Enhancing Customer Personalization in Retail with AI

By Dr. Ayşe Erçil

Associate Professor of Electrical and Electronics Engineering, Yıldız Technical University, Turkey

1. Introduction

Retail is a dynamic business sector. There is a constant pressure on retailers to enhance their services and technologies in order to remain competitive. In their efforts to gain significant competitive advantages through the use of innovative technologies, the retail industry has been experiencing a new wave of changes. The essence of the transformation is powered by the advent of big data, high-speed computing capabilities, and artificial intelligence. It is now possible for the latest AI technologies to revolutionize retail marketing and business intelligence by successfully understanding customer psyche and behavior, and by doing so, customizing each customer's shopping experience. Merely collecting, processing, and gaining insights from big data is insufficient to meet customer satisfaction. Attaining a meaningful shopping experience requires going beyond traditional technological boundaries. With the latest AI systems and procedures, it is envisaged to transform what was logistically and computationally challenging into a simple optimization and operational environment.

Retail practices include understanding consumer phenomena. Terabytes of data are produced every day, enhancing revenue generation through the personalization of consumer preferences and various behavioral digital profiles. The core of this design is that consumer data viewed as a mass is a sum of individual data realities that are also in a constant learning process, as users' prioritizations, categorizations, and preferences go through a continuum. Articulated in broader terms, consumer personalization practices are a must. As this clearly indicates, understanding consumer behavior is of great importance. The usage of data continues to grow. AI engines, along with advanced analytics, tend to be the viable technology to analyze ubiquitously produced shopping data. AI represents the new wave of contemporary computing systems that have succeeded in mastering the difficult task of automated processing and analyzing large volumes of data. They can deal with different types of data, such as numerical, textual, and categorical data. To some extent, artificial neural networks are frequently used as computer vision to denote a method that analyzes complex data that humans assess with their visual abilities.

1.1. Background and Significance

Retailing has evolved from humble individual establishments to mass merchandising techniques, to self-service supermarkets, and now to distribution centers that deliver directly to our doorsteps. Through systemic developments in customer information creation, storage, and retrieval, retailing has incrementally transitioned to strategies based on data, not just on product management. The development of electronic point of sale has enabled great strides in the use of data in retailing, and the advent of fully integrated enterprise resource planning materials management systems may well align producers with customers to an extent previously unimagined.

The shift of major retailers' focus from product to customer has not been without its difficulties. First, the experiment revealed that no one really knew what to do with customer data. The possibility exists that retailers may yet have too much customer data available to sort through. Second, for most retail businesses, it is notoriously difficult to satisfy the many and varied wants and needs of the customer. These retailers, for example, must first understand what customers want and also provide it to them in a profitable way. Despite these two initial hiccups, the significance of the process described in reducing costs and enhancing customer loyalty, thereby ameliorating competition, is beyond debate. Furthermore, the widespread expectation by consumers of a personalized service demonstrates the environmental suitability of this transformative introduction of AI processes for overcoming these challenges.

Following a brief historical supertrend analysis, this discussion covers the advantages for retailers and consumers of using AI to personalize customers' shopping experiences.

1.2. Research Objectives and Scope

This section defines the research objectives of the study with specific questions that the study seeks to answer. It narrows the research domain by identifying the scope of the study and by presenting segments of the market to focus on. Another boundary is proposed by including the discussion of technological trends associated with AI adoption in commerce. The section also shows the expected practical implications of the study.

This paper seeks to answer the following dual research objectives: In the retail environment, what AI personalization methods can produce a positive customer response? How can retailers use these strategies to make more money? Our domain of interest is identifying AI approaches that retailers can apply to enhance customer personalization efforts. We naturally recognize other advanced technologies that are transforming the retail sector. We limit our investigation to AI, as the literature on AI and ML, in particular, is primarily limited to the marketing field, and there are few practical examples of AI personalization in the retail sector. We, therefore, consider two perspectives: AI-based personalization strategies that produce real benefits for customers and future trends. In doing so, our goal is to provide an industry-focused study in the retail sector, focusing on customer personalization strategies, particularly in the domain of fashion retail. The study focuses on theoretical frameworks and practical examples of AI-based strategies.

