VILNIUS UNIVERSITY
BUSINESS SCHOOL

DIGITAL MARKETING PROGRAMME

ZIHAN, DING

MASTER FINAL THESIS

DINAMINĖS KAINODAROS ĮTAKA VARTOTOJŲ PASITENKINIMUI DAUGIAKANALIOJE MAŽMENINĖJE PREKYBOJE	**THE IMPACT OF DYNAMIC PRICING ON CONSUMER SATISFACTION IN OMNICHANNEL RETAILING**

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SUMMARY

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THE IMPACT OF DYNAMIC PRICING ON CONSUMER SATISFACTION IN OMNICHANNEL RETAILING

Supervisor: Prof., Dr. Sunil Sahadev

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Short description of the thesis: This paper explores the application of dynamic pricing in omni-channel retail and its impact on consumer satisfaction. By constructing a theoretical framework and using quantitative analysis methods, this paper studies how dynamic pricing affects consumers' immediate and long-term satisfaction through mediating variables such as trust and price fairness and analyzes the role of moderating variables such as price sensitivity and channel preference.

The question with this thesis: In the context of omnichannel retail, what is the specific impact of dynamic pricing on consumer satisfaction? Is the impact significant? Are there other variables (such as trust, price fairness) mediating this process?

The aim of this thesis: This research aims to systematically analyze the impact of dynamic pricing in an omnichannel retail environment on consumer satisfaction and establish its conceptual

model, focusing on how dynamic pricing can simultaneously bring about positive (such as personalization, competitive pricing) and negative (such as price fluctuations, perceived unfairness) effects, and explore the role of mediating mechanisms, so as to fully understand its impact on consumer behavior, trust, and overall satisfaction.

The main tasks of the thesis:

1. Explore the application of dynamic pricing in omnichannel retail and its role in channel management.
2. Evaluate the dual impact of dynamic pricing on consumer satisfaction, including positive (personalization and competitive pricing) and negative (price fluctuations and perceived unfairness).
3. Construct a theoretical model to analyze the relationship between dynamic pricing and consumer satisfaction and the role of other key mediating variables.
4. Propose suggestions for optimizing dynamic pricing strategies to balance corporate profitability and consumer satisfaction.

Research methods used in thesis: This study adopts a quantitative research method and collects data through a questionnaire survey, covering key variables such as price fairness, trust, immediate and long-term satisfaction. The data are statistically analyzed using SPSS software, including descriptive statistics, correlation analysis, multiple regression analysis, and moderation and mediation effect analysis.

Research and results obtained:

1. Dynamic pricing significantly impacts immediate and long-term satisfaction by influencing consumers' perception of price fairness and trust.
2. Price-sensitive consumers are more sensitive to the negative impact of dynamic pricing, while high transparency and consistency can mitigate this impact.
3. Dynamic pricing personalization strategies are particularly effective in improving consumer experience and long-term satisfaction.

Conclusions of the thesis: Dynamic pricing strategies excel in enhancing personalized shopping experiences, optimizing resource allocation, and improving long-term satisfaction. However, when price fluctuations lack transparency or fairness, it may lead to a decline in consumer trust, especially for consumers with high price sensitivity. This study verifies the flexibility and applicability of dynamic pricing in an omni-channel retail environment, and provides practical suggestions for retailers to optimize pricing strategies and improve consumer satisfaction.

SANTRAUKA

VILNIAUS UNIVERSITETAS VERSLO MOKYKLA
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ZIHAN DING

DINAMINĖS KAINOJIMO POVEIKIS VARTOTOJŲ PATENKINTUMUI VISUOMENINĖJE MAŽMENINĖJE PREKYBOSE

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Trumpas baigiamojo darbo aprašymas: Straipsnyje nagrinėjamas dinaminės kainodaros taikymas daugiakanalioje mažmeninėje prekyboje ir jos įtaka vartotojų pasitenkinimui. Kuriant teorinę sistemą ir naudojant kiekybinės analizės metodus, šiame darbe tiriama, kaip dinamiška kainodara veikia tiesioginį ir ilgalaikį vartotojų pasitenkinimą per tarpininkaujančius kintamuosius, tokius kaip pasitikėjimas ir kainos teisingumas, ir analizuojamas moderuojančių kintamųjų, tokių kaip kainų jautrumas ir kanalo pasirinkimas, vaidmuo.

Š **ios tezės klausimas:** koks konkretus dinaminės kainodaros poveikis vartotojų pasitenkinimui yra daugiakanalio mažmeninės prekybos kontekste? Ar poveikis reikšmingas? Ar šiame procese tarpininkauja kiti kintamieji (pvz., pasitikėjimas, kainos teisingumas)?

Baigiamojo darbo tikslas: Šiuo tyrimu siekiama sistemingai išanalizuoti dinamiškos kainodaros poveikį daugiakanalioje mažmeninės prekybos aplinkoje vartotojų pasitenkinimui ir sukurti koncepcinį modelį, sutelkiant dėmesį į tai, kaip dinamiška kainodara vienu metu gali

sukelti teigiamą (pvz., personalizavimą, konkurencingą kainodarą) ir neigiamą (pvz., kainų svyravimus). , suvokto nesąžiningumo) poveikį ir ištirti tarpininkavimo mechanizmų vaidmenį, kad būtų galima visiškai suprasti jų poveikį vartotojų elgesiui, pasitikėjimui ir apskritai pasitenkinimas.

Pagrindinės baigiamojo darbo užduotys:

1. Ištirkite dinaminės kainodaros taikymą įvairiais kanalais veikiančioje mažmeninėje prekyboje ir jos vaidmenį kanalų valdyme.
2. Įvertinkite dvejopą dinamiškos kainodaros poveikį vartotojų pasitenkinimui, įskaitant teigiamą (personalizavimas ir konkurencinga kaina) ir neigiamą (kainų svyravimai ir suvokiamas nesąžiningumas).
3. Sukurti teorinį modelį, skirtą analizuoti ryšį tarp dinaminės kainodaros ir vartotojų pasitenkinimo bei kitų pagrindinių tarpininkavimo kintamųjų vaidmens.
4. Pateikti pasiūlymus, kaip optimizuoti dinamines kainodaros strategijas, siekiant subalansuoti įmonės pelningumą ir vartotojų pasitenkinimą.

Baigiamajame darbe naudojami tyrimo metodai: Šiame tyrime taikomas kiekybinis tyrimo metodas ir anketinės apklausos būdu renkami duomenys, apimantys pagrindinius kintamuosius, tokius kaip kainos teisingumas, pasitikėjimas, tiesioginis ir ilgalaikis pasitenkinimas. Duomenys statistiškai analizuojami naudojant SPSS programinę įrangą, įskaitant aprašomąją statistiką, koreliacijos analizę, daugkartinę regresinę analizę ir moderavimo bei tarpininkavimo efektų analizę.

Tyrimai ir gauti rezultatai:

1. Dinaminė kainodara daro didelę įtaką tiesioginiam ir ilgalaikiam pasitenkinimui, nes daro įtaką vartotojų suvokimui apie kainų teisingumą ir pasitikėjimą.
2. Kainoms jautrūs vartotojai jautriau reaguoja į neigiamą dinamiškos kainodaros poveikį, o didelis skaidrumas ir nuoseklumas gali sušvelninti šį poveikį.

3. Dinaminės kainodaros personalizavimo strategijos yra ypač veiksmingos gerinant vartotojų patirtį ir ilgalaikį pasitenkinimą.

Baigiamojo darbo išvados: Dinaminės kainodaros strategijos puikiai pagerina personalizuotą apsipirkimo patirtį, optimizuoja išteklių paskirstymą ir didina ilgalaikį pasitenkinimą. Tačiau kai kainų svyravimai trūksta skaidrumo ar sąžiningumo, gali sumažėti vartotojų pasitikėjimas, ypač vartotojų, kurių kainos yra labai jautrios. Šiame tyrime patikrinamas dinaminės kainodaros lankstumas ir pritaikomumas įvairiuose kanaluose veikiančioje mažmeninės prekybos aplinkoje ir pateikiami praktiniai pasiūlymai mažmenininkams, kaip optimizuoti kainodaros strategijas ir pagerinti vartotojų pasitenkinimą.

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INTRODUCTION

Research background

In the backdrop of rapid advancements in mobile computing and smart technologies, the retail industry is undergoing unprecedented transformations. The outbreak and ongoing impact of the COVID-19 pandemic have accelerated the shift of consumers towards online shopping channels, compelling traditional retail to swiftly adapt from single-channel to Omnichannel retail, and progressively transitioning to omnichannel retail (Liu et al., 2024). According to a report by Statista on global e-commerce decision-makers, in 2021, 48% of global e-commerce companies considered omnichannel a very important strategic focus for their company, with another 31% deeming it "fairly important" (Zhou et al., 2021). By 2023, over 80% of retailers had transitioned to omnichannel retail to meet the increasingly diverse and personalized consumer demands. The extensive use of omnichannel retail aims to provide shoppers with a seamless Omnichannel experience (Chenavaz et al., 2021).

Omnichannel retail is a retail model that integrates online and offline resources to provide a consistent shopping experience by seamlessly connecting different sales channels (Jo & Bang, 2024). In an omnichannel environment, channel integration allows customers to buy goods online through mobile devices or websites while visiting physical stores. This means that consumers can shop in any channel and compare prices across channels and products (Zhou et al., 2021). At the same time, of course, pricing must be carefully balanced with related costs (such as delivery and fulfillment), which makes dynamic pricing an indispensable tool for achieving efficiency and competitiveness in the omnichannel market (Elnaz et al., 2015).

On the one hand, dynamic pricing can improve consumer satisfaction by offering personalized and competitive prices. It raises concerns about fairness and transparency, especially when price fluctuations lead to perceived inequality among consumers. Such perceptions can negatively impact consumer trust, satisfaction, and long-term satisfaction. As dynamic pricing continues to gain traction in omnichannel retail, retailers must recognize and address its dual impact on consumer satisfaction. By carefully calibrating pricing strategies to balance profitability and consumer trust, companies can better manage the complexity of omnichannel retail while maintaining long-term customer relationships (Chenavaz et al., 2022; Taheri et al., 2024; Xu et al., 2023; Zhou et al., 2021).

Research question, purpose, objectives and significance

Short description of the thesis: This thesis explores the application of dynamic pricing in omni-channel retail and its impact on consumer satisfaction. By constructing a theoretical framework and using quantitative analysis methods, this paper studies how dynamic pricing affects consumers' immediate and long-term satisfaction through mediating variables such as trust and price fairness and analyzes the role of moderating variables such as price sensitivity and channel preference.

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Thesis structure

The Introduction chapter introduces the research background, problem statement, and research objectives, and outlines the importance of dynamic pricing in omnichannel retail and its impact on consumer satisfaction. The research questions and research hypotheses are clearly stated, laying the foundation for the subsequent chapters.

The Literature Review systematically reviews relevant literature and analyzes the key dimensions of dynamic pricing, the definition and challenges of omnichannel retail, and the role of consumer satisfaction and trust in the context of dynamic pricing. Finally, a theoretical framework is constructed and research hypotheses are proposed.

The Methodology chapter explains the research methods, including questionnaire design, data collection, and analysis methods. A quantitative research method is used to verify the hypotheses and quantify the impact of dynamic pricing on consumer satisfaction through multiple regression analysis and moderation effect test.

The Results of Research presents the results of the data analysis in detail, including sample statistics, reliability and validity analysis, and hypothesis testing. The results show that dynamic pricing significantly affects consumer behavior through trust and satisfaction paths, and the role of moderator variables is also verified.

The Discussion chapter discusses the research findings, explains the dual impact of dynamic pricing on consumer satisfaction, and compares it with existing literature. The theoretical contribution and practical significance of this study are analyzed, while the research limitations and future research directions are pointed out.

The Conclusion summarizes the main findings of the study and proposes suggestions for optimizing dynamic pricing strategies. The paper emphasizes the value of dynamic pricing in omni-channel retail, while reminding companies to pay attention to consumers' price sensitivity and fairness perception.

References and Appendices include all literature and appendices cited in the study, such as questionnaire design and data samples.

1. LITERATURE ANALYSIS

Gaps in the current literature

The positive impact of dynamic pricing on consumer satisfaction. Although there have been studies on the deployment of dynamic pricing in the retail industry, most of them appeared in the early stages of dynamic pricing development or when omni-channel retail was not fully developed. Current research tends to show that dynamic pricing will have a negative impact on consumer satisfaction, or emphasizes the excellence of dynamic pricing in sales and profitability, but often ignores the possibility that dynamic pricing can improve consumer satisfaction in certain situations.

Pricing in the context of omnichannel retail. Although many studies have explored the application of dynamic pricing in a single channel (whether online or offline), there is still a clear gap in the systematic exploration of dynamic pricing strategies in omnichannel retail environments and their collective impact on consumer satisfaction. The complexity and heterogeneity of omnichannel retail requires further and more detailed research to fully grasp the unique challenges and prospects it presents. Dynamic pricing strategies are indispensable tools in omnichannel retail, but they have profound impacts on consumer behavior.

1.1 Dynamic pricing strategies

Dynamic pricing is now widely used in omnichannel retail. Saharan et al. (2020) described dynamic pricing as "a reactive pricing method based on regulated prices." And the goals of enterprises implementing dynamic pricing are also obvious - to improve profit margins, regulate the allocation of resources and goods, and improve system efficiency.

1.1.1 Key dimensions of dynamic pricing

Dynamic pricing, as a multifaceted strategy, can be dissected into four core dimensions: price volatility, price personalization, price transparency, and omnichannel consistency.

Price Volatility

Price volatility refers to the frequency and magnitude of price changes in response to real-time market conditions. It is the most intuitive manifestation of dynamic pricing, allowing companies to adjust prices due to changes in demand and supply, and it also plays a key role in understanding consumer behavior. Price volatility profoundly affects consumers' decision-making process, not only due to economic calculations, but also through psychological perceptions of value and fairness. It is one of the important components of dynamic pricing by exploring how price volatility interacts with consumer characteristics, preferences and market strategies.

Price fluctuations appear to be directly related to consumers’ price sensitivity, perceived fairness and transparency of prices, and consumer satisfaction. Han, Gupta, and Lehmann (2001) developed a model that included thresholds for the probability of price increases and decreases, showing that consumers’ sensitivity to price changes depends on price fluctuations and competitive pricing strategies. Wan et al. (2017) linked economic theory to digital markets and proposed a model that integrates consumer preferences and price sensitivity into personalized recommendation systems. On a psychological level, Ramírez and Goldsmith (2009) identified key factors that influence price sensitivity, such as long-term brand satisfaction, engagement, and perceived brand parity, Hsieh and Chang (2004) analyzed consumer engagement, and Narasimhan (1989) illustrated how initial market adoption affects pricing dynamics over time. Duvvuri and Gruca (2010) used a Bayesian multilevel factor analysis model to reveal variations in price sensitivity and perceived fairness and transparency of prices across different categories of households. Dominique-Ferreira, Vasconcelos, and Proença (2016) showed how bundling strategies and long-term brand satisfaction affect price elasticity, providing practical insights for pricing decisions. Kim, Blattberg, and Rossi (1995) used a random coefficient model to reveal the distribution of price changes among different consumer groups.

Price Personalization

Price personalization describes tailoring prices based on individual consumer data, such as purchase history, preferences, and demographics. This dimension leverages advanced analytics and big data to create highly targeted pricing strategies. Studies have confirmed that personalized pricing boosts consumer satisfaction and long-term brand loyalty when these pricing effects are viewed as fair and advantageous (Priester et al., 2020).The different insights in the literature show how personalization contributes to better consumer engagement and enhanced firm profitability by harnessing consumer data and advanced analytics. Some of Babatunde et al.'s(2024) attributes of artificial intelligence(AI) in personalizing marketing initiatives go on pricing. AI enables the firm to analyze massive amounts of data that help dynamically change prices based on the individual consumer's behavior, preferences, and demographic insights, encouraging customer satisfaction and ultimately improving conversion rates. Yin (2002) sets price personalization within the context of the "new age of marketing," referring to the transition from mass marketing towards individualization emphasizing customizable price strategies towards specific consumer needs whilst centering price as one of the compositions of the marketing mix and progressing from one followed by all to more personalized, consumer-fitted models. In an extensive converging review of conceptual insights into personalization, Kaushik and Sharma (2023) state that price personalization relieves consumers of cognitive burdens, aligning the offers to their perceived value. Tong, Luo, and Xu(2020) introduce a mobile-based framework for personalized marketing, where emerging dynamic pricing strategies reside mostly under key applications. Decision-tree induction techniques in price and other personalized marketing rules are explored by the works of Kim et al.(2001).

However, personalization in pricing comes with ethical and practical challenges. If consumers are unable to find they'll regard pricing as invasive or discriminatory, the state of affairs will be that they would want to proceed and would rather hold purchasing decisions abused from a central controller, with their prices being a few notches above others.

Price Transparency

Price transparency may be defined as how much consumers comprehend the pricing mechanisms and the criteria on which dynamic price increases or deductions are based. Transparency is a significant variable in building signaling trust for consumers into the pricing system. Procedural justice theory is contrasted with price transparency, as they both focus on giving every party an equal opportunity in the process that determines outcomes, specifically in pricing policies. The literature highlights that the importance of transparency is paramount in ensuring fairness and promoting trust in interactions with markets. Ferguson, Ellen, and Bearden (2014) stated that procedural fairness was a great determinant of overall price fairness. Their results suggest that consumers are more likely to judge that prices are fair when the processes used to make pricing decisions were perceived as fair and transparent, especially in the case of price changes. Chapuis (2012) makes a distinction between fairness of prices (outcome-focused) and fairness of pricing processes (process-focused), emphasizing that explaining why a price was made has a larger impact on customer satisfaction than justifying the price itself. This allows us to grasp the mix of procedural fairness with price transparency, whereby the communication of pricing processes influences the perception of fairness.Rothenberger, 2015, examines in depth the interplay between price fairness and transparency. He found that consumers perceive more fairness when pricing is made transparent. It, in turn, creates a spirit of customer satisfaction and future loyalty. Rothenberger provides large dataset structural equation modeling to base transparency for procedural fairness in the price of goods. Carter and Curry (2010) explore how transparent pricing modifies consumer behavior and utility functions. In their controlled experiments, they have documented that consumers are willing to pay higher prices when cost allocation is transparently communicated. This is thus a clear case of the power of transparency, which allows consumer values to line up with pricing practices. This, in turn, is aligned with procedural justice principles, where clear, fair processes get positive consumer reactions. Ashworth and Darke (2006) take this discussion further to explain how violations of prescriptive norms in pricing processes lead to perceptions of procedural injustice. The authors have shown that directional perceptions of procedural fairness are an independent determinant of consumer evaluations, regardless of the final price. Transparent pricing mechanisms reduce consumer anxiety about potential exploitation, thus boosting satisfaction.

