The Impact of Online Dynamic Pricing Strategies on Consumers' Trust, Fairness Perceptions, and Loyalty

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AFFIDAVIT

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ABSTRACT

With the rapid boom of e-commerce, numerous online retailers joined this fierce competition to make profit. By leveraging the dynamic pricing strategies, online retailers could maximize their profit and achieve specific organizational goals such as providing excellent consumer service and creating business merit. Nevertheless, inappropriate dynamic pricing strategies might backfire: Online retailers who frequently change the price might cause a negative effect on consumers' perception of price fairness, and this violation of fairness negatively affects consumers' trust, as well as the satisfaction toward online retailer.

This study investigates the relationships between price fairness perception, trust, satisfaction, and consumer loyalty under a frequent price change scenario. Structured online surveys were conducted by employing a one-factor, two-level, fractional factorial research design. The statistical analysis showed a significant relationship between those cognitive perceptions (fairness perception, trust, satisfaction, loyalty); hence, it can be concluded that consumer trust and loyalty are negatively affected if the price fairness is perceived negatively as caused by frequent price changes. In addition, the analysis also reveals that the degree of the consumers' trust increases is positively related to consumer satisfaction, resulting in consumer loyalty.

The entire study provides the online retailers a profound theoretical foundation based on a comprehensive literature review on extant studies dealing with the dynamic pricing strategies. Benefit from the literature review, this study had chance to bridging the gap between online consumers’ price fairness studies and online consumer trust studies. Moreover, even this study failed attempt to disclose the dynamic pricing strategy due to the comprehensiveness of the manipulation control question, but this attempt still illustrated a direction for the future scholars’ research design. Last, but not least, this study also emphasizes the impact of trust-building between consumers and online retailers; therefore, long-term cooperative relations and mutual benefit are expected to come.

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1. INTRODUCTION

Under the circumstances of COVID-19, industries such as tourism and traditional retail stores have suffered a hard blow from certain government restrictions and policies. Based on the latest report from IBM's U.S. retail index, the number of department stores and sales has gone through a significant decline by 25% in the first quarter of 2020, and it deteriorates to 75% in the second quarter (Perez, 2020). These numbers indicate that department stores are expected to decline continuously. However, the e-commerce business was planned to increase by approximately 20% in 2020, which is a significant year alone (Perez, 2020). Not coincidentally, as the industry tycoon in e-commerce, Amazon has become one of the world's largest companies during the COVID-19 pandemic (Klebnikov, 2020). According to Klebnikov (2020), Amazon's market capitalization currently has gained $570 billion, and its stock has increased by more than 60% this year. Amazon's rapid growth directly reflected that more people have begun shopping online rather than going to physical shops. Digital shopping as the inexorable trend in the near future has accelerated its transition from physical shopping by five years (Perez, 2020). As stated by the WTO (2019) world trade statistical review, current trade statistics cannot quantify and represent the international trade level to digital transactions, because digitally ordered and digitally delivered goods or services are hardly being tracked. This evidence shows that e-commerce is becoming the major trend of retailing. Based on Quellette's (2020) research, the global online shopping market scale is predicted to reach 4 trillion in 2020, and retailers will keep focusing on online businesses and expanding to the mobile shopping section. Since the pandemic is reshaping the world and people's lives, it is vital to realize what impact could be created by the e-commerce industry and online retailers.

E-commerce, as the name indicates, means digitally embedded commercial transactions between and among organizations and individuals. "E-Commerce or Electronic Commerce means buying and selling of goods, products, or services over the internet" (Electronic Commerce, 2019). As the current era is the age of a digitally enabled social and commercial life, with the development of information technologies, it seems that e-commerce will eventually influence almost all commerce by 2050 (Laudon & Traver, 2007). Laudon and Traver (2007) mentioned that e-commerce had been categorized and characterized in different types such as Business-to-Consumer, Business-to-Business, Consumer-to-Consumer, Peer-to-Peer.

Since this paper aims to determine the impact of online retail's dynamic pricing strategies, Business-to-Consumer e-commerce is the focus of this thesis.

Offline retailers often implement pricing strategies to maximize the business's profit, and so do online retailers. Online pricing strategies also consider consumer segments, market conditions, competitor actions and reactions, trade margins, and input costs (The Economic Times, 2020). These considerations are indicators that determine the online pricing which is unlikely to be fixed, and it quite often stays dynamic to match with different consumer's willingness to pay (Laudon & Traver, 2007). With the booming of e-commerce, dynamic pricing has become the latest pricing trend that enables online retail businesses to set flexible prices for products based on current market demands. It also refers to selling the product at different prices toward different consumer segments, which represents the price discrimination (Dasgupta and Das 2000). Online retailers are deeply aware that tactically and dynamically product pricing could maximize the expected revenue. The business organizations could also remain competitive in the market against their rival companies by adjusting the prices to a proper level. So, in other words, dynamic pricing can also be considered as one of the powerful strategies of adapting the prices of goods and services constantly in response to the forces of supply and demand. Conducting a dynamic pricing strategy could solve the retailer's typical issues, such as storage issues and time scale issues. Retailers often lack short-term control of the stock and have to face the upcoming deadline for certain products due to perishability (Gallego & van Ryzin, 1994). The adoption of retail and other industries toward dynamic pricing strategies has increased from past years due to three reasons: advanced technology, data availability, and data analyzing tools. According to Elmaghraby and Keskinocak (2003), new technologies allowed price makers to change the price easily in order to adapt to dynamic factors. Also, the availability of demand data has increased compared to the past, and this phenomenon has triggered the development of decision-making tools for analyzing those data as a natural result.

Some late-stage adapters might still be suspicious about the high cost of tracking all those consumer's data. However, new technologies enabled retailers to gather consumer's consumption, demographic, and preferences information at a relatively low cost and exploit them for other purposes too (Elmaghraby and Keskinocak, 2003). Based on the actual practices, dynamic pricing could also be determined by a systematic factor such as time scale and unsystematic factors like weather (Phillips et al., 2006). It is worth noting that leading retailers nowadays started to apply machine learning technology for dynamic pricing. This could help retailers measure their product's price elasticity and demand curve according to the big data (7Learnings.com, 2020). In fact, when business organizations have aimed to tailor the price of goods and services to fulfill a certain level of specific customer preferences, big data can be a great help in order to recognize and understand such patterns of customer’s tastes and preferences.

1.1 Problem Statement and Objectives

In the real world, the fairness towards price is challenging to maintain and regulate at all times, because the consumers perceive the price differently. For example, it happens that consumer A bought a long-expected trendy jacket from retailer X with price P1, and a few days later, the retailer X realizes that the jacket is outdated and decides to sell it at a much cheaper price P2. When consumer A notices this decrease in price P2, they might feel very unhappy about it, because consumer A has certainly made a loss and paid more than necessary for the jacket. As a rational consumer, the one who is facing different pricing at all times, is dynamic pricing a fair strategy experienced by consumers? Price change would create a significant level of confusion for such general and rational consumers since the consumers have to choose between various price ranges for the same product. Quiet often, consumers do not have choice or not even notice when dynamic pricing strategy is applied, so the changes in prices caused by dynamic pricing do not alter the product's satisfaction level or utility, which actually causes a colossal disadvantage for such rational customers (Weisstein, 2013).

To answer this question from an economic perspective, consumers' demand is tied up with their willingness to pay, and they could decide either to pay for the product, or wait when there is a sale or lower price. Economically speaking, consumer A shall be overall comfortable with dynamic pricing because he bought the jacket one day earlier (so the excitement obtained earlier) and agreed with the price he paid. However, consumer A is not that happy and felt unfair in reality later. Also, when consumers are overwhelmed by those massive online pricing strategies, how do they respond to them? Do consumers trust online retailers who employ dynamic pricing strategies? These questions are the interest of this particular research paper.

Against this background, the author has developed two research questions regarding the topic ***The impact of Online Retail's Dynamic Pricing Strategies*** on Consumer Behaviors.

- RQ1: How do dynamic online pricing strategies affect consumers’ perception of price fairness, trust, and loyalty toward online retailers?
- RQ2: How does the consumers’ trust toward dynamic online pricing influence consumers' satisfaction and loyalty to online retailers?

According to the study done by Rohani and Nazari (2012), consumers' trust towards online retail shops could reflect actions like more purchases through the same retailer, recommending shops to friends or relatives constantly, and many more. The ultimate goal of the thesis is to determine how a dynamic pricing strategy will effectively influence consumers' overall behavior, such as trust and loyalty.

It is important to note that the impact of online retail’s dynamic pricing strategies is like a double edge. It creates both impacts on consumers and retailers. To find out the actual impacts on retailers, the author shall collaborate with a real-life online retailer to empirically track their features under different dynamic pricing strategies. However, due to the main focus and the limitations of this study, the impacts on retailers will be revealed in the following chapters of the literature review.

2 LITERATURE REVIEW

This chapter reviewes a large number of articles dealing with the topic dynamic pricing. In detail, it breaks down the topic into seven significant focuses, which will help the readers better understand the mechanism of online dynamic pricing strategy and the formation of trust in an online shopping context. Moreover, this chapter reviewes the possible relationships between trust and associated consumer behaviors such as consumer satisfaction and consumer loyalty. The author has also attempted to find out the linkages between dynamic pricing and consumer trust.

2.1 Online Shopping vs Offline Shopping

This thesis's topic is to determine the impact of online retail's dynamic pricing strategies. Online dynamic pricing strategy as a tool commonly used by online retails can be considered as one attribute of online shopping. Hence, it is necessary to shortly review online shopping's development and impact on consumers. By comparing the online shopping to offline shopping, a throughout discussion of the advantages and disadvantages of online shopping could provide readers with a better understanding of the overall topic and the research.

As mentioned in Quellette's (2020) research, as e-commerce has become the major trend of trade, which raised exponential growth of online shopping, the global online shopping market scale is predicted to reach four trillion in 2020. With the fast penetration of regular internet users, not only the number of online shoppers grow, but the volume of purchases has also increased over-proportionally (Perea y Monsuwé et al., 2004). Aron et al. (2005, as cited in Haugtvedt et al., 2005) argued that within the massive development of online shopping, the impact of online shopping has become apparent in comparison to offline shopping. In a study by Kavya (2016), online shopping's success could be reflected on offline retailer's challenges. Kavya (2016) highlighted several challenges for offline retailers: high costs, limited regulations, and high competition. High costs consist of operational costs, for instance, the cost for buying land, the cost for paying rent, and salary. Regulations could be understood in terms of trade rules or lockdowns launched by the government. The last challenge is the high competition which makes it difficult to offline retailers to stay unique among the massive competitors (Kavya, 2016). These offline retailers' challenges just foiled the characteristics of online shopping, which is flexible, cost-saving, and could be reached by broad segments of consumers. Product and price information could be displayed rapidly and extensively through a screen, so the consumers could rationally make comparisons between the features of different brands (Haugtvedt et al., 2005). Jain (2020) has summarized the advantages of online shopping:

- The convenience, it's available 24/7 (saves time)
- It gives the consumer a chance to find better prices (Price Comparison, on sale)
- It allows the consumer to have a variety of choices
- No crowds and pressures
- It preserves consumer's discreet purchase privacy

In contrast, Haliem (2019) holds a different view toward online shopping and listed several disadvantages as support:

- The risk of fraud is high (non-original items)
- Lack of communication with the seller
- Privacy and security issue (personal information leaking, payment security)
- To receive/return shipment might be complicated
- Time-consuming

Haugtvedt et al. (2005) have also proposed similar views that lack of personal interaction, inability to inspect the product, and issues regarding delivery and information exchange process have been realized as the disadvantage of online shopping.

Relate the advantages and disadvantages of online shopping to the thesis topic, online shopping provides the consumer a chance to find a better price, though by manipulating dynamic pricing strategies, the consumer might invest plenty of time finding an "out of date" price, which lessens their trust. The following subchapters will expose more connections between dynamic pricing strategy and consumers' trust.

2.2 Dynamic Pricing

The adjective word "dynamic" is used here to modify pricing, which indicates that the price is fluctant based on different factors. As explained by Black et al. (2018), imagine the online store is currently facing less goods in stock. E-commerce owners often raise the price to reflect the shortages. Another fact, store owner might change the price because of the competitors' reaction. It could also be the owner's personal decision that raises the price for the last stock units to help achieve specific sales goals etc. Nowadays, price change is just affected by many uncertain factors. According to Black et al. (2018), dynamic pricing is a pricing strategy that takes both external and internal influences to control the price of products.

To get an overview, dynamic strategies commonly used by online vendors are: (Bertulli, 2019; Pascu, 2020; Popovic, 2020):

- Segmented Pricing: offer different prices to different consumer segments (high-value customers charged high price)
- Time-based Pricing: charge more for providing faster services (package arrives the same day ordered), charge more for loyal consumer's priority (fashion brands new release), charge less for consumers who are early interested (early-birds discount)
- Peaking Pricing: charge more due to the high market demand period/peak hours
- Penetration Pricing: new products enter the market with lower price compared to the market price; the goal is to reach a large market share
- Random Market Fluctuations: adjust prices according to various random factors
- Competition Driven Pricing: actively adjust the price according to competitors.

2.2.1 Factors that Affect Dynamic Pricing

For business organizations to decide various ranges of price changes in their product, it requires a proper examination and analysis of various crucial factors within such processes. In order to determine a dynamic pricing strategy, business organizations have to determine and dictate the relevant factors like that of time scale, weather, customer relationship, the elasticity of demand, and many more (Victor et al. 2018). When such multiple factors affect the price range of a particular product and services, it is essential that the business organizations take such factors into consideration.

- **Time Scale and Real-Time**

For a dynamic pricing strategy, the real-time scale is the core element since dynamic pricing's main objective is to provide optimal prices to the consumer as per adjustments required. In fact, the whole idea behind a dynamic pricing strategy is to gather data and information to automatically specify the optimal price (Den et al., 2015). To be precise, Den et al. (2015) further explained that online retailers want to perform all such actions in real-time so they can maximize their revenue. For instance, if a customer is on the verge of making a transaction, a dynamic pricing system could check whether the particular customer has made any previous purchase with the company or not. Based on the history of the purchase transaction, the dynamic pricing strategy can recommend other products or even provide reasonable prices to attract customers. Not only that, but the particular idea can also be adapted to the issue of inventory of companies. In real-time, the companies could automatically check whether a company is liable for a discount or any other financial benefits. While this particular process is evident more in B2C (Business to Customers) format, it could also be adopted in B2B settings (Wang et al. 2011). Unlike the B2C settings, the dynamic pricing strategy can accompany the company's sales department to empower various price changes at the process of price negotiation (B2B).

