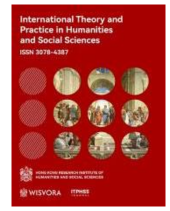
International Theory and Practice in Humanities and Social Sciences
2025 Volume2,Issue4 ISSN 3078-4387



The Impact of Dynamic Pricing Strategies on the Operational Efficiency of Online Retail

Yinuo Wang[1*] Yuqi Zhou[1] Xuanle Ye[1] Jiahe Ding[1]
[1]WENZHOU-KEAN UNIVERSITY, Wenzhou, China

Accepted
29 March 2025

Keywords
Dynamic pricing strategy;
operational efficiency;
online retail companies;
digital competition

Corresponding Author:
Yinuo Wang

https://doi.org/10.70693/itphss.v2i4.324

Abstract
As a pricing method that adjusts the price in real-time according to market demand, competitive environment, and consumer behavior, dynamic pricing strategy has been widely used in the field of e-commerce. This study aims to explore the impact of dynamic pricing strategies on the operational efficiency of online retail companies and take Amazon and JD, two typical online retail companies, as examples. This study adopts a mixture of qualitative and quantitative methods. This study will conduct a case study on the impact of dynamic pricing strategies on the operational efficiency of Amazon and JD. In the quantitative aspect, this study conducted descriptive statistics and regression analysis according to the results of the questionnaire survey. The results show that although dynamic pricing strategy has a positive impact on customer buyback rate and customer satisfaction, regression analysis shows that there is no significant relationship between dynamic pricing strategy and company operating efficiency. The research results provide references for online retail companies to make pricing decisions in digital competition.

1. Introduction

1.1 Field of Research and Provisional Title

The impact of dynamic pricing strategies on the operational efficiency of online retail.

1.2 Background

In the rapidly evolving online retail environment, dynamic pricing strategies have become a key tool for businesses seeking to improve operational efficiency and competitiveness. Dynamic pricing involves adjusting prices in real-time based on a variety of factors such as fluctuating demand, competitor pricing, and consumer behavior, allowing retailers to react nimbly to market conditions. As e-commerce continues to evolve, understanding the implications of these pricing strategies has become critical for retailers to optimize revenue and increase customer satisfaction.

The rise of big data and advanced analytics has enabled online retailers to implement complex dynamic pricing models that can analyze vast amounts of information to inform pricing decisions. This approach not only allows retailers to maximize operational efficiency (profitability, etc.), but also impacts inventory management, customer acquisition, and overall supply chain efficiency.

1.3 Problem Statement

In this era of rapid digital development, the market environment is constantly changing, and the online retail industry is facing very fierce competition. As a result, retailers have introduced dynamic pricing strategies to improve operational efficiency (Sujith et al., 2022). Dynamic pricing is a pricing technique where businesses establish variable costs for goods or services by different algorithms (Kopalle et al., 2023). To get more suitable prices, many retail companies are introducing context-aware technology. Situational awareness uses data monitoring to predict consumers' behavioral preferences, and a widely used technique is real-time location data (Faster Capital, 2024). Some studies suggest that real-time location data can influence the dynamic pricing of retail companies, and this paper will do further research. In addition, some studies have different views on how dynamic pricing affects the operational efficiency of retail companies. Therefore, the correlation between the dynamic pricing strategies of online retail companies and their operational efficiency requires more in-depth study.

1.4 Aim of the Research

This study aims to explore the impact of dynamic pricing strategies on the operational efficiency of online retail and provide suggestions. According to the prior studies, we are the first ones who explore the impact of dynamic pricing strategies on the operational efficiency of online retail. The majority of studies research in the relationship between operation efficiency and customer behavior or the relationship between operation efficiency and customer satisfaction. For dynamic pricing strategies, most of the study research in the model of building dynamic pricing. We are the first to corelate the dynamic pricing strategies and operational efficiency.

1.5 Main Objective of the Research

This study seeks to explore the impact of the operational efficiency of online retail by assessing the typical companies' dynamic pricing strategies based on different contexts.

1.5.1 Sub-objectives

To investigate the dynamic pricing strategies.

To explore the effect dynamic pricing strategies brought to sales volume.

To explore the influence of dynamic pricing strategies on customer satisfaction.

To explore the effect dynamic pricing strategies brought to repurchase rate.

2. Literature Review

2.1 Dynamic Pricing Strategy and Operational Efficiency

According to Neubert (2022), Customers feel less animosity toward the business when they comprehend the rationale behind pricing adjustments, particularly when prices rise. This research indicates that customers' judgments of whether fair or unjust price changes either moderate or worsen their behavior and reactions to dynamic pricing. However, the research (Riquelme et al., 2019). found that generally, consumers hold a view that it is not fair to receive price changes. This is particularly true for loyal clients who make frequent purchases. The findings stated that the price changes would bring great negative influences on consumer behaviors and even lead to consumers' retaliatory online behavior, which will be a barrier to improving and maintaining the operation efficiency. To an extent degree, a dynamic pricing strategy leaving positive and beneficial effects on consumer behavior will be a strong part of improving operation efficiency.

According to Srinivasan, Rajgarhia, Radhakrishnan, Sharma, and Khincha (2017), dynamic pricing techniques are now a potent DSM tool for optimizing customer energy consumption patterns and raising the energy market's overall efficiency. The research indicates the enormous benefits of the dynamic pricing strategy brought on the energy industry and greatly improves the efficiency of energy utilization. According to Jia (2022). Formulating an acceptable price strategy to satisfy the various stakeholders' energetic use is a crucial planning issue, as the demand-side energy use cost is directly impacted by the agents' pricing strategy. To lower demand-side energy costs and boost agents' profitability. The research shows that a dynamic pricing strategy would do well in improving efficiency. However, there are nearly no research and articles concerned with the impact on online retail companies' operating efficiency brought by the dynamic pricing strategy.

Some studies also find positive effect of dynamic pricing on customer satisfaction and operation efficiency. Bakhshizadeh's team (2022) find that customer satisfaction with service recovery is positively and significantly impacted by perceived justice. Furthermore, customer satisfaction resulting from service recovery positively and significantly influences trust, repeat purchases, and word-of-mouth recommendation.

2.2 The Importance of Operational Efficiency in the Online Retail Industry

Operational efficiency is critical to the success of online retailers as it directly impacts customer buyback rates, customer satisfaction, sales, and sustainability. Efficient dynamic price control, supply chain management, logistics optimization, and technology adoption are all key components of operational efficiency in the online retail industry.

The study shows operational efficiency is quite important for new retailing model since the new retail need to combine online and offline selling, which need a high technic for improving operational efficiency (Jiang et al., 2023).

2.3 Elements of Operational Efficiency

Satisfaction serves as a vital measure of operational efficiency. Customer satisfaction is widely recognized as a key metric of operational efficiency, as it reflects how well an organization's operations align with customer expectations. Satisfied customers are more likely to return, make repeat purchases, and spread positive word-of-mouth. According to Anderson, Fornell, and Lehmann (1994), customer satisfaction is not only a result of operational efficiency but also a predictor of long-term profitability and success. The relationship between customer satisfaction and operational performance is bidirectional, with satisfied customers enabling better operational outcomes, and efficient operations fostering satisfaction. Furthermore, dynamic pricing strategies, which adjust prices based on real-time market conditions, can directly influence satisfaction by offering more tailored and competitive pricing (Elmaghraby & Keskinocak, 2003), thus enhancing operational efficiency. Because organizations that efficiently manage their operations are more likely to meet or exceed customer expectations, leading to higher satisfaction levels, our early hypothesis that customer satisfaction is an indicator of operational management efficiency and positively reflects the impact of dynamic pricing strategy on operational management is proved to be likely true.

Sales performance is an important indicator of operational efficiency. According to Homburg, Koschate and Hoyer (2005), organizations with efficient operations are better positioned to understand customer needs, optimize product offerings, and meet demand, which ultimately boosts sales. Efficient resource management, improved supply chain coordination, and effective pricing strategies all play a role in enhancing sales performance. Moreover, dynamic pricing, by adjusting prices to reflect market conditions, can optimize revenue and sales volume, supporting operational efficiency by making the most out of available resources (Kohli & Suri, 2002). organizations that effectively manage their resources and processes are more likely to achieve higher sales levels, demonstrating their capacity to meet customer demands ((Kumar & Reinartz, 2016). This corresponds with our early hypothesis that sales is an indicator of operational management efficiency and positively reflects the impact of dynamic pricing strategy on operational management.

High repurchase rates are indicative of a company's operational effectiveness, as they reflect the ability to meet customer expectations consistently, ensuring satisfaction and fostering loyalty over time (Kumar & Shah, 2004). So, our early hypothesis that customer satisfaction is an indicator of operational management efficiency and positively reflects the impact of dynamic pricing strategy on operational management is a strong evaluation criterion. According to Oliver (1999), customer loyalty driven by satisfaction and trust contributes to sustained business success. Repurchase rates also signal an efficient operation in terms of product quality, customer service, and supply chain effectiveness. Dynamic pricing can further influence repurchase rates by adjusting prices in a way that encourages repeat purchasing while maintaining profitability, thus enhancing both customer retention and operational efficiency (Neslin et al., 2006).