Omnichannel Consistency

The concept of omnichannel consistency emphasizes the uniformity of pricing and inventory management across all sales channels. Because in most consumer scenarios, price differences or availability between different channels will undermine shopper confidence and may undermine the entire shopping experience. The theory of omnichannel integration incorporates a seamless and consistent consumer experience across different channels. This concept has been studied in detail for omnichannel retail, and consistency is at the core of customer satisfaction, engagement, and loyalty. Quach et al. (2020) captured the growing importance of service consistency in omnichannel retailing, thus impacting consumer experiences such as flow and perceived risk. The revelations reaffirm that service consistency across all channels will not only reduce consumer uncertainty but will also build long-term loyalty, thus agreeing with the notion of service quality when it comes to the driver of consumer value. Hossain and collaborators (2020) well thought of "integration quality" to be one of the possible constructs; the key dimensions are consistency of channels in content and process. Further analysis in the study backed up that consistency across all channels was integral to the customer engagement process and buyer intent across all channels, confirming that to the greatest effect the perception of customer value the seamlessness of service is paramount.

Lee and colleagues (2019) assessed channel integration quality to see how this affected customer engagement and found that the more content and process is aligned across the channels, the more engagement will exist. Engagement raises both the intention to repurchase and positive word-of-mouth behavior. Lin and others (2022) applied the commitment-trust theory in analyzing channel integration quality related to content and process consistency as well as customer trust and long-term satisfaction. They arrived at the finding that consistency provided a foundation for trust-building, thus underscoring the importance of consistency in creating strong relationships in an omnichannel environment. Butkouskaya and others (2023) highlight the effect of consistency of integrated marketing communications on customer satisfaction and concluded that consistency in messaging and delivery leads to higher product and service satisfaction. This emphasizes the necessity of uniformity in omnichannel strategies. Neubert (2022) reported that inconsistency across channels-lower online prices versus brick-and-mortar stores-is a source of confusion and discontent among consumers. Matching the pricing across channels enriches the seamless shopping experience and fosters brand trust. For instance, retailers like Walmart take up dynamic pricing algorithms that apply across platforms to ensure consistent pricing, which invokes customer confidence and satisfaction.

Together, these four dimensions—price volatility, price personalization, price transparency, and omnichannel consistency—form the foundation of effective dynamic pricing strategies. By carefully managing these aspects, businesses can not only optimize their pricing to reflect market dynamics but also enhance consumer satisfaction.

1.1.2 Historical development of dynamic pricing

Dynamic pricing is now one of the important tools for enterprises to increase profits and manage the development stage of departments or time, and its development also reflects the evolution of technology and the change of market demand. The first application of dynamic pricing was in the airline industry, where airlines found it highly capable of dealing with uncertain customer needs. However, the purpose of airlines is only to maximize profits (Chen & Chen, 2015). At the beginning of the application of dynamic pricing, airlines adopted the more advanced revenue management system at that time, and they revised fares according to the fluctuating needs of customers and the pricing strategies of competitors. Following the lead of airlines, companies that also often find themselves in situations of uncertain customer demand, such as the hotel and car rental industries, have followed. Driven by the success of the aviation division, they have also gradually adopted dynamic pricing strategies. Hotels began to adjust their pricing based on factors such as occupancy rates, seasonal demand, and prices set by competitors, while car rental companies adjusted their pricing based on demand and fleet availability (Chen & Chen, 2015).

With the passage of time and the progress of technology, dynamic pricing has gradually spread to other industries. In the intermediate stage of the continuous development of dynamic pricing, the development and prosperity of the Internet and e-commerce platforms also strongly promoted the extensive use and development of dynamic pricing. These platforms adopt dynamic pricing to determine the optimal price by analyzing user behavior and market trends in order to remain competitive in the market (Gonsch, Klein, & Neugebauer, 2013). Guizzardi et al. (2021) highlighted the role of big data in dynamic pricing in their analysis, where them mainly observed the aspect of forecasting travel demand location. By collecting and reviewing online pricing data, they found that travel companies are better able to anticipate surges in consumer demand and thus optimize their pricing strategies

In retail, the research of Kayikci et al. (2022) illustrates the important role of big data analytics in retail. Based on the analysis of consumer behavior data, the retailer formulated an optimized dynamic pricing strategy to have the following two advantages. They show in their research that data-driven dynamic pricing not only improves sales and profits, but also reduces waste (Kayikci, Demir, Mangla, & Subramanian, 2022). Victor et al. (2018) explored the use of big data in the Indian online retail market. They found that dynamic pricing using big data is an efficient pricing strategy. Dynamic pricing can flexibly adjust prices according to changes in market demand to maximize sales and profits.

Furthermore, Sarkar et al. (2023) developed a machine learning framework that can optimize dynamic pricing and predict online purchase behavior for e-commerce platforms. This shows that combining web mining and big data technology, enterprises can better understand market trends and consumer preferences, so as to formulate more accurate dynamic pricing strategies.

1.1.3 Impact of dynamic pricing on consumer behavior

In the aspect of negative impact on satisfaction, Neubert (2022) believes that dynamic pricing will make consumers feel unfair because of its price gap. In short, dynamic pricing affects consumers' perception of price fairness. This includes two aspects, one is the frequent price changes of the same platform, and the other is the price difference between different channels, such as online and offline. Lee, Illia, and Lawson-Body (2011) explored the question of whether dynamically priced prices appear fair. Consumers' acceptance of dynamic pricing depends on whether they think the price is fair. If consumers believe that prices are set according to reasonable and transparent criteria, their satisfaction may not be affected much. However, if they feel that prices are not reasonable and transparent, their satisfaction will decrease significantly. Alderighi et al. (2022) similarly found a correlation between consumer satisfaction and the perception of price fairness when researching dynamic pricing on Booking.com. They mentioned that customer satisfaction is a process, depending on the difference between their expectations and actual experience, according to difference theory. When consumers perceive dynamic pricing as unfair, their satisfaction is significantly reduced. In terms of positive correlation with consumer satisfaction, Neubert (2022) believes that personalized dynamic pricing (PDP) can adjust different prices according to different prices, and when consumers feel that prices are tailored for them, their satisfaction will be improved. Meanwhile, Priester, Robbert, and Roth (2020) research the impact of personalized dynamic pricing on consumers' perception of fairness. They found that personalized discounts can significantly improve consumer satisfaction and purchase intention, especially when prices are transparent, and consumers perceive fair prices. Personalized pricing strategy can effectively improve consumers' purchase behavior by meeting consumers' personalized needs. Victor et al. (2018) studied the factors affecting consumer behavior in a dynamic pricing environment through exploratory factor analysis. They found that personalized product recommendations and price adjustments can significantly influence consumer purchasing behavior.

1.2 Omnichannel retail

1.2.1 Definitions of omnichannel retail

Omni-channel retailing is now widely used in the retail industry. As mentioned above, omnicharm retail aims to create a seamless shopping experience for consumers by integrating online and offline multiple channels. Omnichannel is not only a comprehensive Omnichannel retail, but also a more comprehensive and coordinated system (Huang, 2021). He argues that omni-channel retail emphasizes the integration of various channels, including physical stores, online stores, apps and so on, rather than Omnichannel retail. In a research by Hanninen et al. (2020), they summarized the research on omnic retailing over the past 30 years and concluded that the core of omnic retailing is the integration of channels through the application of technology and data

On the other hand, the implementation of omnichannel retail also has quite high requirements for enterprises. Its successful implementation actually requires comprehensive improvement in technology, data management and consumer relationship management rather than channels and services (Mishra et al., 2020). Cai and Lo (2020) also believe that although the definition of omni-channel retail involves multiple dimensions (channel integration, inventory management, distribution optimization), the success of omni-channel retail requires enterprises to carry out comprehensive innovation and optimization in technology and management. Hubner et al. (2022), on the other hand, says that the successful implementation of omnicharm retail requires companies to coordinate and optimize across multiple aspects (such as inventory management, delivery optimization, and customer relationship management) to provide a seamless consumer experience.

1.2.2 Advantages and challenges of omnichannel retail

The benefits of online and offline retail channel integration (i.e., omni-channel retailing) have been recognized by enterprises and markets. Liu et al. (2024) emphasized that the integration of retail channels in omni-channel sales,

Inventory, distribution, and customer service can be better managed, resulting in greater operational efficiency. Moreover, it can satisfy consumers' different preferences because consumers are free to choose whether to shop in-store, online or via mobile devices, and this freedom improves consumer satisfaction. Moreover, omni-channel retailing improves customer satisfaction by creating high-quality streaming experience, enabling customers to change channels for shopping without interrupting the shopping experience. At the same time, it can still collect and analyze consumer data while being cross-channel, helping retailers gain insight into consumer behavior and preferences and facilitating more dynamic inventory management.

On the other hand, Chenavaz et al. (2021) identified a variety of challenges companies face in using omnichannel retailing, including integrating the complexity of different channels, managing a dynamic product and revenue mix, optimizing prices, addressing distribution costs, and adapting to changes in consumer behavior. At the beginning, achieving seamless integration of online and offline channels is itself a challenge to enterprise operation and management. Because synchronizing inventory, distribution, and customer service across channels requires careful coordination (Bell et al., 2014). Not only that, logistics is complex to manage product flows and allocate inventory efficiently, while retailers are also faced with the task of dynamically adjusting product offerings to meet different demands in different channels. In addition, the premise of optimizing pricing strategy is necessarily to coordinate online and offline channels (Cai & Lo, 2020). In addition, the reduction of consumer satisfaction caused by omni-channel retailing in some cases is an unavoidable topic. Dynamic pricing, a feature of which is widely used in omni-channel retailing, can lead to customer dissatisfaction and market disruption (Reinartz et al., 2019).

In addition, pricing differences across channels and platforms may exacerbate price comparison problems, which may reduce consumer long-term satisfaction and satisfaction (Fibich et al., 2003).

1.3 Application of dynamic pricing in omnichannel retail

1.3.1 Role of dynamic pricing in supply chain management

In omni-channel sales, the core part is supplying chain management, and dynamic pricing plays an indispensable role in it. Chen et al. (2016) studied whether the application of dynamic pricing would regulate the whole supply-demand relationship under the Omnichannel pricing strategy, thus significantly optimizing the supply chain performance. Saharan et al. (2020) pointed out through a systematic review that dynamic pricing can effectively balance the supply and demand management among different channels in smart city traffic management, which has a macro adjustment effect.

At the same time, Cohen et al. (2020) proposed a dynamic pricing model, which is used to optimize dynamic pricing in the case of incomplete information, which is helpful to improve the profit of the supply chain and reflects the impact of dynamic pricing on the supply chain from the side. Lu et al. (2018) found that dynamic pricing can effectively regulate power demand and optimize grid operation in smart grid demand response through game-theoretic model research. In the hotel industry, Abrate et al. (2019) analyzed the impact of dynamic price fluctuations on revenue maximization and found that dynamic pricing can significantly increase hotel revenue, although it requires balancing the customer satisfaction issues arising from price fluctuations. Phillips (2005) discussed the connection between supply chain management and pricing strategy. He believed that the reason why dynamic pricing can flexibly respond to market changes is because it improves the response speed and profitability of the supply chain. Misra et al. (2018) proposed a dynamic online pricing algorithm and found that the algorithm can also perform dynamic pricing optimization in the case of incomplete information to improve the profitability of the supply chain. This also explains the conclusion from the side.

1.3.2 Impact of dynamic pricing on customer experience

Dynamic pricing (personalized pricing) has both positive and negative impacts on customer experience, satisfaction, and long-term satisfaction. As mentioned above, dynamic pricing can balance supply and demand, improve resource utilization efficiency and optimize supply chain performance by adjusting prices in real time, which is its advantages for enterprises and the reason why most enterprises choose to use it. However, frequent price fluctuations may cause customers to question the fairness of prices, thus affecting customer experience and satisfaction (Cohen et al., 2020). Abrate and colleagues (2019b) discovered that while dynamic pricing strategies can notably boost hotel revenues, the practice of regularly changing prices can diminish customer satisfaction related to pricing, consequently decreasing the number of hotel patrons. However, an exception to this is seen with personalized pricing mechanisms. Such strategies, according to Tyrvainen et al. (2020), heighten customer satisfaction and fidelity by tailoring prices to meet individual needs and preferences. Furthermore, Capponi et al. (2021) identified that personalized pricing could offer more appealing pricing options, bolster customer allegiance, and diminish the likelihood of customers switching to competitors.

Other studies have shown that instances of dynamic pricing having a negative impact on customer satisfaction are not common, but often the aspect that consumers despise more, because the degree of satisfaction is too high. For example, personalized pricing is believed to significantly enhance customer experience and satisfaction by aligning price and service with customer expectations (Priester et al., 2020). Despite potential concerns about the fairness of personalized pricing, transparent communication of pricing strategies and the provision of corresponding value can greatly improve customer satisfaction. Stein & Ramaseshan (2019) and Molinillo et al. (2022) also report that personalized pricing can significantly enhance customer experience and long-term satisfaction by ensuring that prices and services closely match consumer expectations. Molinillo et al. (2022) also demonstrate how retail applications leveraging personalized pricing and tailored services can significantly augment customer satisfaction and long-term satisfaction.

1.4 Consumer satisfaction

1.4.1 Stages of consumer satisfaction

Consumer satisfaction is the dependent variable in this study, which is affected by the main independent variable, dynamic pricing strategy. This study divides satisfaction into two different stages: immediate satisfaction and long-term satisfaction.

Immediate Satisfaction

Instant gratification is concerned with the extent to which the satisfaction persists with the consumer while the consumption activity continues. It portrays the intuitive attitude of the consumer toward dynamic pricing strategies during the course of consuming. Rothenberger (2015) brings forth the price transparency aspect that builds trust and lowers uncertainty in consumers. By revealing pricing techniques with sufficient clarity, the company will raise perceptions of fairness in consumers, which contributes to higher instant satisfaction. Transparent pricing aids in simplifying the purchase process and lessens any suspicion of price manipulation (Rothenberger, 2015). In a similar context, Ferguson and Ellen (2013) showed that companies that provided clear explanations for price changes, most especially price increases, earned higher trust and fairness evaluations from consumers and, thus, higher immediate satisfaction. This demonstrates the necessity for explaining why something is priced higher, thereby mitigating the chances of negative emotional reactions (Ferguson & Ellen, 2013). The perceived fairness of pricing furthers the concern of immediate gratification. As per Simintiras et al. (2015), when consumers are availed of bulk pricing information, their judgment about pricing fairness becomes more acute, thus accentuating a favorable shopping experience. Pricing transparency, centered on costs detailed in a straight manner, conveys fairness and minimizes post-buy dissatisfaction (Simintiras et al., 2015).

Long-term Satisfaction

Long-term satisfaction means that consumer satisfaction turns into lasting trust and commitment to the brand. Satisfaction as a driver of long-term satisfaction, Martin-Consuegra et al. (2007) confirmed through empirical research that perceived price fairness drives customer satisfaction, which in turn leads to long-term satisfaction. Their findings emphasize that satisfaction is a key mediator in the formation of long-term satisfaction and emphasize the necessity of fair pricing for achieving sustainable consumer relationships (Martin-Consuegra et al., 2007). The role of trust, Oliver (1999) believes that although satisfaction is a necessary prerequisite for long-term satisfaction, other factors such as trust and social relationships also play an important role in strengthening long-term commitment. Transparent and consistent pricing strategies, coupled with positive consumer-brand interactions, will strengthen trust and deepen long-term satisfaction over time (Oliver, 1999). Comprehensive pricing model, Bei and Chiao (2001) proposed a comprehensive model showing that perceived product quality, service quality, and price fairness jointly affect long-term satisfaction. By comprehensively addressing these dimensions, companies can lay a solid foundation for maintaining long-term consumer relationships (Bei & Chiao, 2001).

1.4.2 Levels of consumer satisfaction

Basic Needs: The Impact of Price Transparency and Information Simplicity on Consumer Satisfaction

The basic needs of consumers often start with price comparison. When the price is fair and transparent to consumers, consumers will feel satisfied, and their satisfaction will increase. In the research of Whaley et al. (2019), price transparency has a significant impact on consumer satisfaction. He focused on the medical domain, where consumer satisfaction and trust in services increased significantly when price transparency was used in conjunction with reference pricing. His research concluded that clear and easily understood price information can reduce consumer uncertainty and thus increase satisfaction. However, in terms of information, information conciseness can reduce the cognitive cost and psychological burden of consumers, thereby improving satisfaction. As concluded by the research, simplified marketing information can make it easier for consumers to understand and process, thereby enhancing their purchase experience and satisfaction (Gruner & Soutar, 2021).

Intermediate Needs: The Enhancement of Satisfaction through Personalized Recommendations and Product Relevance

After meeting the basic needs of consumers, a higher level of demand comes. In the same consumption scenario, the service with personalized recommendation can significantly improve consumer satisfaction. After obtaining the experimental results, Rhee and Choi (2020) believe that personalized recommendation can significantly improve consumers' satisfaction and purchase intention, especially when the recommendation system can accurately identify and meet consumers' personalized needs, consumers' satisfaction with the shopping experience will be significantly improved. This is even more important in the e-commerce environment, where the combination of personalized recommendation and product relevance on different platforms has become an important factor to improve consumer satisfaction, and even become a selling point. High-quality e-commerce platforms can reduce the perceived risk of consumers by providing high-energy personalized recommendations, thereby improving satisfaction and long-term satisfaction (Tzavlopoulos et al., 2019).

Advanced Needs: Enhancing Brand Long-term satisfaction and Satisfaction through Social Media and Interactive Platforms

When serving customers through multiple channels such as social media and interactive platforms, it proves that customer satisfaction has reached a high level of demand. Studies have shown that when a brand engages with consumers through multiple channels with high interactivity and engagement, there is a significant impact on consumer long-term satisfaction and satisfaction. When brands engage in highly interactive activities through social media platforms, they can enhance consumers' brand trust, thereby increasing brand long-term satisfaction and overall satisfaction (Samarah et al., 2021). In the research of Jibril et al. (2019), they find that social platforms played a non-negligible mediating role. They believe that the interaction of brands with consumers through social media platforms can enhance consumers' sense of belonging to the brand community, thereby enhancing brand consumer long-term satisfaction and satisfaction.

1.4.3 Specific impact of dynamic pricing strategies on satisfaction

Dynamic pricing stratege is playing an increasingly important role on the enterprise side, as their application has helped businesses significantly increase revenue and improve customer satisfaction. Various studies below reveal the multifaceted effects of dynamic pricing on consumer satisfaction.