Similarly, the time scale is also essential for a dynamic pricing strategy since online retailers have to face the situation of variation in customer demand over a period of time. Some time frames can be busier than other time periods, especially when customers make a huge demand in a specific time period. It holds true for online retailers, especially when they provide massive discounts and gifts to the customers. In fact, there is no universal rule or schedule for the customers to line up their purchase requests in online retailers. Even in online retailers, the website of the company can gain high traffic in a certain period of the day and low traffic in others (Lebedeva, 2017). Hence, it is also essential to know various changes in such time frames so that retailers can further develop the required changes to the price. In fact, a machine learning algorithm can help to adjust the strategy on the basis of various changes in demand and detect various essential patterns to predict the changes in demand of a particular good or service (Lin 2006). By responding in real-time only, online retailers can entice the customers at the right time. As a matter of fact, if a dynamic pricing strategy only considered the price changes without providing such changes in time, it would be a useless strategy. In fact, one cannot gain maximum revenue without acting on time and providing required discounts to price. A practical example would be “Black Friday” online flash sales.

- **Weather**

Like time, the weather also plays an essential role in a dynamic pricing strategy, and in many cases, it would determine how a dynamic pricing strategy should be formulated. A research paper has explored and analyzed the situation of how various factors like day of the week, opponent, promotions, and weather act as the determinants of dynamic pricing strategy (Paul and Weinbach 2013, p. 152). As per the study, it was found that weather remained a considerable determinant to influence the pricing premiums in Major League Baseball. Indeed, weather can directly hamper the demand for tickets on a particular time period by causing fluctuations in the price level eventually. In fact, the attendants in the baseball team are determined from weather conditions as, in severe weather conditions, people are not interested in visiting the stadium and paying for the prices.

Similarly, another study has tried to look at the 15-month experimental tariff of electricity production between the time period of 2003 and 2004 in California and analyzed how the weather has impacted the pricing strategies. As per the findings, it was found that price responsiveness is determined largely by temperatures, as power load curves were more significant in the summer rather than winter. At large, it was found that hot weather was more significant than cold and mild weather. To be precise, the average demand reduction in the manual response group of the research study was 0.23 kW per home in hot weather, 0.03 kW per home in mild weather, and 0.07 kW per home in cold weather. This has shown that differences in weather can largely determine electricity production, and eventually, it will also influence the responsiveness of consumers accordingly. The examples for online retails are numerous, such as the online price of barbecue grill, leather gloves, sunglasses, and raincoats are all mattered by weather change (Weather and eCommerce, 2014).

- **Competitor's Price**

Since the e-commerce industry has developed into one of the fast-growing industries, online retailers have adopted to change the prices of their products within a short period of time (Mahajan, 2020). More specifically, within a day, online retailers can create multiple price alterations. It is essential for the companies to consider the internal factors at all times, but they also have to consider the external factors like that of competitor's price (Kartiwi et al., 2018). In addition, the online retailers need to explore and analyze competitors' data so that they can create benchmark price levels and know the position in the market. In fact, considering the competitor's price, a dynamic pricing strategy can help to adjust the prices to keep up with other online retailers. By learning about rival companies, the online retailers can know whether to increase, decrease or even bring no change in the price level. A study has shown how optimized self-adaptive pricing strategies have resulted in bringing optimal solutions under duopoly competition scenarios. Using the competitor's price and response to it as input for the model, the study has shown that one can control both short and long-term profits mainly by anticipating the competitor's response strategy (Scholsser and Richly, 2019). In fact, the researchers have provided a range of optimized repricing strategies ranging from avoiding extreme prices, making slight undercut in prices, restoration of the price level, and forcing the competitors to raise the price level on a severe level. This all has shown that the competitor's price is an essential component in determining and formulating a dynamic pricing strategy; excluding it would make an incomplete dynamic pricing strategy. Knowing the competitor's price and adjusting as per them is always essential, but the online retailer also has to make sure that the lowering of the price should not touch the margin of cost at all. In the process of automated reciprocals to various adjustments in price, a dynamic pricing system should be set in such a manner that price would never cut into costs (Liu et al., 2019).

- **Organizational Goals**

Organizational goals can be considered as the guiding pathway to direct and lead the actions of any company (Gagne 2018). Thus, in the case of online retailers to formulate a dynamic pricing strategy, the online retailers would require that dynamic pricing should fulfill the organizational goal. It goes by without saying that any pricing strategy should be developed in such a manner that it would align with the organizational goal. Variations and differences in various goals of organizations can lead to the development of various pricing strategies. For instance, if an online retailer wants to build a high-end brand value, the prices of products should not drop from the scope of a premium range. It would create a huge contrast and contradiction between the pricing strategy and the organizational goals. Likewise, if an e-commerce organization wants to become a cost-leader, it would be better for such organization to lower the prices as much as possible. Also, a pricing strategy can be different in various ranges depending on whether the organization wants to impose such pricing strategy on a short-term or long-term basis. So, it is always essential that the pricing strategy should be formulated keeping the organizational goal in mind, so that it can eventually help to achieve such goals (Thompson, Jr., 1984).

- **Elasticity of Demand**

In simple terms, the elasticity of demand refers to an economic measure to examine the change in quantity demanded in relation to the change in price (Fibich et al. 2005). Since the price level of a product or service is mostly dependent on the forces of demand and supply, the elasticity of demand will help to know what kinds of changes in demand cause the changes in the price level of goods and services. Indeed, if a demand for a good is known as elastic, even a small decrease in price can attract people to make a significant level of demand for products. Contrary to that, if the demand for a particular good is inelastic, there would be almost no change in demand for such goods (Fibich et al., 2005; Pindyck & Rubinfeld, 2013). Accordingly, while implementing a dynamic pricing strategy, businesses have to make sure that the elasticity of demand should not be volatile to change with minute external forces. Those temporary external forces guide and direct the online retail business houses to make the elasticity of demand as constant as possible without bringing fluctuations at all. As a dynamic pricing strategy cannot exclude the constant increase and decrease in the price level, it should not bring devastative changes in the demand of the product unless it would bring disappointing outcomes (lose credit with consumer, loss of sales). Before employing the dynamic pricing strategy, retailers should be aware of various changes it would bring to sales, which can also be done by looking at vast historical data of companies. Thence, it can be said that without the inclusion of elasticity of demand, it would be almost impossible for online retailers to formulate and regulate a dynamic pricing strategy (Fibich et al., 2005).

2.2.2 Rule-Based Dynamic Pricing

While price tends to keep on changing under a dynamic pricing strategy, rule-based dynamic pricing strategy bounds such changes of prices within a particular set of rules or law. "Rules-based pricing is the default methodology in traditional revenue management and though these rules provide some control, with increased complexity they often breakdown" (Dynamic Pricing vs. Rules-based Pricing, 2019). Unlike the machine learning approach of dynamic pricing, this particular approach relies on instructions, where there is no learning between the process. So, this particular approach utilizes the existing knowledge base, especially from the domain expert knowledge. Mostly the rules formed in such an approach are formulated in the form of various if-then statements, which further creates a set of instructions for the system. Since the rule-based solutions have to rely mostly on predetermined sets of rules and laws, it does not possess a proper level of flexibility (Cosgun et al., 2012). In other words, it can be said that such a lack of flexibility does not allow the system to add, delete, or adjust as per changes in the environment or other unprecedented events (Schwind and Oliver, 2002). Without proper inclusion of required rules and regulations, the system cannot act independently to adapt to such changes. If one can adequately adopt such dynamic pricing strategies within the pricing strategy, there is a possibility that they can earn an average contribution margin of around 10-20%. "If both alternatives for the pilots are not possible, omnichannel retailers could use the 10-20% average contribution margin increase that Omnia Dynamic Pricing users see as input for their calculations" (Roose, 2017). So, it is imposed on the rule-based pricing dynamic pricing system that it should include all the essential data and information in the form of rules and laws beforehand, so that the system can correctly predict and provide accurate outcomes.

More precisely, Robert et al. (2006) have developed a mechanism to determine how the consumers are sensitive to changes in the product prices, based on past data, and to note that the changes in historical prices became the factor that influenced the current price. In reality, more factors will be taken into account about the price sensitivity function, but the function shown below is just the most straightforward version:

$$F_{PS}(P)=0.2*\{1-[\text{Arc-Tan}\ (\alpha*(P_{\text{final}}-P_{\text{REF}}))*2/\text{Pi}]\},$$

P_{ref} represents the reference price, which strongly relies on the previous data collection. P_{Final} is the final deal price also gathered through data collection. And α is empirically determined according to the past and current sales data. This formula is indicative of big data analysis and big data collection. Robert et al. also used a visualized graph to demonstrate how the dynamic pricing system works nowadays (see Figure 1).

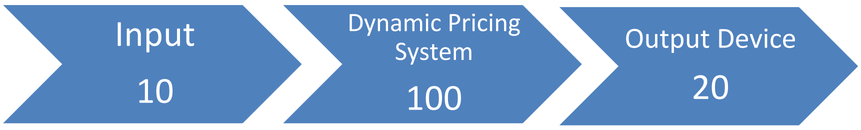

FIGURE 1 DYNAMIC PRICING SYSTEM
Source: Adapted from Robert et al. (2006)

The whole system consists of three processes. From the input side, it contains ten types of sensors for the external data feed. When data is transmitted into the system, it will be filtered and distributed to 100 different processors to analyze. When the analysis is complete, the output results (harvest through 20 different devices) will become the references of the latest price decision.

Big data analysis is gradually becoming a foreseeable benefit to marketers. As proved by Shiller (2014), mass datasets on consumer's individual behavior may reveal information that can be used to develop a hedonic estimation of consumer's reserved values. Thence, firms will benefit from that data-based personalized pricing. According to Shiller (2014), around 5000 web-browsing variables were being analyzed to estimate an individual's reserved value, and as a conclusion, blending the economic models with machine learning could overcome the problems for big data in the later stage.

2.2.3 Machine Learning-Based Dynamic Pricing

A study has shown that machine learning has immense potential for various online retailers, which business organizations are yet to unlock. As per the works of Rajan Gupta and Chaitanya Pathak (2014), it was found that the statistics and other machine learning models help to predict and determine various purchase decisions on the basis of adaptive pricing of products. By developing a generic framework and applicable techniques to apply machine learning algorithms, the article has focused on the fact that model can also further be extended to online marketplaces. In fact, the adoption of such machine learning algorithms can even help to seek a proper and suitable pricing level via the proposed model of the two researchers. "The proposed model considers the amalgamation of three different techniques - to identify the customer segments, appropriate pricing for them, and the prediction for their likely purchase within that price range" (Gupta and Pathak 2014, p. 601). From the study alone, it can be seen that online retailers can easily exploit machine learning to predict the purchase behavior of customers. With a low error rate, it has shown that the powerful ability of machine learning can be directed towards figuring out purchase behavior, and eventually, the analysis extracted from machine learning can help to determine the process of dynamic pricing.

On such a note, another study has utilized Deep Neural Network (DNN) so that one can make expertise adjustments in the price level of hotel rooms. In fact, the study has conducted two various pricing models, which were divided into conventional pricing system and a proposed pricing system based on machine learning. As per the results of the study, it was found that the model based on machine learning provided a more reasonable price than that of previous models. When the researchers compared their "dynamic pricing system with a rule-based pricing strategy made by revenue management experts for evaluation, the results show that our model can suggest more rational price adjustment and make hotel revenue management more efficient" (Zhang et al., 2019, p. 373). In fact, after resulting in a more rational price, the pricing model integrated with Deep Neural Network was more efficient than the traditional price adjustment system. The researchers used the rule-based pricing strategy (developed by hotel revenue managers) for fulfilling three particular objectives - analyzing the performance of hotel and its rival companies to set up a reasonable price base, forecasting future occupancy of the hotel, and lastly, integrating dynamic pricing system on the basis of DNN to make essential price adjustments.

Similarly, another study has explored the usage of machine learning in major e-commerce players like that of Alibaba for dynamic pricing issues (Miao et al., 2019). The researchers of the study have collected sales data of Alibaba to reflect the prevalence of low-sales products. For the particular products reflecting low-sales, the company could alter the price range so that low-sales products could be transformed into high-sales products. It is evident that it would be hard to adopt a single-product dynamic pricing algorithm for such low-sales products, which the researchers have also mentioned in their study. In such regards, the researchers have suggested using the technique of clustering data and identifying products to categorize products with similar demand patterns. To be precise, the researchers have derived the idea of exploring and analyzing the data via clustering. In fact, the whole issue has been developed as one of the adaptive learning algorithms, which has the primary objective of figuring out the similarities between various demand patterns (Miao et al., 2019). Further, the model has tried to extract the hidden information from sales data of unrelated products to improve the pricing decisions of low-sale products. Via the usage of such machine-learning strategies, the researchers have claimed that their algorithms outperform traditional single-product pricing policies. "Our algorithms were further implemented in a field study at Alibaba with 40 products for 30 consecutive days, and compared to the products which use business-as-usual pricing policy of Alibaba" (Miao et al., 2019, p. 1). Eventually, as a result, it was found that the company was able to increase the overall revenue by 10.14%, which was a significant number. While this particular research has only focused on one particular company, it has also indirectly shown an enormous range of potential usage of machine learning.

On an indirect level, such research studies have suggested that machine learning provides a more comprehensive and accurate method for dynamic pricing methods. In fact, machine learning helps to provide a more rigorous approach to dynamic pricing, where one can utilize various powerful algorithms (Raju et al. 2003). As discussed above, machine learning helps to replace human thinking and ability with powerful machines and their learning capacity so that they can solve various issues in a proper pricing system. Admittedly, machine learning shows a significant level of pace and accuracy in figuring out various patterns, which would be hard to explore for human minds. Indeed, if humans were to look at a big chunk of data like that of machine learning, there is a massive possibility that human minds would conduct various mistakes and errors during the process. Therefore, machine learning can replace humans in learning the process of dynamic pricing and provide robust and accurate methods to figure out the basic patterns (Ban et al., 2017). To support the argument, various research studies have further shown that the results or outcomes regarding dynamic pricing are more significant than those of traditional methods adopted by business companies. It gains knowledge from data so that it can seek a solution to the issue itself. The unnecessary need for extra programming or rules to keep on providing constant instruction for what to do next revealed the boundedness of rule-based dynamic pricing. "Based on this, companies can steer prices automatically towards their company goals. They do not have to create rules and test their performance" (Machine Learning-based pricing vs. Rules-based pricing, 2020). In fact, data is given as input to the machine learning system continuously, and the more the system gets familiar with data, the more it learns and eventually provides an enhanced form of performance. Frankly, the machine plays the role of learners so that it could keep on learning the required skills to properly explore and analyze the data, which could replace a lot of human effort in the process.

After exploring different online dynamic strategies and price setting mechanisms, it is crucial for online retailers to keep those influencing facors in mind and adjust the price from time to time. However, for consumers, they might only observe the changes in price without being aware of any pricing strategies. As a result of price changing, consumers' trust toward online retailers could be dispelled (Malc et al., 2016; Richards et al., 2016).