2.4 Conceptual Framework

Figure1 shows the conceptual framework of this research. We investigate the effect of dynamic pricing on operating efficiency. Customer satisfaction can represent operating efficiency because satisfaction can show the customer's feeling of the service of operation. At the same time, repurchase rate can show the operating efficiency since the repurchase behavior can also show the feeling of the operation service from customers. Thus, we define operating efficiency with customer satisfaction and repurchase rates.

Figure1.1 Conceptual Framework

3. Methodology

3.1 Introduction

This study provides a detailed description of the research design and methodology. It outlines the study population, sample size, and sampling method, and explains the data collection process in a clear and systematic manner. Additionally, the study includes an evaluation of the research methodology, assessing its reliability and validity, while also addressing its ethical considerations.

This study mainly uses data collected from official websites and surveys, including 100 data surveys for JD website users and 100 data surveys for Amazon website users. To fit in the format of Stata and make linear regression, we collect price change number every half year with different products in year 2023 one by one. We collect sales values from the official website. However, due to too many missing values in different products for sales values, this variable is abandoned from linear regression model. For surveys, we use WeChat to collect the answers and some of the survey results are abandoned from linear regression because of too many missing values.

3.2 Study Design

According to Byrne and Humble (2007), a mixed methodology design combines techniques from both qualitative and quantitative approaches. This study will adopt the mixed methodology. This study adopts a mixed method, which is divided into two parts: qualitative and quantitative. In the qualitative part, case studies are mainly used. Two typical online retail companies, Amazon and JD, are selected as cases, and their specific dynamic pricing strategies and sales conditions will be searched and analyzed, and the relationship between them will be obtained. At the same time, several employees from the two companies will be invited to have an interview. As for the quantitative aspect, this study will randomly select 100 online shoppers to conduct a questionnaire survey. The sample used in this study possesses sufficient representativeness as it includes consumers from Amazon and JD.com, two of the largest and most diverse e-commerce platforms. These platforms serve customers with varying economic backgrounds and purchasing behaviors, making them ideal for studying dynamic pricing strategies. A representative sample ensures that findings can be generalized to a broader population, reducing the risk of sampling bias and increasing the reliability of conclusions (Saunders et al., 2019). By selecting shoppers from both platforms, the study inherently captures a wide range of consumers, from budget-conscious buyers to premium shoppers, thereby ensuring that different income levels and consumption habits are reflected in the research (Malhotra & Birks, 2021). E-commerce platforms cater to a diverse consumer base, offering products that range from low-cost essentials to high-end luxury goods. This pricing structure ensures that both lower-income and higher-income consumers participate in online shopping, making the sample inclusive. Studies have shown that consumer purchasing power and price sensitivity vary significantly based on income levels, with lower-income individuals being more responsive to price changes and discounts, whereas higher-income individuals often prioritize brand loyalty and convenience (Grewal et al., 2019). By using a sample from Amazon and JD.com, this study indirectly incorporates respondents across different income brackets and consumption habits, as these platforms have customer segments spanning multiple economic classes (Chandon et al., 2000). Additionally, digital retail platforms leverage personalized pricing and targeted promotions, which influence spending behaviors differently across various income groups (Shankar & Bolton, 2004).After the data collection, quantitative analysis is required. Microsoft Excel is the best way to do descriptive statistics, analyze this data effectively and efficiently, and provide clear graphs to show the results. The data collected by the questionnaire will be descriptive statistics and crosstabulations will be made to show their relevance. According to the data analysis, we can clearly and intuitively identify the influence of dynamic pricing strategy on the operating efficiency of online retail enterprises.

3.2.1 Qualitative (Case Study)

Qualitative research focuses more on understanding the nature of the research problem, and case study is one of the methods of qualitative research (Bassey, 2002).

JD.com and Amazon were selected as research subjects to explore the impact of dynamic pricing on operational efficiency because: Amazon and JD.com are the two most influential e-commerce platforms in the global and Chinese markets respectively. Both companies have taken an advanced approach to pricing strategy, employing dynamic pricing to optimize sales and inventory management; Both Amazon and JD.com use big data and AI to drive dynamic pricing. The two companies use algorithms to constantly adjust product prices, optimizing them in real time based on market demand, competitor prices, and customer behavior. Amazon's pricing model is based on machine learning, which is able to predict price fluctuations based on historical data and adjust prices using real-time market information. JD.com's dynamic pricing also combines big data analytics to optimize logistics and inventory, ensuring product prices can flexibly reflect market demand.

To gather specific information about the dynamic pricing strategies of Amazon and JD.com, we need to utilize company reports, academic papers, market research, and industry reports. Amazon and JD.com often include information about their pricing strategies and market approaches in their annual reports, quarterly earnings reports, and investor presentations. These documents provide insights into their pricing models, how they adjust prices, and how dynamic pricing fits into their broader business strategy. There are sections in these reports related to pricing optimization, market competitiveness, and revenue growth, which may provide context for dynamic pricing strategies; we can search for academic studies that analyze the dynamic pricing strategies of Amazon and JD.com and use data analysis, case studies, and modeling to understand the effects of dynamic pricing on sales and customer satisfaction. Some relevant journals include: the Journal of Retailing; Journal of Marketing Research; and the International Journal of Electronic Commerce.

3.2.2 Quantitative

Descriptive statistics are often used to describe variables. Descriptive statistics are performed by analyzing one variable at a time (univariate analysis). All researchers perform these descriptive statistics before beginning any type of data analysis (Patel, 2009).

3.2.2.1 Descriptive statistics

This study will search the best-selling products of Amazon and JD.com in the four quarters of 2023 through the official websites and relevant literature reports of the two companies respectively (Amazon: Ice Maker, Air Pods, and Shark. JD.com: iPhone 14 (256GB), Mils Powder), calculate the frequency of their price changes respectively, and collect the sales of the two companies during the same period by searching their financial reports or official reports. Descriptive statistics are used to organize these data into graphs for comparative analysis.

3.2.2.2 Questionnaires

The questionnaire was invented by Sir Francis Galton.a British anthropologist, explorer, and statistician in late 1800. A questionnaire forms the backbone of any survey and its success lies in the designing of a questionnaire. A questionnaire is simply a list of mimeographed or printed questions that is completed by or a respondent to give his opinion (Roopa & Rani, 2012).

Select appropriate channels and methods to distribute questionnaires, such as online survey platforms (e.g. SurveyMonkey, Google Forms). Randomly selected 100 fans who made online purchases on Amazon and Airbnb respectively and issued questionnaires for investigation.

The target population is the group of individuals that the intervention intends to conduct research in and draw conclusions (Barnsbee, 2018). The target population in this study is one hundred for each questionnaire.

The objectives of the questionnaires are as followed:

Understand if users are aware of Amazon and Airbnb's dynamic pricing policies.

Evaluate user satisfaction with the pricing strategy.

Survey customer satisfaction and buyback rates, and then perform simple descriptive statistics on the collected data

3.2.2.3 Linear Regression Analysis

Tests of association only tell you if two or more variables are associated (if two variables tend to occur together). Correlations tell you not only if the variables are associated but also the direction and strength of the relationship (Patel, 2009).

The repurchase rate, sales performance and customer satisfaction rate measure operating efficiency relative to a market benchmark, helping assess the company’s ability to manage operating activities beyond the overall market. Repurchase rate, collected from the survey to cumulate the repurchase behavior on the same product. The customer satisfaction rate is also collected from survey with scores to show the satisfaction of customer on this purchase experience.

$$OperationEffeciency = Repurchase \tag{1}$$

$$OperationEffeciency = Satisfaction \tag{2}$$

To assess the impact of the price fluctuation rate on operational efficiency, we estimate the following multivariate regression model, incorporating controls for factors that are likely to influence operational efficiency.

$$OperationEfficiency_i = \beta_0 + \beta_1 Flactuation_i + \beta_1 InvDum + \varepsilon_i \tag{3}$$

where, for inventory category i, Fluctuation is a measure of price fluctuation number. We include the Income, which is the personal income level, as a set of control variables that influence operation efficiency. We use cross-sectional method and take inventory category as dummy variable to categorize the variables.

After organizing and cleaning the data, the data are ready to set up and run the linear regression model.

For software, this paper uses Stata to clean and analyze data and make linear regression.

Pre-test: A "pilot study" is a scaled-down version of a larger study and serves as a pretest for certain research tools. Data collection and analysis are crucial components of the research process.

Pilot studies play a vital role in refining the study design and improving the overall success rate of the research (Teijlingen & Hundley, 2002). For this study, a pre-survey will be conducted on a small scale, involving a sample of 10 individuals to assess the validity of the questions and ensure clarity in the respondents' understanding of the questionnaire.

4. Analysis and Interpretation of Data

4.1 Introduction

In this chapter, we will specifically use qualitative and quantitative methods to analyze the collected data.