2. AI in Retail: An Overview

Artificial intelligence (AI) influences a sweeping transformation in the retail sector, with technologies such as machine learning, natural language processing, and data analytics propelling digital innovation and operational enhancement. This could occur in manifold retail processes, including customer engagement, market research analysis, demand forecasting, inventory management, quality management, product recommendations, and personalization. AI-driven automation of operational and analytical retail processes can lead to reduced costs of advancements in operational efficiencies and meaningful insights into consumer behavior. With advancements in data availability, technologies, higher computational power, and cost-effective storage, the practical application of AI in retail is on the rise. However, several challenges impede the retail penetration of AI, including investment costs, efficiency obligations, technological barriers of different retail processes, and the upskilling and reskilling of the workforce, countered by a cautious grocery retailer mindset that overlooks the application against offline retail processes and bureaucratic regulation challenges.

AI has applications in various business processes in the retail industry. They include sales forecasting, demand forecasting, customer behavior analytics, marketing, visual analytics, and personalization. The current strengths of AI can be observed in demand/inventory forecasting, inventory management, agnostic customer experience, various sales revenue channels, marketing and visualization analytics, customer service, quality management, staff management, retail supply chain, and penetration in market trends. Technologies equipped with AI are increasingly commanded to offer omnichannel retailing to customers. Grocery retailers are enabling click-and-collect or home delivery in order to offer a single seamless purchase process that is wallet-friendly for consumers. Since such a delivery process is almost seamless for consumers, it is up to grocery retailers to implement effective, efficient, and errorless backend retail process integration across the platforms and distribution channels. Thus, getting AI incorporated to meet last-mile delivery of groceries is equally important as bringing home delivery channels close enough to the consumers. Automatic dispatching of local pickup orders at a nearby delivery hub enables retailers to offer timely pickups abroad and can overcome this. Retailers adopting omnichannels are now integrating them into virtual assistants and chatbots, using AI to enable a seamless retail process for consumers.

2.1. Current Applications of AI in Retail

1. Introduction 1.1. Background 1.2. Current AI Technologies in Retail 1.3. Challenges in Implementing AI in Retail - Cross-domain expertise - Data - Explainability - Ethics 2. Literature Review 2.1. Current Applications of AI in Retail The retail sector has successfully deployed AI in various functional areas. Some of the AI applications used in the retail sector include chatbots, personal digital assistants, recommendation engines, and predictive analytics tools. Chatbots are widely used in the post-sales process, acting as a single point of contact for customer service and support. The personal digital assistants notice incomplete digital shopping lists by sending text alerts to consumers, thereby improving customer service. The use of recommendation engines based on targeted advertising can increase customer engagement and drive product demand. It has also been found that employing personalized influencers can engage customers more effectively. Personalized recommendation engines may also collect all information on a particular customer's preferences and make product recommendations based on those preferences. Inventory management, which helps maintain an optimal inventory level by minimizing stock-out problems and returns, is another important tool for driving customer satisfaction and loyalty by providing a consistent experience across multiple channels. The implementation of AI in operational processes reduces waste by optimizing supply chain management, automating the process, and providing completely customer-driven and personalized services. Personalized demand forecasting uses AI to effectively fulfill individual consumers' requirements. This approach helps capture and convert every demand and gain retrospective business value. There are several case studies that show how AI has been implemented and used by leading retailers around the globe to boost their sales and customer engagement by improving operations. These products represent a broad and practical application of AI in retail industries to optimize their operations.

2.2. Benefits and Challenges

AI is of significant interest to retail due to the numerous benefits it offers. AI allows customer insights, and thus customer interaction points, to be personalized. Customer personalization leads to optimized marketing spend and less wasted marketing dollars by personalizing the delivery and timing of these advertisements. AI in other areas of a retailer's business enables greater operational efficiencies by predicting customer demand at the individual inventory level. AI can also help with task supervision and planning at a systems level more in line with human capability. This understanding of consumer behaviors can be achieved by the utilization of AI and AI-generated models and strategies. Although one of the desired outcomes of AI usage is to offer personalization as a competitive advantage, there are significant challenges to utilizing AI in the retail context.

