Competitive Intelligence and Margin Preservation Through Predictive Analytics: An AI-Driven Framework for Retail Pricing Strategy Optimisation

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1. Introduction to Retail Pricing Strategies

Retail pricing strategies concern decisions regarding pricing levels, techniques, policies, and price adaptation. One common pricing policy in retailing is determining regular prices and subsequently incorporating price promotions using different formats or techniques. Several pricing models have analyzed how, when, and to what extent prices should be reduced by price promotions to attract and retain consumers. Their models use a philosophy of psychological thresholds to explain retail chains' behavior in choosing sales proportions and frequently compute the optimal sales proportions for businesses to be profitable. In retailing, pricing policy is essential, crucial, and an ongoing strategic tool that is complex, difficult, and yet critical to manage effectively. An ambiguous yet certain fact is that the pricing decisions taken by retailers ultimately drive people's buying decisions.

In the modern market, the retailing scenario is very dynamic, and pricing strategies, even when novel, are guaranteed to change by the next quarter. For example, the one-time price-only retail format of a major retailer is now also including "sales annually," "constant low prices," and creating boutiques within the store to offer an exclusive set of branded merchandise. Integrally, the pricing policy adopted by the retailer is used to influence consumer behavior in order to buy greater quantities of stock, often in an assortment. Based on market conditions, some retail organizations thrive on providing high regular prices and then following them up with short, abrupt, and frequent price discounting to encourage buying. Others employ a "consistent price rollback" strategy or "everyday low pricing" along with week-specific or annual offers. For example, with respect to technological goods, a major retailer conceded that corporate executives made the mistake of abandoning an established retail strategy: "had walked away from the one thing that had attracted shoppers far and wide: the promise of the lowest price," to "offered low prices every day, rather than counting on short-term sales to attract customers."

1.1. Overview of Pricing in Retail

Retail pricing is at the heart of the competition that marketers thrive in. Clients' perceptions should be understood and reflected in value propositions that mirror store positioning across geographical and customer segmentation. The pricing of goods and services must merge with business-specific methods to fulfill both consumer and company objectives. The price is set according to various variables that require consideration, such as the expenditure of customers, the result in market, and the expenditure of competitive channels of distribution. The price is divided into three categories: value-based, cost-based, and competition-based, to illustrate an overview of pricing procedures. In terms of consumer surplus and overall demand in a market, cost-based pricing is defined as price-fixing, while market share and customer loyalty are achieved in competition-based pricing by forming new products and services.

As a golden rule, the objectives of retailers must be reflected in the pricing technique except in certain cases. For instance, if outlet stores are floated as discount retail stores, the technique of pricing has a strong association with unit cost (resulting from high quantity buying by aiming for revenue volume margin and flow towards the minimum process of costs). Pricing decisions are primarily essential and sensitive transactions for a retailer because the cost of failing in these might harm the revenue maximization prepared. Retailers are in desperate competition with one another on a daily basis for survival. One of the clear reasons that differentiate consumers is price correction. Dynamic pricing and innovative, time-bound promotional activities are typically a spot that intrinsically attracts customers. Any mispricing policies relative to the competition or customer reaction limit the profit. Non-market leaders might somewhat bravely take any hazard.