For qualitative analysis, we generally analyze the movement of JD and Amazon in dynamic pricing and then analyze the interview content of dynamic pricing. This study looks at how Amazon and JD use dynamic pricing, analyzing its effects on operation efficiency. Interviews with employees provide insights into how these strategies work in practice and their impact. By comparing these two companies, we aim to understand the role of dynamic pricing in different markets and its overall benefits. For quantitative analysis, we analyze the data collected from websites and surveys to explore the correlation between dynamic pricing and operational efficiencies. Although the descriptive analysis shows the interest from many interviewers in dynamic pricing, the regression does not provide a significant result. The reason for the results need a further discussion.

4.2 Qualitative Analysis

4.2.1 Case Study

Dynamic pricing is a flexible pricing strategy that adjusts prices constantly to respond to changes in market demand. In recent years, with the rapid growth of the e-retail industry, more and more online retail platforms, such as Amazon and JD (JD.com), have adopted dynamic pricing strategies to improve operational efficiency to achieve the goal of increasing efficiency and meeting market demand.

The case study focuses specifically on two widely used online retail platforms - Amazon and JD. These two companies represent the major e-commerce platforms in the West and China respectively, with significant representation in terms of technology application and pricing strategy. By analyzing the dynamic pricing practices of these two companies and interviewing employees of Amazon and JD, we explore the implementation and ultimate results of these companies' dynamic pricing strategies.

4.2.1.1 Main objectives of the research

1. Analyze how Amazon and JD implement dynamic pricing strategies.
2. Evaluate the impact of dynamic pricing on the company's sales, customer satisfaction, buyback rate and other operational efficiency indicators.
3. Conduct in-depth discussions on the implementation of dynamic pricing strategy and its impact on operational efficiency through employee interviews.

4.2.1.2 Dynamic pricing practice analysis.

To ensure the reliability and validity of our findings, we used company annual reports, investor news, press conferences, and publicly available market analysis data. Through the annual analysis report, which mainly includes public data on Amazon and JD' s pricing strategy analysis, sales performance, customer behavior, and application research of dynamic pricing technology, analyze how companies use dynamic pricing strategies.

We found that both Amazon and JD use big data and artificial intelligence to drive dynamic pricing. The two companies use algorithms to constantly adjust product prices and optimize them in real time based on market demand, competitor prices, and customer behavior. Amazon's pricing model is based on machine learning, which is able to predict price fluctuations based on historical data and adjust prices using real-time market information. JD' s dynamic pricing also combines big data analytics to optimize logistics and inventory, ensuring product prices can flexibly reflect market demand. Then, we use comparative analysis as a method to compare Amazon with JD based on their own pricing system and effect.

Amazon's pricing system monitors competitors' prices, user purchase history, inventory levels, product demand, and more in real-time. Based on this data, Amazon automatically adjusts the price of the product. Its pricing system adjusts prices not just for individual items, but for entire product categories. For example, if a competitor lowers the price of a particular category of electronics, Amazon will quickly adjust the price of its own similar products to ensure attractiveness and competitiveness. In an uncertain economic environment, consumers are more sensitive to price changes, especially when consumer spending is more cautious, and retailers' pricing strategies are particularly important. In the fourth quarter of 2023, Amazon launched several major shopping events, including Prime Big Deal Days and extended Black Friday and Cyber Monday events, constantly adjusting prices based on different time periods and promotional intensity to maximize sales and customer engagement (Amazon, 2023). In the report, Amazon mentioned that the 2023 campaign saved customers nearly $24 billion, an increase of nearly 70% over the previous year's savings; By optimizing prices, discounts, and promotions, Amazon can increase consumers' willingness to buy in the short term, offer more attractive prices in comparison, improve customer satisfaction, and promote customer buyback rates, especially among price-sensitive consumers. These activities significantly increased sales by flexibly adjusting prices. During Prime Day in 2023, Amazon's sales increased by more than 50 percent to about $13 billion, compared to 2022 (Amazon, 2023). Amazon successfully attracted a large number of customers to its promotions during the 2023 holiday shopping season, and improved volume and operational efficiency through dynamic pricing.

JD's dynamic pricing is prominent in promotional seasons, such as Double 11 and 618 shopping festivals. Through precise pricing control, JD is able to maximize sales revenue in a short period of time. During the Double 11 shopping festival, for example, JD negotiated pricing strategies with sellers and made rational price adjustments on millions of items through data-driven pricing strategies. Through real-time data analysis, it ensures competitive commodity prices and flexibly introduces discounts and offers based on different product categories and time periods.

4.2.2 Interview

In order to obtain more direct and concrete practical data, we designed and conducted interviews. The interviews were conducted with Amazon and JD employees, including pricing strategists, data analysis team members, and customer service staff. The purpose of the interviews was to understand the reality of the implementation of dynamic pricing, its impact on the company's operational efficiency, and employees' perceptions of this strategy. Researchers tried to search for relevant interviewees such as HR and customer service through LinkedIn, the company's official website, and public contact information and invited them to participate in the interview. 删除[一诺 王]:

4.2.2.1 Selection of Interviewees

Our goal is to ensure that employees interviewed are from different departments and levels, especially those directly involved or affected by dynamic pricing. Consequently, the interviewees include a pricing strategy manager responsible for the design and adjustment of dynamic pricing algorithms, data analysts collecting and analyzing market, consumer, and competitor data, customer service representatives interacting directly with customers and providing feedback on customer response and satisfaction, and sales operations team which is responsible for monitoring sales data, inventory levels, and the effectiveness of promotional activities.

4.2.2.2 Sample Size of Interviews

We plan to conduct interviews with 10-20 employees of Amazon and JD respectively. The selection of interviewees takes into account their different participating departments of dynamic pricing strategy and comprehensively evaluates the implementation effect of dynamic pricing from multiple perspectives.

4.2.2.3 Interview Question Design

The interview questions are designed based on three aspects to fully understand the impact of dynamic pricing on a company's operational efficiency. All interview questions are open-ended, that is, there is some predetermined frame of questions, but there are also appropriate follow-up questions based on the respondents' responses for deeper insights.

4.2.2.4 The Interview Questions

1. Can you briefly describe how the company implements a dynamic pricing strategy? What technologies or methods are used to support this strategy?
2. After the implementation of dynamic pricing, has the company observed significant changes in sales, customer buyback rates, customer satisfaction, etc.?
3. Does dynamic pricing have a positive or negative impact on customers' purchasing decisions? If so, how is it affected?

Based on interviews and data analysis, we reached the following conclusions:

Amazon: Above all, in terms of the implementation of dynamic pricing, Amazon uses machine learning and artificial intelligence technology to adjust commodity prices in real-time. These systems are able to optimize prices in real-time based on market demand, competitor prices, user buying behavior, and inventory equity factors. Amazon uses its vast data resources to support these technologies through the powerful computing power provided by AWS (Amazon Web Services). The implementation of the dynamic Pricing system also involves Amazon's Pricing Algorithm, an algorithm-driven pricing strategy that helps Amazon make pricing decisions through big data analysis. At Amazon, algorithms dominate the price adjustment process, and the system automatically makes price adjustments based on real-time data. However, in some special cases, such as holiday promotions or special promotions, there may be human intervention. For example, during key sales such as Black Friday and Prime Day, human teams do a final review of pricing to ensure it is competitive and in line with promotional strategies. In addition, from the perspective of operational efficiency, dynamic pricing has significantly increased Amazon's sales and market share. By adjusting prices in real time, Amazon keeps the competitive advantage in dynamic market conditions and directly drives profits. In addition, dynamic pricing can also improve customer buyback rates, because regular price adjustments will stimulate customers' desire to buy. According to Amazon statistics, the average Prime member buys two to three times more per year than the average user. By offering personalized offers through dynamic pricing, Amazon has managed to maintain high customer loyalty and buyback rates. We have also observed that through targeted pricing, Amazon can tailor prices to different consumer groups, such as by observing the number of searches and browsing for specific items to provide reasonable discounts, thereby increasing user stickiness and loyalty.

Based on the information provided by employees about customer reaction and satisfaction, dynamic pricing generally has a positive impact on customer purchase decisions. Through precise discounts and personalized offers, Amazon can meet the different needs of different consumers. Customers can get more attractive prices for specific time periods, which not only promotes instant purchases, but also increases long-term loyalty. However, individual customers may feel some dissatisfaction with price fluctuations, especially when they purchase goods and find that the price suddenly drops. But in general, customers prefer price transparency and personalized discounts.

JD: In terms of the implementation of dynamic pricing, JD has adopted big data analysis and machine learning technology to achieve dynamic pricing. JD 's pricing system monitors competitor prices, user behavior, product sales and market trends, and makes price adjustments based on these real-time data. JD, in combination with its JD Cloud platform, uses cloud computing and data mining technologies to provide powerful support for real-time pricing of a large number of items. JD 's dynamic pricing system is mainly automated by algorithms, but in some specific business scenarios, such as major promotions or brand partnerships, human decisions are still important. For example, during big promotions such as Double 11 or 618, JD 's pricing strategy is fine-tuned based on real-time market feedback, while final confirmation is carried out by a human team to ensure that the price is not only reasonable, but also in line with the brand and market strategy.