There have been greater demands for digital privacy of late, all the while the cost and scale needed for AI retail personalization are very large. Technological infrastructure, including QA processes, is also needed for any system fidelity to allow the adoption of AI technologies into business retail processes. In the coming years, there will be much capital expenditure on overcoming these issues. Currently, there are only a few retailers that collect the data needed for AI personalization and even fewer that can afford to implement this AI model personalization. Indeed, companies are quickly finding that they are unable to deploy AI models to operate in real time when trying to rapidly pull in data from disparate sources and quickly serve them up suitably modeled offers and messages, especially when the home logistics system was overloaded. Overall, there are a range of benefits associated with AI implementation in retail; at the same time, there are many challenges that must be overcome in order to be a successful adopter of this technology.

3. Customer Personalization in Retail

In retailing, offering goods or services that suit individual end-user needs and preferences is of growing importance and is thought to be a success factor in achieving customer satisfaction and loyalty. Personalization of shopping experiences or integrated solutions that are adjusted to individual needs are important drivers of customer satisfaction and loyalty. The expectation behind this is that customers desire to be recognized and treated as unique individuals. Inadequate personalization strategies cause customer churn. Personalization strategies support customer retention, the length of customer relationships, and customer spending per interaction, thus indirectly supporting the corporate bottom line. The increase in the return of revenues is, for instance, 1% per 1% of an increase in customer satisfaction.

The general idea behind personalization is to adapt product offerings or processes of an organization to the needs of individual customers, as opposed to offering generic or one-size-fits-all services. Such a customized approach is based on analytical methods that reveal customer preferences and behaviors. The pursuit of excellence is to be able to provide customers with exactly what they need as accurately as possible, and more specifically, when they need it, in which form, on which side, or to which place - all customized to suit the idiosyncrasies of the customer concerned, as a person. A significant percentage of consumers switched providers due to a lack of trust and a lack of personalization capabilities. With the unbelievable growth of e-commerce and its importance to business, personalization has become an essential ingredient of marketing strategies to increase brand-customer relations and revenues at the same time. Retailers who fail to offer a uniquely personal experience will alienate themselves from their customers. A detailed understanding of individual customers, which is often identified with segmentation in marketing or e-commerce, is the foundation stone of personalized marketing.

3.1. Importance and Impact

Personalization has become a vital strategy for retailers and directly impacts the bottom line. Due to high customer expectations, personalization is now considered a necessity rather than a luxury. Research has shown that shoppers who receive a high degree of personalization have a higher purchase frequency, greater brand loyalty, and are more likely to recommend the business to others. Indeed, the most successful companies tend to be personalization leaders in their industries.

There is a psychological aspect to personalized experiences that is often understated. In general, consumers tend to purchase more when they receive relevant offers. Experiences and interactions feel more personal and resonate more deeply with customers when the content is tailored to them. This has been shown to lead to customer satisfaction with purchases, an increase in the likelihood of making future acquisitions, and growth in loyalty and brand investment. A survey found that 75% of consumers are much more likely to shop with a retailer that recognizes them by name and makes recommendations based on their purchase history. For example, one company saw an 18% increase in online sales by leveraging personalization capabilities to better segment visitors and customers, while another generated significant revenue in relevant product recommendations to millions of digital customers. In the US, for every $1 spent on personalization, it drove a return of $30.

As a result, delivering personalized experiences is no longer a "nice to have," but a competitive differentiator. More than three quarters of retailers believe AI is the only way to meet or exceed client expectations. The importance of investing in these strategies, which are of highest importance to retailers, cannot be understated.

3.2. Traditional Methods vs. AI-based Personalization

Traditional methods tend to make use of rather simplistic data interpretation techniques and are often based on demographic information or purchase histories to segment customers. They then provide context-based recommendations and personalization messages to different customer segments. However, in trying to personalize at scale, these systems offer a significantly less tailored and relevant experience because they use limited data across many customers. Additionally, traditional personalization solutions require data stewards to maintain the manual creation of segments and rules in order to implement these solutions. Manually categorized segments might be too narrow or generally miss shifts in consumer behavior and needs.

AI, on the other hand, can analyze vast quantities of data across different channels of interaction as well as historical data for a specific individual consumer. They can also assess data in near real-time using predictive analytic algorithms to suggest highly personalized offers, discounts, or messages based on this data. Effective personalization requires constantly updated information about customer needs, wants, and behaviors. The modern customer is continually being consulted and is constantly evolving. As a result, a retail company that relies only on historical data to personalize customer experience might as well be permanently out of date. The use of AI in the context of personalization can in part solve this issue, analyzing large data sets that are continually updated to present companies with a near real-time picture of the customer.