Dynamic pricing that improves customer satisfaction is conditional, and dynamic pricing strategies that are actively and effectively deployed satisfy this condition. This dynamic pricing serves three functions: to promote price transparency and fairness, to meet individual needs, and to effectively manage consumer expectations and psychological satisfaction. These strategies skillfully reconcile the mismatch between customer satisfaction and profit maximization, even in different market situations. Friedman and Lewis (1999) argued that the ability to adjust prices flexibly ensures that enterprises can better meet consumers' expectations and needs, thus improving satisfaction. However, the dynamic pricing strategy can just adjust the price in real time through market dynamics and competitive scenarios to ensure that consumers always get fair pricing, thus improving their satisfaction.

In e-commerce, dynamic pricing and markets that tend to "price at will" work together to create synergies that greatly improve consumer satisfaction. Hinz et al. (2011) pointed out that dynamic pricing has the ability of personalized and adaptive pricing, which can improve customer satisfaction, because this model makes consumers have the feeling of "pricing for me," thus establishing trust and satisfaction in enterprises. Moreover, the role of multi-period pricing strategies in shaping consumer satisfaction cannot be underestimated. A well-thought-out dynamic pricing scheme can improve consumers' perception of price fairness and ultimately enhance their satisfaction (Chung & Li, 2013).

Converse, dynamic pricing also presents potential pitfalls that are difficult to fix, with implications for customer satisfaction and long-term satisfaction. Research shows that if customers perceive unfair pricing, it will lead to a decrease in their satisfaction. Price fairness and transparency become particularly important, and a slight misstep can seriously affect the level of customer satisfaction. Especially in e-commerce, perception of pricing unfairness caused by dynamic pricing can adversely affect purchase decisions and overall satisfaction. Moreever, combining dynamic pricing with dynamic bundling strategies may further exacerbate perceptions of price unfairness. Research has shown that this mix may impair customer perceptions of pricing fairness, which can adversely affect their satisfaction and future purchase intentions. This is because such a combination of dynamic pricing and bundling strategies may result in consumers clearly perceiving unfair pricing, which significantly reduces satisfaction and the likelhood of repeat purchases.

Moreover, the strategic behavior and psychological satisfaction of consumer similarly fluctuate according to the pricing and inventory decisions of retailers. It has been shown that dynamic pricing strategs can lead to a decrease in the psychological satisfaction of consumers, which in turn affects their overall satisfaction. Therefore, in real time dynamic pricing, consumer psychology should be properly considered before deployment.

1.5 Price and consumer trust theory

1.5.1 Price fairness: distributive and procedural fairness in dynamic pricing

Price fairness is an important concept in consumer behavior and marketing and has important implications for dynamic pricing strategies. It contains two main dimensions: distributive fairness (examining the fairness of pricing results) and procedural fairness (assessing the transparency and reasonableness of the pricing process).

Distributive fairness focuses on whether consumers believe pricing outcomes are fair, especially when compared with other outcomes. Fluctuations in price are in direct conflict with distributive fairness. Price volatility, when excessive, leaves consumers feeling rather arbitrary or exploited by price outcomes. As Ferguson, Ellen, and Bearden (2014) assert, consumers compare the prices of one another and arrive at fairness as a function of their perceived differences. Large price swings with little explanation can amplify the perception of unfairness, which diminishes trust and long-term satisfaction (Ferguson et al., 2014). An average shopper is more willing to shop for deals when tidiness to price volatility is believed to be in search of higher profits (Katyal et al., 2019). Equity theory has offered consumers a lens for distributing fairness. Consumers compare their ratios of inputs and outputs-the price they pay and the value they get-to reference groups. Zhang (2020) notes that within high price volatility environments, consumers usually see themselves at a disadvantage whenever they sense that value is not being assessed equitably with similar others. In on-line group-buying situations, it sees further that this unfairness orientation greatly diminishes satisfaction and a willingness to purchase (Zhang, 2020). The impact of price volatility is enhanced in the sharing economy since the platforms use dynamic pricing models. Angerer et al. (2018) have demonstrated that consumers in the sharing economy are highly sensitive to differences in price applied by different user groups, which lowers their perception of distributive fairness. It becomes really visible when the price seems to favor one user group (like renters) over another (like suppliers) (Angerer et al., 2018).

Procedural fairness looks into the pricing process's transparency, legitimacy, and consistency with customer expectations. Given the flaws in any pricing method, keeping it apparent and fair might lessen adverse customer reactions. Transparency in dynamic pricing is crucial toward procedural fairness. When the reasons for price changes are transparent and understandable to consumers, their perception of fairness is enhanced, as shown by Ferguson et al. (2014). Transparency lowers the degree of suspicion regarding the opportunism and improves the trust in retailers (Ferguson et al., 2014). Also, Katyal et al. (2019) observed that transparent communication of dynamic pricing rules would improve consumer satisfaction and post-purchase satisfaction in competitive settings (Katyal et al., 2019). The theory on procedural justice points to the need for decision-making procedures which are fair and transparent. Mushagalusa et al. (2021) indicate that transparent pricing mechanisms significantly increase customer trust and decrease the likelihood of customers switching in the context of microfinance. Results, therefore, suggest similar dynamic pricing models that are transparent and effectively communicated may work well when applied in retail contexts (Mushagalusa et al., 2021). Access to dynamic pricing and clarity of its processes and rationale for it were two leading determinants for fairness. Kallus and Zhou (2020) contend that personalized pricing schemes may gain acceptance by customers based on personal preferences and not be seen as discrimination. Such a balance of power is important to minimize resistance to dynamic pricing and maximize the number of such customers participating actively and continuously in a marketplace (Kallus & Zhou, 2020). Ethically sensitive issues can also shape perceptions of procedural fairness. According to Angerer et al. (2018), ethical considerations figure significantly in the sharing economy, where dynamic pricing could appear to border on exploitation unless enough transparency is provided. Sound pricing policies can diffuse such anxieties and serve to aggrandize consumer trust (Angerer et al., 2018).

1.5.2 Price elasticity theory

In 1890, Marshall pioneered the concept of price elasticity, an important economic principle that shows how the demand for a product is affected by changes in its price. According to him, price elasticities, especially demand elasticities, are assessed by looking at the correlation between percentage price fluctuations and changes in the quantity demand of the corresponding good. If there is a small price adjustment but a large change in quantity demanded, the product is considered to have a high price elasticity. In contrast, if the price change hardly affects the quantity demanded, the price elasticity of the product is considered to be low.

In the field of dynamic pricing, understanding the concept of price elasticity is conducive to making informed decisions. Elmaghraby and Keskinocak (2003) studied the dynamic pricing strategy in depth. They believe that the focus of dynamic pricing was real-time inventory control, and they emphasized that the application of price elasticity plays a central role in guiding the pricing strategy: Knowing price elasticities allows firms to anticipate the impact of price adjustments on demand, allowing them to make more informed pricing decisions. Therefore, the effectiveness of dynamic pricing strtegy depends on the comprehensive grasp and investigation of price elasticity to help enterprises improve market advantage and profitability while meeting consumer demand.

1.5.3 Price discrimination theory

Pigou (1920) and Varian (1989) analyzed three main ways of price discrimination to help us understand how firms set prices according to consumers' willingness to pay. First, perfect price discrimination, or first-order price discrimination, implies that each customer receives a personalized offer based on the highest price they are willing to pay. The goal of this strategy is to convert all the potential value that customers can bring to the business, although in practice this is difficult to achieve.

Next, second-degree price discrimination focuses on setting different prices by quantity purchased or by different assortations of customers, such as by offering discounts for bulk purchases. The purpose of this is to encourage customers to choose the right category of goods according to their own needs and purchasing power, so that the enterprise can obtain a part of the customer surplus.

Both forms of price discrimination share a common goal: they seek to maximize profits and economic efficiency by ensuring that the profit maximizing price is in line with the marginal cost of production, P=MC, to allocate resources efficiently.

Finally, third-degree price discrimination is the most common strategy, and it is achieved by setting different prices for different groups of customers. These groups are classified according to differences in their demand elasticities, such as age, location, or time of purchase. Different from second-degree price discrimination, this method directly formulates pricing strategies for different customer groups based on demand information.

Through these flexible methods of price discrimination, firms can set prices more strategically, not only to maximize profits, but also to adapt to the different needs and customer behavior of the market, driving a more dynamic and responsive pricing strategy.

1.6 Theoretical framework and hypotheses

In this chapter, hypotheses and conjectures are made on the relationship between variables based on the above literature analysis.

Dynamic Pricing → Trust in Pricing System

In dynamic pricing strategies, consumers' trust in the pricing system plays a key mediating role. Price fluctuations in dynamic pricing may weaken consumers' perception of pricing fairness, especially when there is a lack of transparency in pricing rules. However, when dynamic pricing is implemented with high transparency, consumers are more likely to understand the reasons for price fluctuations, thereby enhancing trust in the pricing system.

Dynamic Pricing → Trust in Brand

Dynamic pricing further influences consumer behavior through brand trust. Dynamic pricing can improve consumer trust in a brand, especially when prices and information are consistent across online and offline channels. However, if there are significant inconsistencies across channels, such as asymmetric price or promotion information, it may undermine consumer brand trust.

Trust in Pricing System → Immediate Satisfaction

Consumers' trust in the pricing system significantly affects their immediate shopping experience. When consumers believe that the pricing system is fair, transparent, and reasonable, their satisfaction will be significantly improved. On the contrary, if trust is insufficient, consumers' acceptance of dynamic pricing will decrease, resulting in lower immediate satisfaction.

Immediate Satisfaction → Long-term Satisfaction

Immediate satisfaction is an important foundation for long-term satisfaction. When consumers experience high satisfaction in shopping, they are more likely to continue to choose the brand or retailer in the future. This accumulation of satisfaction is a core indicator of the long-term effectiveness of dynamic pricing strategies.

Price Sensitivity (Moderator) → Dynamic Pricing / Trust in Pricing System

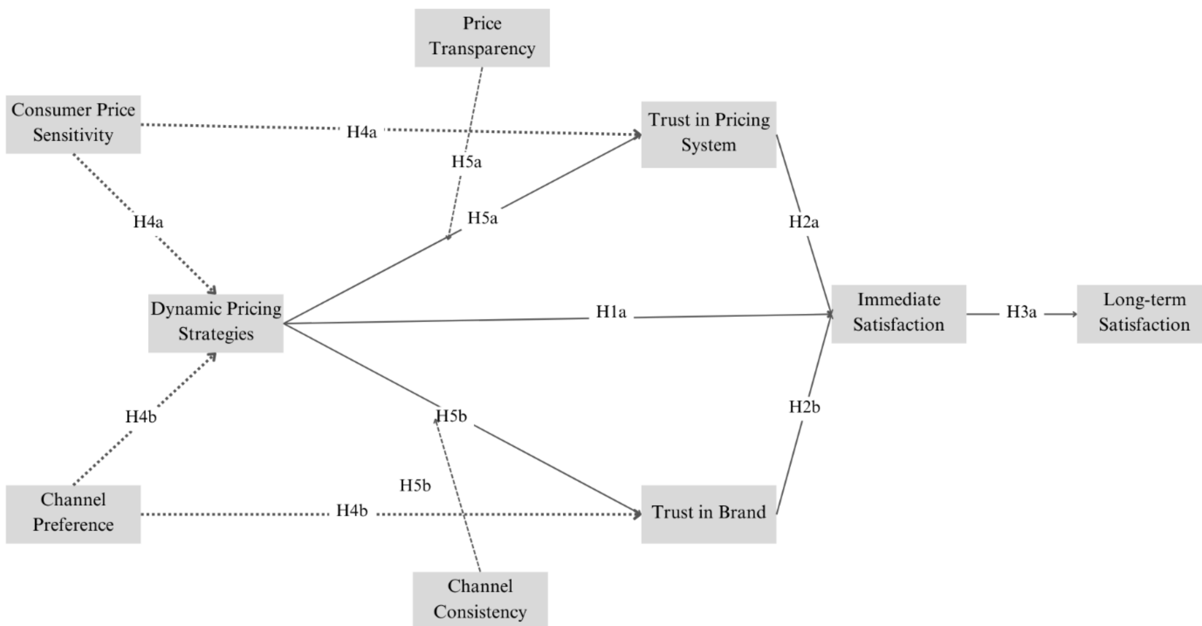
Price sensitivity plays a moderating role in the impact of dynamic pricing on trust in pricing systems. For consumers with high price sensitivity, frequent price fluctuations may significantly reduce their trust in pricing systems. For consumers with low price sensitivity, this effect is weaker, and the negative impact of dynamic pricing on trust may be mitigated by price transparency.

Channel Preference (Moderator) → Dynamic Pricing / Trust in Brand

Channel preference moderates the relationship between dynamic pricing and brand trust. Consumers who prefer a particular channel (e.g., online or offline) are more susceptible to inconsistent prices or information across channels, which can weaken their trust in the brand. For consumers who prefer multiple channels, increased consistency may significantly increase brand trust.

The theoretical model proposed based on literature analysis is as follows:

Figure 1 - Research framework



Source: compiled by the author

The theoretical framework proposed above is based on the researcher's understanding of existing literature and research to infer the variable relationship between dynamic pricing strategies, mediating variables and consumer satisfaction results in the omni-channel retail environment. The purpose of this theoretical framework is to explain the direct and indirect effects of dynamic pricing on consumer satisfaction, which is also inseparable from the combination of price fairness, customer trust and other mediating variables, such as the moderating role of consumer price sensitivity and channel preference in the mediating variables, which will also have a subtle impact on these variable relationships.

Based on the theoretical framework in the figure above, this study proposes a series of hypotheses to systematically test the causal relationship between key variables. The specific hypotheses are as follows:

Direct and indirect effects of Dynamic Pricing

H1a: Dynamic Pricing has a positive impact on Immediate Satisfaction.

H1b: Dynamic Pricing indirectly affects Long-term Satisfaction through Immediate Satisfaction.

The mediating role of trust

H2a: Trust in Pricing System mediates the relationship between Dynamic Pricing and Immediate Satisfaction.

H2b: Trust in Brand mediates the relationship between Dynamic Pricing and Immediate Satisfaction.

The cascading effect of satisfaction

H3a: Immediate Satisfaction has a positive impact on long-term satisfaction.

The role of moderating variables

H4a: Price Sensitivity mediates the relationship between Dynamic Pricing and Trust in Pricing System. Among them, it is assumed that when price sensitivity is higher, the negative impact of dynamic pricing on trust is stronger.

H4b: Channel Preference mediates the relationship between Dynamic Pricing and Trust in Brand. Among them, it is assumed that consumers who prefer a single channel are more sensitive to the inconsistency of dynamic pricing, which affects brand trust.

The reinforcing effect of pricing transparency and channel consistency

H5a: Price Transparency enhances the positive impact of Dynamic Pricing on the Trust in Pricing System.

H5b: Channel Consistency enhances the positive impact of Dynamic Pricing on Trust in Brand.

In the framework hypothesized in the theoretical part, dynamic pricing affects consumer behavior directly or through the trust and satisfaction paths. Trust in Pricing System and Trust in Brand are key mediators. Immediate Satisfaction and Long-term Satisfaction form a cascading effect. The moderating variables (Price Sensitivity and Channel Preference) affect the relationship between dynamic pricing and trust. The reinforcing variables (Price Transparency and Channel Consistency) can mitigate the potential negative effects of dynamic pricing.

1.7 Summary of literature analysis

Through the review and analysis of known literature, this study clarifies the concepts and known research of the main variables. As an independent variable, dynamic pricing is centered on real-time price adjustment to adapt to market demand, inventory status and consumer behavior. In the literature analysis, we first start from the key dimensions of dynamic pricing (and historical development) and explore how dynamic pricing shapes consumer experience by affecting consumers' fairness perception and behavioral decisions. Omni-channel retail, as a research background, is defined as a retail model that deeply integrates online and offline channels to provide a seamless consumer experience. The analysis explores its advantages and challenges, and also reviews the application of dynamic pricing in omni-channel retail in previous studies. Dynamic pricing not only improves efficiency by optimizing resource allocation in supply chain management, but also significantly affects the omni-channel consumer experience. Studies have shown that the implementation of dynamic pricing can enhance consumer perceived value, but inconsistency in price information may lead to trust issues, thereby affecting consumer satisfaction.

Consumer satisfaction, as a dependent variable, is divided into Immediate Satisfaction and Long-term Satisfaction. The literature review pointed out that the impact of dynamic pricing on satisfaction often depends on consumers' perception of price fairness and transparency. In the context of dynamic pricing, satisfaction not only reflects the overall feeling of the shopping experience, but also directly affects consumers' long-term loyalty. Among the mediating variables, the literature analysis needs to focus on the price and consumer trust theory. Such as price fairness, price elasticity theory and price discrimination theory.

Based on the above literature analysis, this study constructs a theoretical framework and proposes 9 core hypotheses. The framework focuses on how dynamic pricing affects consumer behavior through trust (including trust in the pricing system and brand trust) and satisfaction paths, and explores the role of moderating variables (price sensitivity and channel preference) and enhancing variables (pricing transparency and channel consistency).

2. METHODOLOGY

2.1 Research preparation

In order to systematically explore the impact of dynamic pricing strategies on consumer satisfaction in the context of omnichannel retail, this paper designs a structured research scheme based on theoretical and empirical basis. Through the theoretical framework and assumptions presented above, this section will explain in detail the theoretical inference method, data sampling details, and the process and basis of questionnaire development.

2.1.1 Research approach

This research adopts quantitative research method to explore the influence of dynamic pricing strategy on consumer satisfaction in omnichannel retail environment. The method of data collection is to use structured questionnaires, convert variables into corresponding questions, and adopt Likert scale for statistics. The theoretical framework constructed in this research illustrates the causal relationship between dynamic pricing strategies, mediating variables such as price fairness and trust, and consumer satisfaction outcomes. In addition, the framework incorporates moderating variables, such as consumer price sensitivity and channel preferences, to account for variation in the data.

In order to test the proposed theoretical framework and the extended hypotheses, this study conducted a cross-sectional survey (one-time questionnaire) and type sampling. The questionnaire adopted the Likert scale to collect values. Finally, the respondents' answers (scores) were analyzed and exported into charts using SPSS, and then the meaning of the charts was analyzed.

2.1.2 Theoretical framework application

The theoretical framework of this research proposes a hypothesis for researching the relationship between consumer satisfaction outcomes of dynamic pricing strategies in the context of omnichannel retail. Based on the theory of consumer behavior and the theory of fairness, the theoretical framework determines the changes of dynamic pricing on consumer satisfaction and the interaction between various variables, and then investigates the objectives of the paper.

