitative data collection methods better to validate the precision and rationality of big data algorithms and enhance algorithmic transparency to increase user trust in platforms. Via transparent and fair algorithmic practices, platforms will achieve sustainable development and ultimately maximize user and platform benefits.

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