2.3 Trust and Consumer Trust

As an aspect of human relationships, a trust could also be dynamic because trust must be initiated, maintained, restored, and continuously authenticated (Flores & Solomon, 1998). Various scholars were proposed different explanations to describe trust according to their specific sphere of learning (McKnight et al., 2002). Psychologists define trust as a tendency of cognition to trust trustee, but sociologists define it as a characteristic of the institutional environment (McKnight et al., 2002). Economists refer to trust as a tool that can reduce market failure from asymmetric information (Furlong, 1996). The moral philosopher Annette Baier (1986) interpreted trust as leaving good grounds of confidence in another's kind. It requires accepted vulnerability to another's possible but not expected spite toward one. Based on that, Mayer et al. (1995) came up with a more widely accepted definition, which argues trust is the willingness to engage in risk-taking behavior rather than an act of taking the risk. This indicates that trust is depending on the people's assessments of harm that might incur and the kindness from others (Friedman et al., 2000). From a business perspective, it describes trust more from the behavioral level. Trust in business is perceived as a financial arrangement between parties that hold a legal entity for a benefit (Sraders, 2019). According to the definitions mentioned above, trust is identified at both levels of perceptual and behavioral.

Consumer trust can influnce the consumer's attitude, perception, behavior, and loyalty (Hong & Cho, 2011; Koufaris, 2005; Sohn & Lee, 2005). Consumer trust in online business refers to the trust relationship between the consumer as trustor and retailer/firm as trustee.

Consumer trust in line with the consumer's expectation, which requires the service provider, is dependable and trustworthy to carry out their promises (Sirdeshmukh et al., 2002). Auh and Johnson (1998) discussed that a consumer's propensity is systematically affected by the external trust environment, so consumer trust should be defined as consumer satisfaction with a high level of loyalty. Online consumer satisfaction comes from different sets of antecedents, such as trustworthy behaviors, which foster the general trust toward online vendors (Sirdeshmukh et al., 2002).

2.3.1 Formation of Trust and Online Consumer Trust

Flores and Solomon (1998) have proposed four types of trust that need to be distinguished. First is a simple trust, the trust which is naive and unchallenged. Then is the blind trust that stands for obstinate, sometimes self-deluding. The third is the basic trust cultivated by the sense of physical and emotional security. The last is named authentic trust, as opposed to simple trust, it's built upon the acquired understanding of risks and vulnerabilities (Flores & Solomon, 1998). Followed by Lewicki and Wiethoff (2000), trust was breaking into two types: "calculus-based trust" and "identification-based trust". Calculus-based trust describes that people or a workplace tend to build trust step by step in a frame. The participant's satisfaction comes from the ultimate result but not the process while completing it. That means if one mistake is made, the whole trust built might retrogress or collapse. Thence, the interactions are impersonal in calculus-based trust, so one would show a high expectation toward others. Identification-based trust is more about developing a collective identity among different individuals and their mutual benefits. This type of trust helps people or parties work together as a solid team and understand each other's expectations and needs. Therefore, identification-based trust is leaner to individuals' compatibility (Lewicki and Wiethoff, 2000). This multitude of proposed trust types generated plenty of controversies due to the lack of sufficient data to prove them. Also, the importance of empirical research was also neglected in previous research (Freitag & Traunmüller, 2009). To cover the research gap, and finally find out the attributes of trust, as well as the formation, Freitag and Traunmüller (2009) have empirically examined trust in the scope of particular and general. Particularised and generalized trust were broadly accepted and cited by various researchers (Stolle, 2002; Yamagishi & Yamagishi, 1994; Uslaner, 2002). Particularised trust is a more social proximity-based trust that could be detailed to person, trusters, and trustees knowing each other from daily based interactions. Generalized trust is a rather bit rough attitude toward people in general; trustees could be strangers sometimes. Particularized trust and generalized trust are seemed to be highly independent. However, the positive relationship between these two forms of trust was carried out from their later data analysis (Freitag & Traunmüller, 2009). Thence, it is clear to identify what type of trust is being researched in this thesis. Consumer's trust toward online retails is the trust that is authentic, mostly calculus-based, and generalized.

Review the definition and categorization that made by previous scholars, trust has been frequently interpreted, whereas the formation of trust remains a blur. Glanville and Paxton (2007, cited in Freitag & Traunmüller, 2009) have mentioned two formations of trust that are theoretically found in significant perspectives. The first method suggests that a person's trust is formed by their own rational evaluation of trustworthiness in social activities, and the second method believes that trust is an attribute formed by a person's innateness and predisposition (Freitag & Traunmüller, 2009). The trustworthiness formed in the first method mostly draws from past behavior and reputation, and it corresponds to the particular trust. In the second method, a person's predisposition of trust is more perceived as a stable personality trait, so the trust is generalized no matter the trustee is known or unknown (Freitag & Traunmüller, 2009).

Clearly, these single dimension forms are narrow to conclude trust. Therefore, a suggestion of multidimensional trust construct is growing its acceptance among scholars (Garbarino & Lee, 2003). Garbarino and Lee (2003) stated that overall trust is formed in combination with benevolence trust and competence trust. Benevolence trust stands from the trustee's point that they are willing to benefit the interest of different parties with genuine solicitude. Competence trust speaks from the trustee's attention and ability that the overall goal is to fulfill the promises (Singh & Sirdeshmukh, 2000, as cited in Garbarino & Lee, 2003). Koufaris (2005) has put forward a similar structure that trust is formed upon the trustee's competency in a specific context, trustee's integrity (follow ethic principle), and trustee's benevolence concern (goodwill). This compound construction of trust engaged by Freitag and Traunmüller (2009), a specific logic of trust formation (concerning experiences evaluation and disposition) was derived from their study, and the author has adapted this formation according to the relevance of this thesis, showing below as Table 1.

	Trust	
	Particularised Trust	**Generalized Trust**
Experiences & Evaluation	Experiences from people who already know	Experiences with strangers
(Pre)Dispositions	Familiar contexts Familiar person	Cope with wider community with general optimism

TABLE 1 ADAPTED THE SPHERE OF TRUST

Source: Freitag and Traunmüller (2009).

This crosstabulation displayed the interactions between trustee's experience and disposition and also revealed the differences under different conditions. From the perspective of particularized trust, a familiar person and environment are essential for its formation. From the perspective of generalized trust, experiences and dispositions are beyond familiar perception, which extends the trust to the broader sphere.

Toward online consumer trust formation, differentiating from the traditional models or formations mentioned above, the web context decided that the formation shall be adapted in light of e-commerce constructs: personal innovativeness, web experience, and perceived site quality (McKnight et al., 2002). Nevertheless, online customer trust inherited all the aspects from online consumer behavior, which enabled the customer to have a dual identity in this nature because customers are instantaneously both online shoppers and web users. In order to figure out how online consumer trust has emerged, the model of traditional formations shall still be concerned (Koufaris, 2005).

McKnight, Cummings, and Chervany (1998) proposed an integrative model that included a wide range of trust types: institution-based, trusting intention, trusting beliefs, and dispositional trust. The advantage of this model is that all trust types could be statistically measured with a given scale. This model presents that trusting beliefs come from two crucial antecedents: institution-based trust and disposition trust. Under this precondition, trusting beliefs could lead to consumer's attitudes toward trusting intentions. Trusting intentions are the key to drive consumers to finally execute their trust behavior (McKnight et al., 2002). Trusting intentions are based on trusting beliefs. At this stage, trusters are encouraged with a willingness to depend on trustees. And eventually, the trusting intentions will elaborate to behavioral intention and cause actual behavior. Trust-related behaviors in e-commerce practice include: sharing personal information, making a purchase decision, or reacting to the information offered by online vendors (McKnight et al., 2002).

Considering the attributes of e-commerce, McKnight, Choudhury, and Kacmar (2002) adapted McKnight's (1998) model from a previous study and added personal innovativeness, web experience, and perceived site quality as components into the frame (Figure 2).

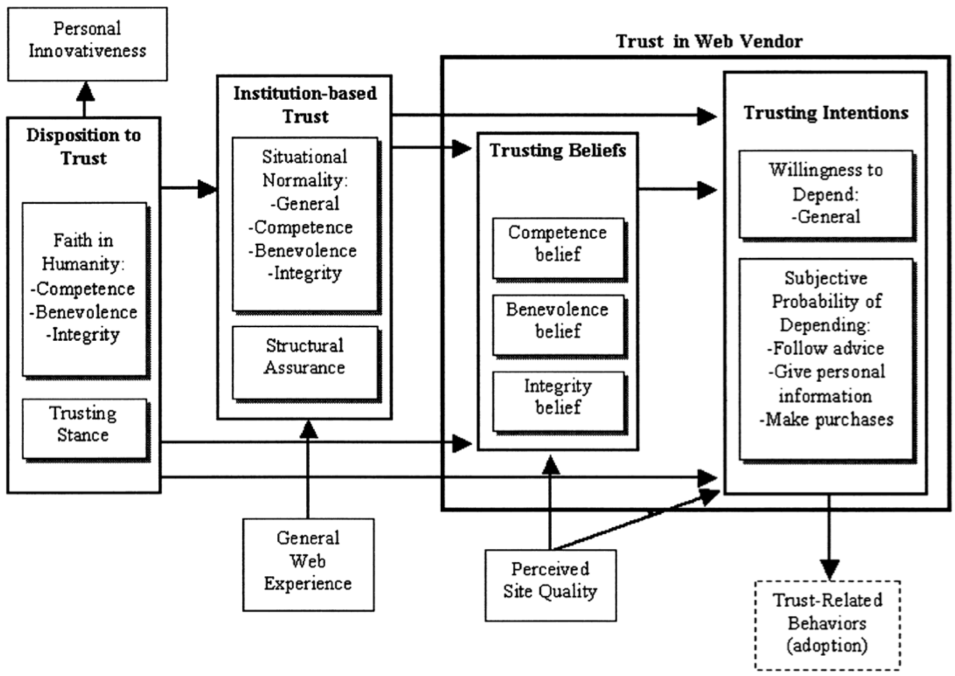

FIGURE 2 CONSUMER WEB TRUST MODEL

Source: McKnight et al. (2002).

Note that all the links within the model are proposed to be positive for further analysis and interpretation. Therefore, the disposition to trust shall positively reflect the consumer's general optimism toward the internet and enhance personal innovativeness (Uslaner, 2000; McKnight et al., 2002). Personal innovativeness was noticed by Agarwal and Prasad (1998). It includes 3 phases: starting from people gathering information about new I.T. through the various channels, so they will generate a perception toward new technology, their intention will decide whether to use or not use the new technology. In short words, it's about people's confidence and adoption regarding new technologies. To ensure consumer's trust toward technologies, legal protection is needed, and it became the footstone of institution-based trust. As a result, the base trust of general web experience is guaranteed (Zucker, 1986, as cited in McKnight et al., 2002). To further illustrate the relationships among trust constructs, perceived site quality will effectively impact consumers' trusting beliefs and trusting intentions toward web vendors. The website's design and appearance will display the online vendor's taste, and it affects consumers' first impression (beliefs and intentions) directly.

2.3.2 Factors that Influence Online Consumer Trust

To define this sub-chapter's goal, it aims to find out the factors that are causing online trust violation. Lewicki and Wiethoff (2000) precisely explained how trust is violated, and it is because the mutual expectations can't be set between individuals or parties. When this violation happens, it might result in the formation of negative feelings that directly influence the consumer's beliefs and attitudes. However, the consequences much dependon the type of relationship that has been set, and there is still plenty of space for individuals or parties to fix the problem. In order to tackle the factors that influence online consumer trust, various research activities have been conducted during the past years. Koufaris (2005) proposed that customer's trust online determines factors depending on the consumer's perception about the company, the company's website, and the web in general. In addition, Koufaris mentioned individual’s trait could also be the influencing factor. Later, Chan and Huang (2011) published their findings of the factors that affect consumer trust in online shopping, and the study categorized those factors into eight categories:

I. Reputation (vendor’s size, vendor’s perceived competence and integrity)
II. Security (consumer perceived security and privacy toward vendors)
III. Third-Party Intervention (concerned about the third party's certification)
IV. Recommendation (Word-of-Mouth)
V. Product (inappropriate product information)
VI. Order Fulfilment (refers to the completion of the online orders)
VII. Web Design
VIII. Service (service quality, shopping experience)

However, these factors listed above are somehow one-sided, and some are overlapped (reputation and recommendation) in the author's point of view. A systematic analysis of those factors is urged. Bauman and Bachmann (2017) have summarized and wrote a literature review about studies published from 2004 to 2014. Three significant research focuses toward online consumer trust were carried out from this literature: trust models, technological factors impacting online trust, and social factors impacting online trust. This study serves as a holistic review of the past research, and it reveals that scholars often initiate the online trust research based upon several trust models, then seek to influence factors through social and technological aspects. Social factors such as Word-of-Mouth, social presence, culture, trust recovery, and green trust were listed to distinguish from technological factors like e-commerce acceptance, privacy, website design, and trust signals (Bauman & Bachmann, 2017). To further explain those factors one by one, Word-of-Mouth refers to the positive/negative reputation (consumer reviews) left to the online products or services, and it shows the power of communication. Social presence could be understood as a lack of human touch. For instance, online shopping is perceived as impersonal and lacks social interactions. Culture, as a factor mentioned here, means the online consumers are sharing different values. Thence, the difference in their intentions might impact trust accordingly. Trust recovery reflecting good complaint management is needed for solving consumer's dissatisfaction because failure to address the problem will lead to a reduction in trust, and vice versa (Pizzutti & Fernandes, 2010). Green trust, it defined as “a willingness to depend on a product, service, or brand based on the belief or expectation resulting from its credibility, benevolence, and ability about its environmental performance" (Chen & Chang, 2013). E-commerce acceptance stands for the consumer's adoption toward shopping online, and the degree of this adoption indirectly reflects the degree of consumer's trust (Bauman & Bachmann, 2017).

Privacy issues are the most frequently mentioned factors that violate consumer’s trust (Friedman et al., 2000; Garbarino & Lee, 2003; Bauman & Bachmann, 2017; Culnan, 2000). Due to the fast development of technology, collecting consumer’s private data online became an easy thing to help marketers understand consumer's needs. This explosively increased personal data accompanied with particular risk (payment, personal data leak), which might impact consumer's trust perception (Bauman & Bachmann, 2017). Web site design is pivotal, as mentioned in the previous chapter, the design and appearance of the website will display the online vendor's taste, and it directly impacts the trusting beliefs and trusting intentions of consumer toward web vendors. When the online vendors are aware of the essence of web design, they are likely to involve some elements in design, like trust signals, to relieve consumer's concern toward privacy and security, thus enhancing their trust (Aiken & Boush, 2006). A good practice of trust signal could be putting a photo of the salesperson on the site to imply the creditability.

To shortly conclude the factors mentioned in different sorting methods, those frequently mentioned factors fasten mainly on three common grounds: privacy and security, web design, and reputation.