4. Machine Learning Models for Tailoring Recommendations

To tailor product recommendations for a given customer, retailers typically leverage machine learning models that capitalize on analyzing the customer’s behavior, implicitly or explicitly, and predicting what other products the customer would be interested in. There are three main types of recommendation models: collaborative filtering, content-based filtering, and a hybrid approach. Collaborative filtering models predict user interests based on similarities to other users. Content-based filtering models leverage consumable features or attributes of an item to generate item recommendations. Hybrid models combine collaborative and content-based approaches to boost accuracy and potentially enhance user satisfaction. These recommendations can be personalized by leveraging user-specific features and other data within the machine learning model. In retail use cases like in-store, these recommendation models can be combined with other relevant prerequisites that customers are buying to build personalized store trips.

Each of the recommendation model types has some strengths and weaknesses. The collaborative filtering models are popular because they require no domain knowledge in the item space. That said, in large-scale retail, as well as many other domains, we find that the content-based filtering models can achieve slightly better accuracy. This is because the content-based filtering models can better generalize across browsed products with differences in relevance—i.e., whether people are just looking at a product or genuinely interested in buying it. The hybrid approaches are becoming increasingly popular, in part due to the success of one of the early retail applications of hybrid models, which accounts for around one third of their catalog of video recommendations. Hybrid models are popular since they leverage the strengths of both methods; hence, they can blend results that can be more appealing than solely relying on one of these methods. Hybrid models are used today in retail to combine approaches that feature what our customers need in a recommendation. Hybrid approaches, recently gaining intense popularity, combine two or more recommendation types. From a business standpoint, machine learning researchers and product teams select the best options based on business needs and the data types available. Hybrid models can also be more effective where both methods individually have their own limitations, for example, in the case of cold starts and sparse data.

4.1. Collaborative Filtering

Collaborative filtering is a popular method for generating personalized recommendations in retail. It allows businesses to identify the relationships and similarities between users based on their interactions, like ratings in review-based systems. Then, it finds user and item similarities to get the predicted ratings for the target user to predict whether the user will like the item or not. Over the years, this simple but beautiful metaphor has been adopted for countless recommendation scenarios. This recommendation technique is highly efficient and can make personalized recommendations. The key idea of collaborative filtering is to leverage the user-item interaction data to predict the ratings of the items not rated or purchased by a user.

One of the major benefits of collaborative filtering recommendation models is that they can find hidden patterns behind the interactions and make efficient suggestions to users based on the historical interactions. Although this technique has many merits and offers a great user experience, it also presents various challenges like the cold start problem. Personalization is reshaping retail strategies and customer experience, which is a cornerstone of the success and future growth of brick-and-mortar businesses. It anticipates the needs of buyers and leads them to their desired purchases. Therefore, various recommendation models are designed to support creating a personalized user experience. For instance, an end-to-end recommendation system starts from exploration to publication and enhancement of item recommendations. Several real-life applications are being powered by recommendation systems, such as movie recommendations, job recommendations, course recommendations, and so on. In this paper, we have given an extensive thought process to explain the collaborative filtering-based recommendation.

4.2. Content-Based Filtering

Traditional AI-driven recommendation systems are often based on the principle of content-based filtering that recommends items based on their features or attributes. They analyze the available attributes of an item, such as text, image, or any other descriptive information, and the profiling of the user in order to understand item consumption. The relationship of consumed items and the user and item features are used to profile the user and item preference, generating a detailed personal suggestion based on the item features the user has previously interacted with. Items that share associative patterns in attributes that the user has already engaged with are recommended, with a higher focus toward more recently engaged content and attribute features as the user's profile is continually updated via these engagements. The steps for content-based filtering include collecting data on the user's behavior and opinions on the items. The user's profile is subsequently created by using a representation of the user's historical interactions with items. This allows for the development of models capable of generating personalized recommendations as the user's requirements and preferences are consistently reshaped. This strategy utilizes both feature-based data on items and consumer interaction data, such as consumer ratings and preference patterns to measure a user's needs and preferences. The requirement for both item feature and user opinion data provides a dichotomy between the two techniques; however, this lack of data results in instances without recommendations and inherently recommendations that contain little or no diversity.