This research conceptualizes dynamic pricing strategies in four key dimensions: price volatility, price personalization, price transparency, and omnichannel consistency. These dimensions represent the main independent variable: dynamic pricing strategies, which reflect the multifaceted nature of pricing mechanisms in an omnichannel retail environment. The framework assumes that these strategies influence consumers' perceptions of fairness, which are divided into distributive fairness (perceived fairness of pricing outcomes) and procedural fairness (perceived fairness of pricing processes). Furthermore, the framework uses trust as a key mediating variable, distinguishing between trust in the pricing system and trust in the brand. Trust is the bridge between fairness perception and consumer satisfaction, indicating that positive pricing system experience can improve satisfaction and long-term satisfaction, so as to measure the positive and negative impact between dynamic pricing and consumer satisfaction. This research divides consumer satisfaction into three levels: immediate satisfaction, cumulative satisfaction, and long-term satisfaction.

The theoretical framework of this research also incorporates feedback loops to demonstrate how consumer satisfaction affects feedback behavior, which in turn affects long-term satisfaction. The framework discusses the moderating effects of consumer price sensitivity and channel preferences. These variables account for individual and environmental differences, often providing a nuanced understanding of how certain factors can enhance or mitigate the effects of dynamic pricing strategies on fairness, trust, and satisfaction. This structured approach ensures that the research systematically explores the direct and indirect effects of dynamic pricing strategies

2.1.3 Research objectives

The primary objective of this research is to explore the impact of dynamic pricing strategies on consumer satisfaction in the context of omnichannel retailing. To achieve this primary objective, the research addresses the following specific goals:

Examine the Effects of Dynamic Pricing Strategies on Price Fairness and Trust

The research investigates how key dimensions of dynamic pricing—price volatility, price personalization, price transparency, and omnichannel consistency—affect consumers' perceptions of distributive fairness, procedural fairness, and trust. This objective focuses on identifying which aspects of pricing strategies contribute positively or negatively to fairness and trust.

Analyze the Mediating Roles of Fairness and Trust

By examining the intermediary roles of fairness (distributive and procedural) and trust (in the pricing system and the brand), the research seeks to understand how these variables mediate the relationship between pricing strategies and consumer satisfaction.

Evaluate the Impact of Dynamic Pricing Strategies on Consumer Satisfaction and Long-term satisfaction

The research aims to assess how fairness and trust influence consumer satisfaction at three levels—immediate, cumulative, and long-term—and how these satisfaction levels translate into consumer long-term satisfaction. This objective provides a comprehensive view of how pricing strategies shape both short-term and long-term consumer outcomes.

Identify Moderating Factors that Influence Pricing Strategy Effectiveness

The research examines how individual characteristics, such as consumer price sensitivity and channel preference, they how to moderate the effects of dynamic pricing strategies on fairness, trust, and satisfaction. By achieving the above objectives, this research will contribute to the theoretical understanding and practical application of dynamic pricing strategies in the retail industry by providing a balanced perspective on their advantages and challenges.

2.2 Research design

In order to achieve the objectives of this research and test the proposed hypotheses, a clear target group was selected for this research. I chose to distribute the questionnaire to users of retailers exposed to dynamic pricing strategies and omnichannel retailing, who were divided into two general groups: from the Asia Pacific region and from the Europe region. By surveying consumer groups from different regions, ages, and incomes, and without specifying a specific retailer, this research can collect a larger sample of behaviors to understand the impact of dynamic pricing strategies in an omnichannel retail environment.

2.2.1 Target population

The target group of this research is consumers who regularly use omni-channel retail platforms that implement dynamic pricing strategies. Considering the research context of omni-channel retailing, the participants were drawn from regions with mature omni-channel retailing markets, including Asia-Pacific and Europe.

2.2.2 Sampling technique

This research used a non-probability convenience sampling method to recruit participants. This method facilitated reaching a geographically diverse target group through online survey distribution. In addition, through snowball sampling methods, respondents were encouraged to share the survey link within their networks to increase participation. These methods are suitable for exploratory studies with limited resources and time.

2.2.3 Sample size and justification

The sample size was determined based on statistical requirements for hypothesis testing and structural equation modeling (SEM). A minimum of 10 responses per measured variable was targeted, aligning with recommendations for robust SEM analysis. Given that the research involves 25 survey items, a target sample size of at least 200 participants was established. This threshold ensures adequate statistical power for detecting significant relationships among variables.

2.2.4 Data collection process

The data collection process was completed through an online survey platform over a one-month period. Survey links were distributed via social media, email invitations, and targeted consumer groups associated with the omni-channel retail platform. Participants were required to fulfil the following criteria:

a. Be at least 18 years old.
b. Have previous consumer experience with an omni-channel retailer that uses a dynamic pricing strategy (e.g. Freshipo, Jingdong, Lidl or similar platforms).

The questionnaire was designed to be completed in approximately 10 minutes, ensuring brevity to increase willingness to participate. To ensure data quality, questionnaires that were not completed or had inconsistent responses were excluded from the final data set.

The data collection process followed strict ethical guidelines. All participants were informed of the purpose of the research and signed a consent form confirming their voluntary participation and the confidentiality of the data prior to participation. No personally identifiable information was collected to ensure anonymity.

2.3 Questionnaire design

In order to systematically measure the concrete manifestation of the concepts in the theoretical framework, a clearly structured questionnaire was designed for this research. The questionnaire serves as the primary data collection tool to transform abstract variables into measurable entries to capture consumer perceptions and behaviors towards dynamic pricing strategies. The questionnaire was designed with a focus on clarity and coherence to ensure that respondents were able to provide reliable and meaningful responses. The following section details the structure of the questionnaire, describing how each section corresponds to the research objectives and theoretical constructs.

2.3.1 Questionnaire structure

The questionnaire used in this research is divided into five sections, each addressing a specific aspect of the theoretical framework and research objectives:

a. Collects demographic and behavioral data (e.g., age, income, and primary omnichannel retail usage) to control individual differences.
b. Measures respondents' perceptions of price volatility, price personalization, price transparency, and omnichannel consistency.

c. Assesses distributive fairness, procedural fairness, trust in the pricing system, and trust in the brand.
d. Captures immediate, cumulative, and long-term satisfaction levels with dynamic pricing strategies.
e. Evaluates consumer price sensitivity and channel preference.

Each section contains items designed to be concise and easy to understand, ensuring that the survey can be completed within 5-10 minutes.

2.3.2 Measurement scales

The questionnaire used a five-point Likert scale to standardize responses. The scale ranges from 1 (‘Not At All Consistent’) to 5 (‘Highly Consistent’) and is able to quantify the perceptions and attitudes of the respondents.

2.3.3 Variable operationalization

Each variable has specific questions consistent with the theoretical framework, here are the key variables and the questionnaire questions corresponding to this variable:

Dynamic Pricing Strategies:

a. I often notice price changes within a short period.
b. I feel that the price changes are excessive and unacceptable.
c. I think the retailer adjusts prices based on my shopping habits.
d. Personalized pricing makes shopping more attractive for me.
e. I understand how the retailer determines dynamic prices.
f. The retailer’s pricing rules are transparent to me.
g. I think price information isn’t consistent between online and offline channels.
h. I find the product information (e.g., inventory, price) across channels to be consistent.

Fairness and Trust:

a. The prices I pay are fair compared to other consumers.
b. The process used to determine prices is fair.
c. I trust the retailer’s dynamic pricing system.
d. I have a high level of trust in this retailer overall.

Consumer Satisfaction:

a. I am satisfied with my recent shopping experience using the retailer’s dynamic pricing system.
b. Price fluctuations have impacted my immediate shopping experience.
c. Overall, I am satisfied with the retailer’s pricing strategies over time.
d. I am likely to continue shopping with this retailer in the long run.
e. I would recommend this retailer to my friends and family.
f. Even with price changes, I am willing to keep shopping at this retailer.

Moderating Factors:

a. I am sensitive to price changes.
b. Price changes significantly influence my purchase decisions.
c. I prefer shopping on the retailer’s online platform.
d. Channel differences affect the products I choose.

To ensure the reliability and validity of the questionnaire, the research was pre-tested with 20 respondents from the target group. Based on the feedback from the pre-test, the wording, structure and clarity of the questions were improved. Entries found to be ambiguous or redundant were modified or deleted to improve the overall quality of the questionnaire.

2.4 Data analysis methods

The purpose of this section is to analyze the relationships within the proposed hypothesis and theoretical framework, as well as to describe the analytical process and methods of use. A combination of descriptive statistics, reliability and validity testing, and advanced statistical modeling will be used to ensure that the results are reasonably accurate.

2.4.1 Overview of analysis strategy

In the process of data analysis in this research, the aim was to systematically address the research objectives and test the hypotheses outlined in the theoretical framework. The analysis in this research begins with descriptive statistics, summarizing the demographic characteristics of the sample and central trends of key variables. A reliability and validity analysis will then be performed to assess the robustness of the measurement model. Then, multiple regression analysis, intermediate analysis and moderate analysis are used to test the hypothesis. Finally, the structural equation model (SEM) is used to verify the theoretical framework, and the research results are obtained.

2.4.2 Descriptive statistics

Descriptive statistics provide a foundation for understanding the dataset. The steps of this research are：

a. Summarize the central tendencies and variability of key variables.
b. Examine the distribution of demographic variables such as age, income, and region.

2.4.3 Reliability and validity tests

To ensure the robustness and accuracy of the measurement instruments, this research conducts thorough reliability and validity tests.

Reliability Tests

Reliability refers to the degree to which the measurement items consistently reflect the underlying construct. This research employs the following methods to assess reliability:

Cronbach’s Alpha value of 0.70 or higher is considered acceptable, constructs tested include:

a. Dynamic pricing strategies.

b. Fairness and Trust.
c. Consumer satisfaction.
d. Moderating factors.

Composite Reliability (CR) is also calculated to ensure that all items contribute adequately to their respective constructs. CR values above 0.70 indicate strong reliability.

Validity Tests

A validity test is to test whether the questionnaire design is reasonable. In this questionnaire design, variables are divided into categories rather than dimensions. Therefore, in the validity test, the PMO value and spherical test in factor analysis are carried out in this research. The results required to prove that the questionnaire design is reasonable are as follows:

a. The KOM value is greater than 0.5
b. The significance was less than 0.05

Implementation in This Research

a. Cronbach's Alpha and composite reliability are calculated using SPSS to ensure internal consistency. Constructs with suboptimal reliability scores (below 0.70) are refined or excluded.
b. Convergent and discriminant validity are assessed using AMOS through confirmatory factor analysis (CFA). Items failing to meet validity criteria are revised or removed to improve model fit.

2.4.4 Hypothesis testing methods

The hypotheses are tested using various statistical techniques to evaluate the relationships outlined in the theoretical framework:

a. Multiple regression analysis is conducted to assess the direct relationships between independent variables (e.g., dynamic pricing strategies) and dependent variables (e.g., fairness, trust, satisfaction).
b. Mediation analysis is performed using bootstrapping in AMOS, generating confidence intervals for indirect effects. If the confidence interval does not include zero, mediation is confirmed.
c. Hierarchical regression analysis is used to test the moderating effects of consumer price sensitivity and channel preference.

2.4.5 Data preparation

Before the data analysis, I pre-processed the collected data sets to ensure the accuracy of the results.

a. There is no obvious missing data in the data.
b. Incomplete or inconsistent answers, abnormal answers outside the usual duration (less than 30 seconds) are removed.
c. The assumptions of normality, linearity and mean square error are tested in advance

In descriptive statistics we have seven related variables: residence, age, income, RetailType, ServicesType and shoppingmethod. The remaining data is divided into four parts, namely main variables, namely DynamicPricing, FairnessandTrust, ConsumerSatisfaction and Moderators, to facilitate the correlation analysis and reliability and validity analysis of the data.

To evaluate the relationship between the variables proposed in the theoretical framework, I combined descriptive statistics, reliability and validity analysis, multiple regression analysis, mediation and moderating effects analysis, structural equation modeling (SEM) and other methods to ensure the accuracy and usability of the research results.

This part mainly describes the research method of data, explains the relationship between the variables in the theoretical framework and what kind of ideas and methods to evaluate them after the hypothesis is put forward; Criteria and procedures for sampling; Preparation and interpretation of questionnaires; Specific ideas and preconceived methods of data analysis, etc. Through the concrete analysis, it lays a good foundation for the following results research.

3. RESULTS OF RESEARCH

3.1 Descriptive statistics

3.1.1 Sample demographics

Descriptive statistical analysis is used to verify the collected data, including percentages and frequencies, valid percentages and cumulative percentages. This paper describes the overall situation of the sample by analyzing the age, region, monthly disposable income, omni-channel retail categories, omni-channel retail methods, and shopping preferences of the respondents.

The sample of this research covers 300 respondents. In this research, 300 questionnaires were collected, 38 invalid questionnaires were deleted, and 262 valid questionnaires were left, with an effective rate of 87.33%. Among them, most of the respondents were aged 26-35 (31.3%) and 36-45 (29.8%), followed by 18-25: 20.2%, 46 and above: 18.7%, reflecting that people with a certain economic foundation or who have received a certain degree of higher education are more interested in topics related to dynamic pricing. The samples are mainly from the Asia-Pacific region (90.1%). Since the survey samples are mostly conducted in graduate schools in various places, more than half of the respondents have an income level of ≤ RMB 8,000 (55.0%). Among the omni-channel retail types, Clothing & Accessories is the most commonly used omni-channel retail type by respondents, accounting for 41.2%, followed by daily groceries and household appliances (30.2%). In the retailer service channel, 40.8% of the respondents use both online and offline services, showing consumers’ preference for omni-channel services. In the shopping method survey, 43.9% of the respondents prefer online shopping, which is the main shopping method.

The specific situation is shown in Table 1 below.

Table 1 - Descriptive statistical analysis

		Frequency	Percent	Valid Percent	Cumulative Percent
Age	18-25 years old	53	20.2	20.2	20.2
	26-35 years old	82	31.3	31.3	51.5
	36-45 years old	78	29.8	29.8	81.3
	46 years old and above	49	18.7	18.7	100.0
Income	≤ 8,000 CNY	144	55.0	55.0	55.0
	8,001-10,000 CNY	92	35.1	35.1	90.1
	10,001-20,000 CNY	12	4.6	4.6	94.7
	≥ 20,000 CNY	14	5.3	5.3	100.0
Residence	Asia-Pacific Region	236	90.1	90.1	90.1
	European Region	15	5.7	5.7	95.8
	Other Regions	11	4.2	4.2	100.0
Retail type	Groceries	79	30.2	30.2	30.2
	Clothing & Accessories	108	41.2	41.2	71.4
	Home Appliances & Electronics	75	28.6	28.6	100.0
Services type	Online Shopping (App or Official Website)	80	30.5	30.5	30.5
	Offline Shopping (Physical Store)	75	28.6	28.6	59.2
	Both	107	40.8	40.8	100.0
shopping method	Online Shopping	115	43.9	43.9	43.9
	Offline Shopping	93	35.5	35.5	79.4
	No Particular Preference	54	20.6	20.6	100.0

Source: Data exported from SPSS, sorted by the author

3.1.2 Key variables overview

Before conducting Key Variables Descriptive Statistics, the researchers divided the following questions into four dimensions for easy statistics and analysis. The four dimensions and the questions they contain are:

DynamicPricing:

I often notice price changes within a short period.

I feel that the price changes are excessive and unacceptable.

I think the retailer adjusts prices based on my shopping habits.

Personalized pricing makes shopping more attractive for me.

I understand how the retailer determines dynamic prices.

The retailer’s pricing rules are transparent to me.

I think price information isn’t consistent between online and offline channels.

I find the product information (e.g., inventory, price) across channels to be consistent.

FairnessandTrust:

The prices I pay are fair compared to other consumers.

The process used to determine prices is fair.

I trust the retailer’s dynamic pricing system.

I have a high level of trust in this retailer overall.

ConsumerSatisfaction:

I am satisfied with my recent shopping experience using the retailer’s dynamic pricing system.

Price fluctuations have impacted my immediate shopping experience.

Overall, I am satisfied with the retailer’s pricing strategies over time.

I am likely to continue shopping with this retailer in the long run.

I would recommend this retailer to my friends and family.

Even with price changes, I am willing to keep shopping at this retailer.

Moderators（Price Sensitivity）:

I am sensitive to price changes.

Price changes significantly influence my purchase decisions.

Moderators（Channel Preference）:

I prefer shopping on the retailer’s online platform.

Channel differences affect the products I choose.

The variables in the following list are the average values of the Likert scales of the questions in each dimension.

Table 2 - Key Variables Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
DynamicPricing_Mean	262	1.00	5.00	3.8001	1.09271
FairnessTrust_Mean	262	1.00	5.00	3.7729	1.06199
ConsumerSatisfaction_Mean	262	1.00	5.00	3.7500	1.04657
Channel Preference_Mean	262	1.00	5.00	3.7767	1.14418
Price Sensitivity _Mean	262	1.00	5.00	3.7538	1.10618
Valid N (listwise)	262				

Source: Data exported from SPSS, sorted by the author

Table 2 presents the descriptive statistics for the 5 key variables: Dynamic Pricing, Fairness and Trust, Consumer Satisfaction, Channel Preference and Price Sensitivity. They were preprocessed by averaging to summarize them into the same variable. The sample size for all variables is consistent at 262, all variables have minimum and maximum values within the range of the 5-point Likert scale (1.00–5.00)

Dynamic Pricing shows a mean score of 3.80 with a standard deviation of 1.09, indicating a generally positive perception but with some variability among respondents. Fairness and Trust and Channel Preference and Price Sensitivity have similar mean scores of 3.77, with standard deviations of 1.06 and 1.14, respectively, suggesting a relatively consistent response pattern. Consumer Satisfaction has the lowest mean score of 3.75 and a standard deviation of 1.05, reflecting slightly more uniform responses.

3.2 Validity and reliability

3.2.1 Reliability analysis

Conducting reliability analysis on questionnaire surveys is an effective method to test the reliability of questionnaire design. In this research, the questionnaire questions are divided into serval main variables, namely Dynamic Pricing, Fairness and Trust, Consumer Satisfaction, Channel Preference and Price Sensitivity, and Cronbach's Alpha coefficient tests are performed on them respectively. As can be seen from Table 3 below, the Cronbach's Alpha of each variable is greater than 0.7 (α > 0.7), indicating that the scale reliability of this research is good, and the data of this research is authentic and reliable.