2.3.3 Measure the Online Consumer Trust

Online consumer trust could be measured practically and empirically. In real-world practice, a survey has shown more than one-third of consumers consider customer feedbacks as the primary factor that encouraged their trust toward online vendors (Awasthi, 2017). According to this survey, online customer reviews were used to measure the consumer trust. Similarly, most of the influencing factors mentioned above also could be used to assess consumer trust. To measure the online consumer trust, the measurements are heavily relying on the trust constructs that the researcher is working on, as well as the measurement scales (Hasley et al., 2020). "The empirical literature on measuring trust has focused on responses to certain questions," said Glaeser et al. (2000). Therefore, the Likert scale, especially the 7-point Likert scale, was widely adopted by researchers to measure the perceptual scales and degree of trust.

Garbarino and Lee (2003) used a 7-point Likert scale to capture benevolence trust, competence trust, and overall trust. A general social survey has been conducted by Glaeser et al. (2000) to find out precisely what trust-related question measures. In this survey, attitudinal questions were designed mainly about trusting attitudes and trusting behaviors and 7-point Likert scale was also implemented in the survey question design. Deepak Sirdeshmukh, Jagdip Singh, and Barry Sabol (2002) even adapted 7-point Likert scale to a ten-point semantic differential scale to measure trust related value, loyalty, and satisfaction.

However, several criticisms have been put forward in relation to those trust testing tools. Associated trust measurements either being too specific toward a specific vendor's context, lacking experiment process control, lacking rigorous validation of the data used, or being too conceptual related to the organizational trust. These drawbacks made previous research less convincing and indicated that previous research was not entirely focusing on trust and trust antecedents (Corritore et al., 2005). Thus, Corritore et al. adapted the trust measuring model that was developed by himself to a new model which could potentially be applied in a variety of contexts. This model measures online consumer trust through external factors and perceived factors (Corritore et al., 2005). External factors are factors caused by the physical or psychological environment, such as web site's design, the accuracy of the online content, the website's reputation, and truster's propensity (experience with vendors, individual characteristics). Perceived factors are the general call for the perception of credibility (represents honesty, expertise, predictability, reputation), ease of use (website), and identified risk. By measuring those antecedents, the impact on online consumer trust was observed in the study.

After explored the previous research, those methods and trust measuring tools provide a hint to the author for the upcoming research design. The measurement of consumer trust toward dynamic pricing strategies for the author's research will be discussed further in the chapter research methodology.

2.4 Consumer Fairness/Unfairness Perception towards Dynamic Pricing

Even though dynamic pricing brings along a range of benefits for business organizations, it imposes a significant level of unfairness for consumers. Indeed, when the price of a particular product keeps on changing, consumers have to face the situation of a dilemma in which the price range is considerably correct. Also, when the price of a particular product keeps changing, consumers might feel that they might be paying more than the actual price of the product. After experiencing various changes in price, they would feel that business organizations are haphazardly determining various price ranges for the same product as per their financial benefit, which is consumer exploitation. In an attempt to understand the impacts of price manipulation on trust, Ellen Garbarino and Sarah Maxwell have conducted research using an experimental setting by taking a survey of around 400 respondents. As per the study, the chosen 400 subjects were allowed to buy a specific digital camera from only two stores, where one of the stores was a very renowned one and another hardly known (Garbarino and Maxwell, 2010). While the prices varied amidst the two stores, the new customers were also at a significant advantage of gaining a discount than that of established customers. The two researchers were also able to find that personal pricing negatively impacted perceived pricing fairness and even lower trust, benevolence trust, and many more. Consumers lowered their purchase intentions and even provided a significant number of complaints. In this way, it can be seen that consumers tend to be more skeptical regarding price differentiation caused by dynamic pricing. In fact, after purchases were made by consumers, only 15.5 percent of subjects or respondents described the whole price differentiation process as a fair process. The researchers have concluded that consumers would provide negative reactions to price differentiation and the longer such differentiations remain, the more severe the negative response of consumers will become. The study has clearly described that the price changes and differentiation in retail business occurring from dynamic pricing strategies would not remain as beneficial in the long term.

A study has tried to explore the notions of consumer perceptions developed after experiencing a dynamic pricing strategy. In fact, the researchers of the study, Anna Priester, Thomas Robbert, and Stefan Roth have created a unique set of individual-consumer prices for the same product or service. The analysis of the article has found that dynamic pricing strategies are responsible for provoking negative fairness perceptions in consumers, which imposes a significant level of reluctance for managers to implement (Priester et al., 2020). By exploring two various price develoment dimensions (price individualization and segmentation base), the article has further explained that consumers have to face more unfairness in individual prices than segment prices. "The findings reveal that privacy concerns intensify the likelihood that consumers perceive individual pricing as less fair than segment pricing" (Priester et al., 2020). From this study alone, it can be seen that consumers develop a form of negativity toward various changes in price levels due to dynamic pricing strategy. From the perspective of consumers, it is only an exploitation tool for online retailers to maximize their revenue and profit without providing any concern for the welfare and benefit of the consumers. Relying on such various studies regarding consumer fairness and dynamic pricing, it can be implied that the two hold an indirectly proportional relationship with each other.

Therefore, the first hypothesis read as $\mathbf{H_1}$ could be derived from the studies mentioned above:

$\mathbf{H_1}$: Frequent price changes decrease the consumers' perception of fairness.

2.5 Perceived Price and Perceived Trust

Consumers are not really aware of or know the actual price of a product. Nevertheless, they subjectively perceive the price as expensive or cheap (Shintaputri & Wuisan, 2017). However, there are some pieces of evidence which show that "consumers do pay attention to the price paid by others, and that the differential pricing strategies used by marketers are perceived as unfair by consumers not eligible for the special offer"(Schiffman & Kanuk, 2007). Derived from this fact, consumers' perception of price unfairness may affect further aspects such as perceived product quality and value (Shintaputri & Wuisan, 2017). Zeithaml (1988) has defined perceived price as consumer's subjective perception of what is sacrificed to acquire the product. Different from perceived price, Zeithaml (1988) further explained that perceived value is based on perceived benefit and perceived sacrifice (cost). According to Thaler (1983), the link between perceived price and perceived value could emphasize the differences between the objective selling price (from marketers) and the consumer's reference price. Consumer's reference price is "any price that consumer uses as a basis for comparison in judging another price" (Schiffman & Kanuk, 2007). Schiffman and Kanuk (2007) still note that reference price could be either external or internal. Retailers could use external reference price in an advertisement and offer a relatively low price for sales. This pricing strategy could make consumers deluded and perceive the product is worth buying. The internal reference price more tends to reflect consumer's subconscious perception and evaluation toward a product. This subconscious evaluation may be retrieved from the past experience or other retailer's selling price.

Based on consumer's perception of the product's value, Schiffman and Kanuk (2007) also illustrated three pricing strategies that marketers and retailers are broadly conducting nowadays. First is satisfaction based pricing, the pricing strategy that provides value by recognizing and reducing consumer's perception of uncertainty. This concept could be implemented in various ways, such as selling products with service guarantees or setting flat-rate pricing. The second perceived value-focused pricing strategy is relationship pricing. This strategy is encouraging consumers to engage in a long term relationship with the retailers or vendors. Consumers, therefore, became beneficiaries. Long-term contracts or membership system would be the practice of this pricing strategy. Next, the efficiency pricing strategy provides value by understanding the product's cost-saving and reducing the cost from the consumer. It is usually implemented as cost-leadership pricing (Schiffman & Kanuk, 2007).

In connection with trust, two types of utilities that trigger consumer's purchase intention shall be introduced: acquisition utility and transaction utility. Acquisition utility reflects the consumer's perceived economic gain or loss, and it decides by the product's utility and price. Transaction utility is determined by the difference between the reference price and purchased price, and it observes the consumer's perceived value (Schiffman & Kanuk, 2007). Chiles and McMackin (1996, as cited in Achyar & Setiawan, 2013) stated that perceived trust could reduce the cost of non-monetary transactions, as well as time and effort spent by consumers to decide the preferred seller, therefore reduce the level of risk in online transactions.

To organize these scattered vital elements and find out connections, Achyar and Setiwan (2013) proposed that "perceived trust toward online vendor could potentially increase consumers acquisition utility and non-monetary aspects of transaction utility, therefore increase the consumer's perceived value." In short words, perceived trust and perceived price together determine the consumer's perceived value. If one component altered, the rest alters as well. These subtleties brought great enlightenment to the author in developing associated hypotheses for later research, and the second hypothesis read as $\mathbf{H_2}$ is displayed below:

$\mathbf{H_2}$: Consumers' perception of fairness has a positive influence on trust towards online retailer.

2.6 Dynamic Pricing's Effects on Consumer Trust

Price has always played a crucial role for consumers to generate their purchasing decision. So, in the setting of the e-commerce industry and the internet age, there is a huge possibility that individual-level price discrimination might provide a noteworthy level of profitability in the firm. However, from the perspective of consumers, it does not remain a good practice. Examining and analyzing particularly two crucial factors (benevolence and competence trust), a study has shown that experience of dynamic pricing events could largely impact the levels of trust on consumers.

To be precise, such experience of trust and direction of pricing discrimination can easily hamper the mean levels of trust and weight of trust provided to various dimensions of online retailers. The results of the study have shown that mean benevolence trust is significantly lower, resulting in a marginal decrease in overall trust (Malc et al., 2016). It could be seen that even though internet retailers could gain a large sum of money as profit from such price discrimination, such business houses have to keep consumer trust at stake. Dynamic pricing will only lower the trust level of consumers in a very significant manner, and as many research studies have shown that as long as such variations in price are conducted from such dynamic pricing strategies, it will intensify the drop of consumer trust in a similar manner (Richards et al., 2016). Eventually, dynamic pricing has to carry the constant risk of losing consumer trust over the product of companies. In the long-run, the drop in the trust level of consumers towards online retailers could eventually lead to the downfall of the company's reputation and goodwill (Xia et al., 2004). In fact, the product of such online retailers may slowly lose its charm and attention despite causing no changes to the shape, size, and other factors of the product or commodity. The loss of trust in consumers can be a significant spark to create bigger negative impacts on the reputation of companies, and in worst cases, it could even lead to the downfall of the whole company. While the primary objective of a dynamic pricing strategy is to create maximum revenue for online retailers, it could cause a large chunk of customers to be discouraged from purchasing the products of the company (Weisstein et al., 2013).

A similar study was done by Grewal et al. (2004), who have examined the effects of buyers identification and purchase timing on consumers' perceptions. These two influencing factors were implemented and manipulated in their experiment to see the changes on consumer's trust, price fairness and repurchase intentions. The experimental results reveal that the price differences cause a significant effect on trust, fairness, and willingness to buy; In addition, this effect is more pronounced when firms do not disclose the price change reason toward consumers (Grewal et al., 2004).

Associated with this thesis, to explore the dynamic pricing's effect on consumer's trust experimentally, the third hypothesis is derived accordingly :

H_3 : Disclosing the dynamic pricing strategy to consumers has stronger positive influence on trust toward online retailers than not disclosing to consumers.

In a nutshell, it can be said that dynamic pricing strategy refers to the idea of changing the price level constantly on the basis of requirement and gaining both financial and non-financial advantages. The particular strategy has its own advantages and disadvantages, which would provide both benefits and drawbacks to the online retailers. The research has explored various aspects of the dynamic pricing systems and tries to pinpoint what kinds of impacts it causes to online retailers. Besides that, the research has also tried to accumulate various advantages and disadvantages the organization has to face from the adoption of dynamic pricing strategy (Grewal et al., 2004). Integrating with various advanced technologies like that of machine learning, dynamic pricing can help to predict and determine favorable changes to the price and earn massive levels of revenue from such changes in the price. However, in the process of conducting changes in prices time and again, it can threaten the organizational performance in the long run, particularly by disrupting the consumer-business relationship. At large, consumers can experience a very negative level of consumer unfairness and exploitation via such changes in prices for the same commodity or product, which would impose a huge disadvantage for business organizations (Grewal et al., 2004).

2.7 Online Consumer’s Trust, Satisfaction and Loyalty

With the advancement of information technology in recent years, the internet has become one of the primary tools for local and international business. For a quicker transaction, relatively affordable cost, and convenient ordering method, buyers turn to online sellers who recognize no physical borders between far-flung locations within a city, around a country, and even across the globe. If consumers want something, they could simply browse for a specific desired product online. It will be delivered in a timely manner to consumers, therefore, bring convenience, satisfaction, and more. People can also purchase gifts for someone else who is in a different location. There is no need to trouble themselves with dropping off present in a package forwarding establishment. However, there are concerns with online shopping for its ability to provide online consumer satisfaction and trust. Cases of fraud, as well as inconsistencies in products and costs, have been causing buyers to lose trust in their favorite brands and online stores. It is effortless for a cybercriminal to set up a website, upload photos of various goods, and pretend to be legitimate online seller. They'll entice consumers into purchasing their products, even give them better deals, then take their private information to steal, or do other crimes.

Besides these bad images, and to analyze and understand consumer's satisfaction in an online context, it is vital to revisit the definition of online trust. When shopping through the internet, consumers put themselves in a risky situation where they present their needs and share their private information with an online seller. In return, buyers expect an honest and professional manner of completing their transaction. Beldad, de Jong, and Steehouder (2010) defined online trust as an attitude of confident expectation in an online situation of risk that one’s vulnerabilities will not be exploited. In exchange for quality goods and services, consumers give information that might compromise their safety if the merchant is a fraud. They give sensitive data such as complete names, addresses, and bank account details. Chen & Barnes (2007) describe online trust as a critical factor of a business strategy by reducing risk and creating positive word-of-mouth which influences customer’s decision to buy. At the view point of a merchant, establishing trust is necessary to further their business success and gain more customers. Consumer's trust generates positive experiences and satisfaction, ultimately leading to repeat transactions and positive reviews. Kim, Ferrin, and Rao (2009) said online consumer satisfaction and trust with the business transaction form the foundation for the long-term commercial relationship between an online vendor and a consumer.

Derived from these studies, a trusted vendor can expect to have a loyal customer because the customer is satisfied with their transactions. It is now up to the merchant to provide consistent quality of products and services. And, if a particular unavoidable difficulty arises, a loyal customer will be willing to continue their patronage because of the many positive experiences they've had in previous transactions (experiences).

From here, the fourth hypothesis read as $\mathbf{H_4}$ is derived below:
$\mathbf{H_4}$: Trust towards online retailers has a positive influence on consumer satisfaction.

In terms of consumer loyalty, every business wants to acquire a good number of customers and maintain a long-term business relationship. In order to gain potential customers, the importance of customer satisfaction must be acknowledged. Customer satisfaction certainly has a significant impact on the entire business operations and is one of the determining factors of a merchant's failure or success. Satisfied customers also help create the possibility of the new customers. If existing customers are satisfied with the product and service, then it is possible for them to give recommendation to the new ones. This will lead to an increase of a company's number of customers and help maintain a good relationship with their current ones. Therefore, it is imperative for the merchant to know what the customer's need is and how to gain their trust and loyalty.

To further expose the relationship between trust and loyalty, Hong and Cho (2011) found out that consumers' trust could influence both attitudinal loyalty and purchase intentions toward online retailers. Hence, the fifrth hypothesis read as $\mathbf{H_5}$ is proposed:
$\mathbf{H_5}$: Consumer Trust towards online retailers has a positive influence on consumer loyalty.