4.3. Hybrid Models

Hybrid models represent a more sophisticated approach in contrast to using either collaborative or content-based filtering methods individually. At their core, hybrid recommendation systems combine elements from both user-based and item-based systems to overcome the limitations of either one. In this way, two general architecture options are available. They can operate as two separate modules or be integrated into a single model. Overcoming the restrictions that singular models possess, hybrid models aim to leverage the advantages of both user interactions and item features to enhance recommendation accuracy. Collaborative models largely rely on user purchase histories and shopping sessions. As a result, they tend to be biased towards popular items. On the other hand, content-based models often fail to generalize users' shadow preferences. To counteract the identified limitations, hybrid recommendation systems may deploy memory-based or model-based strategies.

Hybrid models that adopt memory-based strategies are able to effectively combine predictions from singular models. However, when each model is encoded separately, predictions flourish automatically. Unfortunately, this mechanism causes result repetition and may prevent accurate representations of user preferences. In contrast, hybrid models based on model-based strategies encode combined predictions from both collaborative and content-based models by calculation. As a result, the approach tends to be more powerful and enhances personalization accuracy. Additionally, deploying hybrid models may serve to increase the proposed recommendation diversity as they often provide the ability to understand user-item preference dynamics more effectively. Practical applications of hybrid recommendation models are abundant. Online retailers often leverage hybrid models to personalize their shopping experience. Using this strategy, significant success resulting from increased sales volume has been achieved. The plethora of successful case studies and strategies that leverage hybrid models to drive their business decisions across a wide range of businesses showcases the flexibility and adaptability of collaborative and content-based hybrid models. Retailers are able to train their systems using information such as browsing histories, search queries, purchase data, user-item interactions, geographical information, and timestamp data, among others. As such, they are adopting and increasingly committing to advanced personalization strategies driven by AI technology.

5. Developing AI-based Marketing Strategies

To ensure the usability of the information and marketing strategies created, they need to be supported by data. This type of knowledge-based decision-making will provide a conceptual basis for retail segmentation and targeting. The primary description is based on the challenges associated with correct positioning in the retail market. The outcome of segmentation and targeting is demonstrated in digital marketing, dynamically adjusted according to individual needs; personalized campaigns and special offers are also shown.

A form of influencing purchasing decisions is to dynamically modify displayed promotional effectiveness through personalized campaigns and targeted offers. This is often achieved through the use of dynamic pricing—a pricing strategy that continuously adjusts prices to maximize profit based on consumer behavior patterns. Developed tools that use customer labeling and loyalty program cards can estimate demand elasticity for products purchased by individual segments more precisely: this results in fine-tuned pricing for individual buyers. On the other hand, dynamic pricing systems, still monitoring demand, will set prices in real-time rather than for weeks or even months. The systems use thousands of data points across the web and price up or down with dynamically changing market conditions in order to maximize revenue and profit. Increased income and loyalty are driven by meaningful experiences with different aspects of the brand.

5.1. Segmentation and Targeting

Developing successful AI-based marketing strategies starts with a clear understanding of how retailers value individuality. In other words, if you treat the customer as a person, with specific behaviors and basic attitudes, retailers can bring all of the data to bear effectively. This helps in positioning the message to the customer, addressing differences from one segment to another, and optimizing relevancy. Segmentation is the most common approach in the categorization of customers into homogeneous categories based on behavior, specific customer insights, demographics, psychographics, or other characteristics. Retailers, in many cases, can define customer segments through AI-derived analytics, patterns of behavior over time, purchase patterns, and simple demographic characteristics. The more complex the segmentation, the more opportunities there are for personalizing and being appropriate with marketing recommendations and trials. Segmentation emerges naturally along aspects of customer acquisition, value, and retention based on industry and economic value of a customer strategy. In the use of AI in targeting the right customer for the message or service, the retailer must clearly have insights into best customers, probable best customers, new customers, and customers at risk. This ties in nicely with ad targeting or email targeting, where a retailer can categorize and create a call to action on the customer, product, or service on a real-time basis. Segmentation allows the retailer to hit the masses with a marketing message or select customer segments or clusters of customers where the message can be tailored. Personalized marketing efforts can lead to a significant increase in engagement and conversions. In essence, mass marketing is being replaced by micro-segment marketing. Traditional approaches in segment and cluster analytics lack the scalability to analyze large, scrubbed data from primary and secondary sources, and huge customer data embedding customer demographics and transaction details. Artificial Intelligence provides a very valuable approach to analyze huge data, seeks insights in micro-segments or single customer interactions, and recommends targeted marketing strategies. Best-in-class retailers have adopted AI technologies, stating it gives their organization a competitive advantage, and the cost is worth the investment.