In terms of sales and operational effects, dynamic pricing has had a positive impact on JD 's sales. With the introduction of algorithmic pricing, JD is able to respond more accurately to market demand and competitive pressures. For example, during the Double 11 and other promotional activities, through the flexible adjustment of prices, JD significantly increased sales and order volume in 2023, JD Double 11 sales reached about 410 billion yuan, an increase of about 15% (JD.com, 2023). It is also closely related to the implementation of flexible pricing strategy; During the 618-promotion period in 2023, JD' s total sales exceeded 350 billion yuan, an increase of about 20% over 2022. For the buyback rate, JD 's JD PLUS members are its core loyal customer base. According to official data from JD.com, the average annual buyback rate of JD PLUS members is four to five times that of the average consumer. Dynamic pricing allows JD to offer personalized offers based on user behavior, which improves customer loyalty and buyback rates. Overall, dynamic pricing has helped JD maintain a strong market share in a highly competitive market environment.

In terms of customer response and satisfaction, dynamic pricing has had a positive impact among JD's customers. Thanks to price transparency and real-time adjustments, consumers feel able to get the best price and are able to seize the various offers in a timely manner. Through personalized recommendations and targeted pricing, JD helps customers save a lot of shopping expenses and enhances their purchasing decision-making power. JD said in 2023 that 67 percent of consumers are satisfied with personalized offers obtained through dynamic pricing, especially during the promotion period when customers' purchasing decisions become more flexible by adjusting prices and offer in real time (JD.com, 2023). JD noted that while offering real-time discounts through big data and smart pricing, 48% of customers said they were more satisfied with the transparency and fairness of price fluctuations. However, some items with high price fluctuations may cause doubts among some customers, especially consumers who are less aware of price fluctuations and may ask questions about the transparency of pricing. Therefore, JD has also strengthened price transparency and customer communication to reduce this negative impact.

By comparing the differences between Amazon and JD in the implementation of dynamic pricing, the study analyzes the effect of dynamic pricing applied by the two companies in different market environments and technical bases and then draws a comparative conclusion.

4.3 Quantitative Analysis

4.3.1 Descriptive Statistics

According to this article (Griliches, 1964), small price fluctuations are caused by the different dynamic pricing strategies of Amazon and JD. For the convenience of research, this study finally counts each significant peak and trough as a price change.

In this study, the PriceGrabber tool (Check Online Store Ratings and Save Money with Deals at PriceGrabber.com, n.d.) was used to retrieve the historical price of each product.

The researchers selected the top three best-selling products in 2023 on JD's official website, which are milk powder (annual sales of 78 million), mattresses (48 million), and mobile phones (sales of 46 million). The researchers selected the top three best-selling products in 2023 on JD's official website, which are Milk Powder (annual sales of 78 million), Mattresses (48 million), and Mobile Phones (sales of 46 million). In this study, we will select the best-selling brand model among these three products to study the frequency of price changes. The researchers selected the three best-selling products on Amazon in the last 12 months: Ice Makers, Air Pods, and SharkNinja. In this study, the researchers will select the best-selling brand model among these three products to study the frequency of price changes. First, we will collect the price changes of these brand models over the last 12 months.

According to the official website of JD.com, among JD's milk powder products, Apamex milk powder occupies a large market share. Mattress products, Xilimen mattress sales highest. Apple's best-selling model is the iPhone 14 (256GB). According to Amazon's official website, Air Pods occupy a large market share among Amazon's Electronics products. In the category of Tools and Home Improvement products, Silonn Ice Maker Countertop has the highest sales. In the Kitchen product category, Shark Steam and Scrub with Steam Blaster Technology All-in-One Hard Floor Steam Mop with 3 Steam Modes & LED Headlights S8201 is the most popular product. The following is the trend of how their prices have changed over the past 12 months.

4.3.1.1 Mattresses

Figure 2.1 Mattress Prices Change Over the Past Year ($ per unit)

From the graph, there are distinct price changes at roughly eight points throughout the last 12 months. These points are where the price either rises or falls significantly.

To calculate the frequency of these price changes over a year (assuming 365 days), Frequency is equal to the Number of Changes divided by the Total Days in the Year. With 8 changes, the Frequency is equal to 0.0219 which means the price change 0.0219 times per day. This means the product's price changes approximately once every 46 days (1/0.0219)

4.3.1.2 Milk Powder

Figure 3.1 Milk Powder Price Changes in the Past Year ($/per unit)

According to the graph provided, the frequency of price changes for the product shown over the course of the year can be estimated, this research will count each significant peak and trough as a price change.

It appears that there are approximately 11 significant price changes throughout the year. This count includes all major movements where the price distinctly rises or falls and then remains at that level or changes again.

To calculate the frequency of these price changes over a year (assuming 365 days), Frequency equals the Number of Changes divided by the Total Days in the Year. With 11 changes, Frequency is equal to 0.0301 which means the price change is 0.0301 times per day. This calculation suggests that the price changes occur approximately every 33 days on average (1 divided by the frequency per day).

4.3.1.3 iPhone 14 (256 GB)

Figure 4.1 iPhone 14 (256 GB) Price Changes in the Past Year ($/per unit)

According to the graph, significant movements where the price clearly changes from one stable level to another. From the graph, it appears there are about 10 significant price changes. These changes are marked by a noticeable shift in the price level that then stabilizes or shifts again.

To calculate the frequency of these price changes over a year (assuming 365 days), Frequency is equal to the Number of Changes divided by the Total Days in the Year. With 11 changes, Frequency is equal to 0.0274 which means the price change is 0.0274 times per day.

This calculation suggests that, on average, the product's price changes approximately once every 36 to 37 days. This frequency indicates a moderate level of price volatility, where the product experiences roughly monthly price adjustments throughout the year.

4.3.1.4 Ice Maker

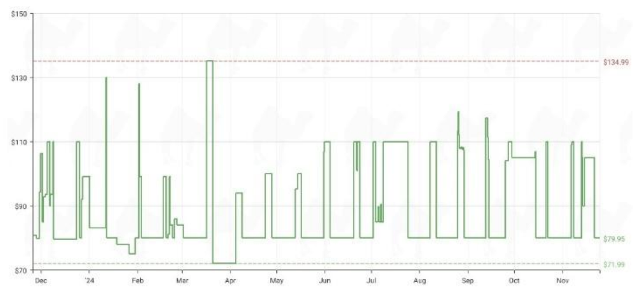


Figure 5.1 Ice Maker Price Changes in the Past Year ($/per unit)

By examining the graph, it can be noticed that there are several vertical movements that indicate changes in price. Each significant vertical line (either going up or down)will be counted as a price change.

Visually, there are about 23 significant changes where the price rises or drops distinctly.

To calculate the frequency of these price changes over a year (assuming 365 days), Frequency is equal to the Number of Changes divided by the Total Days in the Year. With 23 changes, Frequency is equal to 0.0219 which means the price change 0.063 times per day.

This calculation suggests that, on average, the product's price changes approximately once every 16 days.

4.3.1.5 Apple AirPods Max Wireless Over-Ear Headphones

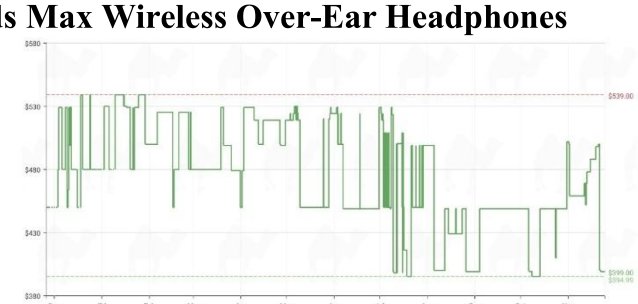


Figure 6.1 Apple AirPods Max Wireless Over-Ear Headphones Price Changes in the Past year ($/per unit)

The graph shows a series of vertical movements representing rises and falls in the product's price. Each distinct movement will be counted as a change.

By examining the graph, it appears there are about 29 significant price changes.This count includes every distinct upward or downward movement that marks a change in price level.

To calculate the frequency of these price changes over a year (assuming 365 days), Frequency is equal to the Number of Changes divided by the Total Days in the Year. With 29 changes, Frequency is equal to 0.0795 which means the price change 0.0795 times per day.

This calculation means that, on average, the product's price changes approximately once every 12.6 days (which is about once every two weeks). This suggests that the product experiences frequent price volatility, possibly due to factors like promotional activities changes in supply and demand, or adjustments in market strategy.