Khadka & Maharjan (2017) stated that the customer plays a crucial role in customer satisfaction and customer loyalty is the root of the success. If the customers are satisfied with the quality of the goods and services provided by the company, they also gain consumer loyalty. Customer satisfaction is the critical component of business profitability because once the customer reaches their satisfaction level, it may influence them to continuously consume the service. Moreover, they will have the propensity to share their experiences with other people, which creates the possibility of new customers. In the same way, dissatisfied people will also give their opinion about the products and share their negative experiences. They can also contribute towards a declining number of customers.

With the rise of online platforms dedicated to selling goods and services, there are many options for a buyer. The same product can be sold across a wide range of online shops. The first time, buyer will not have any previous experience to refer to in choosing an online merchant. Each seller will not only have to make the necessary effort to attract and satisfy customers but also establish trust and encourage customers to adopt online shopping. By providing satisfactory products and services, they will gain popularity and gain more loyal customers. These loyal customers will generate lasting revenue and are much less expensive to retain than it is to find new ones. They will also help create word-of-mouth advertising at zero cost and are easily accessible for marketing promotions. To ensure consumer satisfaction and establish customer trust in an online environment, Khadka & Maharjan (2017) suggests business needs to provide the following:

- Detailed information

Before making any purchases, smart buyers gather as much information as they can about the seller. Online merchants assure their buyers of their legitimacy by providing their names, contact details, what kind of services they provide, and their shop’s terms of service or privacy policy. More published details about the seller make a good sign of reliability.

- Safe payments

Another indication of a legitimate and trustworthy online store is a payment company's logo, such as Visa, MasterCard, American Express, and other similar logos. Online stores that can process online payments go through meticulous checks conducted by financial institutions, which make them reliable business partners.

- Positive feedback

Although some online vendors can write fake reviews on their own websites, there are still other sites for checking reviews. Online buyers can google the name of the store or seller or use social media platforms such as Facebook and Twitter. Some online tools like Web of Trust (www.wot.com) also give ratings on a website's trustworthiness, vendor reliability, privacy, and child safety. To secure positive feedback, an online business must consistently provide good service to their new and existing customers, which will leave positive notes on them all over the internet.

Through customer satisfaction, more customers are retained and their loyalty can be guaranteed. In the link between customer satisfaction and loyalty, switching costs plays a vital role. Switching between suppliers could cause a considerable amount of money, time, and effort to the buyer. If the market is competitive and switching costs are high, satisfied customers will repurchase products from the same online store. This has long been recognised and researched by several academic disciplines, particularly in marketing, economics and strategy. Caruana (2003) mentioned that switching costs are essential in achieving competitive advantage. Recent research shows that they are becoming even more strategic in the increasingly networked competitive environment. Caruana (2003) also defined switching costs as deterring customers from switching to a competitor's product or service. Fornell (1992) described switching costs as an element of loyalty function on top of customer satisfaction. Jones (1996) also mentioned it as one of the factors that determine the competitiveness of the online market environment. They argue that high switching costs discourage customers from switching from current product vendors or service providers because it discourages changing from a current provider, thereby yielding less incentive for businesses to actively compete. Bateson and Hoffman (1999) claim that satisfaction and switching costs are the most important antecedents of repurchase behavior. Switching costs influences satisfaction which also contributes to consumer loyalty.

Drawing short conclusion, online consumer satisfaction is highly dependent on business's trustworthiness. By establishing trust, they can guarantee repeat orders and consumer loyalty. Without it, a consumer will be hesitant in sharing their sensitive information. Buyers will not think to risk wasting their time, money, and energy in a suspicious transaction. It is therefore an online merchant's responsibility to build trust and satisfy their customers. Once consumer satisfaction is achieved, loyalty will follow. And, with loyalty will come good reviews and recommendations that will increase seller's client base. Even with high switching costs, an unsatisfied customer will be hesitant to order from the same merchant because experience, trust, and satisfaction could make or break an online business.

According to the researches stated above, the following hypotheses are present below:

H_6 : Consumer satisfaction has positive influence on consumer loyalty.

H_7 : Frequent price changes have a negative influence on consumer loyalty.

For a better overview of this thesis's logic flow, **Figure 3** displayed the core focuses of this study.

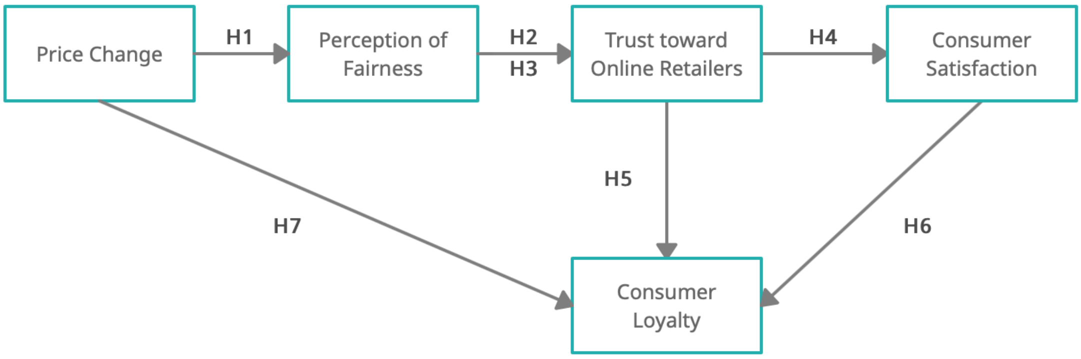

FIGURE 3 THE CONCEPTUAL FRAMEWORK OF THE STUDY

3 RESEARCH METHODOLOGY

This chapter describes the thesis's entire research method. Starting with the research approach and methodology selection, this section will provide sufficient evidence to justify the selected method, and a detailed research design will be developed. The subchapters will further illustrate the item measurement, data analysis approach and research instrument. In addition, sampling procedures will be mentioned as well. Lastly, a pilot test will be conducted to examine the comprehensibility of the survey. By doing the pilot test, the survey content's clarity and consistency will be enhanced and ensured.

3.1 Research Approach and Selection of methodology

The hypotheses proposed in the literature review embody that the quantitative method would be the most suitable research method to test the conceptual research framework. A review of existing studies and presentation of three new studies will be done, which will give constructive inspiration toward the author's detailed research method and design. In the following text, it will be outlined how these three extant studies guided the development of this thesis's research design. Beginning with the research completed by Garbarino and Lee (2003), dynamic pricing's effects on consumer trust were studied using a between-subjects experiment. In their study, two similar mocking websites were developed as stimuli to ensure initial trust's unbiasedness, and price change in percentage was used as a manipulating variable, either 15% above or 15% below. Relate to the current thesis, and it would be hard to experiment with the mocking websites; however, the designing idea of scenario with the manipulating factor was considered as promising approach for the study design. Grewal et al. (2004) researched the effects of pricing difference on consumers' perception of trust, price fairness, and purchase intention. The results of this relevant study reveal that the different final purchase price has a significant effect on consumer's trust, fairness, and intention of purchase. Relying on this outcome, the author has decided to observe the price fairness, trust, and repurchase intention in the experiment to better understand the impact of price change (dynamic pricing) on trust. Part of the measurement scales from this study provides a significat guide in finding the appropriate scales for each cognitive variable. Another highly relevant study was done by Martín-Consuegra, Molina, and Esreban (2007). In order to find out the correlations between fairness, satisfaction, and loyalty, this research indicates that the consumers' perception of fairness could influence consumer satisfaction and loyalty. Moreover, the results of this study have shown a successfully implemented measurement scale for consumers' purchase satisfaction, and this scale can be adapted for this thesis's survey design.

Since this study intends to determine the impact of online dynamic pricing strategies on consumers' fairness perception, trust, satisfaction, and loyalty, the author has decided to apply the posttest-only control group design as a code of conduct to support further research. Posttest-only control group design is one of the true experimental designs that randomly allocated the participants to the experimental groups. Only the experimental group participants will be observed with treatments, and a post-test is executed to all groups (Creswell & Creswell, 2018). By comparing the different variables' composite scores from groups, the differences could be used to justify the effectiveness of treatment toward specific variable in the experiment (Black, 1999). This reveals the advantage of experimental designs that could identify casual relationships between variables. Thus, through further consideration of this method, it becomes evident that the experiment could be designed as a one-factor factorial design (the one factor being the frequent price change). As this particular factor has two levels regarding price (no change and frequent change), the experiment shall employ two groups. Since the author also wanted to explore the scenario when the dynamic pricing strategy is disclosed, the author has decided to observe three groups and adapt the entire experiment to **Fractional Factorial Design**. What's more, several advantages of this research method were pointed out by Joseph Voelkel (2004) in the stduy of efficiencies of fractional factorial designs. The main advantage is the efficiency of data collection, because this method allows the researcher to measure the variables under main-effects-only, so the design could lie in its smallest-sized projection properties and reduce the time spending on unusable context (Voelkel, 2004).

To ensure the experiment's validity, as mentioned above, the author decides to experiment with a given scenario because setting a scenario could improve the participants' engagement, knowledge retention, and performance toward the experiment (Hout, 2020).

Finally, the statistical analyses, such as the Chi-Square test and reliability test, will be carried out to check the manipulation and scale reliability accordingly. Afterwards, the analysis will be proceeded with the hypotheses testing.

3.2 Research Design

As mentioned in the last section, this study employed a fractional factorial one factor between subjects' design, with price change frequency and disclosure as manipulated variables.

The experiment had one experimental group where only frequent price change was manipulated (EX1), another experimental group where frequent price change and disclosure has been both manipulated (EX2), and a control group (CG), with no price change and no disclosure at all. An example of scenario (EX2) is shown below, and the other scenarios can be found in Appendix.

- **Frequent price change** and **Disclose** dynamic pricing strategies:

"You are planning to buy home fitness equipment so you can do exercises at home. You went to the online retailer MasterXu (online fitness equipment retailer) to research the jumping rope price.

*The displayed price is **20** Euro. You want to place the order with **20** Euro immediately; however, your online banking was in maintenance, and you couldn't finish the payment, so you left it in the shopping cart.*

Two days later, you recognize that you haven't placed the order yet. You decide not to buy it and wait for few days.

*A few days later, you checked the price, and it's selling **19** in the morning before you start your work. You decide to purchase in the evening when you finish your work; however, when you check your shopping cart in the evening, the price has risen to **23** Euro.*

In the shopping cart, you read a short notification informing you that the retailer applies dynamic pricing strategies. "

An online experiment survey was sent under the randomizer feature, and all participants received the questionnaire with one of the designed three scenarios randomly. Before the experiment starts, an introduction page was set to inform the participants about the author's thesis topic, the study's purpose, and instruction of the following steps. Following this the scenario page appeared; a timer (25 seconds) was plugged in so that participants cannot easily skip the reading, and it ensures the scenario's effectiveness. Two manipulation check questions were set to assess the manipulation. On the next page, the consumers' perception of fairness was measured, and a proper, previously used measurement scale was adapted accordingly. Once completed, the following page will be designed to understand the consumer's evaluation of trust toward online retailer. By knowing the trust evaluation, consumer's satisfaction toward the different final prices shall be observed. When the consumers' purchase satisfaction is well observed, future behavioral intentions such as repurchase and frequent purchase shall be indicated by the consumer. Therefore, the satisfaction was hypothesized to impact consumers' loyalty. On the last page, the demographic information was collected for the consumer segments analysis, and it will represent the attributes (gender, age, education level, and shopping frequency) of each participant. The author was also interested into participants' dispositional trust levels, since this variable represents an important covariate for the main analysis. Thus, one question toward consumers' initial trust was asked at the end of the survey to see their general trust level.

3.3 Item Measurement

After reading the scenario, two questions for the manipulation check (yes/no) were asked to ensure the experiment's effectiveness – “Did you notice a price change in the scenario?” and “Did the online retailer inform you about the reason for the price changes?”.

In the first section of the experiment, a set of questions were designed to measure the online consumers' perception of fairness closely. The measurement scale was adapted from the relative price fairness measuring study conducted by Chung and Petrick (2015). According to Chung and Petrick (2015), adapted questions toward fairness are also divided into three measurements: distributive price fairness, procedural price fairness, and affective price fairness. Affective fairness was measured by asking about the participant's fairness perception toward frequent price change. The bipolar rating scale was employed accordingly; the scale measures from 1 (negative, annoyed, unhappy) to 7 (positive, pleased, happy), respectively. Participants were asked questions regarding distributive price fairness and procedural price fairness. To indicate their degree of agreement toward few statements, a 7-point Likert Scale from strongly disagree (1) to strongly agree (7) was applied.

The next section of the experiment measures online consumers’ trust toward online retailers. This observation of online consumers’ trust is vital for assessing the changes between experiment groups. The measurements and measuring scale were adapted from the online consumer experience study of Rose et al. (2004). The participants were asked to indicate their degree of agreement toward the retailer's reliability and trustworthiness. Four questions were asked and a 7-point Likert Scale measured each question from strongly disagree (1) to agree strongly (7).

In the following section, satisfaction was measured. Martín-Consuegra et al. (2007) suggest that negative responses arising from purchase satisfaction or dissatisfaction are more relevant to describing the consumers' perception. According to this approach, the degree of disappointment was taken as a measurement in this section to imply consumers' purchase satisfaction. Adapted from Martín-Consuegra et al. (2007), an indication of agreement toward a set of statements about customer satisfaction was asked. A 7-point Likert Scale measured both questions from strongly agree (1) to strongly disagree (7).

The continued section was designed to measure the consumers' loyalty, and the measurement intends to measure consumer’s future repurchase intention to reflect consumer loyalty indirectly. Items such as "repurchase from the online retailer", "regularly repurchase from the online retailer," et cetera were adapted from Rose et al. (2012) and again measured by a 7-point Likert Scale from strongly disagree (1) to strongly agree (7).

In the last section of the experiment, general demographic questions toward gender, age, education level, and online shopping frequency were asked. In addition, the level of consumer's dispositional trust toward online retailers was measured to display the initial level of trust. A 7-point Likert Scale from strongly disagree (1) to strongly agree (7) was applied to keep the consistency of the measurement scale.

3.4 Data Analysis Approach

To ensure the reliability and comprehensiveness of the study, it is crucial to develop a proper plan for data analysis. Since all the collected data will be processed by statistical software SPSS, the entire raw data set will be checked and sorted as a preparation for later stages of analysis. The descriptive analysis will be carried out and reported first because it summarizes the fundamental features from the collected data set. This includes gender, age, education, online shopping frequency, and consumers' dispositional trust level to online retailers.

Then, the author will run the Chi-Square test for the manipulation check. The reason for doing a manipulation check is that it is the key to indicating whether the respondents noticed the manipulation factors. It is a necessary procedure to examine the experiment grouping method. After this step, the reliability check for all the measurement scales will be performed. According to Cronbach’s Alpha, the author will eventually know how reliable the adapted measurement scales are.