1.2. Importance of Dynamic Pricing and Promotional Offers

Dynamic or personalized pricing refers to changing the price tag on an item per store basis, often in real time, to quickly adapt to changing market conditions. These changes are driven by algorithms that are tuned to maximize profits; by doing so, prices reflect the absolute value that a customer is willing to pay for the good—a price point a customer is willing to pay based on available substitutes and opportunities. However, pure price discrimination is tricky; customers who suddenly learn that they were charged 'more' for the same item will feel unfairly treated, angry, and will leave negative reviews, so brands primarily focus on developing optimal audience and tailored promotions for each audience segment. High-impact promotions are often used by brands in retail to make prices appear lower than the reference prices. They stimulate demand, increasing customer flow in a slow period and ensuring the highest possible inventory turnover. Three main forms of promotion do this. Firstly, a pre-announced sale moves most of its revenue to when it is price-cut; secondly, a loss leader can be sold at a small loss and can be designed this way as the item chosen is not in demand, but allows the purchase of tickets sold later at a higher price; thirdly, add-on promotions are short-term discounts for buying specific items. Promotions should aim to limit increases in stock. To be effective, they must have a sense of urgency; if shoppers feel they can buy in the near future, then they can wait to shop. Promotional offers must also catch the attention of potential customers and convince them of their relevance. However, setting an effective promotion offer is not necessarily straightforward—combining discounts with timing, investment focus, competition, inventory status, or new customers is crucial. The value of promotion can lead to much higher sales with only a small lift in spend. In addition, customers treated as deal levels may spend time with a brand, totaling over 87 minutes with a brand over something less, as with coupon users, while also being 2% more likely to leave a brand experience with a conversion. Customers who receive special offers, such as limited-time or location deals, are 14% more likely to make a purchase in-store and 24% more likely to make a purchase across all sales channels. Successful promotion planning is crucial in a difficult retail marketplace because it is a valuable tool in increasing ticket value—62% of customers buy something extra when they use a coupon. Targeting promotional offers should be sent to high-measured audience segments, who experience higher average scores of KPIs than any other segment. Non-testing creatives should use promotions; they performed 39% better than non-discounted creatives. Timing promotions and site changes is crucial to customer uplift as there are peak shopping windows throughout the week. Brand spend; reviewing the overall results can be spent as it can bring a 50% boost in unique users.

2. Foundations of Machine Learning in Retail

The objective of these lectures is to familiarize retail practitioners with the foundational principles of machine learning and AI that constitute today's predictive engines. In general, four ideas apply for using machine learning (in any field, not just retail): 1. Algorithms: Learning algorithms take in behavioral data and output a set of decision rules. These decision rules can be as simple or as complicated as the degree of accuracy required in the predictions. The greater the required accuracy, the more complex the decision rule. 2. Data: The heart of a machine learning application is the data with which the model is trained. The model is only as good as the data that feeds it. If the data is flawed or insufficient, so will be the model. 3. Training: First, called model training or, equivalently, model validation. During the training phase, the machine learning model uses a subsample of historical information to recognize patterns and learn from the relationships between the data features. In statistical terms, the algorithm calculates the optimal set of model parameter estimates that minimize errors in the predictions. This process establishes the various weights of the rules, meaning the importance of each historical data point in predicting the future. 4. Use: After training, the model leaves the gym and tries out a new set of data. This out-of-sample data should be truly new to the model, which will prevent the algorithm from cheating by recognizing old patterns it saw during training. In this test, the data the algorithm takes in comes from a new set of customers.

Retail operators optimize the prices of their portfolios not so much by looking at customer groups and trying to figure out the hedonic model or trying to assess the price elasticity of the products by considering the attributes of the products. Retail practitioners are very busy and are mostly looking to come up with solutions that are time- and work-efficient. Today, through machine learning, it is much easier to understand the changes and interdependencies in such complex systems. The basic transactional data can, in fact, very well uncover individual customer behavior but at the same time can be used as a very good proxy in many cases for making statements about customer segments or group behavior. In particular, we are interested in forecasting how the sales volume and timing would be. For these latter types of machine learning, in principle, a variety of observations are needed because the group features of the customers play a significant role in deriving the predictions: First, the transactional data on individual product sales over a longer history is required to train the model. This, together with customer identifiers, is necessary along with the product features. In many cases, some additional data will also be good, such as behavioral clustering and modeling. For customer modeling, longitudinal data improves the performance of models significantly. This models loyalty, price sensitivity, among others. It is also important to take into account that in order to get converged predictions, one needs to point one's models with enough features. With the right feature set, you could get the right predictions.

2.1. Basic Concepts of Machine Learning

Machine learning, especially a subset called deep learning, has hit the mainstream and made significant progress in recent years. As a result, machine learning has a significant impact on company processes and workflows, including pricing optimization. To lay the groundwork for applications, it is necessary to understand the basic concepts of machine learning.