4.3.1.6 Shark

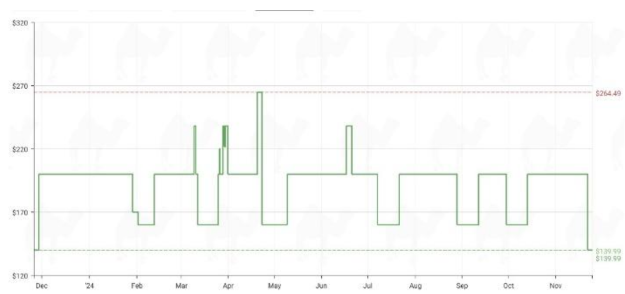


Figure 7.1 Shark Price Changes in the Past Year ($/per unit)

According to the graph, significant vertical movements indicate a change in price. Each vertical movement from one stable level to another counts as a change.

As can be observed from the graph, it appears there are about 13 significant price changes throughout the year. This includes every notable rise or drop that stabilizes or shifts again.

To calculate the frequency of these price changes over a year (assuming 365 days), Frequency is equal to the Number of Changes divided by the Total Days in the Year. With 13 changes, Frequency is equal to 0.0356 which means the price change 0.0356 times per day.

This calculation suggests that, on average, the product's price changes approximately once every 28 days (which is about once a month). JD's revenue for the twelve months ending September 30, 2024, was approximately $156.955 billion, which reflects a 5.53% increase from the previous year. (JD.com Revenue 2011-2023, n.d.)

Over the last twelve months leading up to October 2024, Amazon's revenue further increased to around $620.13 billion, marking a growth of 11.93% year-over-year. (Stock Analysis, 2023)

4.3.2 Data from Questionnaires

The sample size for each questionnaire is 100 participants, and the researchers randomly selected 10 percent of them to serve as the pretest group for the questionnaires. Researchers found that 15 percent of participants' answers were invalid because they did not understand dynamic pricing strategies. The majority (85 percent) of participants had valid answers, indicating that both questionnaires were valid.

4.3.2.1 Answer to the First Question in Questionnaire One

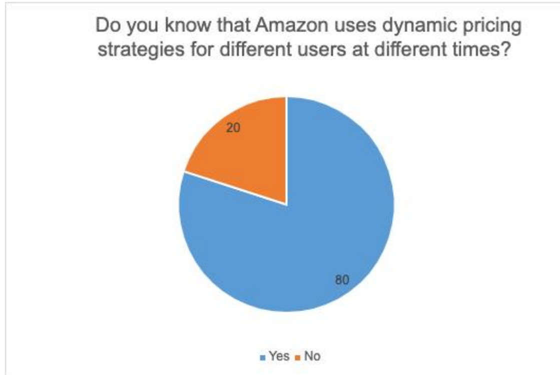


Figure 8.1 The Participants' Answers to Question One

This pie chart shows the responses from the 100 participants to the question: "Do you know that Amazon uses dynamic pricing strategies for different users at different times?" 80 percent of the participants answered "Yes". And 20 percent of the participants answered "No." The majority of participants are aware of Amazon's use of dynamic pricing strategies. Refer to Table 1.1 for details.

4.3.2.2 Answer to the Second Question in Questionnaire One

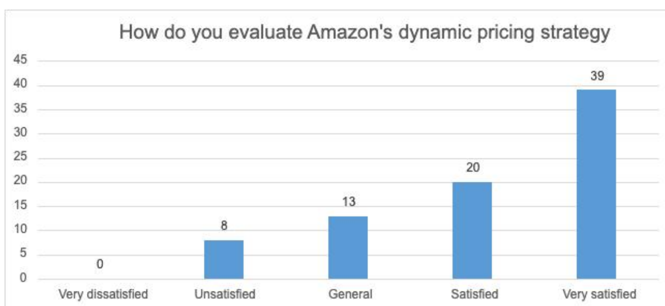


Figure 9.1 The Participants' Answers to Question One

This bar chart illustrates people's evaluation of Amazon's dynamic pricing strategy. The majority, 39 respondents, are very satisfied, followed by 20 who are satisfied. Additionally, 13 respondents rated it as neutral, while 8 expressed being unsatisfied, and none chose very dissatisfied. Overall, the feedback is predomin antly positive, indicating general approval of Amazon's dynamic pricing strategy. Refer to Table 2.1 for details.

4.3.2.3 Answer to the Third Question in Questionnaire One

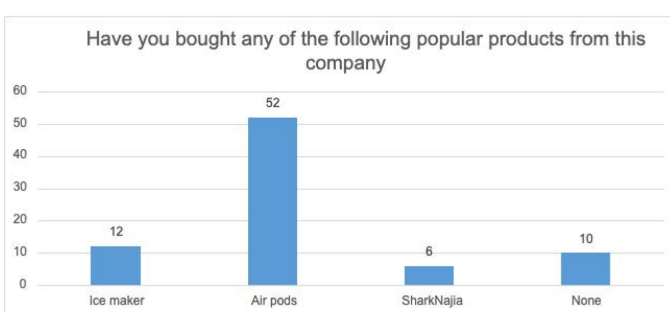


Figure 10.1 The Participants' Answers to Question Three

This bar chart shows the purchasing preferences for certain popular products from Amazon. Among the respondents, 52 participants purchased AirPods, making it the most popular choice. 12 participants bought Ice Makers, and only 6 participants chose SharkNinja. Additionally, 10 participants stated that they had not purchased any of these products. Overall, AirPods stand out as the dominant product in terms of popularity. Refer to Table 3.1 for details.

4.3.2.4 Answer to the Forth Question in Questionnaire One

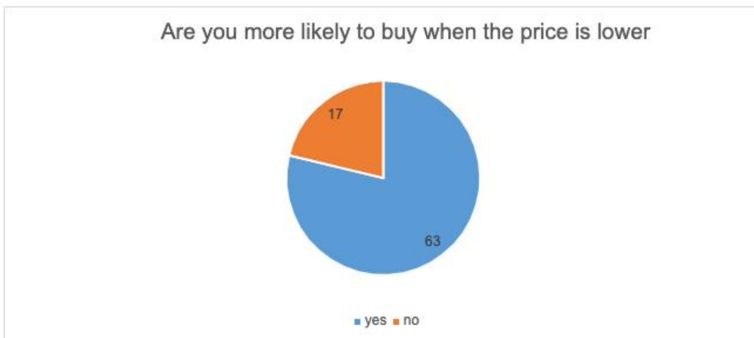


Figure 11.1 The Participants' Answers to Question Four

This graph shows whether people are more inclined to buy when the price is lower. According to the data in the chart, 63% of people said they would buy when the price was lower, while only 17% said they would not buy. This suggests that most people are more likely to want to buy when prices are low. Refer to Table 4.1 for details.

4.3.2.5 Answer to the Fifth Question in Questionnaire One

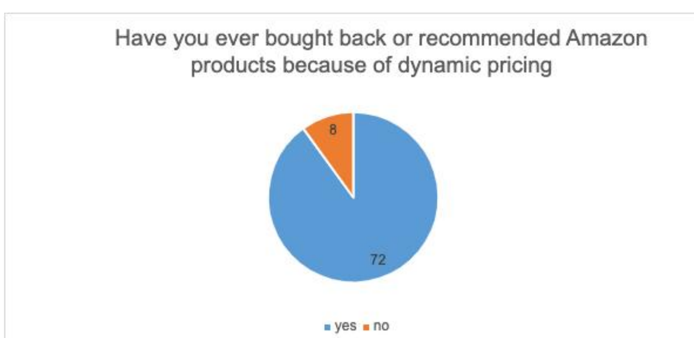


Figure 12.1 The Participants' Answers to Question Five

According to the pie chart, 72% of participants have bought back or recommended Amazon products due to dynamic pricing, while 8% have not. This indicates that the majority of people have been influenced by Amazon's dynamic pricing strategy, which adjusts product prices based on various factors, to make purchasing decisions. The data suggests that Amazon's dynamic pricing model has been effective in driving customer purchases and recommendations, as most respondents have experienced this phenomenon. Refer to Table 5.1 for details.

4.3.2.6 Answer to the Sixth Question in Questionnaire One

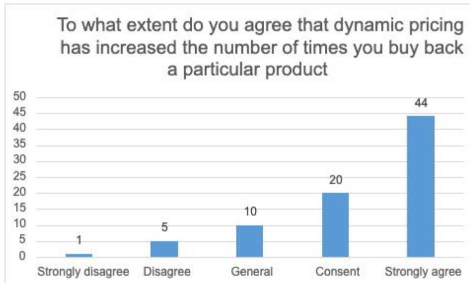


Figure 13.1 The Participants' Answers to Question Six

According to the bar chart, 44 percent of the participants strongly agree that dynamic pricing has increased the frequency of their buybacks. 20 percent of the participants agreed with the statement. 10 percent of the participants generally agreed on the impact of dynamic pricing on their buyback behavior. 5 percent of the participants disagreed with that statement. Only 1 percent of the participants strongly disagree that dynamic pricing has increased the frequency of their buybacks. The data suggests that the majority of respondents, over 60 percent, either agree or strongly agree that dynamic pricing has indeed increased the number of times they buy back a particular product. This indicates that dynamic pricing strategies employed by retailers have been effective in influencing consumer purchasing behavior. Refer to Table 6.1 for details.