The next step involves the main analysis, which aims to find out the direct effects from a price change. Each experimental group's composite scores of fairness and loyalty will be analyzed accordingly by performing the ANCOVA (Analysis of Covariance) test. Thence, leading to the retention or rejection of the hypotheses (**H_1** and **H_7**).

To test the remaining hypotheses, the author will run linear regression through SPSS to explore **H_2** to **H_6**. When all the hypotheses are tested, a clear answer to the two research questions shall be drawn from the reliable results.

3.5 Research Instrument and Sampling

Given the nature of this study, the online survey would be the preferred method for collecting data. The author intended to design the survey questions by using an online custom template; following this, the link was posted on Facebook, Instagram Story, WhatsApp groups, and Wechat . The reasons for choosing this method are the possibility of saving cost, accelerating the survey process, and saving time (Creswell & Creswell, 2018). Therefore, the online survey platform SoSci was chosen for developing the entire questionnaire. Another reason for using SoSci is that it facilitates the raw data transformation in the later analysis stage, reducing data entry errors (Creswell & Creswell, 2018). Especially during the Corona pandemic, this remote way of data collection could ensure both the researcher's and the respondents' safety.

To define the sample population and sample size, since the venue of this research is taking place online, the targeted study population would be the online consumers who had online shopping experiences in the past month. As a student, to prevent additional costs, the most feasible sampling method for this experiment would be the non-probability method, and the author decides to use convenience sampling and snowball sampling to reach many participants who are willing to participate. To define the proper sample size, this research's topic can be seen as a study relevant to marketing test studies (how dynamic pricing strategy will affect consumers' perception). According to the marketing test sample size proposed by Nunan et al. (2020), the usual minimum sample size used in marketing research studies is about 200. Indeed, finding 200 participants would be challenging to achieve by the author. As an alternative, the author also had a look at other studies that related to the thesis topic, and the previously used sample size was ranged from 53 to 130 (Grewal et al., 2004; Martín-Consuegra et al., 2007; Rohani & Nazari, 2012; Weisstein et al., 2013; Haws & Bearden, 2006).

Thence, as this study relies heavily on its research design, the author has decided approximately 100 would be the feasible total sample size (roughly 33 to each group) to assure the applicability of the selected analysis method.

The survey was available to everyone who clicks the link and lasted approximately one month (from February 24th – March 24th). However, since the number of respondents have met the targeted sample size, the link was deactivated.

3.6 Pilot Test

The pilot test is vital for examining the survey's content validity and internal consistency (Creswell & Creswell, 2018). Thus, a pilot test was conducted before the author sent out the survey links. This test aims to help the author get participants' evaluation of survey questions, format, instructions, and duration; this serves as a means to improve the overall quality of the survey.

In order to detect the mistakes that might appear in the survey, four native English-speaking volunteers were invited and participated in this pilot test to examine the text comprehension and completion time. According to the study done by Revilla and Ochoa (2017), the ideal web survey length is a median of 10 minutes. The author pretested the average completion time, and it was approximately five minutes which is acceptable regarding the survey complexity.

After the pilot test, one volunteer has reported a typing error in which one letter was typed twice; however, it did not affect the associated question's comprehensiveness. Another volunteer reported a wording mistake which might cause the participants' misunderstanding of that statement. Also, the minor mistake about the variable's numerical anchor setting consistency was pointed out by one volunteer. All volunteers have suggested to the author minor changes to the scenario as it would have likely generated confusion among participants when answering the questions to follow. By revising the survey, all suggestions were taken into account and the respective corrections were made. The final version of this survey could be found in Appendix.

4 RESULTS AND DISCUSSION

In this chapter, the author is starting with the report of descriptive analysis results to reflect the features of collected data sets. Then the author will perform a manipulation check for the experiment, and a reliability check for the testing variables. After that, the main analysis will primarily focus on examining the proposed hypotheses by performing ANCOVA test and linear regression test. All meaningful results will be interpreted accordingly, thus, a justification of hypotheses will be carried out. Furthermore, a short discussion on the overall results will be drawn out and the research question will be answered in the end of this chapter.

4.1 Demographic Features

As a first step, an analysis of frequencies was used to report the demographic features of overall data sets (see **Table 2**).

	Entire Study (n=103)
Age	
Minimum	18
Maximum	44
Median	27
Gender (%)	
Male	39.8
Female	60.2
Education (%)	
No compulsory	1
Compulsory	1.9
Vocational Secondary	2.9
A-Levels/International Baccalaureate	1.9
University degree	87.4
Other qualification (Master's degree)	4.9
Frequency of online shopping (times/month)	
Maximum	30 (n=2)
Minimum	0 (n=5)
Mean	5.71

TABLE 2 DEMOGRAPHIC RESULTS

In total, 103 valid cases were randomly collected and respondents were randomly assigned to the three different experimental groups (CG=35, EX1=35, EX2=33). The range of the age distribution begins at 18 years old and extends to 44 years old. The median value of this study group's age is 27, and this shows the respondents are mostly young adults. The female participants occupy a large proportion out of 103 participants, which accounts for 60.2%, and the male participants hold 39.8%. The majority of the survey participants possess a university degree, which makes up 87.4% of the total cases. The author also analyzed the participants' online shopping frequency from the past month, and the result shows that two participants shopped 30 times a month, and five participants did not shop online at all. Besides these extreme cases, the entire study group's average shopping frequency is 5.71 (round to 6) times.

The author was also interested in the participants' initial trust level toward online retailers; a statement "Even if not monitored, I would say online retailers are reliable and I can rely on online retailers to keep the promises that they make" was asked to participants to indicate their level of agreement from 1 (strongly disagree) to 7 (strongly agree). The results show the mean value is 4.84, which means the average level of dispositional trust is above the scale midpoint. The median value is 5, and this reflects the middle score of the agreement level, which is also positive. Also, the mode value is 6, and this tells 6 was the choice that appears the most in the results. Therefore, the overall results imply the investigated people intend to trust online retailers in general. A histogram (see Figure 4) shown below illustrates the outcomes better.

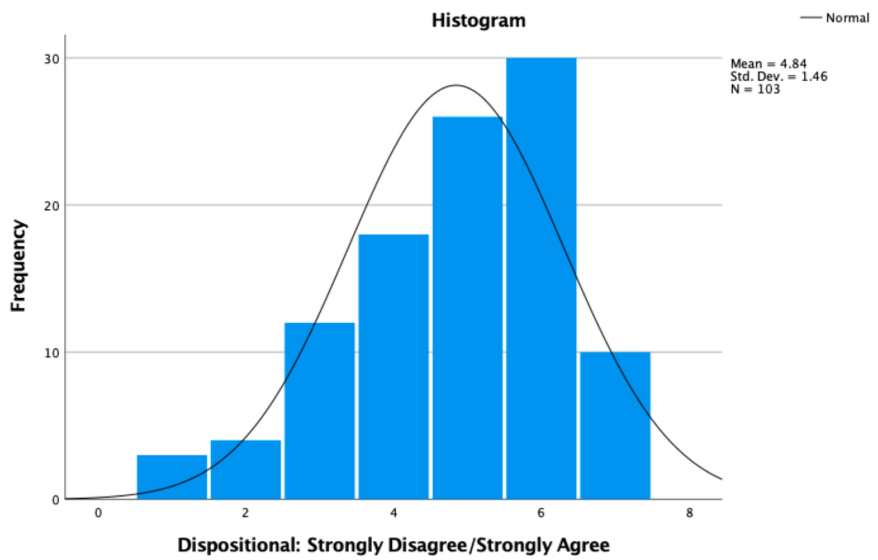

FIGURE 4 DISPOSITIONAL TRUST LEVEL DISTRIBUTION

4.2 Manipulation Check and Scale Reliability Check

4.2.1 Manipulation Check

In order to ensure that all participants of the experimental group were aware of the manipulation factors, a manipulation check analysis was performed. The table below shows the summary of the manipulation check analyses.

	Did you notice a price change in the scenario			***Did the online retailer inform you about the reason for the price changes***		
Experimental Groups	CG	EX1	EX2	CG	EX1	EX2
Yes	4	34	32	2	3	13
No	31	1	1	33	32	20
Chi-Square test						
Pearson Chi-Square		77.814[a]			16.274[a]	
Degrees of freedom		2			2	
Asymptotic significance (2-sided)		<.001			<.001	

TABLE 3 ANALYSES OF MANIPULATION CHECK

For the first 'manipulation check' question regarding price changes, 34 out of 35 participants in the EX1 correctly identified that there had been frequent price changes; 1 out of 33 participants in the EX2 incorrectly identified that there had been frequent price changes. A Chi-Square test reveals a Pearson Chi-Square value of 77.814[a], with 2 degrees of freedom. The test was significant at $p<.001$. Therefore, the result shows that participants in the two experimental groups correctly identified the manipulation factor – frequent price changes.

For the second ‘manipulation check’ question about disclosure of dynamic pricing strategies, 32 out of 35 participants in the EX1 correctly identified that they overlooked the price change reason provided by the retailer; 13 out of 33 participants in the EX2 correctly identified that they had seen a notification in the shopping cart which explains dynamic pricing strategies were applied. The result of another Chi-Square test indicates that the Pearson Chi-Square value was 16.274[a], the degrees of freedom was based on 2, and it was significant at $p<.001$. However, only 13 respondents noticed the price change in EX2, so there was no significant difference between expected and actual cases (13 and 20), which is why the value of Pearson Chi-Square is low. Two reasons might cause this outcome: First, the disclosure stimulus was probably weak since the author only mentioned: "dynamic pricings strategies were performed by the retailer" and did not give a further brief description of the strategies, so the participants did not evaluate it as a disclosure of dynamic pricing strategy. Secondly, the manipulation check question for disclosure was not that well-formed because the "dynamic pricing strategies were performed" cannot be a reason understood adequately by participants. Based on this result, the author has decided to collapse the experimental groups EX1 and EX2 to analyze only one experimental group for the later analysis. Hence, the data do not allow proper testing of hypothesis $\mathbf{H_3}$.

4.2.2 Reliability Check

Checking the reliability of all adapted scales is pivotal before starting the primary analysis because it provides a piece of clear information about the associations between each measurement item in the scale. It also helps with adjusting the accuracy of measurement items. The author ran a reliability check for the adapted scales of fairness, trust, satisfaction, and loyalty. The results of the reliability analysis are displayed in the table below.

Scale (7-point Likert Scale)	*N of Items*	*Cronbach's Alpha*	*Improved Cronbach's Alpha*
Fairness	11	.958	√
Trust	4	.957	√
Satisfaction	5	.616	.727 (4 items)
Loyalty	4	.950	√

TABLE 4 RESULTS OF RELIABILITY ANALYSIS

From the **Table 4** showing above, Cronbach's alpha value for all fairness items is 0.958, which is satisfying. Each item within the scale also exceeded 0.6, thence the reliability of the adapted fairness scale is accepted. The Cronbach's value of four trust measurement items also displayed an adequate level of reliability. The general Cornbach's value of adapted trust scale is 0.957, which is also satisfying and accepted by the author. Same to the adapted loyalty scale, the Cronbach's value read as 0.950, which implies a high level of reliability. In comparison, the Cronbach's value of the adapted satisfaction scale was read as 0.616, which is sufficient but not that satisfying. The Cronbach's value of Item "I would feel differently, if I purchased again from this retailer" was negative, and deleting it would improve the overall Cronbach's value to 0.727. As a result, this item was deleted, and four measurement items remain on the scale.

Since the reliability check for all scales is completed, then the composite scores could be calculated. The composite scores of fairness, trust, satisfaction, and loyalty were added as four new variables in the data set by applying this method.

4.3 Hypotheses Testing

4.3.1 The Impact of Frequent Price Change

H_1: Frequent price changes decrease the consumers' perception of fairness.
H_7: Frequent price changes have a negative influence on consumer loyalty.

To find out how dynamic pricing directly influences the consumer's perception of fairness, the univariate analysis of variance (ANCOVA) test was run for the analysis because the ANCOVA test is often used when there are differences between experimental groups. Thence, the composite score of fairness was added as the dependent variable, and the dispositional trust level was also added as a covariate because dispositional trust could be the factor that influences fairness. Correspondingly, the recoded experiment groups were set as a fixed factor.

From the analysis, it was apparent that two different experimental groups have a significant effect on the dependent variable fairness. The significant p-value $p<0.001$ indicates there are statistically significant fairness perception differences between the experimental group and the control group, $F(1,100)=23.538$, $p<0.001$. Approved by the mean value, the mean value for the control group is 4.82, for the experimental group is 3.25. The higher mean value for the control group indicates that participants in the group without frequent price changes had a higher perception of fairness.

Furthermore, to explore the direct effect of dynamic pricing on consumers' loyalty, another ANCOVA test was conducted. The composite score of loyalty was added as the dependent variable, and the dispositional trust level was again added as a covariate to control the effects of the frequent price change (dynamic pricing). Similarly, the analysis revealed that the two different experimental groups also differ significantly in terms of loyalty, $F(1,100)=18.366$, $p<0.001$. The significant p-value $p<0.001$ indicates there are statistically significant loyalty perception differences between groups. Also confirmed by the mean value, the mean value for the control group is 4.61, while for the experimental group is 3.13. The higher mean value for the control group indicates that participants in the group without frequent price changes had a higher perception of loyalty.

Table 5 Summarizes the mean values, corresponding standard deviations among the control group and the collapsed experimental groups, as well as the F-values and significant values for the two dependent variables, fairness and loyalty.

	CG		***EX1 & EX2***				
Dependent Variable	***Mean***	***Std. Deviation***	***Mean***	***Std. Deviation***	***df***	***F***	***Sig.***
Fairness	4.82	1.29	3.25	1.39	1	23.538	P<0.001
Loyalty	4.61	1.23	3.13	1.53	1	18.366	P<0.001
Significant at p ≤ 0.05 two-tailed, 95% confidence intervals							

TABLE 5 SUMMARY OF ANCOVA TEST RESULTS

In sum, the analysis collaborated $\mathbf{H_1}$ - Frequent price changes decrease the consumers' perception of fairness. Thence, the $\mathbf{H_1}$ is **accepted** here. The analysis allowed the acceptance of frequent price changes to negatively influence consumer loyalty; therefore, the $\mathbf{H_7}$ is **accepted** here.

4.3.2 Consumers Trust and Perception of Fairness

$\mathbf{H_2}$: Consumers' perception of fairness has a positive influence on trust towards online retailer.

The conceptual research framework of this thesis suggests that consumers' perception of fairness could serve as an antecedent that influences consumers’ trust towards online retailer. To justify the correlation between perception of fairness and trust towards online retailer, the author has created a scatterplot (see **Figure 5**). Hence, a linear regression analysis was chosen to further analyze the postulated impact of fairness.