5.2. Personalized Campaigns

Establishing personalized marketing campaigns is an important part of creating an offering personalized down to the individual. These require much more sophisticated data analysis and offer process customization than any personalized system before them has, and they drive offers and communications closer to true 1:1 instead of bespoke segments. Personalization is fundamental to the way that these initiatives need to be shaped and can't be a generic part of any marketing campaign, as it is the foundation that is able to set these campaigns apart.

The major benefit of these models is that they are able to analyze customer data in real time and offer individualized services custom-designed for the customer, maximizing the offer relevancy and offer acceptance rate, as well as maximizing the relevance of the marketing and event-driven triggers. AI-powered campaigns like this have seen great success, leading to a significant increase in week-of-sale and Big Ticket items, across both new and existing customers, with no decrease in margin. The campaigns are able to understand more about the customer and use predictors such as what other products they have bought or browsed. The predictive analytics element even runs on the individual level, meaning that you understand not only a customer's average behavior but can predict their behavior in the current session to make the most relevant marketing campaign. Additionally, not only are customers more satisfied due to the relevancy, but they are also more satisfied due to the element of convenience, with a significant percentage of customers wanting services that save them time and effort. Campaigns like this are also able to optimize the timing of the offer through analysis, predicting the online presence peak for the customer.

Campaigns aim directly at users' carriers by gauging what advertisements users want, what city they live in, and the mobile site they are browsing in and the time of day; some platforms even gauge what vacation country a user is in, all regardless of privacy concerns. The challenge is predicting individual behavior in a given session and delivering the best message for you in the time you are with us, regardless of what we know about you. An example of this type of approach fully integrated with CRM functionality can launch best offer decisions as a batch, or it uses predictive analytics to model individual behavior and drive messaging in real time and is able to track and update as outcomes, whether customers do purchase or they call. Campaign testing and shaping need to be continuous as the expected response to a valid offer in a known customer does not always go the way you expect, and the offer policies can need continuous fine-tuning. This is a great opportunity to set yourself apart, as this kind of personalization is much more technical to achieve and, although there are many systems to create a segment-based personalization offering, these systems are only now just starting to emerge. It is most commonly manifested as an effort to offer customers the products they are more likely to buy based on their actions such as browsing behavior, buying behavior, or communications behavior.

5.3. Dynamic Pricing

With the advent of AI, dynamic pricing, or the practice of adjusting prices in near real-time based on demand fluctuations, consumer behavior, and the competitive landscape, has become an effective lever for personalization in retail. Apart from maximizing revenue and optimizing inventory turnover, dynamic pricing can help in customer segmentation and enhance customer satisfaction. While pricing is only part of the personalization strategy, retailers can use it to understand what price certain segments are willing to pay and what sort of promotions can maximize their yield. Moreover, dynamic pricing also allows retailers to adjust supply and demand for optimal outcomes. Personalization has gained a lot of importance owing to digitalization. It can not only increase the efficiency of the sales process but can also drive higher satisfaction among not just the current customers but also potential customers who were previously evaluating the retailer's services. As a result of growing demand for dynamic pricing, technologies have quickly evolved and are under adoption at an increasing pace in the retail industry. However, there are challenges related to understanding the market reactions and customers' willingness to use dynamic pricing. Retailers fear they could end up alienating certain customer segments if they feel like they are being priced unfairly. Unfairness perceptions associated with dynamic pricing can have serious reputational damages at both the frontier of private data usage and ultimately the transparent and ethical stance of the retailer. One of the key questions is how transparent and 'fair' retailers should be in their dynamic pricing practices as well as how the non-monetary benefits should be distinguished across different segments of the customer lifecycle. Given initial consumer reaction, it is benefiting from customer feedback-driven strategies and frequent updates of their systems to adjust their pricing mechanisms better. An evolving market has only underlined the importance of analyzing consumer reactions and market trends to continually fine-tune their pricing strategies for maximum personalization impact. Thanks to advanced analytics, it is easy for retailers to understand the patterns associated with customers in terms of when they want products at what prices. Such patterns can be related to the day of the week, time of day, location, months, or even the weather. Several retailers have become savvy with their dynamic pricing strategies and have reported a strong uptick in personalized offers and customer retention.