4.3.2.7 Answer to the First Question in Questionnaire Two

Figure 14.1 The Participants' Answers to Question One

The figure shows that of the 100 participants, Ninety-two percent of participants were aware of JD’s dynamic pricing strategy, and eight percent were not aware of the strategy Refer to Table 7.1 in the appendix for specific frequency distribution. Since the following survey was based on participants' familiarity with JD's dynamic pricing strategy, the answers of 8 participants who did not understand the strategy were regarded as invalid data.

4.3.2.8 Answer to the First Question in Questionnaire Two

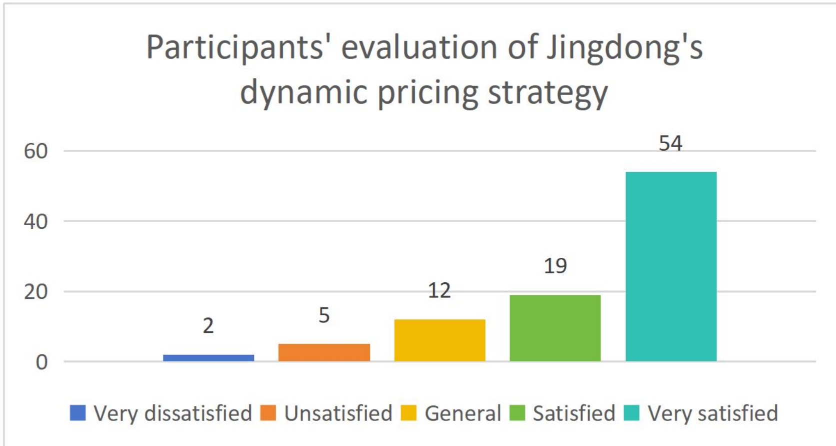


Figure 15.1 The Participants' Answers to Question Two

Based on Table 10.1 above and Table 8.1 in the appendix, the evaluation of dynamic pricing strategies by 92 valid participants was analyzed 59 percent of participants were very satisfied with JD's dynamic pricing strategy, 21 percent of participants were satisfied, and only 8 percent were dissatisfied with the strategy.

4.3.2.9 Answer to the Second Question in Questionnaire Two

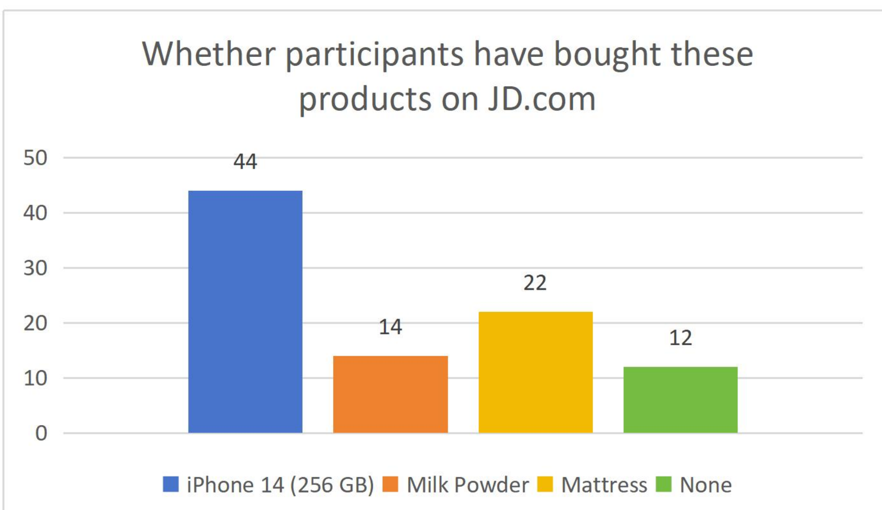


Figure 16.1 The Participants' Answers to Question Two

As can be seen from Figure 15 and Appendix Table 9.1, of the 92 valid participants, 48% had purchased iPhone 14 (256 GB), 15% had purchased milk powder, and 24% had purchased mattresses. Only 13% of participants had not purchased these products on JD.com.

4.3.2.10 Answer to the Third Question in Questionnaire Two

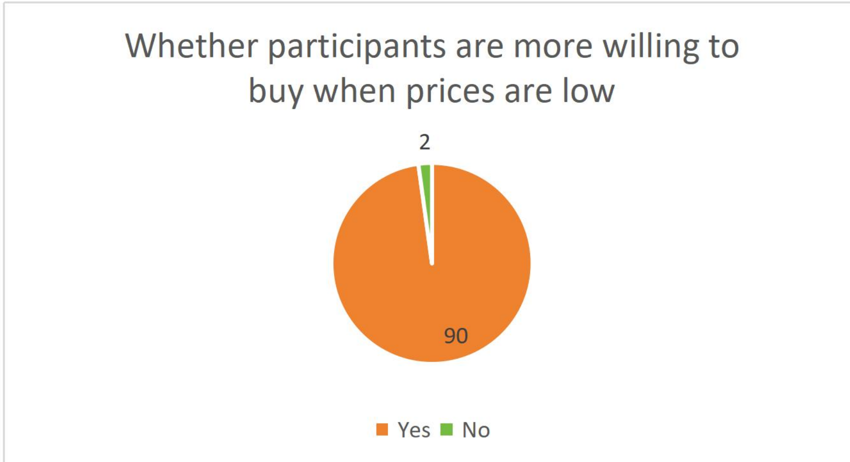


Figure 17.1 The Participants' Answers to Question Two

As to whether participants are more willing to buy at a lower price, according to Figure 16 above and Table 10.1 in the appendix, 98% of participants are more willing to buy and only 2% are not.

4.3.2.11 Answer to the Fourth Question in Questionnaire Two

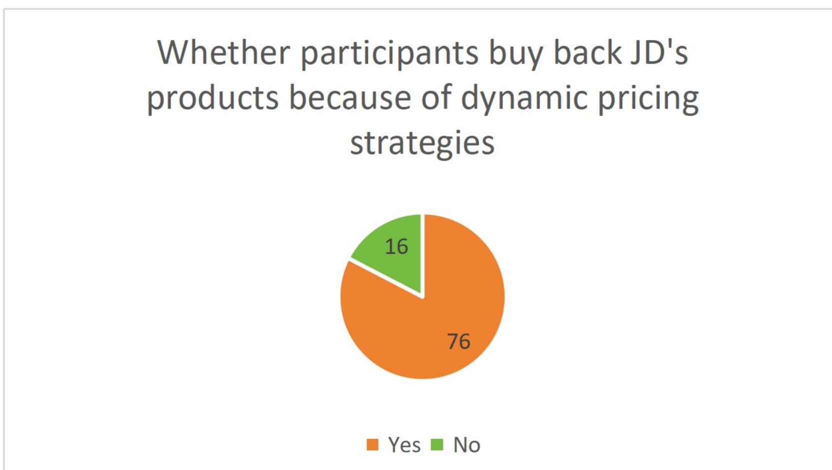


Figure 18.1 The Participants' Answers to Question Two

Figure 18.1 above and Table 11.1 in the appendix analyze the distribution of 92 valid participants who made repeat purchases due to JD's dynamic pricing strategy, and the vast majority (83%) of participants believe that they will buy again because of this strategy, only a small number (17%) of participants do not think so. The specific frequency distribution is shown in Appendix Table 11.1.

4.3.2.12 Answer to the Fifth Question in Questionnaire Two

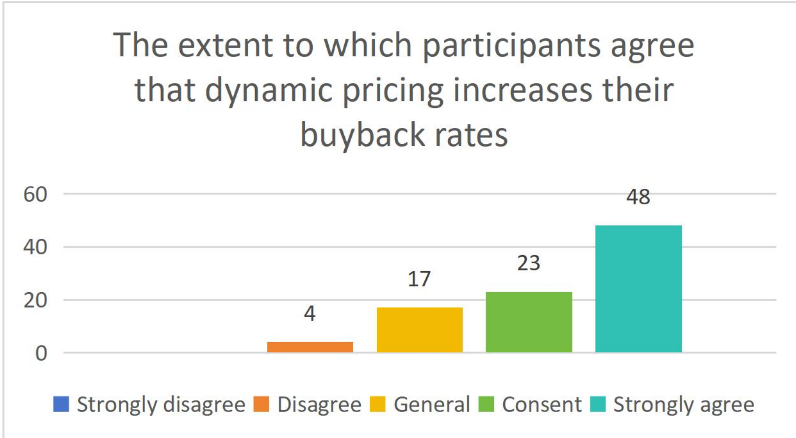


Figure 19.1 The Participants' Answers to Question Two

The figure shows the distribution of the 92 valid participants to what extent they agree that JD's dynamic pricing strategy has increased their repurchase rate, with 53% of participants strongly agreeing that the strategy has increased their repurchase rate, and only 4% of participants disagreeing that the strategy has increased their repurchase rate. The specific frequency distribution is shown in Appendix Table 12.1.