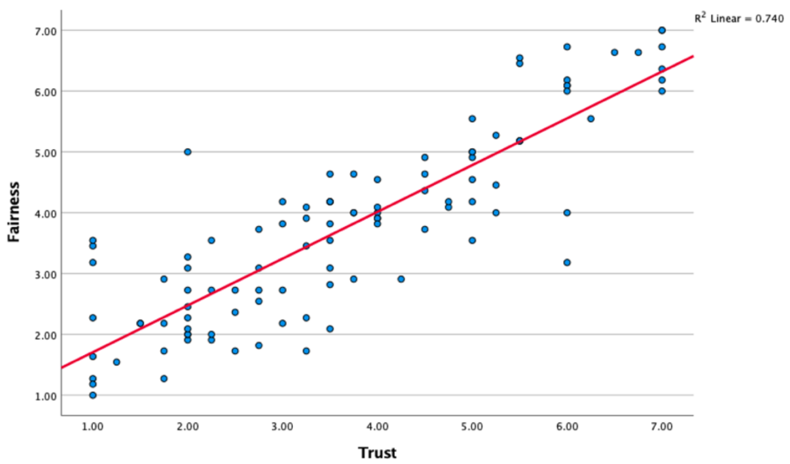

FIGURE 5 CONSUMER TRUST FAIRNESS RELATIONSHIP SCATTERPLOT

	R	R^2	*F*	*B(Constant)*	*B(Fairness)*
Value	0.860	0.740	287.185	0.062	0.962
Significance			p<0.001		p<0.001

Significant at p ≤ 0.05 two-tailed, 95% confidence intervals

TABLE 6 RESULTS OF REGRESSION ANALYSIS

The output of linear regression analysis (see above **Table 6**) revealed a positively correlated relationship between trust and fairness (R=0.860). The value of R^2 equals 0.740, which tells that fairness accounts for 74% of the variation in trust. Furthermore, the F ratio is 287.185, with the significance p<0.001. This result means that there is less than a 0.1% chance that an F ratio this large would happen if there is no correlation between trust and fairness; therefore, this regression model significantly predicts trust.

For the values of the coefficients, the constant B value was read as 0.062, which means there will be nearly no trust observed when there is an extremely unfair situation. Furthermore, the B value for fairness is 0.962, which means that when the consumers' perception of fairness increases by 1 level, the level of trust will be increased by 0.962. Therefore, the price fairness perception significantly contributes to consumers' trust toward online retailers (p<0.001). Overall, the results support hypothesis **H_2**, namely that consumers' perception of fairness has a positive influence on their trust towards online retailer. Hence, the **H_2** is **accepted** here.

4.3.3 Consumer Trust and Consumer Satisfaction

H_4: Trust towards online retailers has a positive influence on consumer satisfaction.

Kim, Ferrin, and Rao (2009) said online consumer satisfaction and trust with the business transaction form the foundation for the long-term commercial relationship between an online vendor and a consumer. Hence, for the purpose of investigating the relationship between trust toward online retailers and consumers' satisfaction, a scatterplot (see **Figure 6**) was first created to visualize the distribution of the values, and then the linear regression test was again run for the analysis. The consumers' satisfaction was specified as the dependent variable, and trust toward online retailers was defined as the independent variable.

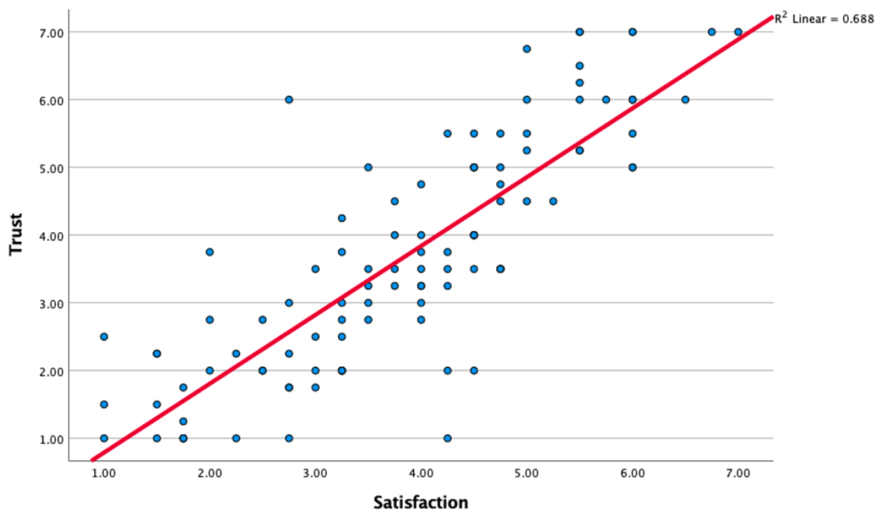

FIGURE 6 CONSUMER TRUST SATISFACTION RELATIONSHIP SCATTERPLOT

	R	***R^2***	***F***	***B(Constant)***	***B(Trust)***
Value	0.829	0.688	222.463	1.361	0.677
Significance			p<0.001		p<0.001
Significant at p ≤ 0.05 two-tailed, 95% confidence intervals					

TABLE 7 RESULTS OF REGRESSION ANALYSIS

The linear regression analysis output revealed a positively correlated relationship between consumers' satisfaction and trust toward online retailers (R=0.829). The value of R^2 equals 0.688 which tells that trust toward online retailer accounts for 68.8% of the variation in consumer satisfaction. The F ratio reported as 222.463, with the significance p<0.001. This result means that there is less than a 0.1% chance that an F ratio this large would happen if there is no correlation between consumer satisfaction and consumer trust. Indeed, this regression model predicts satisfaction significantly well.

For the values of the coefficients, the constant B value was read as 1.361, which means there will be at least a 1.361 level of purchase satisfaction observed when there is no trust toward online retailers. The B value for trust is 0.677, and it means when the consumers' trust toward online retailer increases by 1 degree, the degree of purchase satisfaction will be increased by 0.677 accordingly. Therefore, online retailers' trust makes a significant positive contribution to consumers' purchase satisfaction ($P<0.001$). This result is in line with **H_4** and leading to acceptance of the **H_4**.

4.3.4 Consumer Trust and Loyalty toward Online Retailer

H_5: Consumer trust towards online retailers has a positive influence on consumer loyalty.
H_6: Consumer satisfaction has a positive influence on consumer loyalty.

Previous results justified that online consumer satisfaction is highly dependent on a business's trustworthiness. By establishing trust, the satisfaction from the consumer can guarantee repeat orders and consumer loyalty. In order to illustrate how consumers' trust and satisfaction exert an influence on consumer loyalty, a multiple regression test was performed to seek the answer. Again, using the scatterplot to visualize the relationship between consumer trust, satisfaction, and loyalty (see **Figure 7**), it shows that consumer loyalty can be predicted by the other two predictor variables in this three-dimensional model.

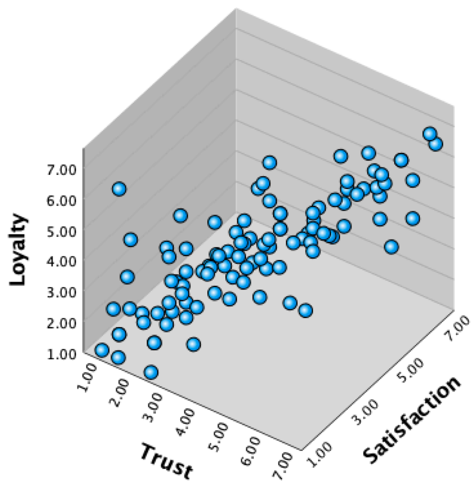

FIGURE 7 TRUST SATISFACTION LOYALTY MODEL

	R	***R^2***	***F***	***B(Constant)***	***B(Satisfaction)***	***B(Trust)***
Value	0.792	0.628	84.319	0.586	0.277	0.533
Significance			$p<0.001$		$p=0.027$	$p<0.001$

Significant at $p \leq 0.05$ two-tailed, 95% confidence intervals

TABLE 8 RESULTS OF REGRESSION ANALYSIS

The output of multiple linear regression analysis (**Table 8**) revealed a highly significant regression model of consumers' loyalty. The satisfaction and trust toward online retailers predicted the loyalty well in this model, $F(2,100) = 84.319$, $p<0.001$. The value of R^2 equals 0.628, hence, trust in online retailers and satisfaction accounts for 62.8% of the variation in loyalty. The F-ratio was 84.391, significant at p<0,001, meaning that there is less than a 0.1% chance that an F ratio this large would happen if there is no regression correlation between consumer loyalty, consumer satisfaction, and consumer trust.

For the values of the coefficient, the constant B value is read as 0.586, which means there will be at least a 0.586 degree of consumer loyalty observed when there is no trust and satisfaction from the consumer. This indicates consumer's perception might be the cause contributing to that initial degree. The B value for satisfaction is 0.277, meaning that when the consumers' satisfaction toward online retailer increases by 1 degree, the degree of consumer loyalty (repurchase intension) will be increased by 0.277 accordingly. As approved by the coefficients significance level (p=0.027), the consumer purchase satisfaction toward online retailers significantly contributes to the consumer's loyalty. The B value for trust is 0.533, thus, when the consumers' trust toward online retailer increases by 1 degree, the degree of consumer loyalty (repurchase intension) will be increased by 0.533 accordingly. Confirmed by the coefficients significance p<0.001, the consumers' trust toward online retailers contributes significantly to consumer's repurchase intention (loyalty). Concerning the results, consumer trust seems to have a more significant influence on consumer loyalty than consumer satisfaction. In sum, the results have supported that consumer trust toward online retailers and consumer satisfaction both have positive influence on consumer loyalty, and consumer loyalty is interpreted as repurchase intention here. For this reason, **H_5** and **H_6** are both **Accepted**.

From above, the following **Table 9** displays all hypotheses with associated statistical test results to provide a holistic view of this Study.

Manipulation Check	Chi-Square test	***Partially Supported***
Scale Reliability Check	Reliability Analysis	***Fully supported***
H_1: Frequent price changes decrease the consumers' perception of fairness.	ANCOVA	***Accepted***
H_2: Consumers' perception of fairness has a positive influence on trust towards online retailer.	Regression Analysis	***Accepted***
H_3: Disclosing the dynamic pricing strategy to consumers has a stronger positive influence on trust toward online retailers than not disclosing to consumers.	Manipulation Partially Failed	***na***
H_4: Trust towards online retailers has a positive influence on consumer satisfaction.	Regression Analysis	***Accepted***
H_5: Consumer trust towards online retailers has a positive influence on consumer loyalty.	Regression Analysis	***Accepted***
H_6: Consumer satisfaction has a positive influence on consumer loyalty.	Regression Analysis	***Accepted***
H_7: Frequent price changes have a negative influence on consumer loyalty.	ANCOVA	***Accepted***

TABLE 9 THE SUMMARY OF HYPOTHESES STATISTICAL RESULTS

In the following, the author will synthesize the relevant hypotheses to answer the research questions of this Study:

RQ1: How do dynamic online pricing strategies affect consumers' perception of price fairness, trust, and loyalty toward online retailers?

RQ2: How does the consumers' trust toward dynamic online pricing influence consumers' satisfaction and loyalty to online retailers?

The hypotheses **H_1** and **H_7** have answered the part of the **RQ1** that frequent price change could decrease the consumers' perception of fairness, as well as consumer loyalty. Analysis of the **H_2** reveals that the higher the consumers' perception of fairness is, the more trust from consumers comes toward online retailers. This direct proportional relationship could be used to interpret the **H_1** further that frequent price change could decrease the online retailer's trustworthiness as well. Accordingly, to answer **RQ1**, the consumer trust and loyalty are negatively affected if the price fairness is perceived like negative, as caused by frequent price changes.

The hypotheses **H_4**, **H_5**, **H_6** together provide the evidence to answer the **RQ2**: consumer's trust toward online retailer's dynamic pricing has a significant influence on consumers' satisfaction and loyalty. The degree of the consumers' trust increases is positively related to consumer satisfaction, resulting in consumer loyalty. Hence, the **RQ2** is answered.

5 CONCLUSION AND DISCUSSION

Observing from the angle of collected data, the survey of this study shows that 95% of the 103 respondents have shopped online in the past month, reflecting that online shopping has become an indispensable activity for most people's lives. Unlike offline shopping, the vast extending of online shopping behavior result from the boom of information technology and e-commerce. Conforming to this trend, many online retailers have achieved their success through the increasing market demand and pricing strategies. A flexible and dynamic price-setting implies a dynamic pricing strategy widely used by online retailers among the confierce price competition. Nevertheless, a dynamic pricing strategy with an inappropriate and frequent price change can alter the consumers' cognitive perceptions. Hence, this thesis's main aim was to discover the actual impact of the dynamic pricing strategy on online consumers' perception of fairness, trust, satisfaction, and loyalty.

To better understand the dynamic pricing strategy and its mechanism, six current widely used dynamic pricing strategies were summarized as following: Segmented Pricing, Time-based Pricing, Peaking Pricing, Penetration Pricing, Competition Driven Pricing, and Random Market Fluctuation Pricing. Most importantly, based on those commonly used strategies, the author studied the influencing factors that caused price change. Time scale, weather change, competitors' price, different organizational goals, and market demand elasticity are the key factors that contribute to online price fluctuation. In addition, the literature review suggests that machine learning-based pricing represents the future trend of price setting. Different from the rule-based dynamic pricing, the advancement of big data analysis could enable machine learning to provide a more comprehensive and accurate model for dynamic pricing methods (Raju et al., 2003).

After reviewing many pieces of literature, the author has developed a conceptual framework to structure the later study. In the conceptual framework, trust serves as the outcome of fairness perception and an antecedent to provoke consumer satisfaction and loyalty. Therefore, trust was studied in detail as it is one of the focused consumer perceptions in this thesis. Various scholars have defined trust formation; scholars widely accepted the “Benevolence and Competence” trust model to emphasize trust in the online shopping context (Garbarino & Lee, 2003). Consumers’ benevolence trust comes from their disposition, and it indicates the general trust toward online retailers. The competence trust represents the trust obtained later, which is influenced by the online retailers' reputation, web design, service (shopping experience), etc. By concentrating on the shopping experience associated with consumer behaviors, consumers' perception of price fairness and other components (satisfaction, loyalty) within the framework were theoretically identified by the author. Thus, the hypotheses were drawn to find out the relationships between these components.

Before testing the stated hypotheses, a one-factor, three-level fractional factorial experiment design was chosen, where the author randomly allocates the participants to groups. The experiment was conducted through an online survey platform which has allowed the author to observe three groups for further analysis (experimental group EX1 where only frequent price change was manipulated, another experimental group EX2 where frequent price changes and disclosure of dynamic pricing strategy has been both manipulated, and a control group CG, with no price change and no disclosure). In order to ensure the effectiveness of the manipulation, two questions were asked to participants whether they noticed price change and disclosure of dynamic pricing strategy or not. Unluckily, most participants' manipulation of disclosing dynamic pricing strategy was not ideally noticed (13 out of 33); therefore, the author could not test the fairness perception difference between EX1 and EX2. Since the manipulation factor "disclosing dynamic pricing strategy" could not be considered, the remaining two experimental groups were combined as one by the author.