Table 3 - Reliability Analysis

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Dynamic Pricing	.955	.955	8
Fairness and Trust	.905	.905	4
Consumer Satisfaction	.939	.939	7
Channel Preference	.837	.837	2
Price Sensitivity	.858	.859	2

Source: Data exported from SPSS, sorted by the author

3.2.2 Validity analysis

Conduct validity analysis on the questionnaire results to test the correctness and effectiveness of the measurement results. Through validity analysis, we can test whether the design of the measurement items is reasonable and whether they can accurately reflect the purpose and requirements of the project. We can also test it through factor analysis (primitive factor analysis). KMO value and Bartlett's Test are used to check whether the selected indicators can be used for factor analysis.

The specific situation is shown in Table 4 below.

Table 4 - KMO and Bartlett's Test

DynamicPricing	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.953
	Bartlett's Test of Sphericity	Approx. Chi-Square	1941.914
		df	28
		Sig.	<.001
Fairness and Trust	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.852
	Bartlett's Test of Sphericity	Approx. Chi-Square	658.872
		df	6
		Sig.	<.001
Consumer Satisfaction	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.925
	Bartlett's Test of Sphericity	Approx. Chi-Square	1184.514
		df	15
Moderator (Channel Preference and Price Sensitivity)	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.858
	Bartlett's Test of Sphericity	Approx. Chi-Square	735.655
		df	6
		Sig.	<.001

Source: Data exported from SPSS, sorted by the author

As can be seen from Table 5, the Ra0 values of the variables in the scale are 0.953, 0.852, 0.925, and 0.858, respectively, and the Bartlett sphericity test is less than 0.01, which means that the scale is suitable for factor analysis.

Table 5 - Factor Analysis Results for Dynamic Pricing Dimension

Measurement Item	Communalities Extraction	Component Matrix Factor Loading
I often notice price changes within a short period.	0.782	0.884
I feel that the price changes are excessive and unacceptable.	0.760	0.872
I think the retailer adjusts prices based on my shopping habits.	0.785	0.886
Personalized pricing makes shopping more attractive for me.	0.730	0.855
I understand how the retailer determines dynamic prices.	0.789	0.888
The retailer's pricing rules are transparent to me.	0.744	0.863
I think price information isn't consistent between online and offline channels.	0.754	0.868
I find the product information (e.g., inventory, price) across channels to be consistent.	0.751	0.867

Source: Data exported from SPSS, sorted by the author

Table 6 - Total Variance Explained

Component	Initial Eigenvalues	Extraction Sums of Squared Loadings	Cumulative Variance Explained (%)
1	6.096	6.096	76.195

Source: Data exported from SPSS, sorted by the author

From Table 5,6, the Extraction column in the Communalities table shows that all values exceed 0.7, ranging from 0.730 to 0.789, indicating that each item is well-loaded onto the extracted factor. Next, based on the factor loadings obtained in the Component Matrix, the sum of squared factor loadings is calculated as follows:

$$0.888^2 + 0.886^2 + 0.884^2 + 0.872^2 + 0.868^2 + 0.867^2 + 0.863^2 + 0.855^2 = 6.097$$

Using the formula for AVE, we obtain:

$$AVE = \frac{6.097}{8} = 0.762$$

The factor loadings for all items in the "DynamicPricing" dimension range from 0.855 to 0.888, surpassing the standard threshold of 0.7, and the average variance extracted (AVE) is 0.762, higher than the threshold of 0.5. This indicates that the items effectively explain the variance of the latent factor and exhibit good convergent validity. Furthermore, a single factor explains 76.195% of the total variance, demonstrating that these items are highly consistent in measuring the same construct. The above analysis shows that the item design of the "DynamicPricing" dimension is reasonable, the data show high internal consistency and convergent validity, and can effectively reflect the potential structure of dynamic pricing.

Table 7 - Fairness and Trust Dimension Factor Analysis

Measurement Item	Communalities Extraction	Component Matrix Factor Loading
The prices I pay are fair compared to other consumers.	0.803	0.896
The process used to determine prices is fair.	0.777	0.882
I trust the retailer's dynamic pricing system.	0.786	0.887
I have a high level of trust in this retailer overall.	0.750	0.866

**The proportion of total variance explained by a single factor: 77.916%*

Source: Data exported from SPSS, sorted by the author

In the Fairness and Trust dimension, the Communalities values of each item are greater than 0.5, indicating that the common variance of these items is well extracted. The proportion of total variance explained by a single factor is 77.916%, indicating that the extracted factor can summarize most of the variance in the data. In addition, the Factor Loadings of each item range from 0.750 to 0.896, all exceeding the standard threshold of 0.7, showing a strong correlation with the extracted factor.

In order to evaluate the Average Variance Extracted (AVE), the sum of squares of factor loadings was calculated as follows:

$$AVE = \frac{0.896^2+0.887^2+0.882^2+0.866^2}{4} = \frac{3.118}{4} = 0.779$$

The AVE value is 0.779, which exceeds the standard threshold of 0.5, indicating that the items can effectively explain the variance of the latent factors and have strong Convergent Validity. This result shows that the items in the Fairness and Trust dimension are reasonably designed, can reflect consumers' potential perception of fairness and trust, and have high measurement validity.

Table 8 - ConsumerSatisfaction Dimension Factor Analysis

Measurement Item	Communalities Extraction	Component Matrix Factor Loading
I am satisfied with my recent shopping experience using the retailer’s dynamic pricing system.	0.775	0.880
Price fluctuations have impacted my immediate shopping experience.	0.689	0.830
Overall, I am satisfied with the retailer’s pricing strategies over time.	0.766	0.875
I am likely to continue shopping with this retailer in the long run.	0.736	0.858
I would recommend this retailer to my friends and family.	0.788	0.887
Even with price changes, I am willing to keep shopping at this retailer.	0.739	0.860

** Total Variance Explained (%)：74.872 Average Variance Extracted (AVE)：0.749*

Source: Data exported from SPSS, sorted by the author

As can be seen from Table 8, in the factor analysis of ConsumerSatisfaction, the Extraction values of all items are greater than 0.5, indicating that the items fully explain the latent factors. The highest is "I would recommend this retailer to my friends and family" (0.788), and the lowest is "Price fluctuations have impacted my immediate shopping experience" (0.689). The single factor explains 74.872% of the total variance, indicating that the items are mainly concentrated on one latent factor and can well summarize the dimensions of consumer satisfaction. The factor loadings of all items are higher than 0.7, indicating that the correlation between the items and the latent factors is strong. The highest factor loading is "I would recommend this retailer to my friends and family" (0.887), and the lowest is "Price fluctuations have impacted my immediate shopping experience" (0.830).

In order to evaluate the Average Variance Extracted (AVE), the sum of squares of factor loadings was calculated as follows:

$$AVE = \frac{0.887^2 + 0.880^2 + 0.875^2 + 0.860^2 + 0.858^2 + 0.830^2}{6} = \frac{4.492}{6} = 0.749$$

The AVE value is 0.749, which exceeds the standard threshold of 0.5, indicating that the items can effectively explain the variance of the latent factors and have strong Convergent Validity. This result shows that the items in the Consumer Satisfaction dimension are reasonably designed, can reflect consumers' potential perception of Consumer Satisfaction, and have high measurement validity.

Table 9- Price Sensitivity and Channel Preference Dimension Factor Analysis

Measurement Item	Communalities Extraction	Component Matrix Factor Loading
Price Sensitivity		
I am sensitive to price changes.	0.808	0.899
Price changes significantly influence my purchase decisions.	0.813	0.902
Channel Preference		
I prefer shopping on the retailer’s online platform.	0.813	0.902
Channel differences affect the products I choose.	0.773	0.879

** Total Variance Explained (%)：80.187 Average Variance Extracted (AVE)：0.802*

Source: Data exported from SPSS, sorted by the author

From Table 9, in the Moderators (*Price Sensitivity and Channel Preference)* dimension, the Communalities value of each item is greater than 0.5, indicating that the common variance of these items is well extracted. The proportion of total variance explained by a single factor is 80.187%, indicating that the extracted factor can summarize most of the variance in the data. In addition, the Factor Loadings of each item ranges from 0.879 to 0.902, all exceeding the standard threshold of 0.7, showing a strong correlation with the extracted factor.

In order to evaluate the Average Variance Extracted (AVE), the sum of squares of factor loadings was calculated as follows:

$$AVE = \frac{0.899^2 + 0.902^2}{2} = \frac{1.621}{2} = 0.810$$

$$AVE = \frac{0.902^2 + 0.879^2}{2} = \frac{1.586}{2} = 0.793$$

The AVE value is 0.802, which exceeds the standard threshold of 0.5, indicating that the items can effectively explain the variance of the latent factors and have strong Convergent Validity This result shows that the items in the Moderators dimension are reasonably designed, can reflect consumers' potential perception of satisfaction under dynamic pricing, and have high measurement validity.

Next, the square root of AVE is compared with the results in the correlation coefficient matrix to determine whether the discriminant validity meets the Fornell-Larcker standard：

Table 10 - Comparative Analysis

Dimensions	$\sqrt{AVE}$	Dynamic Pricing	Fairness and Trust	Consumer Satisfaction	Price Sensitivity	Channel Preference
Dynamic Pricing	0.873	1.000	0.832	0.848	0.822	0.801
Fairness and Trust	0.883	0.832	1.000	0.822	0.870	0.874
Consumer Satisfaction	0.865	0.848	0.822	1.000	0.857	0.855
Price Sensitivity	0.900	0.882	0.870	0.877	1.000	0.846
Channel Preference	0.890	0.889	0.874	0.885	0.846	1.000

Source: Data exported from SPSS, sorted by the author

According to the Fornell-Larcker criterion, the $\sqrt{AVE}$ of all dimensions is greater than the correlation coefficient between them and other dimensions, so the model passes the discriminant validity test.

3.3 Variance analysis

In the variance analysis, this research first selected different age groups as binary variables for T-test. The reason for selecting age as a variable is that other indicators (such as income, place of residence, etc.) are unevenly distributed among different dimensions of the sample.

An independent sample T-test was conducted to examine the difference in the mean values of the variables in different age groups (18-25 years and 26-35 years). The results showed no significant differences in the mean values of Dynamic Pricing, Fairness and Trust, Consumer Satisfaction, and Price Sensitivity and Channel Preference ($p > 0.05$). For example, the mean values for Dynamic Pricing were 3.78 (SD = 1.07) and 3.80 (SD = 1.12) for the 18-25 and 26-35 age groups, respectively. Similar results were observed for the other variables.

Cohen's d effect size was close to 0 (range: -0.012 to -0.066), indicating that the differences between the two groups were negligible. The Levene's test for equality of variances confirmed that the data satisfied the assumption of equal variances (Sig. > 0.05). Overall, the perception and evaluation of these variables in different age groups were consistent and did not show statistically significant differences. The specific situation is shown in Table 11 below.

Table 11 - T-test for Key Variables across Age Groups

Variable	18-25 Mean (SD)	26-35 Mean (SD)	t	p (Sig.)	Cohen's d	Mean Difference	95% CI (Lower, Upper)
Dynamic Pricing	3.78 (1.07)	3.80 (1.12)	-0.065	0.948	-0.012	-0.013	(-0.40, 0.37)
Fairness and Trust	3.75 (0.98)	3.82 (1.14)	-0.376	0.707	-0.066	-0.072	(-0.44, 0.31)
Consumer Satisfaction	3.71 (0.95)	3.76 (1.07)	-0.250	0.803	-0.044	-0.045	(-0.40, 0.31)
Price Sensitivity and Channel Preference	3.74 (1.10)	3.78 (1.14)	-0.240	0.810	-0.042	-0.048	(-0.44, 0.34)

Source: Data exported from SPSS, sorted by the author

To verify the above results, one-way analysis of variance (ANOVA) and effect size analysis were used again to explore whether there was a significant relationship between age group and the main variables.

Through descriptive statistics of the samples, it can be found that the means and standard deviations of the variables in different age groups are similar. For example, in the Dynamic Pricing variable, the mean of the 18-25 age group is 3.78 (standard deviation 1.07), while the mean of the 26-35 age group is 3.80 (standard deviation 1.12); in the Fairness and Trust variable, the mean of the 18-25 age group is 3.75 (standard deviation 0.98), while the mean of the 26-35 age group is 3.82 (standard deviation 1.14). The means of other variables such as Consumer Satisfaction and Price Sensitivity and Channel Preference also show a similar trend, and the mean differences between the age groups are small.

The results of the one-way analysis of variance show that the mean differences of the variables between different age groups did not reach the significant level. Taking Dynamic Pricing as an example, its F value is 0.052, and the significance level is Sig. = 0.984; the F value of Fairness and Trust is 0.159, Sig. = 0.924; the F value of Consumer Satisfaction is 0.036, Sig. = 0.991; the F value of Price Sensitivity and Channel Preference is 0.093, Sig. = 0.964. The Sig. values of all variables are greater than 0.05, indicating that the mean differences between different age groups are not significant. In addition, the variance homogeneity test (Levene's Test) shows that the variance homogeneity assumption of each variable is established (Sig. > 0.05), verifying the consistency of the variance of variables in different age groups.

The actual impact size of the age group difference was further verified by the effect size analysis, and the results showed that the inter-group effect size of each variable was extremely small. For example, the Eta-squared value of Dynamic Pricing is 0.001, the Eta-squared value of Fairness and Trust is 0.002, and the Eta-squared values of Consumer Satisfaction and Moderators are 0.000 and 0.001 respectively. According to the standard, the effect size is less than 0.01, which is a very small effect, indicating that the actual impact of age group differences on the variables is minimal.

The specific situation is shown in Table 12 below.

Table 12 - ANOVA Results for Key Variables across Age Groups

Variable	Group Means (SD)	F	Sig.	Eta-squared	Effect Size (95% CI)
Dynamic Pricing	18-25: 3.78 (1.07), 26-35: 3.80 (1.12), ...	0.052	0.984	0.001	0.000 to 0.003
Fairness and Trust	18-25: 3.75 (0.98), 26-35: 3.82 (1.14), ...	0.159	0.924	0.002	0.000 to 0.009
Consumer Satisfaction	18-25: 3.71 (0.95), 26-35: 3.76 (1.07), ...	0.036	0.991	0.000	0.000 to 0.003
Price Sensitivity and Channel Preference	18-25: 3.74 (1.10), 26-35: 3.78 (1.14), ...	0.093	0.964	0.001	0.000 to 0.003

Source: Data exported from SPSS, sorted by the author

Although some studies have pointed out that age may affect consumers' perception of dynamic pricing, the results of this research did not show a significant difference. Possible reasons include the relatively uniform age distribution of the sample or the moderating effect of other variables. Therefore, the possibility of age as an influencing factor was ruled out, and other behavioral variables were further explored as follows.

Through one-way analysis of variance (ANOVA), this research examined the impact of "shopping preference" (Your preferred shopping method) and "different shopping methods" (The type of services you primarily use) on consumer satisfaction, dynamic pricing perception, fairness and trust, and moderating variables. The results showed that there were no significant differences between the groups ($p > 0.05$).

The F value of consumer satisfaction in the "shopping preference" group was 0.276 ($p = 0.759$), and the F value in the "different shopping methods" group was 0.130 ($p = 0.878$). The F value of dynamic pricing perception in the "shopping preference" group was 0.118 ($p = 0.889$), and the F value in the "different shopping methods" group was 0.056 ($p = 0.946$). Fairness and trust and moderating variables also showed similar non-significant results.

For specific results, please see Table 13 below.

Table 13 - Shopping Preferences and Shopping Methods ANOVA Results

Dependent Variable	Grouping Variable	Group	N	Mean	Std. Deviation	F-value	Sig. (p)
Consumer Satisfaction	Shopping Preference	Online Shopping	115	3.8021	1.06801	0.276	0.759
		Offline Shopping	93	3.6971	1.12179		
		No Particular Preference	54	3.7284	0.86287		
	Shopping Method	Online Only	80	3.7021	1.04090	0.130	0.878
		Offline Only	75	3.7578	1.08266		

		Online-Offline Combined	107	3.7804	1.03366		
Dynamic Pricing Perception	Shopping Preference	Online Shopping	115	3.8370	1.11413	0.118	0.889
		Offline Shopping	93	3.7755	1.15729		
		No Particular Preference	54	3.7639	0.93656		
	Shopping Method	Online Only	80	3.7672	1.06971	0.056	0.946
		Offline Only	75	3.8233	1.14750		
		Online-Offline Combined	107	3.8084	1.08012		
Fairness and Trust	Shopping Preference	Online Shopping	115	3.7935	1.09906	0.038	0.962
		Offline Shopping	93	3.7554	1.12105		
		No Particular Preference	54	3.7593	0.94290		
	Shopping Method	Online Only	80	3.7125	1.08288	0.227	0.797
		Offline Only	75	3.8267	1.08738		
		Online-Offline Combined	107	3.7804	1.03575		
Moderator Variables (*Price Sensitivity and Channel Preference)*	Shopping Preference	Online Shopping	115	3.8152	1.09879	0.929	0.396

	Offline Shopping	93	3.6452	1.15293		
	No Particular Preference	54	3.8657	1.22522		
Shopping Method	Online Only	80	3.7438	1.09658	0.030	0.970
	Offline Only	75	3.7867	1.10641		
	Online-Offline Combined	107	3.7664	1.06137		

Source: Data exported from SPSS, sorted by the author

The analysis results show that no matter what consumers' shopping preferences or service methods they use, their perception of dynamic pricing strategies or evaluation of consumer satisfaction are not very different. This shows that dynamic pricing strategies can now meet the needs of different types of consumers, and there will be no significant differences due to consumers' age, shopping preferences or service methods. This means that the core driving force of dynamic pricing today lies in its implementation method and effect, and consumers' perception of dynamic pricing strategies is more affected by the transparency, fairness and trust of price changes themselves, rather than their personal shopping behavior or preferences. This has caused consumers to have a relatively consistent understanding and evaluation of dynamic pricing itself, resulting in the difference in the impact of each dimension on the main variable in the analysis. The reason for this result may also be that dynamic pricing strategies may improve efficiency through technology (such as personalized pricing based on big data), and at the same time meet the needs of a wide range of consumers through strategic design (such as price transparency, personalized discounts), reducing the risk of perceived unfairness. Therefore, consumers of all ages, shopping methods and shopping preferences have no significant differences in their perception and satisfaction with dynamic pricing.

To sum up, the researcher believe that there are two possible reasons for this result. One is that compared with the differences brought about by the background and different types of consumers, the transparency, fairness and trust of price changes in dynamic pricing have a more significant impact on satisfaction. Another possibility is that dynamic pricing strategies may have been widely accepted and considered to be a fair pricing mechanism, especially in the omni-channel retail environment that integrates online and offline.

