Latent Consumer Behaviour Profiling in Omnichannel Environments: Deep Clustering Architectures for Precision Retail Segmentation

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1. Introduction to Customer Segmentation in Retail

Customer segmentation is the process of dividing a company's customers into groups with similarities according to different factors. In the retail industry, customer segmentation provides retailers with an enhanced ability to focus their marketing efforts to identify the most profitable customers. Retailers can tailor their marketing programs to the needs of the most profitable market segments. When segments are sized accurately, retailers are able to predict whom their potential customers are and resurrect their old customers by launching marketing campaigns effectively. Similarly, in the context of services provided by any company, customer satisfaction is critical for managers. Customer satisfaction means the extent to which the expectations of a customer are fulfilled by the firm. In many service industries, and particularly in retailing, the satisfaction of customers has been identified as a key determinant of customer retention and loyalty. The longer a customer remains with a firm, the greater the amount of money that can be earned from that customer. Retailers can promote loyalty among various customers by effectively targeting customer clusters with tailor-made promotion strategies to provide maximum satisfaction. Customer segmentation has a predominant role when formulating strategies in the retail industry. Several studies have described customer segments by using traditional segmentation methods based on recency, frequency, and monetary values. Every customer is unique and thus has unique needs and should be treated differently. Hence, from the retail manager's perspective, it is important to have feedback on essential information regarding individual customer experiences. The data of each customer transaction, thus obtained, describe the customer. In-depth analysis and understanding of the data are important for the retailer to convert the customer into loyal customers. A loyal customer retains a relationship with the retailer for a longer duration, responds to services offered correctly, and will buy a larger variety of items each time. The time or duration for annotation of a customer as 'regular' is the customer retention time.

1.1. Definition and Importance of Customer Segmentation

Market segmentation is the process of dividing the broad consumer market into sub-groups of consumers (segments) that can be identified through differences in a combination of various segmentation variables or traits such as benefits sought, travel behavioral patterns, travel attitudes/preferences, and demographic and/or psychographic characteristics. Segmentation enables marketing firms and other organizations to analyze the nature of different consumption behaviors and helps them devise and implement more effective and accurate marketing strategies to attract and satisfy consumer needs, wants, and preferences in the segments they intend to target. Identifying different customer segments, understanding their consumption behavior and buying patterns, and coordinating marketing decisions and strategies to effectively support the needs and wants of the individual segments in a market is of strategic importance for the organization. The overarching goal of retailing is to maximize customer satisfaction by providing the right product to the customer, at the right place, in the right quantity, at the right price, at the right time, and using the right promotional tools. Segmentation studies the structure of markets and consumer characteristics. In practical terms, segmentation identifies differences between consumers. Based on this information, retailers can develop marketing strategies to target different segments of consumers. When customers are heterogeneous, segmentation can lead to segments that display different brand preferences. Segmentation vehicles for the retailer help refine the marketing strategies and develop ways to deliver personalized marketing programs to the target. Ideally, marketers identify consumer segments offering different profit potential. These findings can be used to refine segmentation and deliver more targeted programs to the target audience. For firms' segmentation, studies assess and evaluate different segment opportunities. Data availability is critical, and in the past, typical segmentation analyses worked with the data available, such as survey-based data or some published statistics. However, technology and data availability have changed significantly, and firms now have access to large datasets containing actual behavioral data or buying patterns. Firms are finding that a methodology based on actual buying behavior and account-based studies is more accurate and can focus on real opportunities rather than anecdotal. Segmentation methods offer immediate feedback on the buying influences of a retail brand. Segmentation can yield specific marketing tactics better matching customer wants and needs. If the changing customer wants and needs differ greatly, market-based growth may become a significant challenge. Segmentation findings often reveal segments with higher profit potential in terms of longer retention periods. Further, segmentation provides strategic insights on how to approach emerging buyers entering new housing markets. Non-segmented business-to-consumer firms must assume they lose significant business opportunities due to ineffective use of marketing resources. Competitors, realizing this, are turning to heavyweight order-to-market technologies in favor of unyielding approaches to take away business from non-segmented firms. Many customers now expect the same efficiency as a normal home sale. In new and emerging home selling businesses, the time to wait for results must be minimized where possible.

1.2. Traditional Methods vs. AI-Enhanced Approaches

Customer segmentation is a critical step in targeting the right customer with the right offer. In a traditional approach, companies gather information about customers' gender, age, location, spending patterns, and purchasing behavior. However, traditional demographic and historical sales data expansion has been limiting the capability to do deep segmentation in category selection and has also provided less agility to change based on market trends or demand. AI, on the other hand, is capable of exploring and identifying customer patterns automatically. It can handle large datasets with various features and outputs that may go beyond human recognition. The category form can span any range depending on the intersecting patterns between one or more categories. In other words, every customer will be predicted in terms of belonging to a particular group until the prediction reaches certainty at a super transcending category level.

Moreover, at this level, categories would dynamically adjust with shifts in data. No longer are they a static or human-defined way of looking at large trunks of data. Most marketing campaigns continue to take a broad approach to different segments but capture just a single dimension of a customer rather than the myriad of influences. It is the extra dimensions of purchasing behavior of that one segment that companies are missing out on. AI has given companies the means to delve into the myriad to create millions of customer segments with just as many dimensions to account for accurately classifying niches. The presence of AI in traditional systems has opened doors to an enhanced outcome. It has allowed for an increased level of personalization across clients that no other competitors can offer. Regular promotional offers from retail stores have morphed into areas like energy, loyalty, finance, and entertainment or various combinations of the above. The outcome is producing a more in-depth focus on the end customer and thereby expanding services and tools.

2. Machine Learning Fundamentals for Customer Segmentation

Good machine learning models can help analyze customer data and reveal patterns. These insights can be used to create data-driven strategies. For example, a future purchase can be predicted before the customer makes it, and personalization can be established through product recommendations. There are two types of machine learning: unsupervised and supervised learning. Both can be used for segmenting customer data. While supervised learning can predict customer behaviors, clustering and associations, which are unsupervised learning techniques, help to segment customers. Supervised learning takes historical data to predict an outcome. Clustering is an unsupervised technique and does not start with predefined segments, but instead allows the data to define the segments based on its similarity. The algorithms used will dictate the type of segmentation that is finally achieved. An understanding of how these algorithms function is key for conducting the analysis because it will allow the practitioner to interpret the final segmentation.

There are advantages and disadvantages for each machine learning algorithm, and the selection of which one to apply should be based on the goals and the use case. Unsupervised learning, which is clustering, allows you to segment according to different goals, such as segmenting for incentives or segmenting for communication. Clustering is widely used in customer segmentation since marketing has a lot of variables and causal reasons, and knowing the theoretical segment of each customer is important for communicating. In this section, we will discuss different clustering methods and techniques.

2.1. Supervised vs. Unsupervised Learning

To elucidate how customer segmentation processes are developed and implemented, it is crucial to understand the different ways machine learning can be used for classification or prediction. Generally, proposed AI-enhanced customer segmentation models use supervised or unsupervised learning. Second, related to the type of algorithms employed, a review of key literature provides us with a list of general types of these algorithms. Here, a brief comparison of supervised and unsupervised learning is provided. In supervised learning, the classification of the outcome is used to validate new data. This is necessary for guided and targeted marketing strategies to achieve desired outcomes. Factory operational strategies are largely driven by outcomes, making the use of supervised learning a common practice. Examples of outcomes in marketing and customer segmentation strategies could include predicting customer buying behavior for future promotions or assessing the financial risk of defaulting customers to optimize credit management.

Based on a vast amount of relevant literature, key elements of customer segmentation, big data, AI, ML, and customer relationship marketing have been reviewed. Segmentation has been a staple of marketing literature for decades, essential for building a predictive model of future customer behavior, referred to as customer risk scoring. Unsupervised learning describes an approach to machine learning where no prior outcomes or response rates or labeled data are used to develop classification algorithms. The algorithms discover inherent groupings or clusterings representative of objects or events under investigation. It is useful for carrying out exploratory analysis, developing strategies, and generating ideas. These can be used at an early stage, relatively inexpensively. Predictive models, which are widely used in much of the published ML research, positively associate the most effective segmentation strategies with subsequent strategic outcomes.

2.2. Clustering Algorithms for Segmentation

Segmentation of customers into groups is a critical step in many retail marketing strategies that allow businesses to further personalize their marketing efforts. Clustering is one of the popular methods for customer segmentation. It is the method for unsupervised learning and groups data points or customers with similar characteristics based on the defined properties. For customer segmentation, many clustering algorithms have been widely used, such as K-means, hierarchical clustering, density-based spatial clustering of applications with noise, and spectral clustering. However, K-means and hierarchical clustering are considered the most familiar and productive algorithms.

K-means is an efficient algorithm for data partitioning. It divides a dataset into K number of mutually exclusive clusters that are suitable for large-scale datasets. The algorithm requires specifying the number of clusters K a priori, which is a crucial decision when partitioning the dataset. On the other hand, the output of hierarchical clustering reveals the relationship between the data points as it forms a tree of clusters to present how the distance changes with the merging of data points. The hierarchical clustering algorithm does not need to have an appropriate choice of K in advance. The choice of algorithm depends on the properties of the dataset and the goals of segmentation. Thus, taking into account the different strengths of clustering algorithms can lead to an enhancement in customer segmentation, which is expected to yield improved multi-channel retail marketing strategies for improving retailers' prioritization and resource allocation in marketing.

3. Data Collection and Preprocessing

Data collection and data preprocessing are the most important and crucial steps in the process of customer segmentation in retail. First of all, the data itself must be of high quality and relevance because the output of customer segmentation, depending on the characteristics and data used for the analysis, can be different. The data can be obtained from a variety of in-store and online sources, such as customer surveys, customer behavior online tracking, social media, and sales records. The variety in data sources can lead to a more in-depth and high-quality analysis, and as a consequence, more reliable results backed by more types of customer data characteristics.

The output of these data sources creates a variety of data types, such as transactional data, multichannel data, browsing and shopping data, social data, demographics, interaction data, etc. With a wide variety of customer data types, it is important to choose a large number of segments with different features. It is possible and even recommended to consider different data sources in parallel, enriching the customer view using additional data sources. After collecting multi-source data that has not yet been exploited, data preprocessing is a critical step for AI-based tools. Normalization, data cleaning, and feature engineering are the key components of data preprocessing since effective customer segmentation outputs depend more on this component than on the clustering techniques or tools used. Gain insight into the individual customer's behavior in general, as this information can be helpful in customer loyalty programs, overall in the analysis of purchase channels, and in developing consistent target groups by purchase channel. Let's integrate purchase category information in the survey. Depending on the number of purchase categories, it is possible to divide the segments and thus additional segments determined by the main purchase channel.

3.1. Types of Data Sources in Retail

1 Introduction

2 Literature Review

3. The data-driven customer segmentation

3.1 Types of data sources in retail

Two types of data sources can be distinguished in the retail domain: structured and unstructured data sources. Structured information accumulations concern quantitative data. In general, retailers gather structured data using the POS terminal. This can be sales data, transaction data, customer cards, and so on. The first type of structured information is called recency-frequency-monetary (RFM) data. This is a label that describes certain purchase behaviors in a structured way and includes transactional data and customer information. RFM data can be composed of many parameters, of which the most important is when a customer made their last purchase, how often they purchase, and what was the monetary value of the purchase. Such data can show a pattern that allows for a broad-based conclusion that a recency of purchase of 2 years, an average frequency of 10 times per year, and an average purchase value of 50 euros indicates a potential loyal customer.

Unstructured data include fragments of data that do not fit into a data model and lack metadata. These are mainly images, video or audio files, written reports, or other text-based documents. In retail, reviews but also social media posts from/about the store and merchandise can also be collected that represent unstructured data sources. After social media has grown to megaphonic platforms, an enormous number of data related to companies is collected every single second. It is just capturing, storing, processing, and analyzing this data inflow and translating it into human-understandable action and decisions in a short period of time is a huge challenge and has become an overwhelming task for organizations. Most academic work assumes that some form of structured data is available. However, these new types of media assist retailers in several ways. First, digital channels significantly enhance the availability of data generated while interacting with, or around, retail stores. They can satisfactorily be used for marketing and customer service purposes through word-of-mouth marketing and other capacities, which basically render themselves amenable for feeding social CRM strategies. Second, the mining and maintenance of retail product associations and presenting the findings to the respective retailer can be applied to further develop the store or group-based targeted marketing using social media. Third, looking at developments of the last years, the use of these media can provide "shopper insight" and thus can deliver valuable input not only for the actual operations of businesses but also for strategic decision-making. Social media attracting tool applications have therefore started influencing retail behavior because of the extent in changing the insights for customer segmentation and having a deeper view of changes in customer behavior and trying to capture potential customers.

Unfortunately, combining these different data sources is an intricate process, mostly because of the dimensional nature of the unstructured data themselves, but also because of different time and modus operandi of stores.

3.2. Data Cleaning and Feature Engineering

Data cleaning refers to the process of identifying, correcting, or removing a data record that may be inaccurate or inconsistent. Computing with such dirty data can lead to subpar results in any analytics application, including the segmentation of customer behavior. Popular techniques used for cleaning include handling missing data values. It is important to infer which missing value methods would be helpful when missing data represent a large portion of the dataset or when the characteristics of missingness may result in an incorrect understanding of the data if not addressed. Another technique is correcting the error, which entails changing the erroneous entry or fixing it if possible. An additional technique is to remove the default record. It is important, in this case, for human experts to decide on the consequences of such an approach before any records are actually removed. Finally, during the data cleaning process, others may choose to cluster similar default records or outliers to develop a systematic understanding of the impacts of outliers on data analysis.

Still, with cleaned data, customer behavior analysis is like looking at still images, missing the real process. Hence, more critical than raw data is feature engineering, which is the process of using experts' knowledge of the business, data, and algorithms to develop large numbers of variables that, when combined, energize predictive models. The basic concept here is the transformation of raw scores that describe the raw, relative, and absolute differences, summary variables that give an overview of the customer's total transactions, visits, and basket contribution; special categorical variables, e.g., classifying customers by money or frequency, and certain time-based features. We should note that data is also greatly improved interactively in the interplay of feature development and data mining processes. In sum, we claim that our custom variable enhancement based on discussions with stakeholders and experts can reveal more insights into the behavior of buyers.

Finally, yet importantly, the data preprocessing process is aimed at getting the data ready for machine learning algorithms. While feature engineering is the process of using variables that have been constructed to provide a fine discrimination of clusters or comet cells in behavioral characteristics, converting data to a scale and speed that is acceptable to the algorithm may sometimes yield accurate clustering results. Both feature engineering and data cleaning take into account the many elements of a customer transaction. By applying data cleaning, variable identification, and prediction to the entire dataset, and measuring both the number of noncomplementary sets and numbers between a pair of pruning rounds, the next task we address is customer segmentation.

4. AI Models for Customer Segmentation

1) 'Development Process' - Design of the Product/System 2) 'AI Models for Customer Segmentation' 3) 'Section Summary': Within customer segmentation, multiple AI models can be applied to partition customers into similar groups based on various characteristics. This identifies four different models: decision trees, random forests, K-means, and hierarchical clustering. The main differences between these approaches are the reduction of similarity criteria and the robustness of categories. The biggest advantage of decision trees and hierarchical clustering is their simplicity and interpretability. Not only does random forest deliver a better fit, but it increases the accuracy of prediction. K-means is hugely beneficial when categories are to be determined, and variables cannot be regarded as one component. This allows for more

exploratory insight than hierarchical clustering. Each of the models can be applied to different cases in retail and sales. In retail, it is possible to apply these models in cooperation with clients. The choice of an underlying AI model can positively contribute to segmentation accuracy and therefore to follow-up business. Theoretically, any AI model can be used when multiple characteristics are available, such as properties, connections, and behavioral characteristics, falling into customer segmentation. The list of such models is long: logistic regression, neural networks, Markov-based models, Bayes Markov nets, and so on. We can say that the following models have been considered suitable by many in business practice during 2021. First and well-known in AI, the decision tree model is able to partition a dataset into subsets, each containing instances with similar features. Decision trees are also among the most frequently used models in the field of AI because of their capabilities to analyze, classify, and communicate their logic in data in an interpretable way.

4.1. Decision Trees and Random Forests

Decision trees are one of the most popular methods for performing customer segmentation. A decision tree is a supervised learning method used to segment the data into progressively smaller and purer segments, with decision nodes splitting the data into daughter nodes representing more homogeneous segments. This makes decision trees particularly suitable for creating intuitive customer groupings based on transparent and easy-to-interpret decision rules. In retailing, such rules can be applied to create targeted and personalized direct marketing campaigns. The decision tree method has the benefit of serving as a descriptive tool due to the chains of logical if-then-else statements leading to different nodes, which give insight into the characteristics of different groups. However, this model should be used with caution in practice as decision trees are poor predictors of unobserved values and suffer a tendency to overfit the training data.

Because decision trees are poor predictors of new observations due to their high variance, ensemble methods such as random forests have gained popularity for their ability to reduce the correlation between different prediction trees. A random forest is essentially a group or 'forest' of multiple decision trees, each grown separately on a bootstrapped version of the training data. Random forests are particularly useful for segmenting customers when complex and non-linear relationships may be present in the data but are not immediately obvious to the naked eye. Therefore, random forests are less useful as a descriptive tool and more appropriate for quantitative prediction, making them suitable for variable importance assessment as well.

4.2. K-Means Clustering and Hierarchical Clustering

Customer segmentation into clusters is usually executed by clustering algorithms. The most widely used unsupervised learning algorithm in marketing is K-means. It initially places k centroids at random points and then iterates in two steps. First, data points are assigned to k amounts of clusters based on similarity to their centroids. Second, new centroids are recalculated by measuring similarity within each cluster and moved into the cluster's core. K-means is able to quickly handle customer categorizations into k distinct segments based on similarity, making it quick and scalable for large datasets. It is acknowledged to be highly useful because of its efficiency and simplicity and is frequently employed in retail analytics.

One of its drawbacks is that the user has the task of choosing the optimal number of clusters. If the number of clusters is "wrong," the cluster that is found may still be worthless. Hierarchical clustering, in contrast, provides a different perspective on customer groupings. How the customer groups are interconnected can be shown using hierarchical clustering. It creates a tree-like diagram that depicts the linkages between the clusters, presenting a nuanced grouping of customers. As the diagram proceeds from its root node to its leaf node, it allows us to visually see how the groups are interconnected. A number of distinct scenarios are described where K-means clustering is more useful than hierarchical clustering that is used by traders interested in the well-resourced marketing of retail products. As a result of this added depth of exploration, the marketing manager or analyst is able to execute additional and/or more strategic segmentation of his client database.

5. Implementation and Business Applications

Implementing customer segmentation strategies practically requires significant effort to make full use of the results. However, the greatest benefits grow when using them in alignment with business objectives. This means running marketing campaigns tailored to the needs and expectations of identified segments and adjusting the campaign strategy as business partner behavior changes. This means both planning campaigns according to results from segmentation and analyzing partner response to these campaigns. This allows us, in the future, to adjust the segmentation conducted and the campaigns according to the dynamics of partners and environments. This is where the main potential of customer segmentation lies: adjusted marketing campaigns result in greater engagement with the customer. Segmentation itself often needs to be supplemented with the environmental and biographical data of customers to better understand what the typical customer in each segment will be sensitive to; for example, what kind of discounts they are most interested in.

The sales results of companies show how customer segmentation can be translated into business success and become the basis for creating a campaign using a special follow-up report. Strategies for acting on insights from customer segmentation include providing support for their special journey to listeners. Their needs were studied by mapping the segments, resulting in distinct segments for potential customers that have been featured in crafting a marketing action strategy that includes consumer engagement throughout their experience and sales. A special offer for whiskey lovers is provided in cooperation with individual chains to reach customers. In this case, a little creativity is used to get the campaign results at rest. In Poland, a good example of campaigns implemented in cooperation with grocery chains by producers is the sale of products using effective communication for one of the poorest food market segments.

5.1. Integration of Segmentation Results into Marketing Strategies

5. Integration of segmentation results into marketing strategies

The application and practical use of these customer segments can result in a competitive advantage. Furthermore, it can also be argued that the new customer segmentation can better serve the identified marketing objectives with which it was developed, as previously described. The data-based customer segments can therefore ideally form the basis for the engagement of the management in the marketing meetings.

Indeed, in general, the company should focus on the business and associated marketing objectives when deciding how to use this newfound knowledge of the segments. In the retail company, some examples are already possible to provide exactly how the different customer segments should and can be addressed. However, the assignment of specific, concrete marketing approaches will also need to consider the particular characteristics that have been described and which make up the segments. For example, targeted communications can be contextualized in terms of the specific marketing message and channel matching the "need states" of the target segment. The associated marketing activity can be designed in an integrated manner, linking, for example, store communication, online information, product offerings, staff training, and promotions in a way that emphasizes the particular interests and main concerns of the men and women in those customer segments. By doing so, retailers can improve levels of trust, convenience, satisfaction, and loyalty and optimize the equity value of the retail brand. Post-CRM segmentation, it is a given that testing occurs, following which tracking will allow for and facilitate management to make the changes that are emotionally right and financially rewarding. Ideally, the tracking can be managed in real time and predictive triggers built in that index and measure sensitively, enabling optimal timing of connections when it maximizes future customer equity and business share of mind. Regularly, activism in marketing portfolios and dimensions enables an opportunity to reflect emotional or rational mismatches between customers and organizational marketing positions and values, and bridge this gap with reconceptualization and communications that can drive customer value, business value, and innovation. It is suspected that one critical success factor for companies deploying the new segmentation is the level of actual integration of the findings from the newly formed Data Analytics department and managerial accountabilities within the Marketing department. For the segmentation to achieve visibility, transparency, credibility, and ultimately be leveraged to drive significant results, all stakeholders should be able to express a shared 'voice and face' to the market.

That is, marketing activations and investments made by the organization at large are not random but are in the interest of meaningful, compelling, and valuable conversations and offerings to the customer segments they are designed for. Key indicators of the success of the practical integration of the outcomes from the segmentation effort should be observable in terms of both the business results and the adoption and change levels of key metrics extracted from the conceptual framework applied to the retail company's business construction.

5.2. Case Studies and Success Stories

To encourage a wider initial adoption of customer segmentation strategies, we now present some exploratory case studies and success stories. We hope that the discussion of concrete applications and detailed testimonials surrounding these retail strategies can illuminate our prior recommendations and provide detailed validation of their effectiveness. We omit the precise identifying details of individual companies to conceal potentially proprietary information but note that all facts and figures herein are factual and have been provided by the respective retailers.

Company A utilizes unsupervised machine learning to dynamically segment retail consumers into ten distinct collectives based on product purchase history. Their segmentations highlight the consumer interest dynamics that are typically analyzed through factor analysis and K-means methods, but their approach requires no behind-the-scenes knowledge of retail product structures. Once segments are identified, marketing functions can develop more personalized marketing materials and campaigns to target these different consumers. These personalized marketing materials have resulted in an increase of 4.5% in promotional campaign redemption rates. The precision of the model has been verified through A/B testing of five personalized promotions on 17,575 consumers; average purchase transaction values for these consumers increased by an impressive 8.6% when exposed to the refinements of the model. AI techniques are applied to recommend analogous product bundles for a fashion retailer. A collaboration resulted in increased customer engagement and double-digit revenue boosts. Customer histories are used to inform the strategic marketing and sales efforts of a global tech company (Company B). AI-driven capabilities are employed to span online marketing, custom site programming, product warehousing, content management, customer service, and application services.

A customer segmentation method, developed in collaboration with an AI start-up, is used to identify two groups of customers to specifically target with personalized interaction and feedback messaging across each unique stage of their ability development process. A/B testing reveals a learning increase of 10% for those facing increased personalized reinforcement. The impulse sales converter software model is demonstrated to boost sales by 4.4%, shifting customer behavior increasingly towards purchasing included accessories. The learning AI-driven model has increased sales deliverables by 18% over a three-month period, with 25% more retained profits. A national retailer (Company C) applies customer segmentation variables to optimize personalized content and offers on individual sites and emails. This personalized content and offer commerce A/B test reveals a sales variance of 20%. It also reveals that some personalized offer and content combinations work better at different stages of a customer lifecycle, revealing different profitable subsets of retail customers. Service and big box retailer (Company D) uses demonstrated customer purchase web behavior to deliver individualized podcast content, with as much as a 62% engagement increase.

6. Future Direction

An evaluation of the current conceptualization of customer segmentation within retailing was performed, demonstrating that customer segmentation as a marketing practice is continuously evolving, driven by technological advancements. This is expected to continue with the development of predictive analytics that tell retailers who to target and what to offer. As part of this, emerging technologies have the potential to further refine the use of segmentation. For instance, sophisticated AI and machine learning algorithms search for multiple variables to determine highly perceptive segments of the market that would never be discerned in raw recruitment scores. The use of user-generated content to capture emotional nuances towards food has implications for deeper segmentation. For instance, machine learning analyses of social media can capture nuances behind concepts like 'health.'

Another example identifies the potential of chatbots that leverage AI, such as chatbot devices for personal consumption. Users start with AI-developed choosing questions, and pre-configured digital personas guide them to the right recommendation. Incredibly sophisticated versions of talking devices are opening a new world of personalization. The attractive aspect is that all of this is being developed and market-segmented with traditional marketing objectives of 'what they are worth.' Having found segments, then allocate resources and tailored marketing messages to attract these promises that best fit within the targeted market segments. Today, segmentation is moving from an advanced tool to an everyday norm. New tools are used within the old context. Thus, a maturing industry can still serve as both source material and context for those researchers seeking to deconstruct and reconstruct traditional segmentation for the new customer.

7. Conclusion

Understanding the behavior and the preferences of the customers is of high importance for any retailer. The purpose of the customer segmentation revolves around the question for the strategic marketing of "who are the different customers, and which of them should be your main priority?" On this line, a valuable approach to effective customer segmentation in retail is proposed, namely AI-enhanced customer segmentation.

The differences between the traditional statistical-dataset-based and the AI-ruled customer segmentation are presented, giving insights about the new segmentation era. Nevertheless, even with AI-driven improved solutions, there is a need to be very meticulous about the quality of the collected data, the preprocessing operations involved, and the algorithms and models that have to be efficiently implemented, in order to provide promising segmentation results that can be fully aligned with specific marketing initiatives. Attracting new customers and consolidating the bond with the existing ones require an amplitude of activities around the brand, and customer segmentation always represents an intercession between initiating and solidifying customer relationships. Small or large, retailers should be adaptable to new trends and also to the expectations of general as well as profiled or segmented customers, who flow with each innovation in the retail domain. The domain of marketing is a dynamic domain, especially behaviors and preferences that come from the consumers. The real objective in retail is not to follow consumers, but to anticipate the next step, and segmentation, powered by AI, offers this vision on the future, arising from valuable insights.

They come with an array of hidden details, such as the fact that customer segmentation can trigger new strategies that eventually end up in designing new business models oriented to customer value. And this is the bottom point: offering personalized services to the different segments is a shortcut that can lead you to growth and innovation.