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Omni-channel Retail: Leveraging Machine Learning for Personalized Customer Experiences and Transaction Optimization

1. Chandrashekar Pandugula,
Sr Data Engineer, Lowes Inc NC, USA, chandrashekar.pandugula.de@gmail.com, ORCID: 0009-0003-6963-559X
2. Srinivas Kalisetty,
Integration and AI lead, Miracle Software Systems, srinivas.kalisetty.ic@gmail.com, ORCID: 0009-0006-0874-9616
3. Tulasi Naga Subhash Polineni,
Sr Data Engineer, Exelon, Baltimore MD, tulasi.polineni.soa@gmail.com, ORCID: 0009-0004-0068-6310
4. Nareddy abhireddy,
Research assistant, nareddy.abhireddy.researcher@gmail.com, ORCID: 0009-0007-2757-1910
5. Dr. Aaluri Seenu,
Professor, Department of CSE, SVECW, Bhimavaram, AP, India, seenualuri@outlook.com

Abstract
In the contemporary retail business model, timely fulfillment of customer needs as well as the supremacy of customer experience is of paramount importance. As such, a win-win model seems to be crucial for both the retailer and the customer alike, while at the heart of the retailer is the mission of enhancing customer relationships. Retailers make efforts to ensure that every gainful interaction is as meaningful and valuable as possible. However, personal recall of customer preferences, the urgency of fulfillment, and the salesperson's ability to bundle the 'right' items are all strong constraints. The customer's transaction history is the only reliable resource that can be depended on to be persistent and recognized. The aim is to identify possible data analytics opportunities in personalizing these transactions as well as to optimize sales opportunities. We also explore the use of a particular artificial intelligence technique, a group of algorithms widely known as machine learning, with task clustering and segment labeling.
Keywords: Artificial Intelligence, Machine Learning, Omni-Channel. Personalization, Retail, Transaction Optimization, transaction clustering, through-channel marketing, online and offline transactions, sales data mining, and transaction optimization.

1. Introduction

Machine learning (ML), an area of artificial intelligence, is revolutionizing retail by improving customer experiences and processes by predicting and optimizing customer behaviors as they shop across retail channels. Through supervised, unsupervised, semi-supervised, and reinforcement learning along with ensemble techniques, implication rules, recommender systems, automated search heuristics, clustering, and predictive analytics, businesses can drive more sales and better serve customers. We use a customer lifetime value analysis to illustrate the need, potential, issues, and opportunities in creating a personalized customer experience. Then we describe how firm performance is enhanced through leading-edge customer-centric management practices by leveraging ML and customer lifetime value analytics. However, major issues such as the lack of accurate data, customer response misconceptions, incomplete or incorrect coding, and wrong predictions may prevent the full realization of the potential.Machine learning (ML) is transforming the retail industry by enabling businesses to predict and optimize customer behaviors, enhancing both customer experiences and operational processes. By utilizing various ML techniques such as supervised, unsupervised, semi-supervised, and reinforcement learning, alongside methods like ensemble techniques, implication rules, recommender systems, automated search heuristics, clustering, and predictive analytics, retailers can drive increased sales and provide more personalized services. One key tool in this process is customer lifetime value (CLV) analysis, which helps identify opportunities to tailor experiences and improve customer retention. Through the application of ML and CLV analytics, firms can enhance their performance by adopting customer-centric management practices that improve decision-making and engagement strategies. However, the full potential of ML in retail is often hindered by challenges such as inaccurate data, misconceptions about customer responses, incomplete or erroneous coding, and flawed predictions, which can impede the effective implementation of these advanced techniques.

Fig 1: omnichannel customer experience

1.1. Background of Omni-channel Retail

Retailing has been rapidly transformed as digital interaction between customers and retailers pervades all stages of the shopping lifecycle, giving rise to omnichannel retailing. With physical and digital footprints across websites, mobile apps, and social networking platforms, established brick-and-mortar retailers resume a competitive advantage in customer relationship management, while digital-only retailers drive optimization and cost efficiency through superior analytics. Harnessing machine learning, a key component of business analytics, this research empowers brick-and-mortar firms to also leverage data assets for personalized customer relationships and transaction optimization. Unlike digital-only firms that offer distant and standardized customer interfaces, brick-and-mortar retailers enjoy a physical and local connection, lending contextual knowledge about customer footprints that digital-only firms might lack.

As a customer inspects items on a shelf, seeking and testing particularly interesting ones, information is communicated to the retailer implicitly. Technology such as analytics, the Internet of Things, and artificial intelligence can coordinate and analyze this information, facilitating dynamic pricing and consistent service across various marketplaces, which manifest as temporary or nearby price cuts, product recommendations tailored to customer needs and peer preferences, price matching, or notification of nearby offers, all dynamically customized by customer household or account; these reduce transaction costs while addressing customer needs dynamically. Such system-level personalization represents a threat to customer-agent level relationships, making retailers more dependent and non-reciprocal, and is governed by asymmetric information beyond customer control.

1.2. Significance of Personalized Customer Experiences and Transaction Optimization

In recent years, customers have been demanding personalized services, experiences, and customized trips. The e-commerce space, in particular, has started witnessing a number of value-back initiatives aiming to provide personalized customer experiences. Often, customers prefer to transact in multi-channel environments, which enables them to select the channel and service type according to their preferences and constraints. The term "omni-channel retail" is used to address this situation. As a major user of services, travel omni-channel provision is a fast-developing field. However, the majority of research efforts to date focus on retailer benefits, assuming that better customer experiences directly translate into higher transaction values. Only a few consider the retail customer as a rational being, with preferences that could support more effective fee, price, and booking structures.

We consider the scenario of multi-channel ticket distribution, where the channels include both direct and indirect users selected according to their discrete preferences. We refer to these users as distribution-optimizing customers and flexible transaction-optimizing customers, respectively, according to their distinctly different customer behavior. Our main goal is to understand how DOCs could be provided with motivations to aid retailer channel optimization, and how FTOCs could be incentivized to smooth demand levels. Customer data typically provide a wealth of both historic traveler behavior and purchase data, which can be used to infer the extent of DOC and FTOC presence. In a rapidly emerging market, retailer inferences may change over time, and so we expect that related retailers regularly carry out such market assessments to determine how best to provide channel flexibility.

Equ 1: Customer Segmentation and Profiling

$$\min_{\{C_k\}} \sum_{k=1}^{K} \sum_{c \in C_k} \|x_c - \mu_k\|^2$$

Where:

- C_k is the set of customers in cluster k.
- x_c is the feature vector of customer c (e.g., spending behavior, frequency of visits).
- μ_k is the centroid of cluster k.

2. Machine Learning in Retail

With data being generated increasingly through digital channels, machine learning models have become common and influential in modern retail, applications of which cover the areas shown. Demand forecasting, price optimization, and inventory management offer retail opportunities to leverage both in-house developed models as well as third-party vendors. Basic rule-based models, as well as sophisticated approaches, are used by retailers to develop demand forecasting systems. These are vital inputs for sales and operations planning, inventory replenishment, and store operations. As retail companies continue to widen their product offerings, the demand forecasting problem becomes substantially complex due to higher data dimensions of SKU inventory and geographical attributes. For instance, one retailer now carries over 100,000 SKUs in their physical stores, while another has 300 million active products across global marketplaces.

The capability to offer low prices, which becomes more complex with the wide variety of products and the strategic temporal dimension of price adjustments, is crucial in digital platforms. Predictive models and rule-based systems are developed in conjunction to determine optimal prices that are used extensively in various competitive segments of big box, grocery, department stores, specialty, and discount stores. Inventory management and replenishment decisions are strategic for brick-and-mortar retail companies. Improper considerations could potentially lead to stock-out situations and excess inventory costs that lead to avoidable markdowns. Machine learning models are developed to forecast inventory statistics and to estimate optimal inventory stocking levels based on the forecasted demand, supply chain lead times, and critical operational constraints. In e-commerce, due to advanced fulfillment resources offered by major players, costly stock-outs can be managed partially or completely while also offering timely deliveries, the drivers of success in the industry.

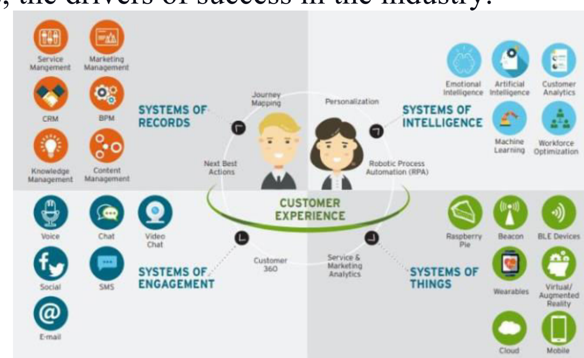

Fig 2: Machine Learning Are Revolutionizing Omnichannel

2.1. Overview of Machine Learning

Machine learning is a field of artificial intelligence that focuses on how to train machines to learn patterns from data and subsequently make decisions. Being a core underpinning technology of a variety of applications and services such as recommendation systems, predictive analytics, image, and speech recognition, machine learning has also been prevalently used in different facets of retail operations ranging from supply chain and inventory management to omnichannel customer engagement. There are three categories of core supervised learning problems. In classification, the output variable is categorical, whereas in regression, the output variable is numerical. In the case of clustering, the goal is to group data points into clusters that have high similarity with one another. Aside from the recognition and partitioning tasks, supervised learning can also aid in ranking as well as in making recommendations.

In addition to supervised learning, there are also unsupervised and reinforcement learning problems. In unsupervised learning problems, the data does not have a ground truth label. Problems such as clustering and generating stylized paintings usually fall into the realm of unsupervised learning. Reinforcement learning, on the other hand, employs rewards or penalties to instill models to master near-optimal policies mapping states to actions. This has been exploited in robotics, video game AI, and also in driving a vehicle with better fuel efficiency while not jeopardizing customer experience. The shared gist of the task of learning still lies in discerning patterns from data. Emerging trends in machine learning research and applications mainly revolve around the prominent themes of the exponentially growing diversity in model architectures, the ever-increasing size of the dataset to be processed, and the emphasis on cross-disciplinary research and applications.

2.2. Applications in Retail

One of the areas where machine learning and data mining have had the most impact on people's daily lives is in customer relationship management, from predicting customer churn to analyzing text feedback and optimizing the next best action. This has been particularly the case in areas associated with telephone or internet service providers and in the retail and financial sectors. In the retail sector, the structured information that is known for each transaction has been used to follow customer habits and to recommend products that a customer is very likely to buy. Textual information from call center records, data from computer-mediated communication such as chats and emails, form data, and transaction history data have been used for various applications related to customer relationship management.

As a matter of fact, in the last few years, many retailers have started pursuing the omnichannel business strategy, often driven by the shift in shopping habits toward multichannel and/or digital channels. In general, the omnichannel strategy relies on providing the customer with a seamless shopping experience so that actions taken in one channel result in a better shopping experience in the same or another channel. Building and preserving such a relationship is of the utmost importance since retaining customers can be up to seven times more profitable than acquiring new ones. Furthermore, in order to maximize customer acquisition, engagement, and as a consequence, revenue, it is essential that the correct message is sent at the right time to the right person.

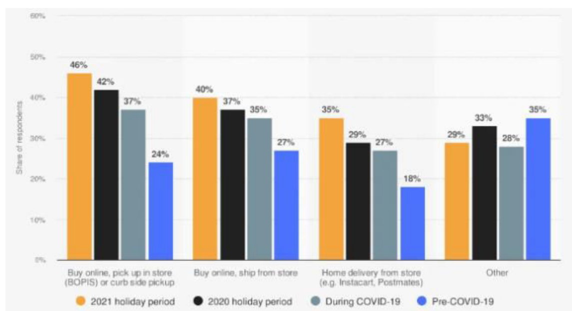

Fig : Omnichannel Marketing Has Changed

3. Omni-channel Retail Strategies

With the rise of digital retail, traditional brick-and-mortar stores found themselves on the defensive. Prior to embracing omni-channels, many retailers experimented with limited offerings, such as allowing customers to order online and pick up in-store. When retailers discovered that siloed, channel-specific strategy execution by business function was not meeting customer expectations or gaining market share, they began to invest in optimizing the consumer experience across all of their channels. Early omnichannel execution frequently demanded expensive, sophisticated technology that combined items from multiple inventory pools with accurate results for on-time in-store pickup or ship-to-home delivery. In contrast, retailers struggle with implementing profitable omnichannel strategies that deliver the expected customer experiences at an economically sustainable low price. They attempt to serve in-store consumers, "click-and-collect" customers, and other groups of online shoppers without incurring extra costs. Serving online and offline customers together offers opportunities for reaching economies of scale and scope that take costs out of the omni-retailer’s supply chain. However, these same techniques create tension by incentivizing consumers to expect to pay less for an omnichannel product mix, placing downward pressure on price and profit.

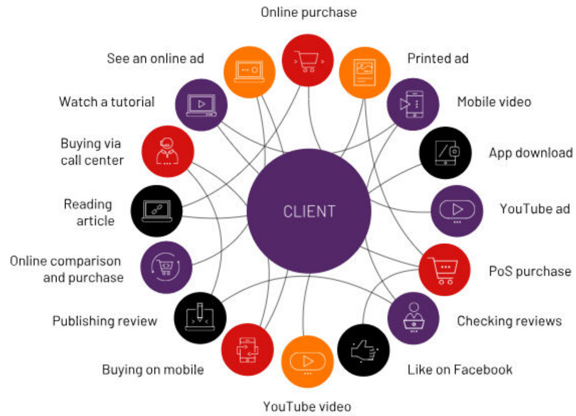

Fig 3: Omnichannel Retail

3.1. Integration of Online and Offline Channels

The first level of omnichannel retailing means that the online and offline channels are entwined, thus the consumer experience could be seamless. First, courier collection and delivery points in stores could provide convenience to consumers. Second, real-time inventory management could provide both comprehensive product selection and precise inventory status, including a pilot scheme to provide exact inventory for consumers. Third, online promotion, real-time price matching, and a sales currency for online transactions could secure, convert, and grow traffic across sales channels for the retailer. Fourth, highly regarded quick delivery response to online orders (consumers demand physical delivery more likely with smaller value orders). All such initiatives build on the store network of the retailer, and this physical infrastructure would be difficult to replicate by an online-only retailer, especially with a large product range or a need for quick delivery.

Such a retail model suggests that the retailer is operating a multi-sided platform – providing network effects for both consumers and suppliers of merchandise. An aside on the economics of two-sided platforms is that both sides of the platform might have to be subsidized by sponsors, and the critical mass for reaching a profit zone would come through the simultaneous marketing of both sides of the platform. Third, omnichannel retailers are likely taking advantage of the big data pouring from both the online and physical channels, mainly the store-based data pertaining to consumer traffic flow in the sales outlet. By understanding how consumers navigate stores, it is possible to target promotions and plan merchandise locations with more precision. Each promoted or nearby item would have a unique and separate visual tag at the shelf edge. Store location analytics could optimize layout and expansion plans.

3.2. Importance of Consistent Customer Experience

The concept of omni-channel implies that a brand offers an almost seamless experience to the customer across physical and digital channels, with the customer being at the center of the shopping process. Retailers need to offer a consistent customer experience in a connected world if they wish to cater to the growing needs of their digitally savvy customers who expect online-like convenience, irrespective of how and where they engage with the brand. When it comes to brands, people have a single image. Traditionally, a brand with an online and a physical store is

viewed as two separate entities. This division influences their operations and creates large gaps in their strategy. However, recent strategies are built around the concept of fostering relationships and targeting instead of segmentation. Factors that led to the emergence of omnichannel retailing:
1. Customers have control. 2. Brands need to provide experiences. 3. Brands see the big picture. 4. It's beyond loyalty.

Equ 2: Transaction Optimization (Pricing)

$$J = \sum_{t=0}^{T} \gamma^t r_t$$

Where:

- γ is the discount factor (reflecting the importance of future rewards).
- T is the planning horizon.

4. Personalization in Retail

Personalization is the art of opportune or suitable action, dealing with each client and prospect as well as with groups of clients having similar characteristics to increase customer value, satisfaction, and retention. The retail sector has benefited from the use of sophisticated big data and machine learning techniques to analyze and model customer interactions, demographics, and preferences. Machine learning techniques can be effectively employed to promote relevant products, provide great customer experiences, and improve customer loyalty. Customer satisfaction is the key to business success, and diversifying and personalizing customer programs can be a great differentiator. Beginning with the process of prospect acquisition, retailers attempt to influence brand loyalty development by exploiting available data concerning individual clientele, including past purchase behavior. Over time, as the clientele history with the company builds, the retailer with access to up-to-date transaction records will be able to track the shopping evolution of each dataset member and attempt appropriate retention marketing strategies. Such marketing attempts, based on data analytics, usually take the form of customized social marketing campaigns, personalized offerings and discounts, and even service assistance or concierge activities for specific customers.

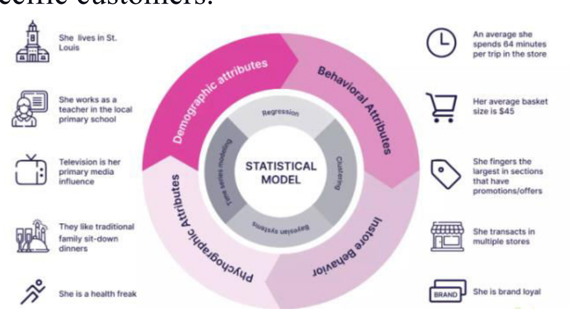

Fig 4: Personalization in Retail is The Essence of Sales

4.1. Types of Personalization

There are two levels of personalization: product and content. Sales efforts that are aimed at individual products are called product personalization. Sales and marketing efforts that occur at the customer touchpoint, regardless of the customer's product choices, are called content personalization. Content personalization refers to the dynamic presentation of site content in real-time or to site visitors in an attempt to modify its look and feel over time. Personalization can be executed using several methods and attributes that lead to requirements, and eventually to rules. A personalization method is a combination of attributes such as recommendation, automated service, customization, bundling, and targeting. Each of these methods addresses a personalization approach: recommended products are related to previous purchases and user profile attributes, targeting products correspond to user profile attributes, and recommended products match new contextual attributes provided by the user through a web browser.

4.2. Benefits and Challenges

In this section, we briefly summarize the benefits and challenges facing retailers in their efforts to leverage machine learning solutions for omnichannel retail. Many established omni-channel retailers have realized substantial financial benefits from the selection, management, and coordination of appropriate customer service in response to shifting customer preferences across all available channels. With the goal of optimizing customer experiences across omni-channel capabilities, companies can access vast specialized customer knowledge and employ sophisticated machine learning and data analysis techniques suitable for diagnosis. This can address previously unresolved research questions relating to customer service design and coordination as well as the evaluation and assessment of the importance and impact of changes in the multi-channel landscape.

There is also considerable potential in the use of new AI capabilities for deeper and more detailed optimizations of critical business processes. Deeper process optimizations can assist in the real-time control of customer service quality, eventually enabling real-time decisions and providing real-time analytics across all customer service channels. Increased data availability in combination with new machine learning techniques and additional computing power is thus changing companies' approaches to customer service. However, while these de facto changes show a high amount of potential benefits, they are fraught with critical challenges that need to be addressed carefully. In this context, one particular challenge closely tied to the AI-based automation of decision-making processes is the risk of losing customer and consumer trust in artificial intelligence if it is not appropriately and responsibly applied.

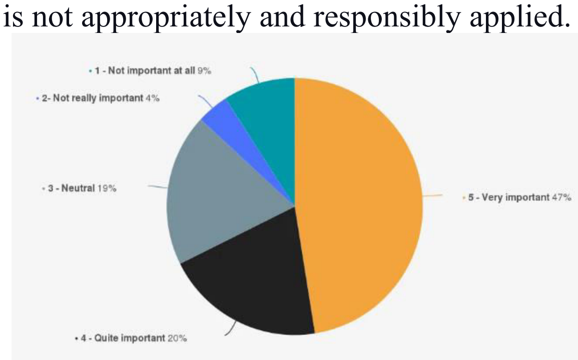

Fig : Omnichannel Retail Strategy

5. Machine Learning Techniques for Retail

Implementation of machine learning models can get a little complex as you need to always keep in mind the Pareto Principle, which is that 20% of the work produces 80% of the results. Here are various machine learning techniques for personalizing customer experiences. Whether the task is classification, regression, or clustering, one needs to begin with the K-nearest neighbors or decision trees, which are intuitive and provide similar decision boundaries to logistic regression. One can use regression trees to handle non-linearity in the data and ensembles like bagging and random forest to increase robustness. To decrease the dimension further and/or deal with multicollinearity, you can use regularized techniques like Lasso regression or Ridge regression. These models are usually easy to explain and are important in identifying relevant features.

When faced with a text problem, all you need to do is convert words into numbers and count the number of times a particular word appears in a conversational turn. This is known as the term frequency. However, every word is repetitive and each word appears so often that it may not be of any value. So to deal with this situation, inverse document frequency is used. These two components are then multiplied together to create a TF-IDF score to determine relevance. A surprisingly common problem that companies face is clustering customers and understanding behavior to inform business strategy. The K-means clustering algorithm achieves this sophisticated task very easily. To evaluate clustering, silhouette coefficient is used and dimensionality reduction techniques like PCA and t-SNE allow us to visualize clusters on a two-dimensional plane.

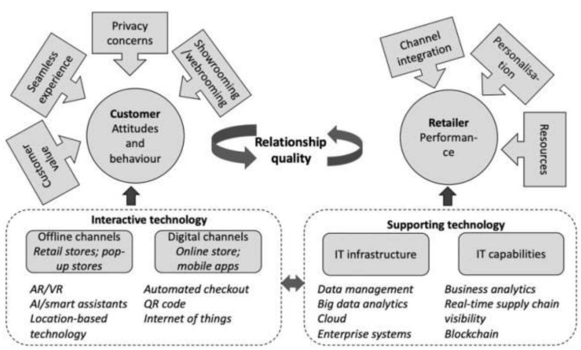

Fig 5: Exploring the Role of Omnichannel Retailing Technologies

5.1. Recommendation Systems

Customers would be overwhelmed with the many choices provided by omnichannel retailers. A smart customer experience method is necessary to service goods to the customers. Customers can get a more personalized experience when they receive recommended products from a massive selection for their demands, preferences, and purchase intents. This is one of the key trends in the development of e-commerce, which is conducted by high-efficiency platforms and has a recommendation system that suggests a wide selection of pre-owned satellite products matching the customer's preferences. A recommendation system is a filtering tool that predicts the preferences of a customer for a product offering.

Recommender systems, especially implicit feedback-based ones, are widely employed across domains such as shopping, streaming, and advertising. An end-to-end neural network is proposed for a recommendation that ranks entire catalogs with a policy-based approach, leading to significant improvements over traditional methods. Contextual information is included in the ranking of fashion recommendation models. An approach to generating more diverse recommendations with a set of rule-based social laws in fashion recommendation, extracted from common fashion observations, is proposed. Matching preferences is difficult for a recommendation system due to the challenge of high numbers of dropouts from observed shopping data with retargeting campaigns.

5.2. Customer Segmentation

Customer segmentation and addressing customer needs remain key strategies for successful retail businesses. Normally, businesses use demographic information, firmographic data, and other information such as purchase history, preferences, and behaviors to segment and understand the needs of their customers. In recent years, retailers have come to realize that there exists a potentially massive demand for unique variations of their products. Data analytics provides an answer to this demand by establishing lookalike models that predict customer shopping behavior and optimize their output. For example, in six months, a retailer incorporated item-level intelligent price optimization through its omnichannel management solution and increased sales significantly.

E-commerce businesses cement customer segmentation by tracking and collecting clickstream data, purchase history, and customer relationships, jumpstarting the discrete personalization of customer-specific offerings. However, the vast majority of retailers struggle to identify and analyze which behaviors to track due to budget constraints. A wide variety of real-world problems such as assortments, stock-keeping unit creation, price optimization, product launch, pricing, sales, and marketing can be addressed by estimating demand elasticity in regard to purchase behavior and preferences. One of today's most expensive, labor-intensive, and error-prone parts of this methodology is turning customer preference data into business and operational intelligence. Mistakes cost companies because customer needs and opportunities rapidly shift and disappear over time due to the changing market landscape, demographics, purchase histories, and other reasons.

Equ 2: Channel Integration and Transaction Flow

$$C_{\text{total}} = \sum_{i=1}^{n} C_i \cdot w_i$$

Where:

- C_i is the conversion rate for channel i (e.g., online, in-store, mobile).
- w_i is the weight or importance of each channel.
- n is the number of channels.

6. Conclusion

In conclusion, we have described the current challenges that retail customers and retailers face. We have reviewed how omnichannel methods can benefit both customers and retailers by integrating different data sources, optimizing transaction costs for multiple parties, and providing personalized customer experiences. We have underlined the retail omnichannel data realization, the criticality of retail omnichannel data integration, and the different experiments and machine learning models currently applied in the retail measurement function. We have demonstrated some of the successful retail use cases for the four machine learning research themes: personalization, transaction cost reduction, revenue generation, low information asymmetry, and transaction time and service level dimensioning. These use cases illustrate four steps in the retail life cycle: attraction, warm-up and trial, conversion, and retention and reactivation. However, many challenges need to be overcome to make more successful retail machine learning happen, and the operating model needs to evolve in the process. Finally, we have presented a research agenda to guide future retail machine learning research and topics that could be interesting for practitioners who are impatient and want to put insights into practice.

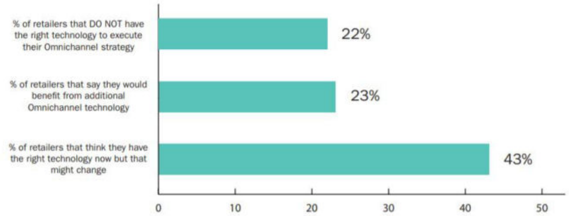

Fig : The Technology Driving The Omnichannel Retail Revolution

6.1. Future Trends

The retail sector is in a continual mode of evolution in its mechanisms for engaging and earning rewards from customers. Here we enumerate some of the critical trends that are becoming drivers of nuance and change in the retail customer experience:

1. Retailers are increasingly integrating their physical stores with web-based offerings. This strategy has created a fusion of web-based search capabilities in the lanes of traditional brick-and-mortar infrastructure, while others have used this strategy to offer in-store grocery pick-ups. There are partnerships that allow customers to pick up orders at locations while buying products in the store. Call it bilateral engagement, a coupling of physical and virtual, progressing towards retail success.

2. Customer insights are providing an excellent way for the retail industry to increase the top line with omnichannel dialogues aimed at growing customer sales. This supports the trend of enhancing the value proposition of customer relationship management. The customization of information and services provides an impact coefficient.

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