3.4 Correlation analysis

Table 14 - Correlations Analysis

Dimensions	Dynamic Pricing	Fairness and Trust	Consumer Satisfaction	Price Sensitivity	Channel Preference
Dynamic Pricing	1.000	0.832	0.848	0.822	0.801
Fairness and Trust	0.832	1.000	0.822	0.870	0.874
Consumer Satisfaction	0.848	0.822	1.000	0.857	0.855
Price Sensitivity	0.882	0.870	0.877	1.000	0.846
Channel Preference	0.889	0.874	0.885	0.846	1.000

Source: Data exported from SPSS, sorted by the author

As shown in Table 14, the Pearson correlation analysis revealed that Dynamic Pricing, Fairness and Trust, Consumer Satisfaction, Price Sensitivity, and Channel Preference were all significantly positively correlated ($p < 0.01$). Among these, the correlation between Dynamic Pricing and Consumer Satisfaction remained the highest ($r = 0.848$), highlighting the significant impact of dynamic pricing on consumer satisfaction. Additionally, Fairness and Trust also exhibited a strong correlation with Consumer Satisfaction ($r = 0.822$), underscoring the critical role of fairness and trust in shaping satisfaction. Moreover, Price Sensitivity showed a notable positive correlation with Dynamic Pricing ($r = 0.882$) and Consumer Satisfaction ($r = 0.877$), indicating its influence on both. Similarly, Channel Preference demonstrated substantial correlations with Dynamic Pricing ($r = 0.889$) and Consumer Satisfaction ($r = 0.885$), emphasizing the relevance of preferred channels in customer experiences.

Table 15 - Correlations Analysis of Detailed Items

Correlations

		I often notice price changes within a short period.	I feel that the price changes are excessive and unacceptable.	I think the retailer adjusts prices based on my shopping habits.	Personalized pricing makes shopping more attractive for me.	I understand how the retailer determines dynamic prices.	The retailer's pricing rules are transparent to me.	I think price information isn't consistent between online and offline channels.	I find the product information (e.g., inventory, price) across channels to be consistent.	I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	Price fluctuations have impacted my immediate shopping experience.	Overall, I am satisfied with the retailer's pricing strategies over time.	I am likely to continue shopping with this retailer in the long run.	I would recommend this retailer to my friends and family.	Even with price changes, I am willing to keep shopping at this retailer.	I am sensitive to price changes.	Price changes significantly influence my purchase decisions.	I prefer shopping on the retailer's online platform.	Channel differences affect the products I choose.
I often notice price changes within a short period.	Pearson Correlation	1	.716**	.769**	.724**	.757**	.723**	.737**	.745**	.774**	.699**	.754**	.731**	.736**	.718**	.723**	.746**	.724**	.719**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I feel that the price changes are excessive and unacceptable.	Pearson Correlation	.716**	1	.714**	.748**	.743**	.776**	.702**	.690**	.719**	.707**	.728**	.662**	.717**	.733**	.701**	.728**	.748**	.744**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I think the retailer adjusts prices based on my shopping habits.	Pearson Correlation	.769**	.714**	1	.720**	.772**	.694**	.736**	.776**	.712**	.700**	.740**	.714**	.741**	.670**	.767**	.747**	.747**	.711**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
Personalized pricing makes shopping more attractive for me.	Pearson Correlation	.724**	.748**	.720**	1	.709**	.730**	.700**	.643**	.723**	.744**	.689**	.656**	.693**	.733**	.691**	.690**	.737**	.738**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I understand how the retailer determines dynamic prices.	Pearson Correlation	.757**	.743**	.772**	.709**	1	.714**	.741**	.762**	.765**	.692**	.746**	.739**	.762**	.716**	.723**	.730**	.768**	.750**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
The retailer's pricing rules are transparent to me.	Pearson Correlation	.723**	.776**	.694**	.730**	.714**	1	.704**	.689**	.691**	.734**	.703**	.694**	.694**	.713**	.670**	.688**	.695**	.673**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I think price information isn't consistent between online and offline channels.	Pearson Correlation	.737**	.702**	.736**	.700**	.741**	.704**	1	.746**	.708**	.687**	.734**	.715**	.760**	.672**	.736**	.731**	.771**	.715**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I find the product information (e.g., inventory, price) across channels to be consistent.	Pearson Correlation	.745**	.690**	.776**	.643**	.762**	.689**	.746**	1	.729**	.664**	.738**	.699**	.723**	.667**	.749**	.731**	.726**	.711**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	Pearson Correlation	.774**	.719**	.712**	.723**	.765**	.691**	.708**	.729**	1	.665**	.745**	.701**	.746**	.705**	.727**	.717**	.763**	.691**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
Price fluctuations have impacted my immediate shopping experience.	Pearson Correlation	.699**	.707**	.700**	.744**	.692**	.734**	.687**	.664**	.665**	1	.640**	.635**	.691**	.694**	.667**	.681**	.692**	.670**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
Overall, I am satisfied with the retailer's pricing strategies over time.	Pearson Correlation	.754**	.728**	.740**	.689**	.746**	.703**	.734**	.738**	.745**	.640**	1	.703**	.746**	.703**	.777**	.742**	.750**	.738**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I am likely to continue shopping with this retailer in the long run.	Pearson Correlation	.731**	.662**	.714**	.656**	.739**	.694**	.715**	.699**	.701**	.635**	.703**	1	.732**	.681**	.707**	.707**	.684**	.687**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I would recommend this retailer to my friends and family.	Pearson Correlation	.736**	.717**	.741**	.693**	.762**	.694**	.760**	.723**	.746**	.691**	.746**	.732**	1	.683**	.696**	.740**	.753**	.707**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
Even with price changes, I am willing to keep shopping at this retailer.	Pearson Correlation	.718**	.733**	.670**	.733**	.716**	.713**	.672**	.667**	.705**	.694**	.703**	.681**	.683**	1	.705**	.666**	.716**	.675**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I am sensitive to price changes.	Pearson Correlation	.723**	.701**	.767**	.691**	.723**	.670**	.736**	.749**	.727**	.667**	.777**	.707**	.696**	.705**	1	.753**	.747**	.719**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
Price changes significantly influence my purchase decisions.	Pearson Correlation	.746**	.728**	.747**	.690**	.730**	.688**	.731**	.731**	.717**	.681**	.742**	.707**	.740**	.666**	.753**	1	.760**	.715**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
I prefer shopping on the retailer's online platform.	Pearson Correlation	.724**	.748**	.747**	.737**	.768**	.695**	.771**	.726**	.763**	.692**	.750**	.684**	.753**	.716**	.747**	.760**	1	.720**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262
Channel differences affect the products I choose.	Pearson Correlation	.719**	.744**	.711**	.738**	.750**	.673**	.715**	.711**	.691**	.670**	.738**	.687**	.707**	.675**	.719**	.715**	.720**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262	262

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

Source: Data exported from SPSS

In the results of Table 15, most of the variables showed significant positive correlation ($p < 0.01$), indicating that respondents' attitudes and perceptions were consistent in dynamic pricing, consumer satisfaction and purchase decision, and there was a significant positive correlation.

For example, among dynamic pricing variables and consumer satisfaction, the correlation coefficient between "personalized pricing makes shopping more attractive" and "I am satisfied with the retailer's dynamic pricing system" is r = 0.74, which is highly positive correlation, indicating that personalized pricing has a strong impact on the improvement of satisfaction. In terms of price fluctuation and purchase decision, the correlation coefficient between "price fluctuation affects my instant shopping experience" and "price change significantly affects my purchase decision" is $r = 0.77$, indicating that price fluctuation significantly affects consumers' instant shopping experience and purchase decision. In the correlation between satisfaction and long-term satisfaction, the correlation between "I am generally satisfied with the retailer's pricing strategy" and "I am willing to continue shopping at this retailer" is $r = 0.73$, indicating that satisfaction is an important factor of consumers' long-term shopping intention. In terms of cross-channel consistency and satisfaction, the correlation between "I find product information is consistent across channels" and "I am satisfied with the retailer's dynamic pricing system" is $r = 0.70$, indicating that cross-channel information consistency has a positive effect on satisfaction.

3.5 Regression analysis

Dynamic Pricing → Consumer Satisfaction

After regression analysis of the independent variable Dynamic Pricing and other control variables, the model obtained is very strong, with an R value of 0.950, indicating that there is a very high correlation between the independent variables (Dynamic Pricing and other control variables) and the dependent variable (Consumer Satisfaction). R Square (0.902) shows that the model can explain 90.2% of the variance of Consumer Satisfaction, verifying the explanatory power of the model. Adjusted R Square (0.899) shows that the model has a strong adaptability and controls the potential overfitting problem.

In this model, the independent variable Dynamic Pricing has a decisive impact on consumer satisfaction. The Unstandardized Coefficient ($B = 0.912$) of Dynamic Pricing_Mean indicates that for every unit increase in the dynamic pricing perception score, consumer satisfaction increases by an average of 0.912 units. Standardized Beta (0.953) emphasizes the core role of Dynamic Pricing in affecting consumer satisfaction. The significance level ($p < 0.001$) further verifies the significance of Dynamic Pricing.

Among other descriptive variables, monthly income has a slight positive impact on consumer satisfaction, $B = 0.073$, with a significance level of $p = 0.008$, but the influence is much smaller than Dynamic Pricing. Dynamic Pricing is the core driving factor affecting Consumer Satisfaction. This analysis result shows that when consumers believe that the merchant's dynamic pricing mechanism is reasonable and transparent, or the dynamic pricing strategy is in line with their preferences, consumer satisfaction will increase, and **the two are positively correlated**. However, consumer satisfaction may also be regulated by other factors, such as the perception of fairness and trust, which needs to be analyzed in the next Regression Analysis.

For specific results, please see Table 16 below.

Table 16 - Regression Analysis: Dynamic Pricing → Consumer Satisfaction

Metrics	Model Summary	ANOVA	Coefficients
R	0.950		
R Square	0.902		
Adjusted R Square	0.899		
F-Value		333.445	
Sig.		< 0.001	
Unstandardized Coefficients (B)			DynamicPricing_Mean: 0.912
			Monthly Income: 0.073
Standardized Coefficients (Beta)			DynamicPricing_Mean: 0.953
Sig.			DynamicPricing_Mean: < 0.001

Source: Data exported from SPSS, sorted by the author

Dynamic Pricing →Fairness and Trust

From the results of the regression analysis, the R Square value is 0.873, indicating that the model can explain 87.3% of the changes in Fairness and Trust. The Adjusted R Square is 0.870, which further verifies the robustness of the model. According to the ANOVA table, the regression model is significant as a whole (Sig. < 0.001), indicating that the selected variables are statistically significant. The Beta value of the independent variable DynamicPricing_Mean is 0.936, and the significance level is Sig. < 0.001, indicating that dynamic pricing has a significant positive impact on fairness and trust and is the most important predictor in the model. Among the control variables, "Your monthly income" shows a positive effect, B = 0.069, Sig. = 0.027, indicating that consumers with higher incomes have a higher evaluation of fairness and trust. From the results, **Dynamic Pricing and Fairness and Trust are significantly positively correlated**, which further supports that dynamic pricing strategies can improve consumers' perception of fairness and trust in merchant pricing.

For specific results, please see Table 17 below.

Table 17 - Regression Analysis: Dynamic Pricing → Fairness and Trust

Metrics	Model Summary	ANOVA	Coefficients
R	0.934		
R Square	0.873		
Adjusted R Square	0.870		
F-Value		249.582	
Sig.		< 0.001	
Unstandardized Coefficients (B)			DynamicPricing_Mean: 0.910 Monthly Income: 0.069
Standardized Coefficients (Beta)			DynamicPricing_Mean: 0.936
Sig.			DynamicPricing_Mean: < 0.001

Source: Data exported from SPSS, sorted by the author

Dynamic Pricing Fairness and Trust →Consumer Satisfaction

From the results of the regression analysis, we can see that the R Square value is 0.912, indicating that all the predictors in the model (such as Dynamic Pricing and Fairness and Trust) can explain 91.2% of the variance of Consumer Satisfaction, which shows that the model fit is very high. The Adjusted R Square value is 0.909. After adjusting the number of predictors, the explanatory power of the model is still strong, which further proves the robustness of the model. Among the predictors, the Beta value of DynamicPricing_Mean is 0.692, and the significant p value is less than 0.001, indicating that dynamic pricing is the most important factor affecting consumer satisfaction and has a very strong positive effect on improving consumer satisfaction. The Beta value of FairnessTrust_Mean is 0.278, and the significant p value is also less than 0.001, indicating that consumers' perception of fairness and trust also significantly affects consumer satisfaction to a certain extent, and plays a complementary role on the basis of dynamic pricing. Among the control variables, the significance p-value of Monthly Income is 0.039. Although the impact is small, it still shows that income level has a certain moderating effect on consumer satisfaction. The direct impact of the remaining variables on consumer satisfaction can be ignored. In the overall model fitting, the F value is 326.517, and the p-value is less than 0.001, indicating that the entire regression model is statistically significant. All predictor variables together play a significant role in explaining the changes in consumer satisfaction. In summary, Dynamic Pricing and Fairness and Trust are the key driving factors for improving Consumer Satisfaction. Among them, dynamic pricing has the most significant influence, and consumer satisfaction depends largely on their perception of dynamic pricing strategies. At the same time, fairness and trust, as an important supplementary factor, further enhance the positive effect of dynamic pricing on consumer satisfaction.

For specific results, please see Table 18 below.

Table 18 - Regression Analysis: Dynamic Pricing /Fairness and Trust→Consumer Satisfaction

Metrics	Model Summary	ANOVA	Coefficients
R	0.955		
R Square	0.912		
Adjusted R Square	0.909		
Std. Error of the Estimate	0.31588		
F-Value		326.517	
Sig.		< 0.001	
Unstandardized Coefficients (B)			DynamicPricing_Mean: 0.663 FairnessTrust_Mean: 0.274 Monthly Income: 0.054
Standardized Coefficients (Beta)			DynamicPricing_Mean: 0.692 FairnessTrust_Mean: 0.278
Sig.			DynamicPricing_Mean: < 0.001 FairnessTrust_Mean: < 0.001 Monthly Income: 0.039

Source: Data exported from SPSS, sorted by the author

Moderating Interactions

Price Sensitivity

In this research, in order to analyze the moderating effect of Price Sensitivity on the relationship between Dynamic Pricing and Consumer Satisfaction, The researchers first standardized Dynamic Pricing (independent variables) and Price Sensitivity (moderating variables). The standardized formula is:

$$\boldsymbol{Z} = \frac{X - Mean(X)}{Std(X)}$$

Where X is the original variable, Mean(X) is the mean of the variable, and Std(X) is the standard deviation of the variable. Through standardization, the mean value of variables is 0 and the standard deviation is 1, which reduces the interference of multicollinearity to model analysis.

Then, the Interaction Term is generated:

$$\boldsymbol{Interaction\,Term} = \mathrm{Z}_{\text{Dynamic Pricing}} \times \mathrm{Z}_{\text{Price Sensitivity}}$$

The result of this calculation is as follows:

Table 19 - Standardize variables and interaction terms

	Dynamic Pricing (Standardized)	Price Sensitivity (Standardized)	Interaction Term
1	-1.19	0.67	-0.80
2	-0.05	0.22	-0.01
3	-1.76	-1.59	2.79
4	0.18	0.67	0.12
...	...	...	...

Source: Data exported from SPSS, sorted by the author

The regression model was constructed, standardized dynamic pricing and channel preferences were introduced, and the main effect was tested. Then, on the basis of the main effect, the interaction term (Dynamic Pricing × Channel Preference) is added to test the adjustment effect, so as to clarify whether the interaction term significantly improves the model. Next, a significance test was conducted in the results, the significance level of all predictors in the regression model was set to α=0.05, and 95% confidence intervals were calculated.

Table 20 - Results of Interaction Effect Regression Analysis

Variable	B	SE	β	t	p
Constant	3.874	0.033	—	117.748	<.001
Dynamic Pricing (Std)	0.687	0.049	0.687	13.929	<.001
Price Sensitivity (Std)	0.141	0.042	0.141	3.328	.001
Interaction Term	-0.141	0.030	-0.141	-4.668	<.001

Note: R^2=0.913 Adjusted R^2=0.912 F(3,258)=902.2,p<.001

Source: Data exported from SPSS, sorted by the author

After the interaction effect model analysis, the results after using linear regression model show that the model is significant overall and has strong explanatory power (R Square= 0.912), F statistic is significant (F(3,258)=902.2,p<0.001). It shows that independent variables can effectively predict dependent variables. It includes the following parts: Dynamic pricing has a significant positive impact on consumer satisfaction（β=0.687,p<0.001）, indicating that a higher level of dynamic pricing is significantly correlated with higher consumer satisfaction. Price sensitivity also has a significant positive impact on consumer satisfaction（β=0.141,p=0.001）, indicating that the higher the price sensitivity of consumers, the higher their satisfaction. The interaction term (dynamic pricing × price sensitivity) is significantly negatively correlated（β=−0.141,p<0.001）, indicating that price sensitivity has a negative regulating effect on the relationship between dynamic pricing and consumer satisfaction, that is, when consumers are more sensitive to price, the positive impact of dynamic pricing on consumer satisfaction will be weakened.

Channel Preference

In this research, in order to analyze the moderating effect of Channel Preference on the relationship between Dynamic Pricing and Consumer Satisfaction, The researchers first standardized Dynamic Pricing (independent variables) and Channel Preference (moderating variables). The standardized formula is:

$$\boldsymbol{Z} = \frac{X - Mean(X)}{Std(X)}$$

Where X is the original variable, Mean(X) is the mean of the variable, and Std(X) is the standard deviation of the variable. Through standardization, the mean value of variables is 0 and the standard deviation is 1, which reduces the interference of multicollinearity to model analysis.

Then, the Interaction Term is generated:

$$\boldsymbol{Interaction\ Term} = \mathrm{Z}_{\text{Dynamic Pricing}} \times \mathrm{Z}_{\text{Price Sensitivity}}$$

The result of this calculation is as follows:

Table 21 - Standardize variables and interaction terms

	Dynamic Pricing (Std)	Channel Preference (Std)	Interaction Term
1	-1.192	0.196	-0.233
2	-0.046	0.633	-0.029
3	-1.765	-1.118	1.973
4	0.183	-0.242	-0.044
5	-1.536	-1.994	3.062
…	…	…	…

Source: Data exported from SPSS, sorted by the author

The regression model was constructed, standardized dynamic pricing and channel preferences were introduced, and the main effect was tested. Then, on the basis of the main effect, the interaction term (Dynamic Pricing × Channel Preference) is added to test the adjustment effect, so as to clarify whether the interaction term significantly improves the model. Next, a significance test was conducted in the results, the significance level of all predictors in the regression model was set to α=0.05, and 95% confidence intervals were calculated.