Most machine learning algorithms are divided into two major categories: supervised and unsupervised. In a supervised learning model, the algorithm learns on a labeled dataset, providing input and the preferred output. In an unsupervised model, unlabeled data is used, and the algorithm tries to find patterns or structures. The rule of thumb for feature selection assists the model in selecting specific attributes. In certain instances, a model might necessitate feature pre-assessment or data cleaning to avoid imperfections or distractions when training a model. In order to make predictions, machine learning algorithms use an acquired algorithmic model on historical data. The training dataset is employed to evaluate algorithm preparation, while the testing dataset is used. The key aim of this learning process is to create a model of how the input and the output affect one another and to use it to forecast future inputs that have not yet been seen by the method.

The most crucial aspect of this machine learning philosophy is evident through the connection between artificial intelligence and machine learning algorithms and the need for broad, flawless, and known input. When historical data is used to forecast spikes in demand for products located on hurricane paths, it serves as a sophisticated pricing signal.

2.2. Applications of Machine Learning in Retail

Recent machine learning developments can have numerous practical applications in retail to optimize various business functions. For instance, one of the most common tasks that machine learning can solve in retail is demand forecasting. Furthermore, machine learning can significantly improve the efficiency of inventory management. Another possible application of machine learning in retail is personalized promotions for customers. To tailor products to the unique preferences of each customer, retailers must gather insights into an individual's characteristics such as color choices, location, browsing device type, and even more advanced dimensions such as a first-time mother, sports enthusiasts, or owners of multiple pets.

Due to the increasing availability of information on individual consumers, such insights can lead to a better shopping experience and are essential to remain competitive in the retail industry. In this context, personalization has become a hot topic in both business and academic research. Another specifically related application of machine learning for retailers is the improvement of the price elasticity model. The price elasticity model is a derived demand model that shows the responsiveness of the quantity demanded of a good to changes in the price. As customer profiles and demands shift, retailers must measure demand in dynamic, real-time metrics with greater granularity to optimize pricing strategies. Machine learning can better automate and scale personalized demand measurement and pricing recommendations. While machine learning is the most impactful in retail pricing within these specific applications, automation and insights from techniques such as data mining can be applied to a number of routine tasks. Ultimately, leading retailers will develop machine learning and econometrics capabilities in-house to maintain keen learnings on customer behavior. This will allow them to effectively compete as the data sets on consumer behavior become less scarce.

3. Dynamic Pricing Techniques

Retailers have a continuous goal of maximizing profitability. To achieve this, companies can employ a range of dynamic pricing techniques. Reactive pricing strategies are those that monitor the market and are able to react to external stimuli. For example, when incorporating inventory clearance during a sale, a retailer adjusts prices accordingly, i.e., reduces acquisition costs to tackle price reductions. Predictive pricing involves a longer-term view over data to determine future pricing trends. As the market shifts based on a range of variables, historical data and pricing behavior are analyzed to predict consumer purchasing cycles. The aim is to provide the most effective price within a range of factors, such as season, customer, and competitor. This section emphasizes the utilization of real-time data analytics for price optimization as predictive pricing continues to adapt price strategies based on consumer demand. In a competitive market, price has a direct correlation with consumer purchasing decisions. Consequently, many offline, online, B2B, and B2C entities are employing sophisticated online pricing algorithms to ensure they are using their prices to their maximum strength. Likely to fluctuate based on the market, quality or value of any product, demand and supply often change, with the interaction of price and demand being the strongest force in the market. Dynamic pricing is especially useful when dealing with price-sensitive customers, as the price can be increased or decreased instantaneously to decrease or increase demand, thereby maximizing profit.

Customers are predisposed to buy more when costs are low, allowing the retailer to discount over-billing and drive revenues. However, the regular use of this can damage a brand's image, with some customers even associating high quality with higher-priced products. Quick in-store reductions can also affect customers in the short term. Key to the success of a company is not only to determine the base price but also to manage inventory levels during these fluctuations in demand and price. Instead, if a company were to drop prices, clear stock in secondary channels, or place it into inventory, then, as stock decreases, prices are raised to capitalize on the increased demand. In e-commerce, pricing algorithms are used to determine and change prices in real time. As an example, a seller using a revenue management system can alter their pricing according to various signals, making price falls occur rapidly. A real-time dynamic pricing system can rapidly change prices based on a range of factors, from competitors' prices to inventory levels and finally the weather.