4.3.3 Crosstabulation

列1	purchasing products on JD.com and being satisfied (including "very satisfied) with its dynamic pricing strategy	purchasing products on JD.com and being not satisfied (including "general, unsatisfied, and very dissatisfied) with its dynamic pricing strategy	Purchased products from JD.com and consented (including strongly agree) to buy them back due to its dynamic pricing strategy	purchasing products on JD.com and not agreeing (including "general, disagree) with its dynamic pricing strategy
Valid participants	72	8	70	10

Table 13.1 Crosstabulation of Questionnaire One

As can be seen from the above cross-table, there are a total of 80 participants who understand JD's dynamic pricing strategy and have purchased its hot-selling products, of which 72 are highly satisfied with JD's dynamic pricing strategy, accounting for 90%. Among them, 70 people agreed with the strategy to improve the buyback rate, accounting for 88%

列1	purchasing products on Amazon and being satisfied (including "very satisfied) with its dynamic pricing strategy	purchasing products on Amazon and being not satisfied (including "general, unsatisfied, and very dissatisfied) with its dynamic pricing strategy	Purchased products from Amazon and consented (including strongly agree) to buy them back due to its dynamic pricing strategy	purchasing products on Amazon and not agreeing (including "general, disagree) with its dynamic pricing strategy
Valid participants	50	20	55	15

Table 14.1 Crosstabulation of Questionnaire Two

As can be seen from the above cross table, there are a total of 70 participants who understand Amazon's dynamic pricing strategy and have purchased its hot products, among which 50 are highly satisfied with Amazon's dynamic pricing strategy, accounting for 71%. Among them, 55 people agreed with the strategy to improve the buyback rate, accounting for 79%.

4.3.4 Linear Regression Analysis

Table 3.1 shows the results of the relationship between price change and operating efficiency in Amazon using different estimation methods. They also used half-year dummies.

Table 3.1 Linear Regression in Amazon

	(1)	(2)
Variables	AmaFeeling	AmaBuyBack
PriceChangesNum	-0.00920	0.00436
	(0.0370)	(0.0361)
Constant	4.208***	4.213***
	(0.500)	(0.488)
Observations	140	140
R-squared	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.1 presents the results of an ordinary least squares (OLS) regression of the Z-score on the number of price changes. The findings indicate that the number of price changes is not associated with Amazon's sentiment. In other words, more price fluctuation does not exhibit a higher satisfaction feeling in Amazon. This result does not support the hypothesis that price change has a positive effect on operating efficiency. The coefficient of price change number is positive but not significant.

Table 4.1 reports the results of the effect of price change number attributes on Amazon buyback. Our operating efficiency measure is the feeling of the website and buyback behavior. We rerun our baseline model while including buy-back behavior instead of the feeling for the website. Taken individually, the coefficients are positive and statistically not significant, suggesting that the price change number has no relationship with buyback behavior. The coefficients on the Amazon buyback behavior suggest that these attributes are not significant.

Table 4.1 provides the results of the relationship between price change and operating efficiency in JD. using different estimation methods. They also used half-year dummies.

Table 4.1 Linear Regression in JD

	(1)	(2)
Variables	JDFeeling	JDBuyBack
PriceChangesNum	0.0325	-0.0217
	(0.0806)	(0.0654)
Constant	4.156***	4.418***
	(0.397)	(0.322)
Observations	166	166
R-squared	0.001	0.001

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column 1 of Table 4.1 presents the results of customers’ feeling for JD. against price change number. The standard errors are robust and clustered by half a year to control for cross-sectional dependence. The results show that the price change number has a positive relationship with the feeling of JD. In other words, more price fluctuation exhibits a higher satisfaction feeling in JD, but not significant. This result does not support the hypothesis that price change has a positive effect on operating efficiency. The coefficient of price change number is positive but not significant. Under otherwise identical conditions, a one standard deviation increase in the number of price changes results in a 0.0325 increase in the sentiment score for JD.

Column 2 of Table 4 presents the results of analyzing the effect of price change number attributes on JD's buyback behavior. The measure of operational efficiency used is the sentiment toward the website and buyback behavior. The baseline model is re-estimated, replacing website sentiment with buyback behavior as the dependent variable. Taken individually, the coefficients are negative and statistically not significant, suggesting that the price change number has a negative relationship with buyback behavior. The coefficients on the JD buyback behavior suggest that these attributes are not significant.

The regression results do not fit in the qualitative results and literature review may due to the customer do not feeling the change of dynamic pricing. The change value of pricing is too small to be sensed. At the same time, the customers may not care about the daily or monthly changes in specific product. In majority of times, they only concern about which product to buy and whether they can afford it. Therefore, if they do not buy the product frequently and in a short time, they may not notice the change of small value of price.

According to table 3.1 and table 4.1, price change number is not significant affect the operation efficiency while the constant affects the operation efficiency significantly at 0.1% level, which can have further discussion.

The significant constants suggest that the operation efficiency (*JDFeeling*, *AmaFeeling*, *JDBuyBack*, *AmaBuyBack*)—have strong baseline values, regardless of the frequency of price changes. For example, the intercept for *JDFeeling* is 4.156, indicating that customer satisfaction toward JD.com starts from a relatively high level even without considering price changes. Similarly, the constants for Amazon models (4.208 for *AmaFeeling* and 4.213 for *AmaBuyBack*) reflect similar baseline levels of customer attitudes toward Amazon.

The low R-squared values suggest that the models explain almost none of the variation in the dependent variables. While the constants are significant, the insignificance of *PriceChangesNum* might indicate that price changes alone do not adequately explain operation efficiency. This could mean the models are missing important variables or that customer behavior is influenced by more complex factors.

5. Discussion and Conclusion

5.1 Implication

5.1.1 Recommendation

Through case studies of Amazon and JD's dynamic pricing strategies, we find that both companies utilize big data, machine learning, and artificial intelligence algorithms to adjust prices in real time. Therefore, companies looking to conduct or improve pricing strategies should invest more in advanced data analytics tools and machine learning technologies. These tools can help monitor competitor pricing, capture customer behavior, and analyze market demand for the sake of promoting the platform to adjust prices constantly and increase sales and market recognition. Both Amazon and JD have improved customer satisfaction and buyback rates by targeting pricing strategies to specific consumer groups and at specific times. This suggests that retailers should invest in segmentation tools and personalization algorithms to provide customized pricing or promotional offers for different customer segments and specific time periods, reducing customer decision time and increasing customer engagement. In addition, while dynamic pricing strategies can improve operational efficiency, relatively frequent price volatility can leave some customers dissatisfied, especially if the price changes once they submit orders. Amazon and JD have made efforts to increase price transparency, such as displaying charts of historical price trends, which can help reduce customer concerns. To mitigate possible consumer reactions, companies should increase price transparency, fully communicate price changes and provide as clear an explanation as possible. Finally, while both Amazon and JD rely heavily on automated pricing algorithms, human intervention is still important during certain high-risk periods, such as during major sales events. Companies should maintain a balance between automated pricing and human oversight, and drive dynamic pricing strategies toward achieving overall business goals and meeting customer needs. At the same time, for the questionnaire survey, this study suggests that other teams should appropriately expand the sample size to ensure that the collected data is more accurate and universal. In terms of linear regression, it is suggested that future studies on this topic should pay attention to controlling variables and exclude the interference of external conditions to obtain more accurate data

5.1.2 Qualitative Study

This study analyzes the dynamic pricing strategies of two online retail platforms, Amazon and JD, then infers their impact on operational efficiency. By analyzing company history and publicly available literature, the study explores how these companies are using big data, artificial intelligence, and machine learning to dynamically adjust prices in response to market demand and gain a competitive advantage. Using these technologies, both Amazon and JD are able to optimize pricing in real time, maximize sales, and increase customer satisfaction and buyback rates, especially during key promotions. The implementation effect and influence of dynamic pricing strategy are further obtained. Based on the fact that sales, customer satisfaction, and buyback rate are indicators of operational efficiency, we finally conclude that dynamic pricing strategies have a certain positive impact on a company's operational efficiency.

5.1.3 Quantitative Study

According to Neubert (2022), when consumers understand the reasoning behind price changes, especially when prices increase, they are less hostile toward the company. A dynamic pricing strategy that has a favorable and beneficial impact on consumer behavior will contribute significantly to increased operational efficiency. It can be observed from Figure 2.1 that 80 percent of the participants are aware of the use of dynamic pricing strategy in Amazon and from Figure 5.1 that 92 percent of the participants have been aware of the use of dynamic pricing strategy in JD.