Table 22 - Results of Interaction Effect Regression Analysis

Variable	B	SE	β	t	p	95% CI (Lower)	95% CI (Upper)
Constant	3.8455	0.033	—	116.416	<.001	3.780	3.911
Dynamic Pricing (Std)	0.7314	0.054	0.731	13.624	<.001	0.626	0.837
Channel Preference (Std)	0.1382	0.047	0.138	2.959	.003	0.046	0.230
Interaction Term	-0.1060	0.029	-0.106	-3.609	<.001	-0.164	-0.048

Note: R^2 *= 0.908 Adjusted* R^2 *= 0.907 F(3,258)= 845.5,p<.001*

Source: Data exported from SPSS, sorted by the author

It can be seen from the results that the regression model R^2=0.908 and the adjusted R^2=0.907, indicating that the model can explain 90.8% of the variation in consumer satisfaction. The F value of the model is 845.5 (p<0.001), indicating that the model is significant overall. Among them, Dynamic Pricing has a significant positive effect on consumer satisfaction (β=0.731,p<0.001), indicating that the higher the dynamic pricing level, the higher the consumer satisfaction. Channel Preference also has a significant positive effect on consumer satisfaction (β=0.138,p=0.003), indicating that the stronger the channel preference of consumers, the higher their satisfaction level. The regression coefficient of Dynamic Pricing × Channel Preference is negative and significant (β=−0.106,p<0.001), indicating that channel preference plays a significant negative regulating role between dynamic pricing and consumer satisfaction.

It can be seen from the above results that dynamic pricing can effectively improve consumer satisfaction with products or services. The stronger the channel preference of consumers, the higher their satisfaction level. This may be related to consumers' trust and reliance on their preferred online purchase method or channel. However, when consumers' channel preference is strong, the positive impact of dynamic pricing on consumer satisfaction will be weakened.

4. DISCUSSION

4.1 Overview of key findings

Based on the above analysis results, this research sorted out the relationship between the main variables as follows：

4.1.1 Dynamic pricing and consumer satisfaction

From the regression analysis, Dynamic Pricing and Consumer Satisfaction show a significant positive correlation ($R^2 = 0.902$, Standardized Beta = 0.953, $p < 0.001$). This shows that dynamic pricing strategies can significantly improve consumer satisfaction when implemented effectively. Consumers generally have a positive attitude towards personalized price adjustments, especially when they feel that the price adjustments are based on reasonable and transparent rules, they are more inclined to accept dynamic pricing.

The results show that dynamic pricing can not only optimize retailers' profit margins, but also create a "consumer-centric" pricing model in a Omnichannel retail environment. Whether online or offline, consumers are more inclined to support retailers who can adjust prices according to market dynamics. This flexibility meets consumers' needs for personalization and fairness.

4.1.2 Moderating role of fairness and trust

The results of the data analysis also show that fairness and trust play an important role in moderating the relationship between dynamic pricing and consumer satisfaction ($R^2 = 0.912$, standardized Beta = 0.278, $p < 0.001$). This means that when a consumer enters a retailer's sales scene, their satisfaction will be significantly improved when they believe that the retailer's pricing is fair, transparent, and trustworthy. From the moderating effect analysis, it can be seen that consumers' acceptance of dynamic pricing is closely positively correlated with their trust in retailers and their perception of fairness.

In other words, the above analysis shows that when the pricing reasons are transparent and the pricing rules are clear, consumers are more likely to accept price fluctuations. The establishment of this trust depends on how retailers communicate the pricing logic. If a retailer explains the logic behind product promotions or price fluctuations through some channel, it will help reduce consumers' concerns about "unfair pricing."

4.1.3 Implications for omnichannel retail

In the survey of this study, the researcher found that dynamic pricing has great potential for application in omnichannel retail environments ($R^2 = 0.916$, $p < 0.001$). Dynamic pricing seems to help retailers balance demand and supply across channels while improving consumers' shopping experience in omnichannel environments.

In today's context of online and offline channel integration, establishing a fair and trusting relationship with customers and successfully identifying customer types are important prerequisites for the successful implementation of dynamic pricing.

4.2 Comparison with existing literature and assumptions

4.2.1 Alignment with existing literature

The results of this research are consistent with the core viewpoints of existing literature, especially in the research field of the impact of dynamic pricing on consumer behavior. Most literature points out that dynamic pricing can improve consumer satisfaction through personalization and flexibility, while bringing higher market adaptability. The regression analysis results of this research further confirm this, showing that there is a significant positive correlation between dynamic pricing and consumer satisfaction.

In addition, the literature also mentioned that consumers' acceptance of dynamic pricing depends largely on their perception of pricing fairness (Fornell & Larcker, 1981). The moderating effect analysis of this research (Moderating Role of Fairness and Trust) is highly consistent with this conclusion, emphasizing the key role of fairness and trust in the effectiveness of dynamic pricing strategies. For example, when consumers believe that pricing rules are opaque or unfair to specific groups, their satisfaction may drop significantly.

4.2.2 Contributions beyond existing literature

Compared with previous studies, the contribution of this research is to examine the impact of dynamic pricing in the context of Omnichannel Retail. Existing literature mainly focuses on dynamic pricing strategies in a single channel, while ignoring the complexity of consumer behavior in the context of Omnichannel integration. By comprehensively analyzing the consumer experience of Omnichannel shopping, this research finds that dynamic pricing can not only improve satisfaction in a single channel, but also enhance consumer trust in a cross-channel environment through information transparency and consistency.

In addition, mediating and moderating variables (Channel Preference, Price Sensitivity and Fairness and Trust) have rarely been systematically explored in previous studies. Through empirical analysis, this research clarifies the role of these variables as a bridge between dynamic pricing and consumer behavior, thereby expanding the scope of application of the existing theoretical framework.

4.2.3 Reflection on research assumptions

Direct and indirect effects of Dynamic Pricing

H1a: Dynamic Pricing has a positive effect on Immediate Satisfaction.

In the study results, the regression analysis between Dynamic Pricing and Immediate Satisfaction showed a significant positive correlation (Beta = 0.953, $p < 0.001$).

H1b: Dynamic Pricing indirectly affects Long-term Satisfaction through Immediate Satisfaction.

The cascading effect of Immediate Satisfaction on Long-term Satisfaction verified the indirect effect of Dynamic Pricing, while the regression analysis showed a direct positive correlation ($R^2 = 0.902$, $p < 0.001$).

The mediating role of trust

H2a: Trust in Pricing System mediates the relationship between Dynamic Pricing and Immediate Satisfaction.

Trust in Pricing System was identified as a significant mediating variable (Beta = 0.692, $p < 0.001$), enhancing the effect of Dynamic Pricing on Immediate Satisfaction.

H2b: Trust in Brand mediates the relationship between Dynamic Pricing and Immediate Satisfaction.

Trust in Brand also acts as a mediating variable, significantly enhancing the impact of Dynamic Pricing (Beta = 0.278, $p < 0.001$).

The cascading effect of satisfaction

H3a: Immediate Satisfaction has a positive impact on long-term satisfaction.

Immediate Satisfaction and Long-term Satisfaction show a strong positive correlation (Beta = 0.955, $p < 0.001$).

The role of moderating variables

H4a: Price Sensitivity mediates the relationship between Dynamic Pricing and Trust in Pricing System. Among them, it is assumed that when price sensitivity is higher, the negative impact of dynamic pricing on trust is stronger.

The results show that consumers with high price sensitivity are more sensitive to the relationship between Dynamic Pricing and Trust in the system, indicating a significant moderating effect.

H4b: Channel Preference mediates the relationship between Dynamic Pricing and Trust in Brand. Among them, it is assumed that consumers who prefer a single channel are more sensitive to the inconsistency of dynamic pricing, which affects brand trust.

The data show that consumers' channel preference significantly affects the relationship between Dynamic Pricing and brand trust, especially when online and offline are inconsistent.

The reinforcing effect of pricing transparency and channel consistency

H5a: Price Transparency enhances the positive impact of Dynamic Pricing on Trust in Pricing System.

Transparency is verified as a moderating variable that significantly and positively affects trust (Beta = 0.669, $p < 0.001$).

H5b: Omnichannel Consistency enhances the positive impact of Dynamic Pricing on Trust in Brand.

The data show that cross-channel consistency has a significant positive impact on brand trust, especially when the information consistency is high.

4.2.4 Theoretical and practical implications

Combined with the discussion of literature and research hypotheses, this research expands the applicability of dynamic pricing strategies, The theoretical significance of this research is that it enriches the theoretical framework of dynamic pricing, especially in the context of Omnichannel retail. In addition, this research also provides practical implications to help retailers better understand consumer behavior patterns in dynamic pricing strategies and design more transparent, fair and effective pricing systems.

4.3 Llimitations and future research directions

Although this research provides important insights into the impact of Dynamic Pricing in the Omnichannel Retailing environment, there are still some limitations that need to be carefully considered when interpreting the research results and provide improvement directions for future research.

The data source of this research is mainly concentrated in a specific retail industry in a fixed region, and the sample has certain regional characteristics. Objectively speaking, consumers in different countries or regions may have different cognitive habits towards Dynamic Pricing and related variables, which will lead to different attitudes towards these variables. Therefore, future research will be extended to other industries and other countries and regions to verify the applicability of the model.

The research method used in this research is a questionnaire survey, which has the following two main limitations: (1) Self-Report Bias: When answering questions about consumer satisfaction, trust, etc., participants may be influenced by social expectations or personal emotions, resulting in deviations between data results and actual behavior. (2) Cross-Sectional Data: The data in this research was collected once and cannot capture the long-term impact of dynamic pricing on consumer behavior. Therefore, future research can conduct more longitudinal studies to fully understand the causal relationship between variables.

Although the theoretical framework of this research includes key variables such as Price Fairness, Trust, and Satisfaction, because it uses quantitative rather than qualitative analysis, more complex consumer behavior patterns, such as consumers' emotional states (such as anger or joy) and social influence (such as word of mouth or recommendation), cannot be fully collected and analyzed. These missing variables may play an important role in the relationship between Dynamic Pricing and Satisfaction. Future research can include these additional moderating variables to further optimize the model.

In data analysis, this research used regression analysis and factor analysis to verify the hypothesis. However, this research lacks multilevel analysis because in an omnichannel environment, consumer behavior may be affected by multiple levels of different channel characteristics, such as the interaction effect of online and offline channels. This research did not further explore this complexity. In the complexity of dynamic pricing, different types of dynamic pricing strategies (such as discount-based dynamic pricing and dynamic price adjustment) may have different effects. This research did not conduct an in-depth classification of different types of dynamic pricing strategies, which may affect the comprehensive understanding of the research results.

Despite the above limitations, this research still provides a new perspective in the research field of Dynamic Pricing on consumer satisfaction. Future research can further improve the research model and analysis results by expanding the sample source, adopting a longitudinal research design, and introducing more variables.

CONCLUSION

The core question of this research revolves around the impact of Dynamic Pricing on Consumer Satisfaction in an Omnichannel Retail environment, focusing on whether dynamic pricing will increase or decrease consumer satisfaction; in an omnichannel retail environment, whether dynamic pricing can affect consumer behavior through mediating variables such as fairness and trust; and whether dynamic pricing strategies have the same impact on different types of consumers (such as price sensitivity), in an omnichannel environment, is a dynamic pricing strategy more applicable (e.g. channel coordination and integration). Through the analysis of this research, the conclusion is Dynamic Pricing strategy can significantly improve consumer satisfaction, especially in pricing scenarios with high transparency and fairness, consumers show higher acceptance and positive feedback on price adjustments. Dynamic pricing has outstanding advantages in enhancing personalized shopping experience and optimizing consumer long-term satisfaction. However, when price fluctuations lack transparency and fair pricing, it may lead to a decline in consumer trust, especially in groups with high price sensitivity. Dynamic pricing has shown significant flexibility and applicability in an Omnichannel environment, which not only optimizes channel coordination, but also improves consumers' brand trust.

This research fully achieved the established objectives as follows.

Application of Dynamic Pricing in Omnichannel Retail and its role in channel management: Data analysis shows that dynamic pricing strategies significantly improve consumer experience in Omnichannel environments through cross-channel price consistency and inventory coordination, while effectively resolving potential conflicts between online and offline channels.

Evaluate the dual impact of Dynamic Pricing on Consumer Satisfaction: The research verifies that the positive contributions of dynamic pricing (such as personalization and competitive pricing) far outweigh its potential negative impacts (such as reduced sense of fairness caused by price fluctuations). At the same time, the negative impacts are effectively mitigated by moderating variables (such as Fairness and Trust).

Construct a theoretical model to explain the relationship between Dynamic Pricing and Consumer Satisfaction: The research constructed a causal relationship model between dynamic pricing and consumer satisfaction through regression analysis and factor analysis, and verified the key role of mediating variables and moderating variables.

Propose strategies to optimize Dynamic Pricing: This research recommends that retailers optimize the effects of dynamic pricing by improving price transparency, achieving cross-channel consistency, and tiered pricing strategies. These strategies not only enhance consumer satisfaction and long-term satisfaction, but also achieve a balance between profitability and operational efficiency.

This research theoretically enriches the application framework of Dynamic Pricing in an Omnichannel retail environment. By analyzing the mechanism of consumer satisfaction, trust, and fairness, it further expands the theoretical boundaries of dynamic pricing. In particular, the analysis of mediating variables (Fairness and Trust) and moderating variables (Price Sensitivity and Channel Preference) provides a new perspective for the theoretical research of dynamic pricing strategies.

RECOMMENDATIONS

Based on the above analysis, this study can make the following recommendations for retailers: (1) Retailers should enhance the visibility of dynamic pricing strategies through digital tools, such as online price descriptions and quotation transparency, to enhance consumers' perception of price fairness. (2) Omnichannel retailers need to ensure the consistency of online and offline price and inventory information to reduce consumer distrust. If differentiated pricing is inevitably adopted, additional value descriptions (such as exclusive services or products) should be used to enhance consumer recognition. Set the upper and lower limits of price fluctuations to ensure that consumers perceive the rationality of price changes. (3) Formulate pricing strategies for consumers with high price sensitivity, avoid frequent price changes leading to consumer dissatisfaction, and balance individual needs with consumers' sense of fairness. (4) When formulating dynamic pricing strategies, enterprises need to fully consider the channel preference characteristics of consumers to achieve higher satisfaction. Especially for consumers who prefer specific purchase channels, enterprises need to carefully use dynamic pricing strategies to avoid its weakening effect on satisfaction. (5) Ensure that dynamic pricing strategies do not undermine consumer trust in the brand, such as avoiding price increases immediately after promotions.

Collect customer feedback on a regular basis and adjust dynamic pricing strategies in a timely manner to ensure that they meet consumer expectations. (6) Combine dynamic pricing with satisfaction programs, such as offering discounts exclusive to long-term customers. Strengthen brand commitment and increase consumers' trust in the brand through quality after-sales service. (7) Dynamic pricing needs to meet the needs of consumers quickly, such as providing preferential prices by responding to market changes in a timely manner. Enhance the match between price and service, such as providing additional value added (such as free shipping or priority service) when prices rise. (8) Focus on long-term relationship maintenance based on dynamic pricing, for example through membership programs and personalized recommendations to enhance customer engagement. Monitor customer satisfaction trends to prevent short-term price fluctuations from damaging your brand image.

This study systematically analyzes the impact of dynamic pricing on consumer satisfaction from the perspective of theory and practice, and fills the gap of dynamic pricing research in omnichannel retail environment. The research results not only deepen the academic understanding of dynamic pricing, but also provide practical suggestions for retailers to develop more efficient and fairer pricing strategies. Future studies could further expand the application scope of the model to provide more comprehensive theoretical and practical guidance for the global retail market.

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APPENDICES

Appendix 1. List of questionnaire

Hello! Thank you for participating in this survey. This survey aims to study the impact of dynamic pricing on consumer behavior and satisfaction in an omnichannel retail environment. Omnichannel retail refers to businesses operating through both online.

- Your place of residence: Asia-Pacific Region/ European Region/ Other Regions
- Your age: 18-25 years old/ 26-35 years old/ 36-45 years old/ 46 years old and above
- Your monthly income: ≤ 8,000 CNY/ 8,001-10,000 CNY/ 10,001-20,000 CNY/ ≥ 20,000 CNY
- The type of omnichannel retail you primarily use: Groceries/ Clothing & Accessories/ Home Appliances & Electronics/ Others
- The type of services you primarily use from this retailer: Online Shopping (App or Official Website)/ Offline Shopping (Physical Store)/ Both
- Your preferred shopping method: Online Shopping/ Offline Shopping/ No Particular Preference

The following questions are scored using the Likert scale, with higher agreement scores

Not At All Consistent=1 / Inconsistent=2 / Neutral=3/ Consistent=4/ Highly Consistent=5

DynamicPricing:

- I often notice price changes within a short period.
- I feel that the price changes are excessive and unacceptable.
- I think the retailer adjusts prices based on my shopping habits.
- Personalized pricing makes shopping more attractive for me.
- I understand how the retailer determines dynamic prices.

- The retailer’s pricing rules are transparent to me.
- I think price information isn’t consistent between online and offline channels.
- I find the product information (e.g., inventory, price) across channels to be consistent.

FairnessandTrust:

- The prices I pay are fair compared to other consumers.
- The process used to determine prices is fair.
- I trust the retailer’s dynamic pricing system.
- I have a high level of trust in this retailer overall.

ConsumerSatisfaction:

- I am satisfied with my recent shopping experience using the retailer’s dynamic pricing system.
- Price fluctuations have impacted my immediate shopping experience.
- Overall, I am satisfied with the retailer’s pricing strategies over time.
- I am likely to continue shopping with this retailer in the long run.
- I would recommend this retailer to my friends and family.
- Even with price changes, I am willing to keep shopping at this retailer.

Moderators:

- I am sensitive to price changes.
- Price changes significantly influence my purchase decisions.
- I prefer shopping on the retailer’s online platform.
- Channel differences affect the products I choose.