3.1. Reactive Pricing Strategies

Reactive pricing strategies are focused on price adjustments in response to competitor actions, essentially performing automated price surveillance. The triggers for pricing updates are primarily competitor price changes, and market requirements such as low demand, shifting stock, and similar factors can also lead to price reductions. Major technology providers in this area typically promise updates within minutes, if not hours.

More immediate updates are promised, especially for reactive adjustments when retailers are resetting their "anchor prices." Retailers engaging in reactive adjustments change their prices several times an hour (for fast-moving goods, where competitiveness is very high) up to once a day or less (for less competitive, higher-margin products).

A retail chain has implemented a reactive pricing strategy for especially price-sensitive products. Their price drops are announced and demonstrated to consumers in their advertising. Via the corresponding apps, consumers can monitor the price development and the current price of every product. The campaign results in localized competitors' price wars, especially around the stores. The most trending report includes a localized bread price war with a reduced price range initially.

Reactive pricing can be run effectively. Price updates within minutes are a good option for resetting "anchor prices" as well. While the IT systems can handle the updates within a matter of minutes, rolling out the updates system-wide, especially in large chains with hundreds of stores, can take up to an hour in some cases. Reactive strategies can bring about a quick reaction to market and competitor trigger events, as such delays are detrimental in the competitive environment. Managers should be aware that proactive changes suggested by pricing software and AI systems, as well as partial price updates, are overall more workable since they are easier to handle logistically and in customer service. This is especially the case with retailers who guarantee prices to consumers, e.g., after purchase if they find a cheaper price compared to the store price.

Reactive pricing strategies require enormous vigilance to act on quick market signals or competitors' strategies. Failing to lower prices quickly makes the retailer uncompetitive in the lowest-price promises. This will lead to a negative customer impression when they check the store's price promise that the retailer is not living up to. Triggers that would indicate quickly updating the price of the product are dependent on the retailer and will include sudden shifts in market demand or competitive response based on the retailer's strategy. A great practice is to have as simple a set of triggers as possible, capturing a wide range of changes that need to trigger price updates. The disadvantage of reactive pricing is that low prices can lead to severely eroded margins, especially if the product does not perform well on a volume basis. The speed and regularity of price updating lead to a perception by consumers that the store is cheap, but stockpiling is difficult. Therefore, reactive pricing strategies are most commonly used in discount stores.

3.2. Predictive Pricing Models

Predictive models are used to predict the future to make value-added decisions. Retailers can forecast optimal pricing based on historical sales data and characteristics using predictive modeling, which is underpinned by a variety of statistical models. Predictive modeling can be realized using sophisticated machine learning techniques that consider various features driving customer purchasing behaviors, on top of predictions. Insight into past sales and prediction of future sales based on the response to price changes, among others, is available to the retailer. By refreshing their models with the latest data, retailers can reprise these predictions whenever needed for the most accurate prediction of sales volumes and prices. It is essential to train the model on historical data and ensure that the model is tailored to specific price-related objectives.

Predictive models are suitable for capturing the essentials of the consumer purchase mechanics people are likely to continue to use in the same manner in the future. Hence, predictive models also predict consumer behavior for new products if their purchase mechanisms are captured in the models. However, just as prescriptions likely won't work for fundamental illnesses in the healthcare sector, predictive models can fail when large market instabilities fundamentally change consumer behavior. Retailers are advised to seek the right balance of prescription and prediction in a multi-model fashion given the importance of market characteristics and predictive modeling. Retailers must keep optimizing their in-store and online prices because of the need to employ long-term product and shelf designs. Technologies such as machine learning and blockchain are promising, and communication can optimize the prices ahead of demand to sequences.