6. Future Direction

6.1. Trends and Technologies Several trends and technologies will shape the retail landscape in the future, including mixed reality, 3D printing, digital IDs, smart logistics, new payment ecosystems, and horizontal data sharing, with applications in Industry 5.0. AI is also expected to expand in the coming years, with an increase in the number of use cases for hyper-personalization, intelligent automation, and predictive tools. Several of our interviewees predict a far wider use of AI-supported personalization applications than today. The power of being able to foresee shopping behavior and create connected and more complete experiences will drive continued investments in those capabilities. Better integration of information to get the most comprehensive view of different customer behaviors will also be good grounds for the future, as well as better evaluating the results and connecting advanced analytics work with the feedback mechanism of the consumer world, which will become more important in order to learn about how customer behavior is the effect of the work done. In line with that, we can also expect that the importance of institutionalizing a learning-from-failure mindset will grow as AI-based strategies also increase the risks. One expert in our study pointed towards continuous innovation to improve the online shopping experience in a way that makes it closest to real life and expects several small actors to be the early birds. Another expected innovation is the use of hologram tools to offer new kinds of in-store expertise. There are also some considerations of consumer expectations most likely about to change, as "now" could be counted as a rather high to extremely personal approach in retail. In fact, several retailers already have access to personal data and/or personal buying behavior data about their customers, whilst only some have all details. The expert's opinion was that the first stage of developing a very personal relation is way beyond where we are today and will require changing legislation to be allowed to take place. Companies will profit a lot, making the profiles richer in the future. Some interviewees suggested that in the future, customer personalization strategies will be governed and reset by ethics, design, emotive intelligence, as well as algorithmic intelligence. It is more likely that personalization strategies will increasingly interact with emotions, will be used more and more interactively, and will also integrate customer-made preferences. Even so, the pace of development is hard to predict, but none of the interviewees assume that personalization of customer relations will be developed to a lesser degree than now. Any contender in retail will find ways to strengthen customer relationships as effectively as they can. Moreover, there is convergence in opinions predicting the development of decision-making and sales management in real time, including the evolution and further application of the use of AI, continuous learning, and real-life customer connection. The use of data collected and processed in real time will be used to understand personal selling communication needs. In addition, customer service advisors become decision laboratory machines with some form of artificial or digital emotion as well. This development is also associated with sharp discussions around ethics and privacy, with the extensive use of predictive analysis and profiling leading to a probable reset.

7. Conclusion

In conclusion, AI is making personalization at scale a reality, reshaping shopping experiences in retail. Technologies such as AI can support the vastly complex process of meeting customers' unique and dynamically evolving expectations. In markets where there are quite undifferentiated products and many different kinds of customers, technologies of this kind will almost surely be integrated into retailers' offerings over the coming years. Moreover, given modern consumer capabilities and demands, simply using point technology is no longer enough. Retailers must work to evolve their operations, processes, and expertise iteratively, continuously, and together as a collective rather than in separate pockets. The fusion between people, operations, data, strategy, and technology is much needed. AI techniques are already showing the benefits in terms of increasing the sale of products recommended by systems.

However, AI does not come without challenges, and finding a solution along with a justified business use case is very challenging for retailers worldwide. Implementing AI into the retail system seems to be really arduous and highly challenging because of multiple reasons, including categorizing and storing data according to the defined model, training an AI model, dealing with independent vendors, and providing intelligent features to the retail market. Not every AI solution provides a 100% result. Retailers may face issues of inventory levels, loss of revenue, and customer retention because of slow adoption of new technologies. It is a modern era demand to sell products anytime, anywhere. In recent years, AI has gained an increasing amount of buzz, more than any other field of computer science. In retail, this poses a demand for customers' purchasing requirements to be studied individually. AI will continue to be hot in the future for finding personalized products according to the customer's choice. This opens up the future directions of AI in retail.

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