According to Figure 9.1, the majority, 39 participants, are very satisfied with Amazon’s dynamic pricing strategy, followed by 20 who are satisfied. According to Figure 15.1, 59 percent of participants were very satisfied with JD's dynamic pricing strategy, 21 percent of participants were satisfied, and only 8 percent were dissatisfied with the strategy. Overall, the participants from Amazon and JD are satisfied with the dynamic pricing strategy. According to Figure 4.1 and Figure 7.1, a great number of the participants who have known about the dynamic pricing strategy of Amazon or JD agree that the dynamic pricing strategy increases their buyback rates. At the same time, the researchers made a cross table for the satisfaction and buyback rate of the participants in the effective questionnaire on the dynamic pricing strategy of JD and Amazon. It shows that the vast majority of the participants are satisfied with the dynamic pricing strategy of these two online retail companies and will buy back because of the strategy. The research (Riquelme et al., 2019), There is a prevalent perception among customers that price adjustments are unfair. This is especially true for regular buyers who are devoted customers. The results indicated that pricing adjustments would have a significant detrimental impact on consumer behavior and might result in retaliatory online behavior from customers, which would make it difficult to maintain and increase operational efficiency. However, the regression finds that the frequency of price change does not affect the operating efficiency. The results are not significant in both JD and Amazon. It cannot prove that the dynamic pricing strategies lead to effect on customers' behaviors and even online retail companies' operational efficiency. According to the regression tables, the constant value shows the significant effect at 0.1% level in both JD and Amazon results, which means even when all explanatory variables are held at zero, there is a substantial baseline level of the operation efficiency. This indicates the existence of inherent factors influencing the operation efficiency that are not captured by the price changes included in the model.

5.2 Conclusion

In general, this study uses case studies to specifically analyze the successful cases of JD and Amazon, two typical online retail companies using dynamic pricing strategies and concludes that dynamic pricing strategies will improve the company's operational efficiency by increasing its sales. On the other hand, through descriptive statistical analysis, the researchers conclude that the dynamic pricing strategy of online retail companies has a positive impact on the operational efficiency of the company by holding higher customer satisfaction and buyback rate. However, this study uses linear regression analysis to explore whether there is a significant relationship between the number of price changes of a company's best-selling products and customer satisfaction and buyback rate. The conclusion is that the relationship between the two is not significant, which means that the linear regression made on the basis of the collected data shows that there is no significant relationship between the dynamic pricing strategy of an online retail company and its operational efficiency. This may due to the purchase habit of customer that they do not need to concern about the monthly price changes. At the same time, the small amount of price change may not able to attract the attention of customers. Elements like marketing initiatives, customer profiles, product quality, and customer service experiences could provide further insight into the variability of the dependent variables. Additionally, incorporating interaction terms or exploring non-linear relationships might enhance the precision of the linear regression models. Due to the limitations of linear regression in this study, the conclusions are inconsistent with the results of previous quantitative analyses and descriptive statistics. Further research by other research teams is recommended.

This study is the first to explore the impact of dynamic pricing on operational efficiency in DJ Company and Amazon. While previous research has primarily examined the effects of dynamic pricing on firm management and customer satisfaction or analyzed factors influencing operational efficiency, this paper fills a significant gap by investigating the relationship between dynamic pricing and operational efficiency using multiple models for efficiency measurement. Through an in-depth case study employing qualitative methods, the study provides a deeper understanding of how dynamic pricing influences operational efficiency, delivering valuable insights for corporate executives.

5.3 Limitations

Limitation: Considering the qualitative analysis, since the interviewees were limited to employees of Amazon and JD and the sample size was not large enough due to external factors, the research conclusions may not be universal and cannot fully represent all online retail companies. In addition, the respondents' position may affect the truthfulness of the answers, especially in relation to the company's sales and customer feedback; Finally, due to confidentiality restrictions on corporate data, all relevant pricing strategies and financial data may not be available for this study. The purpose of this study is to explore the relationship between dynamic pricing strategy and operational efficiency of online retail enterprises. However, the sample size of questionnaire mitigation in this study is not large enough to represent the views of all consumers. In terms of selecting financial indicators to reflect the operational efficiency of online retail companies, the financial indicators selected by the researchers are not comprehensive enough, because the financial data of companies disclosed on the Internet are limited, and some data such as inventory turnover are not fully disclosed. In addition, this study did not carry out effective control variables in the linear regression analysis, which is also due to incomplete data disclosure on the network. It is hoped that these problems can be improved in future studies. Also, the research conclusions may lack universality and fail to fully represent all online retail companies due to the limited price change data and small sample size caused by external factors. Additionally, the absence of control variables could significantly impact the regression results. Factors such as marketing efforts, customer demographics, product quality, or customer service experiences could help explain more of the variation in the dependent variables. Including interaction terms or testing non-linear relationships might also make the models more accurate. Lastly, confidentiality restrictions on corporate data may limit access to crucial pricing strategies and financial information for this study.

References

Amazon. (2023). Amazon.com, Inc. 2023 annual report. Amazon. https://www.amazon.com/ann ualreport

Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer satisfaction, market share, and profitability: Findings from Sweden. Journal of Marketing, 58(3), 53–66. https://doi.org/ 10.1177/002224299405800304

Bakhshizadeh Borj, K., Binai Rad, M., & Salehian Fard, R. (2022). The effect of dynamic p ricing strategy on customer satisfaction with service recovery through perceived justice in int ernet taxi platforms (Case study: Snap intelligent transportation system). CommercialStrategies, 19(19), 107–128.

Barnsbee, L. (2018). Target population – an overview. ScienceDirect Topics. https://www.scien cedirect.com/topics/engineering/target-population

Bassey, M. (2002). Case study research. In M. Coleman & A. R. J. Briggs (Eds.), Research methods in educational leadership and management (pp. 108–121). Paul Chapman Publishing.

Byrne, J., & Humble, Á. M. (2007). An introduction to mixed method research. Atlantic Res earch Centre for Family-Work Issues, 1, 1–4.

Chandon, P., Wansink, B., & Laurent, G. (2000). A benefit congruency framework of sales p romotion effectiveness. Journal of Marketing, 64(4), 65–81. https://doi.org/10.1509/jmkg.64.4.6 5.18071

Check online store ratings and save money with deals at PriceGrabber.com. (n.d.). PriceGrab ber. https://www.pricegrabber.com/ Wikipedia+4Purdue OWL+4Purdue OWL+4

Elmaghraby, W. J., & Keskinocak, P. (2003). Dynamic pricing in the presence of inventory c

onsiderations: Research overview, current practices, and future directions. Management Science, 49(10), 1287–1309. https://doi.org/10.1287/mnsc.49.10.1287.17367
Fornell, C. (1992). A national customer satisfaction barometer: The Swedish experience. Journal of Marketing, 56(1), 6–21. https://doi.org/10.1177/002224299205600103
Grewal, D., Ailawadi, K. L., Gauri, D. K., Hall, K., Kopalle, P. K., & Robertson, J. R. (2019). Innovations in retail pricing and promotions. Journal of Retailing, 95(1), 42–61. https://doi.org/10.1016/j.jretai.2018.11.002
Homburg, C., Koschate, N., & Hoyer, W. D. (2005). Do satisfied customers really pay more? A study of the relationship between customer satisfaction and willingness to pay. Journal of Marketing, 69(2), 84–96. https://doi.org/10.1509/jmkg.69.2.84.60760
JD.com. (2023). JD.com 2023 annual report. https://ir.jd.com/
JD.com revenue 2011–2023. (n.d.). Stock Analysis. https://stockanalysis.com/stocks/jd/revenue/
Jia, S., Peng, K., Zhang, X., Li, Y., & Xing, L. (2022). Dynamic pricing strategy and regional energy consumption optimization based on different stakeholders. International Journal of Electrical Power & Energy Systems, 141, 108199.
Jiang, T., Wu, X., & Yin, Y. (2023). Logistics efficiency evaluation and empirical research under the new retailing model: The way toward sustainable development. Sustainability, 15(20), 15028.
Kohli, R., & Suri, R. (2002). The effects of dynamic pricing strategies on the performance of firms. Journal of Revenue and Pricing Management, 1(1), 1–19. https://doi.org/10.1057/palgrave.rpm.5170052
Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. Journal of Marketing, 80(6), 36–68. https://doi.org/10.1509/jm.15.0414
Kumar, V., & Shah, D. (2004). Building and sustaining profitable customer loyalty for the21st century. Journal of Retailing, 80(4), 317–330. https://doi.org/10.1016/j.jretai.2004.10.007
Malhotra, N. K., & Birks, D. F. (2021). Marketing research: An applied approach (6th ed.). Pearson.
Neubert, M. (2022). A systematic literature review of dynamic pricing strategies. International Business Research, 15(4), 1–17.
Neslin, S. A., Gupta, S., Kamakura, W. A., Lu, J., & Mason, C. H. (2006). Defection detection and prevention: A longitudinal analysis. Journal of Marketing, 70(4), 21–37. https://doi.org/10.1509/jmkg.70.4.21
Nimalasena, A., & Getov, V. (2016). Context-aware approach for determining the threshold price in name-your-own-price channels. In Context-Aware Systems and Applications: 4thInternational Conference, ICCASA 2015, Vung Tau, Vietnam, November 26–27, 2015, Revised Selected Papers (Vol. 4, pp. 83–93). Springer International Publishing.