Appendix 2. SPSS export raw data (partial)

Frequencies

Statistics

		Your age:	Your monthly income:	Your place of residence:
N	Valid	262	262	262
	Missing	0	0	0
Mean		2.47	1.60	1.14
Std. Deviation		1.016	.809	.454
Minimum		1	1	1
Maximum		4	4	3

Frequency Table

Your age:

		Frequency	Percent	Valid Percent	Cumulative Percent
\alid	18-25 years old	53	20.2	20.2	20.2
	26-35 years old	82	31.3	31.3	51.5
	36-45 years old	78	29.8	29.8	81.3
	46 years old and above	49	18.7	18.7	100.0
	Total	262	100.0	100.0	

Your place of residence:

		Frequency	Percent	Valid Percent	Cumulative Percent
\alid	Asia-Pacific Region	236	90.1	90.1	90.1
	European Region	15	5.7	5.7	95.8
	Other Regions	11	4.2	4.2	100.0
	Total	262	100.0	100.0	

Frequencies

Statistics

Your monthly income:

N	Valid	262
	Missing	0
Mean		1.60
Std. Deviation		.809
Minimum		1
Maximum		4

Your monthly income:

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	≤ 8,000 CNY	144	55.0	55.0	55.0
	8,001-10,000 CNY	92	35.1	35.1	90.1
	10,001-20,000 CNY	12	4.6	4.6	94.7
	≥ 20,000 CNY	14	5.3	5.3	100.0

	Total	26 2	10 0.0	100.0

Reliability

Scale: ALL VARIABLES

Case Processing Summary

			N	%
C ases	Val id		26 2	10 0.0
	Ex cluded[a]		0	.0
	Tot al		26 2	10 0.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha	N of Items

	Based on Standardized Items	
.955	.955	8

Inter-Item Correlation Matrix

	I often notice price changes within a short period.	I feel that the price changes are excessive and unacceptable.	I think the retailer adjusts prices based on my shopping habits.	Personalized pricing makes shopping more attractive for me.
I often notice price changes within a short period.	1.000	.716	.769	.724
I feel that the price changes are excessive and unacceptable.	.716	1.000	.714	.748
I think the retailer adjusts prices based on my shopping habits.	.769	.714	1.000	.720
Personalized pricing makes shopping more attractive for me.	.724	.748	.720	1.000
I understand how the retailer determines dynamic prices.	.757	.743	.772	.709

The retailer's pricing rules are transparent to me.	.723	.776	.694	.730
I think price information isn't consistent between online and offline channels.	.737	.702	.736	.700
I find the product information (e.g., inventory, price) across channels to be consistent.	.745	.690	.776	.643

Inter-Item Correlation Matrix

	I understand how the retailer determines dynamic prices.	The retailer's pricing rules are transparent to me.	I think price information isn't consistent between online and offline channels.	I find the product information (e.g., inventory, price) across channels to be consistent.
I often notice price changes within a short period.	.757	.723	.737	.745
I feel that the price changes are excessive and unacceptable.	.743	.776	.702	.690

I think the retailer adjusts prices based on my shopping habits.	.772	.694	.736	.776
Personalized pricing makes shopping more attractive for me.	.709	.730	.700	.643
I understand how the retailer determines dynamic prices.	1.000	.714	.741	.762
The retailer's pricing rules are transparent to me.	.714	1.000	.704	.689
I think price information isn't consistent between online and offline channels.	.741	.704	1.000	.746
I find the product information (e.g., inventory, price) across channels to be consistent.	.762	.689	.746	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation

I often notice price changes within a short period.	26.62	58.957	.845	.719
I feel that the price changes are excessive and unacceptable.	26.53	57.599	.832	.714
I think the retailer adjusts prices based on my shopping habits.	26.62	59.224	.846	.735
Personalized pricing makes shopping more attractive for me.	26.55	58.341	.810	.679
I understand how the retailer determines dynamic prices.	26.59	59.063	.850	.729
The retailer’s pricing rules are transparent to me.	26.63	58.327	.821	.694
I think price information isn’t consistent between online and offline channels.	26.60	59.445	.825	.687
I find the product information (e.g., inventory, price) across channels to be consistent.	26.68	60.119	.821	.712

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I often notice price changes within a short period.	.948
I feel that the price changes are excessive and unacceptable.	.949
I think the retailer adjusts prices based on my shopping habits.	.948
Personalized pricing makes shopping more attractive for me.	.950
I understand how the retailer determines dynamic prices.	.948
The retailer's pricing rules are transparent to me.	.949
I think price information isn't consistent between online and offline channels.	.949
I find the product information (e.g., inventory, price) across	.949

channels to be consistent.

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	262	100.0
	Excluded[a]	0	.0
	Total	262	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha	N of Items

	Based on Standardized Items	
.905	.905	4

Inter-Item Correlation Matrix

	The prices I pay are fair compared to other consumers.	The process used to determine prices is fair.	I trust the retailer’s dynamic pricing system.	I have a high level of trust in this retailer overall.
The prices I pay are fair compared to other consumers.	1.000	.729	.733	.697
The process used to determine prices is fair.	.729	1.000	.706	.678
I trust the retailer’s dynamic pricing system.	.733	.706	1.000	.689
I have a high level of trust in this retailer overall.	.697	.678	.689	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation

The prices I pay are fair compared to other consumers.	11.29	10.415	.808	.654
The process used to determine prices is fair.	11.31	10.469	.785	.619
I trust the retailer's dynamic pricing system.	11.32	10.395	.793	.630
I have a high level of trust in this retailer overall.	11.35	10.603	.762	.581

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
The prices I pay are fair compared to other consumers.	.870
The process used to determine prices is fair.	.878
I trust the retailer's dynamic pricing system.	.876
I have a high level of trust in this retailer overall.	.887

Reliability

Scale: ALL VARIABLES

Case Processing Summary

			N	%
Cases	Valid		262	100.0
	Excluded[a]		0	.0
	Total		262	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.939	.939	7

Inter-Item Correlation Matrix

	I have a high level of trust in this retailer overall.	I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	Price fluctuations have impacted my immediate shopping experience.	Overall, I am satisfied with the retailer's pricing strategies over time.
I have a high level of trust in this retailer overall.	1.000	.681	.637	.708
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	.681	1.000	.665	.745
Price fluctuations have impacted my immediate shopping experience.	.637	.665	1.000	.640
Overall, I am satisfied with the retailer's pricing strategies over time.	.708	.745	.640	1.000
I am likely to continue shopping with this retailer in the long run.	.616	.701	.635	.703

I would recommend this retailer to my friends and family.	.663	.746	.691	.746
Even with price changes, I am willing to keep shopping at this retailer.	.659	.705	.694	.703

Inter-Item Correlation Matrix

	I am likely to continue shopping with this retailer in the long run.	I would recommend this retailer to my friends and family.	Even with price changes, I am willing to keep shopping at this retailer.
I have a high level of trust in this retailer overall.	.616	.663	.659
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	.701	.746	.705
Price fluctuations have impacted my immediate shopping experience.	.635	.691	.694
Overall, I am satisfied with the retailer's	.703	.746	.703

pricing strategies over time.			
I am likely to continue shopping with this retailer in the long run.	1.000	.732	.681
I would recommend this retailer to my friends and family.	.732	1.000	.683
Even with price changes, I am willing to keep shopping at this retailer.	.681	.683	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
I have a high level of trust in this retailer overall.	22.50	39.431	.764	.595
I am satisfied with my recent shopping experience using the retailer’s dynamic pricing system.	22.48	38.542	.826	.688
Price fluctuations have impacted my	22.50	39.040	.764	.596

immediate shopping experience.				
Overall, I am satisfied with the retailer's pricing strategies over time.	22.48	38.404	.826	.696
I am likely to continue shopping with this retailer in the long run.	22.59	40.357	.787	.633
I would recommend this retailer to my friends and family.	22.45	38.670	.829	.702
Even with price changes, I am willing to keep shopping at this retailer.	22.47	38.158	.800	.645

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I have a high level of trust in this retailer overall.	.932
I am satisfied with my recent shopping experience using the	.927

retailer's dynamic pricing system.	
Price fluctuations have impacted my immediate shopping experience.	.932
Overall, I am satisfied with the retailer's pricing strategies over time.	.927
I am likely to continue shopping with this retailer in the long run.	.930
I would recommend this retailer to my friends and family.	.926
Even with price changes, I am willing to keep shopping at this retailer.	.929

Reliability

Scale: ALL VARIABLES

Case Processing Summary

			N	%
Cases	Valid		262	100.0
	Excluded[a]		0	.0
	Total		262	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.917	.918	4

Inter-Item Correlation Matrix

	I am sensitive to price changes.	Price changes significantly influence my	I prefer shopping on the retailer's online platform.	Channel differences affect the products I choose.

		purchase decisions.		
I am sensitive to price changes.	1.000	.753	.747	.719
Price changes significantly influence my purchase decisions.	.753	1.000	.760	.715
I prefer shopping on the retailer's online platform.	.747	.760	1.000	.720
Channel differences affect the products I choose.	.719	.715	.720	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation
I am sensitive to price changes.	11.29	10.803	.816	.667
Price changes significantly influence my purchase decisions.	11.33	11.034	.820	.676
I prefer shopping on the retailer's online platform.	11.27	10.742	.820	.675
Channel differences affect the products I choose.	11.30	10.662	.786	.617

Item-Total Statistics

	Cronbach's Alpha if Item Deleted
I am sensitive to price changes.	.890
Price changes significantly influence my purchase decisions.	.889
I prefer shopping on the retailer’s online platform.	.889
Channel differences affect the products I choose.	.901

Factor Analysis

Communalities

	Initial	Extraction
I often notice price changes within a short period.	1.000	.782

I feel that the price changes are excessive and unacceptable.	1.000	.760
I think the retailer adjusts prices based on my shopping habits.	1.000	.785
Personalized pricing makes shopping more attractive for me.	1.000	.730
I understand how the retailer determines dynamic prices.	1.000	.789
The retailer's pricing rules are transparent to me.	1.000	.744
I think price information isn't consistent between online and offline channels.	1.000	.754
I find the product information (e.g., inventory, price) across channels to be consistent.	1.000	.751

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %
1	6.096	76.195	76.195	6.096	76.195	76.195
2	.440	5.503	81.698			
3	.298	3.731	85.429			
4	.278	3.475	88.904			
5	.253	3.158	92.062			
6	.229	2.864	94.926			
7	.208	2.599	97.524			
8	.198	2.476	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
I understand how the retailer determines dynamic prices.	.888

I think the retailer adjusts prices based on my shopping habits.	.886
I often notice price changes within a short period.	.884
I feel that the price changes are excessive and unacceptable.	.872
I think price information isn't consistent between online and offline channels.	.868
I find the product information (e.g., inventory, price) across channels to be consistent.	.867
The retailer's pricing rules are transparent to me.	.863
Personalized pricing makes shopping more attractive for me.	.855

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Rotated Component Matrix[a]

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

Factor Analysis

Communalities

	Initial	Extraction
The prices I pay are fair compared to other consumers.	1.000	.803
The process used to determine prices is fair.	1.000	.777
I trust the retailer's dynamic pricing system.	1.000	.786
I have a high level of trust in this retailer overall.	1.000	.750

Extraction Method: Principal Component Analysis.

Rotated Component Matrix[a]

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

Factor Analysis

Communalities

	Initial	Extraction
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	1.000	.775
Price fluctuations have impacted my	1.000	.689

immediate shopping experience.		
Overall, I am satisfied with the retailer’s pricing strategies over time.	1.000	.766
I am likely to continue shopping with this retailer in the long run.	1.000	.736
I would recommend this retailer to my friends and family.	1.000	.788
Even with price changes, I am willing to keep shopping at this retailer.	1.000	.739

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.492	74.872	74.872	4.492	74.872	74.872
2	.401	6.684	81.557			

3	.317	5.290	86.847
4	.308	5.129	91.975
5	.253	4.222	96.197
6	.228	3.803	100.000

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
I would recommend this retailer to my friends and family.	.887
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	.880
Overall, I am satisfied with the retailer's pricing strategies over time.	.875
Even with price changes, I am willing to	.860

keep shopping at this retailer.	
I am likely to continue shopping with this retailer in the long run.	.858
Price fluctuations have impacted my immediate shopping experience.	.830

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Rotated Component Matrix[a]

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

Factor Analysis

Communalities

	Initial	Extraction
I am sensitive to price changes.	1.000	.808
Price changes significantly influence my purchase decisions.	1.000	.813
I prefer shopping on the retailer's online platform.	1.000	.813
Channel differences affect the products I choose.	1.000	.773

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.207	80.187	80.187	3.207	80.187	80.187
2	.300	7.497	87.685			

3	.254	6.351	94.035
4	.239	5.965	100.000

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
Price changes significantly influence my purchase decisions.	.902
I prefer shopping on the retailer's online platform.	.902
I am sensitive to price changes.	.899
Channel differences affect the products I choose.	.879

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Rotated Component Matrix[a]

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

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
DynamicPricing_Mean	262	1.00	4.88	3.8001	1.09271
FairnessTrust_Mean	262	1.00	5.00	3.7729	1.06199
ConsumerSatisfaction_Mean	262	1.17	4.83	3.7500	1.04657
Moderators_Mean	262	1.00	5.00	3.7653	1.08112
Valid N (listwise)	262				

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.953
Bartlett's Test of Sphericity	Approx. Chi-Square	1941.914
	df	28
	Sig.	<.001

Communalities

	Initial	Extraction
I often notice price changes within a short period.	1.000	.782
I feel that the price changes are excessive and unacceptable.	1.000	.760
I think the retailer adjusts prices based on my shopping habits.	1.000	.785
Personalized pricing makes shopping more attractive for me.	1.000	.730

I understand how the retailer determines dynamic prices.	1.000	.789
The retailer’s pricing rules are transparent to me.	1.000	.744
I think price information isn’t consistent between online and offline channels.	1.000	.754
I find the product information (e.g., inventory, price) across channels to be consistent.	1.000	.751

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.096	76.195	76.195	6.096	76.195	76.195
2	.440	5.503	81.698			

3	.298	3.731	85.429
4	.278	3.475	88.904
5	.253	3.158	92.062
6	.229	2.864	94.926
7	.208	2.599	97.524
8	.198	2.476	100.000

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
I often notice price changes within a short period.	.884
I feel that the price changes are excessive and unacceptable.	.872
I think the retailer adjusts prices based on my shopping habits.	.886

Personalized pricing makes shopping more attractive for me.	.855
I understand how the retailer determines dynamic prices.	.888
The retailer's pricing rules are transparent to me.	.863
I think price information isn't consistent between online and offline channels.	.868
I find the product information (e.g., inventory, price) across channels to be consistent.	.867

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.852
Bartlett's Test of Sphericity	Approx. Chi-Square	658.872
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
The prices I pay are fair compared to other consumers.	1.000	.803
The process used to determine prices is fair.	1.000	.777
I trust the retailer's dynamic pricing system.	1.000	.786
I have a high level of trust in this retailer overall.	1.000	.750

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues	Extraction Sums of Squared Loadings

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.117	77.916	77.916	3.117	77.916	77.916
2	.330	8.261	86.177			
3	.293	7.327	93.504			
4	.260	6.496	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
The prices I pay are fair compared to other consumers.	.896
The process used to determine prices is fair.	.882
I trust the retailer's dynamic pricing system.	.887
I have a high level of trust in this retailer overall.	.866

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.925
Bartlett's Test of Sphericity	Approx. Chi-Square	1184.514
	df	15
	Sig.	<.001

Communalities

	Initial	Extraction
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	1.000	.775
Price fluctuations have impacted my immediate shopping experience.	1.000	.689

Overall, I am satisfied with the retailer's pricing strategies over time.	1.000	.766
I am likely to continue shopping with this retailer in the long run.	1.000	.736
I would recommend this retailer to my friends and family.	1.000	.788
Even with price changes, I am willing to keep shopping at this retailer.	1.000	.739

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %
1	4.492	74.872	74.872	4.492	74.872	74.872
2	.401	6.684	81.557			
3	.317	5.290	86.847			

4	.308	5.129	91.975
5	.253	4.222	96.197
6	.228	3.803	100.000

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
I am satisfied with my recent shopping experience using the retailer's dynamic pricing system.	.880
Price fluctuations have impacted my immediate shopping experience.	.830
Overall, I am satisfied with the retailer's pricing strategies over time.	.875
I am likely to continue shopping with this retailer in the long run.	.858

I would recommend this retailer to my friends and family.	.887
Even with price changes, I am willing to keep shopping at this retailer.	.860

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.858
Bartlett's Test of Sphericity	Approx. Chi-Square	735.655
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction

I am sensitive to price changes.	1.000	.808
Price changes significantly influence my purchase decisions.	1.000	.813
I prefer shopping on the retailer's online platform.	1.000	.813
Channel differences affect the products I choose.	1.000	.773

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.207	80.187	80.187	3.207	80.187	80.187
2	.300	7.497	87.685			
3	.254	6.351	94.035			
4	.239	5.965	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
I am sensitive to price changes.	.899
Price changes significantly influence my purchase decisions.	.902
I prefer shopping on the retailer's online platform.	.902
Channel differences affect the products I choose.	.879

Extraction Method: Principal Component Analysis.[a]

a. 1 components extracted.

Oneway

Descriptives

		N	Mean	Std. Deviation
DynamicPricing_Mean	18-25 years old	53	3.7830	1.06748

	26-35 years old	82	3.7957	1.12363
	36-45 years old	78	3.8381	1.16864
	46 years old and above	49	3.7653	.96577
	Total	262	3.8001	1.09271
FairnessTrust_Mean	18-25 years old	53	3.7453	.98241
	26-35 years old	82	3.8171	1.14264
	36-45 years old	78	3.7949	1.09733
	46 years old and above	49	3.6939	.96995
	Total	262	3.7729	1.06199
ConsumerSatisfaction_Mean	18-25 years old	53	3.7107	.95360
	26-35 years old	82	3.7561	1.07477
	36-45 years old	78	3.7714	1.11306
	46 years old and above	49	3.7483	1.01557
	Total	262	3.7500	1.04657

Moderators_Mean	18-25 years old	53	3.7358	1.10224
	26-35 years old	82	3.7835	1.14110
	36-45 years old	78	3.8013	1.03616
	46 years old and above	49	3.7092	1.05493
	Total	262	3.7653	1.08112

Descriptives

		Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound
DynamicPricing_Mean	18-25 years old	.14663	3.4888	4.0773
	26-35 years old	.12408	3.5488	4.0426
	36-45 years old	.13232	3.5747	4.1016
	46 years old and above	.13797	3.4879	4.0427
	Total	.06751	3.6672	3.9330
FairnessTrust_Mean	18-25 years old	.13494	3.4745	4.0161

	26-35 years old	.12618	3.5660	4.0681
	36-45 years old	.12425	3.5475	4.0423
	46 years old and above	.13856	3.4153	3.9725
	Total	.06561	3.6437	3.9021
ConsumerSatisfaction_Mean	18-25 years old	.13099	3.4478	3.9735
	26-35 years old	.11869	3.5199	3.9923
	36-45 years old	.12603	3.5204	4.0223
	46 years old and above	.14508	3.4566	4.0400
	Total	.06466	3.6227	3.8773
Moderators_Mean	18-25 years old	.15140	3.4320	4.0397
	26-35 years old	.12601	3.5328	4.0343
	36-45 years old	.11732	3.5677	4.0349
	46 years old and above	.15070	3.4062	4.0122
	Total	.06679	3.6337	3.8968