4. Promotional Offers in Retail

Marketing Programs and Promotions

Retailers can strategically lower prices in exchange for more products sold. There are several ways to persuade customers to buy more. Most retailers, even the smallest ones, use the following types of promotions as tactics to attract more customers and increase the revenue from existing customers. • Discounts • Bundling (combining two or more products and selling the bundle) • Time-based promotions • Frequency-based promotions • Store-wide promotions • Loyalty programs Promotions are used to increase the perceived value of a product for a limited duration. This is why they are used as marketing tactics to bring more revenue – selling more often or selling in larger quantities for particular items can build power in the market. For instance, beer sales increase during game day as a lot of people gather to watch an event. This is a good time for people to meet and drink something with friends. A good pricing strategy can increase the revenue – “off-peak” vacations. Quantify the revenue impact to the following factors: sell more often, sell more at a time.

To measure the financial impact of a promotion, several metrics can be used: - Margin (or profit) lift Factor (MLF): Margin that is associated with marketing and price mechanics promotions are called unplanned margin because it occurs only because of the specific discount. The margin lift factor is the percentage change in the margin as a percentage of sales revenue due to the unplanned volume. - Margin as a percent of reference price: it is the difference between the actual margin and the reference price in % (rounded to the closest integer). Often used in perishable product environments where unplanned take rates are zero. Given the MLF is zero, the percentage margin as a percent of reference price is predicted to be equal to planned margin. In this case, where price elasticity is zero, applying this metric could produce higher profits under certain conditions. The profitability of a product is tied to the number of customers. The more the customers, the more benefits the retailer can achieve. That is why promotions can be used to incentivize the customer to buy, especially at times when they do not plan to buy. Practices are planned only for some businesses. Promotions should be aligned with inventory management policy. The basic approach to developing a pricing and management strategy is to set the performance indicators and based on it determine the following information: - Promotion measurement: how to plan measurable promotions. - Estimation of incremental sales: to report the overall impact of promotions, it is important to quantify the size of cannibalization.

To sum up, offering the customer a specific incentive leads to a variety of benefits for the retailer. The company must recognize that different promotions play different roles; therefore, the measurable outcomes are determined by the purpose of the promotion. While the primary goal of any promotion is to boost sales, the prime reason for increasing sales varies. Depending on the prime reason, the strategy of measuring can also vary. Here are several scenarios to depict the relationship between purpose and strategy of measurement: - Increase the size of the total market by attracting non-category users - Attain a greater share of a user's business compared to competitors - Detract customers from buying from competition - Encourage heavier purchases, using more volume - The organization obtains a greater share of business from existing users.

4.1. Types of Promotions

In retail business, promotions are valuable marketing strategies used to provide customers with additional incentives to stimulate sales of certain products. The most traditional tactics can be used to stimulate sales, and many retailers have been familiar with those for a long time. For instance, special promotions for introductory offers are one of the attention-getting tactics that can be used to introduce new products to the market. Also, when a retailer experiences a reduction in sales, or when one or more items show a noticeable reduction in sales, a temporary price reduction or sale is often the practical and logical promotion tactic to help restore sales.

In particular, promotional tactics can be grouped into a few joint categories, including price reductions/discounts, value added at the regular price, and time-based promotional tactics. Despite their fast revenue generation, promotions can also reduce profit margins on a temporary basis by offering temporary price reductions. In addition, if not used effectively, promotions can also have negative impacts on long-term brand loyalty, as well as decrease customer loyalty and reduce the market's overall price. The decision to select an effective tactic should be based on an ongoing operational procedure tailored to a certain target market, the outlet of the product, the intended goals of running the promotion, and the overall market environment. Usually, a retailer can enhance customer interaction when running a promotional event by engaging effective customer relationship strategies, including social media integration and digital marketing strategies. Some of the techniques above are the most successful promotion events, as long as they are tailored to their sales target model or existing customer base and are based on good market research and one market specialist's knowledge. In practice, these tactics have been regularly used within a variety of retail sectors over the years.

4.2. Effectiveness Metrics

In this subsection, we propose a set of effectiveness metrics that can be used for promotional offer assessment. In essence, the metrics evaluate two main components: how many customers are willing to buy when offered promotional prices or promotions and the financial implications of that. We define and evaluate four main promotion effectiveness metrics: the conversion rate, non-discount sales uplift, discount cost uplift, and return on promotional investment. This allows retailers to assess the financial element of the promotion, coupled with the customer response. In sum, the analysis of these metrics provides a strong position to determine the areas for promotion offer improvement.

To test and further improve a retail marketing strategy, the development of a data-driven process is proposed, which aims to analyze the aforementioned metrics. This will allow retailers to conclude the probability of purchasing an item from the existing customer base and help to optimize retail promotional strategies. In summary, we define specific metrics of effectiveness that can be used to examine how customers respond to promotional offers through the proposed promotion effectiveness metrics. Here, we emphasize that it is important for retailers to make data-driven decision-making by exploiting the data available on their customers to develop a clearer picture; for example, data segmentation to evaluate promotions for different customer segments. They argue that the data suitably enable retailers to assess the difference in marketing effectiveness, which cannot be comprehended by analyzing the sales uplift of segmented promotions.

5. Integration of AI and Machine Learning in Retail Pricing

AI technologies and machine learning techniques are increasingly permeating retail business operations, including pricing strategies. While AI and machine learning have garnered attention in pricing as a new area of adopting advanced analytical technologies, retailers face significant challenges and new opportunities in integrating these technologies into their pricing decision-making processes. AI's success in implementation demands a robust data infrastructure where computer systems can effectively learn from raw data. While offering promising potential in bolstering customer trading and creating value, retailers are also faced with new challenges in the digital age. The primary difficulty facing retailers is how to secure big data to create critical insights for guaranteed success. A few initial firms have already experienced positive outcomes in using smart data and have begun to serve as role models for this area.

Prime retail groups have successfully used the potential of AI for what might be considered the retailer's most important task: optimizing retail pricing. Demand forecasting is crucial as a factor for robust pricing optimization through an improvement in historical demand forecasting as an indispensable decision-maker. In practice, retail design has also experienced smart technological changes in framework algebra to present a reliable forecasting model. Price optimization tends to be improved and adapted through machine learning technical advances by the propensity of algorithms to gradually increase data sensitivity.

One of the critical concerns that hinders AI in retail is the issue of ethics. Research specifically examines the practice of price discrimination as very unethical by a clear majority of the public, but if transparently explained, they perceive it as less unethical. The primary innovation of AI in retail pricing may be the degree of automation at every level of product positioning, distinguishing customer roles and setting up individual prices along a customer's entire purchasing process. Predictable patterns could result in five common ethical problems to which industry experts agree.

5.1. Challenges and Opportunities

Pricing is one of the most critical profit levers for retailers. Hence, for several decades, machine learning and AI have been increasingly considered to provide decision support for retailers to define optimal prices at various levels. This section outlines challenges and provides opportunities associated with the adoption and integration of AI and machine learning into retail pricing strategies.

5.1.1 Challenges. A consistent number of challenges for AI and machine learning in retail pricing have been articulated by the majority of practitioners we interviewed. Therefore, even though adoption has been experiencing growth, the broader and more profound promise of AI and machine learning in optimizing retail pricing is still unfulfilled. Foremost, data privacy is a major concern when collecting customer and retail data. Furthermore, the use of black-box algorithms and their lack of transparency continue to be challenges critics raise. Personnel are another aspect. A serious challenge is the experience and expertise of the personnel at the retailer's premises to take advantage of the strong capabilities AI and machine learning techniques provide. This challenge has been deemed relevant as those personnel may require more sophistication in order to interpret the data-driven insights from AI. Finally, retailers must meet the coming requirements and harmonize their strategy and regulatory contexts. This involves technological deployments to automate human-like decisions and technologized storage and sharing processes for secure and transparent use. 5.1.2 Opportunities. It is clear that AI and machine learning include job processes where there are diverse and powerful possibilities for retailers. Big data and machine learning technologies can create a broad range of decision-making aids and suggest data-driven optimizations for retail price strategies at various organizational levels. However, once granted, there is further opportunity in the interaction between human judgment and machine learning forecasting and pricing tools. Researchers express machine learning's all-encompassing ability to identify and join any and every potential data source in ways traditional forecasting has not yet realized. Additionally, the use of human judgment to assess machine learning forecasts in conjunction with the system also serves as another primary leverage on a retailer's behalf. But practitioners are careful to also caution its limitations. They advise that human judgment can introduce cognitive biases in addition to the lack of machine learning integration and data interoperability across retailer functions. Thus, the area of contention is ultimately between the machine's and the human's capabilities in forecasting, decision aids, and integrating them in a harmonized fashion.

5.2. Case Studies and Success Stories

The application of AI and machine learning in retail pricing has resulted in success. We present here case studies showing that integrating various retail sectors and solutions has tangible benefits. It is impressive how the e-commerce and physical store sectors can adapt these solutions for improvement. In all case studies, retailers benefit from more accurate pricing and thus sales increase. Retailers can also get valuable feedback from customers about who might buy the product or how the product is perceived.

5.2. Case Studies and Success Stories The online retailer is a pioneer in using machine learning for dynamic and optimized pricing strategies. A cornerstone of their success is that they inform customers about dynamic product price changes before purchasing, making adjustments between multiple merchants. As a result, online prices are adjusted several times a day, yielding pricing frequency unmatched by any other player. The French multinational company, with more than 12,600 stores in over 30 countries. As of 2017, the company adopted the price optimization application across its stores in Taiwan. Price Optimization helped accurately determine the right price to architect and sustain competitive prices. This solution also gave the ability to gain real-time insights and dynamic competitive response scenarios from the floor by workers containing every customer of a subsidiary in Japan. Data collected by consulting this marketing research is compiled using surveys completed by customers.

6. Future Direction

Since pricing is a critical element closely following the development of technology and consumer behavior, we are not surprised by the burning interest in this topic from both academics and practitioners. Although retail pricing strategies have evolved from single pricing through multi-channel pricing to omni-channel strategies, there are limited applications and discussions of AI and machine learning in the field. Especially, their contribution to pricing or combined pricing strategies is revealed by only a few sources. Furthermore, these sources do not discuss current technology or machine learning application techniques and future potential applications in pricing.

Future researchers or researchers who want to conduct this study regarding pricing are encouraged to research and apply AI or ML for anticipating retail changes or predicting customer preferences and offer combinations. This study could be taken as an anchor to predict the future pricing scopes in the field. Despite the advantages of machine learning, it has raised some challenges since its application can result in market disruption. There are also other risks such as data privacy issues, complexity of models, or not getting clear results. Challenges will continue to emerge and, therefore, it is important for retailers to continue to learn, innovate, and lead or use state-of-the-art systems in their operations. In conclusion, it is highly recommended for retailers, the role of which is closely tied to advanced technology and innovations that are customer-oriented and engaged based on these technological advancements.

7. Conclusion

Pricing strategies play critical roles in attracting customers and therefore achieving retail success. Dynamic pricing helps to get the best bargain or benefit from a product.

Companies use promotions to put their products at the forefront of customers' minds. Most companies depend on human intelligence to forecast prices. The use of contemporary technologies like big data, machine learning, and artificial intelligence has the potential to forecast prices more accurately and effectively. Many companies are in the process of adopting artificial intelligence by 40% every year. Today, we talked about retail pricing strategies, from dynamism in prices to promotional pricing and value. The experimentation with controlled and strategic pricing was also examined, along with AI's potential role in that. To summarize some of our key findings: AI can enhance the suitability of pricing, as it can predict with a high degree of precision even with relatively little input. Customers derive a feeling of fairness or value when they perceive that offers are personalized for them. Future work should consider the impact of how different mechanisms for generating demand change the effect of pricing, as in this work they were simply linear. As technology moves forward, businesses will need to be agile to shift with the trends and opportunities that arise. The market is constantly in a state of flux.