Besides $\mathbf{H_3}$, the rest of the hypotheses were all accepted. The statistical results have shown the retained hypotheses were fully supported in answering the research questions. The author found out that participants in the group without frequent price changes had higher price fairness perception due to the higher composite mean value. Hence, the price change will decrease consumer's perception of price fairness. In both experimental groups' scenarios, the final selling price of the jumping rope was set higher than the original price, and this indicates the price inequality is the reason that was mediating the perception of fairness. This finding is consistent with what Xia et al. (2004) have suggested. Xia et al. (2004) stated that disadvantaged inequality is associated with the negative emotions that occur in price fairness. Taking a step forward and looking at the analysis results of price fairness perception's influence on consumers' trust towards online retailer, a positive and significant correlation between online retailers' trust and consumers' price fairness perception was observed, and the price fairness perception significantly contributed to consumers' trust toward online retailers. Relate to the findings between a frequent price change and price fairness perception, and it is clear that a negatively perceived price change decreases online retailers' trustworthiness. Grewal et al. (2004) also empirically confirmed that the amount of price difference has a significant effect on trust and fairness, which refers to the negative price changes resulting from the lessening of consumer trust and fairness perception. The author further analyzed the direct effect of frequent price changes (a form of dynamic pricing strategy) on consumers' loyalty. The ANCOVA test results displayed that consumers' perception of price fairness significantly affected their online retailer's loyalty. The statistical result stated the group without frequent price changes had a higher degree of loyalty which implies the influence of negative price change on loyalty (interpreted as repurchase intention). Therefore, the reliable answer of RQ1 was drawn according to the findings from above, that consumer trust and loyalty are negatively affected if the price fairness is perceived unfair as caused by frequent price changes.

For the answer of RQ2, the consumers' trust toward online retailers was proven in this study to have a positive influence on consumer satisfaction and loyalty (repurchase intention). The linear regression analyses' results all suggested a significant p-value ($p<0.05$) which supports the regression models. However, multiple regression analysis results demonstrate that trust in online retailers and satisfaction account for 62.8% of the variation in loyalty. The results suggest that there might be other cognitive variables that predict loyalty. Indeed, as mentioned above, the negative price change reduces consumers' loyalty (purchase intention); hence we could say that perceived price unfairness shall also influence consumer loyalty, and this was justified by previous studies (Grewal et al., 2004; Martín-Consuegra et al., 2007). As Rose et al. (2012) claimed in the study about online customer experience in e-retailing, the greater the level of trust in online shopping, the greater the level of online shopping satisfaction, which results in the greater level of online repurchase intension. According to the statistical results, the author also determined that the increase of consumers' trust is positively related to consumer satisfaction, as well as consumer loyalty (repurchase intention).

Generally speaking, this study aimed to discover the dynamic pricing strategy's actual impact on online consumers' perception of fairness, trust, satisfaction, and loyalty. Based on a quantitative analysis of undisclosed frequent price changes in response to the consumers' cognitive perceptions, it can be concluded that consumers' trust toward the online retailer could be seen as one of the outcomes caused by price fairness perception. As an intermediate derived from price fairness perception, consumer trust also serves as an antecedent to provoke consumer satisfaction and loyalty. The results indicate that the negatively perceived final purchase price, which is the price above the perceived reference price, can lead to consumer perceptions' downturn.

Lastly, this study failed to reveal the consumer perceptions change in a disclosed dynamic pricing strategy context; however, this thesis has shown how frequent price changes can directly shape the consumer's cognitive perceptions. With the improvement in the efficiency and commercial feasibility of big data implementation, the prices online will be displayed more dynamically according to the different consumer segments, resulting in more dynamic pricing strategies being adopted by online retailers. Hence, online retailers should be cautious while implementing those dynamic prices because the adverse influences on consumer's trust, satisfaction, and loyalty might occur in the next second.

5.1 Theoretical Implication

Dynamic pricing strategy as a research area has been studied for decades, whereas the research of online dynamic pricing strategy could still be considered as a newly developing market research area that arouses various researchers' interest. The earliest study in this area could date back to the later 90s, and same as online trust-building, a considerable number of studies have been conducted (Bauman & Bachmann, 2017; Gefen, 2000). One of the primary focuses of previous research on dynamic pricing strategy was finding out how the price fairness perception affects consumers' behavior, such as satisfaction and loyalty. The research approach toward the relationship between consumer trust toward online retailers and price fairness perception was rarely studied. Even though some researchers noticed this domain and dissected trust under specific trust models, further impact of violated trust and its implications toward consumer satisfaction and loyalty did not draw their attention (Garbarino & Lee, 2003). By writing this thesis, the author had a chance to inspect these approaches in a holistic view and determine the gaps and better understand the impact of dynamic pricing and trust-related consumer cognitive perceptions.

An important point to notice is that this study was bridging the gap between online consumers' price fairness studies and online consumer trust studies. In past online consumer price fairness studies, the price fairness perception was perceived to directly impact purchase satisfaction and repurchase intention. Furthermore, in the past online consumer trust studies, online trust was derived from the general web experience, web design, products and services quality, and purchase satisfaction (Bauman & Bachmann, 2017). Nevertheless, as this thesis's findings reveal, the consumer trust toward online retailers can be seen as the outcome of price fairness perception and an antecedent that provokes consumers' purchase satisfaction and repurchase intention. Therefore, this study thoroughly emphasized the central relationships between consumers' trust, fairness perceptions, and loyalty in a dynamic pricing context.

In addition, this study complied with the one-factor fractional factorial design and attempted to disclose the dynamic pricing strategy toward survey participants and see if there was a more decisive effect created by disclosure manipulation. Even the attempt failed due to the comprehensiveness of the manipulation control question, it still illustrated a direction for the future scholars' research design.

5.2 Practical Implication

This thesis was standing from the online retailer's point of view to observe the outcomes of implementing dynamic pricing strategies on consumers. By bearing this in mind, the main goal was to help the online retail beginners to understand the overall online price-setting mechanisms better, thence maintaining good relationships with online consumers.

To be more specific, firstly, online retailers need to master the commonly used dynamic pricing strategies, so they could fast react to the market demand or competitor’s tactics. Simultaneously, online retailers shall also be able to acquire comprehensive information from the potential price influencing factors, thereby adjusting the price correspondingly. It is suggested to price the products flexibly by considering the time scale, competitor's price, organization goals, the elasticity of the market demand, even weather situation. Nevertheless, as mentioned in the literature, with the help of big data analysis and machine learning, all those influencing factors and consumer purchasing behaviors will be integrated and analyzed systematically to tackle the target consumer segment accurately.

Secondly, according to this thesis's results, it is not advocated for online retailers to adjust the price frequently. Especially when the final price is higher than the original price, consumers will perceive the price as unfair and the online retailer as untrustworthy. Moreover, the following consequence will reflect a decrease in consumer's online purchase satisfaction and repurchase intention. More seriously, these could lead to consumer churn and other losses.

All in all, online retailers shall be cautious with the pricing decisions and try to build trust among the consumers. In return, a satisfactory experience will be memorized by the consumer; thereby, the repurchase intention will follow naturally. Probably making the pricing strategy transparent is another solution for online retailers to build trust with consumers, but this needs to be examined in the future study.

5.3 Limitations and Future Research

Apart from the theoretical and practical implications, the limitations of this study shall also be valued. The first and foremost is the failed attempt to disclose the dynamic pricing strategy in experiment EX2, making the overall experiment less meaningful. Only 13 out of 33 participants in the EX2 noticed the manipulation control question, which might have been caused by the weak disclosure stimulus and blurry manipulation check question. Therefore, to guarantee manipulation stimulus effectiveness in future studies, the manipulation stimulus shall be declared and highlighted.

Sticking with the limitations of the research method, the one-factor, three-level, the fractional factorial design was not the best method to discover the impact of dynamic pricing strategies on consumers. As the name suggests, a dynamic pricing strategy implies that various factors drive the price. So, the complete factorial design is needed for future study because the fractional design can only partially reveal the impact. In this study, the author only examined the negative impact caused by frequent price changes, and the final price was above the reference price and perceived unfair by consumers. In contrast, the positive impact caused by a fair price could also make sense for further study. Indeed, more manipulation factors could be used to undercover the impact of dynamic pricing strategy. For instance, the extent of rise or drop in price (or price affordability) could be studied to find out the range of “safety” price adjustment (safety means without negative influence).

From the literature review, the formation of consumer trust toward online retailers was introduced in detail, and trust was segmented into benevolence trust and competence trust. And these were reflected in the survey questions by investigating the initial trust level and the trust after purchase. However, the question investigating initial trust was listed by the end of the survey, and it cannot really show the actual initial level of trust. This is because after reading the different scenarios, participants are biased. This bias could be well explained by the mean value of the initial trust (4.84) in general, and the mean trust value (4.82) in the control group as there was not much significant difference. Thence, if the future study intends to discover the difference in trust across the time, the initial trust measures (questions) shall be set before the treatment (in author case refers to scenarios).

Some limitations remained in the sampling procedure and came along with the sample size. Due to the challenge in finding more participants, the sample size was decided for approximately 100, which is small compared to the regular marketing research's sample size (minimum 200). The demographic results of this study stated 103 participants with ages ranging from 18 to 44. However, the median value of this study group's age (27) revealed the respondents are primarily young adults. To investigate the topic more precisely, a future study is suggested to enlarge the sample size, thereby enhancing the study population's heterogeneity. Other limitations, such as budget constraints and location (the author is based in Vienna), could also be improved to obtain a greater sample size.

Finally, this study has profoundly illustrated the relationships between consumer fairness perception, trust toward online retailers, purchase satisfaction, and repurchase intention. The previous literature review suggested that there are some interactions among the price fairness perception, satisfaction, and loyalty. Since the author had limited time in conducting this study, the author could not discover the interactions between the cognitive perceptions mentioned above. By noticing this research approach, the future researcher could also study the interactions between those perceptions to understand the dynamic pricing strategy better.

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APPENDICES

a) Survey Scenarios

Scenario 1 EX1

You are planning to buy home fitness equipment so you can do exercises at home. You went to the online retailer MasterXu (online fitness equipment retailer) to research the jumping rope price.

The displayed price is **20** Euro. You want to place the order with **20** Euro immediately; however, your online banking was in maintenance, and you couldn't finish the payment, so you left it in the shopping cart.

Two days later, you recognize that you haven't placed the order yet. You decide not to buy it and wait for few days.

A few days later, you checked price and its selling **19** in the morning before you start your work. You decide to make the purchase in the evening when you finish your work, however, when you checked your shopping cart in the evening, the price has raised up to **23** Euro.

Scenario 2 EX2

You are planning to buy home fitness equipment so you can do exercises at home. You went to the online retailer MasterXu (online fitness equipment retailer) to research the jumping rope price.

The displayed price is 20 Euro. You want to place the order with 20 Euro immediately; however, your online banking was in maintenance, and you couldn't finish the payment, so you left it in the shopping cart.

Two days later, you recognize that you haven't placed the order yet. You decide not to buy it and wait for few days.

A few days later, you checked the price, and it's selling 19 in the morning before you start your work. You decide to purchase in the evening when you finish your work; however, when you check your shopping cart in the evening, the price has risen to 23 Euro.

In the shopping cart, you read a short notification informing you that the retailer applies dynamic pricing strategies.

Scenario 3 CG

You are planning to buy home fitness equipment so you can do exercises at home. You went to the online retailer MasterXu (online fitness equipment retailer) to research the jumping rope price.

The displayed price is **20** Euro. You want to place the order with **20** Euro immediately; however, your online banking was in maintenance, and you couldn't finish the payment, so you left it in the shopping cart.

Two days later, you recognize that you haven’t placed the order yet. You decide not to buy it and wait for few days.

A few days later, you checked price and its selling **20** in the morning before you start your work. You decide to make the purchase in the evening when you finish your work, however, when you checked your shopping cart in the evening, the price is remaining **20** Euro.

b) Survey Questions

Did you notice a price change in the scenario?

- Yes
- No

Did the online retailer inform you about the reason for the price changes?

- Yes
- No

In this section, we would like to know if you experience the purchase process with this retailer. Please indicate the extent you disagree/agree with the following statements.

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
The final price were fair.	○	○	○	○	○	○	○
The final price were acceptable.	○	○	○	○	○	○	○
The final price were understandable.	○	○	○	○	○	○	○
The online retailer’s pricing decisions were reasonable.	○	○	○	○	○	○	○
The online retailer’s pricing decisions were fair.	○	○	○	○	○	○	○
The online retailer’s pricing decisions were acceptable.	○	○	○	○	○	○	○
I think the final price were based on cost.	○	○	○	○	○	○	○
All online consumers were treated equally by the online retailer’s pricing decisions.	○	○	○	○	○	○	○

How did the final price make you feel

Annoyed	○	○	○	○	○	○	○	Pleased
Unhappy	○	○	○	○	○	○	○	Happy
Negative	○	○	○	○	○	○	○	Positive

In this section, we would like to know how you evaluate the retailer. Please indicate the extent you disagree/agree with the following statements.

	Strongly disagree 1	2	3	4	5	6	Strongly agree 7
Online shopping at this retailer would be reliable .	○	○	○	○	○	○	○
In general, I could rely on this online retailer to keep the promise he makes.	○	○	○	○	○	○	○
This online retailer can be trusted, there are no uncertainties.	○	○	○	○	○	○	○
Online shopping at this retailer is a trustworthy experience.	○	○	○	○	○	○	○

In this section, we would like to know how satisfied you would have been with you purchase from this retailer. Please indicate the extent you disagree/agree with the following statements.

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I would be satisfied with my purchase decision if I would have bought at the final price.	○	○	○	○	○	○	○
I would consider my choice was wise if I would have bought at the final price.	○	○	○	○	○	○	○
I would feel differently, if I purchase again from this retailer.	○	○	○	○	○	○	○
I would feel bad about my purchase decision.	○	○	○	○	○	○	○
I think that I would have selected the right online retailer.	○	○	○	○	○	○	○

In this section, we would like to know your future behavioural intentions toward this retailer. Please indicate the extent you disagree/agree with the following statements.

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
It is very likely that I will repurchase from this online store in the near future.	○	○	○	○	○	○	○
I anticipate repurchasing from this online retailer in the near future.	○	○	○	○	○	○	○
I would regularly repurchase from this online retailer.	○	○	○	○	○	○	○
I expect to repurchase from this online retailer in the near future.	○	○	○	○	○	○	○

What is your gender?

○ female

○ male

How old are you?

I am ____ years old

What is the highest level of education you have completed?

○ No compulsory education

○ Compulsory education

○ Vocational secondary certification (completion of specialized secondary school/college)

○ A-levels/International Baccalaureate, subject-related higher education entrance qualification

○ University degree

○ Other school-leaving qualification: ____

How many times have you shopped online in the past month?

____ times/month

Even if not monitored, I would say Online retailers are reliable and I can rely on online retailers to keep the promises that they make.

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree