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Chapter 7: Predictive personalization and micro-segmentation techniques in customer engagement

7.1. Introduction

Personalized marketing relies on predictions of customer behavior that are accomplished by analysis of historical data. Predictive personalization is a marketing approach that is employed by companies to provide genuinely tailored promotions for individual customers, as well as dynamic website variations that are geared towards increasing sales with a targeted customer. Micro-segmentation further drives the effectiveness of predictive personalization using the same data-driven techniques used for larger segments to identify small clusters of customers. These are the customers whose profile combinations have distinct responses to the promotional activities offered at that time. This discussion covers techniques in predictive personalization which should form the backbone of any marketing department in a company that collects and maintains an accurate record of historical customer purchase activity and considers developing a predictive analytics capability in-house as the techniques are not advanced in complexity from those adopted in CRM and other customer data mining applications (Arora et al., 2008; ; Kumar et al., 2010; Boerman et al., 2017).

A necessary pre-requisite for any CRM initiative is a reliable data infrastructure that collects, stores, and transforms customer-specific transactional data into information that supports the identification of patterns for developing the underlying predictive models. For most companies, transactions happen over multiple channels and require information from each of these to be merged together with customer profile information into a single transaction record for each customer before marketing analysis can begin. The transaction data should cover a strategic period of past behavior long enough to include the life cycles of a sample set of spending groups. This could be years for major retailers or a few months for niche providers with few loyal customers. Data from CRM marketing response campaigns or panels can also fill gaps in transactional data or supplement the insights from historical sales and inventory (Liu et al., 2016; Wedel & Kannan, 2016).

7.1.1. Overview of Predictive Personalization Concepts

Despite considerable interest in personalized customer interactions, with many companies proposing personalization solutions, there have only been limited empirical studies examining the process of personalization or the personalization principles that are important to implementing successful solutions. Past research into successful business practices shows that successful customer engagement relies on a wide understanding of the heterogeneity of customer needs and motivations combined with a robust assessment of the engagement strategies that can reliably evolve according to changing external customer-dependent or contextual situation-dependent mechanisms. While basic personalization approaches use service choice, channel choice, timing, or presentation formatting to differentiate services, the more robust and effective systems utilize predictive processes that internally segment the customer into finite micro groups that repeatedly and consistently exhibit similar needs, motivations, and responses behaviors according to customer-defined, noncontextual behavioral variables, as well as according to context-defined, contextual variables describing the situation and environment associated with specific engagement needs. Despite the general utility of predictive personalization for supporting customer engagement behaviors across a diversity of service businesses and customer clusters, it is widely recognized that many personalization attempts are perceived to be irrelevant or intrusive. These customer feedback responses can lead to the disestablishment of predictive personalization associated with the engagement, causing structural disconnects between customer and service business and influencing customer decision-making in favor of other businesses. Consequently, the relevant personalization must combine considerable industry and service category knowledge, it must utilize a supervised machine learning algorithm that is specific to the customs service engagement need and it must build and update holistic customer analytics-driven predictive models that appropriately balance between the insights gained from traditional macro-level models of service customer activity and from the detailed, micro-level predictive models, augmented with any context data relevant to the decisions to be examined. Given these limitations, this chapter aims to explore the specific predictive personalization and micro-segmentation techniques that can enable successful service engagement and facilitate its evolution across a balanced and diverse customer service portfolio.

7.2. Understanding Predictive Personalization

Predictive personalization is a form of personalization using data to predict what an individual or group might do next (e.g., make a purchase) and how the experience can be created for them (e.g., what offers can be shown where). Predictive personalization identifies relevant content, product, and experience combinations to optimize for customers and brands, and how that combination changes based on which customers have the highest probability to engage with it. Predictive personalization is also described as a full-funnel marketing strategy as it touches the entire customer journey, from gaining new customers to retaining existing ones. The importance of personalized customer experiences is emphasized, and the complexity understood by the brand is a key aspect of the brand-consumer relationship, stating that existing brand communication approaches are limited and proposing predictive personalization as a strategy where brands leverage data collection with individuals' consent to algorithmically decide what potential customers want and where information of relevant content is tied to be placed to increase the propensity for these individuals to take their intended action.

Fig 7 . 1 : Predictive Personalization

When discussed in a CRM context, sales and marketing are described as the main drivers, where the other company departments play a supporting role. Additionally, in-depth interviews also showed that CRM's focus in practice is streamlined to sales and marketing only. It is stated that while companies use a marketing-oriented CRM strategy, they worry about their neglected background roles for operations or service. Thus, asking for further insights into interactions between marketing, sales, and service at a strategic interfunctional level. Findings agree with earlier conceptual CRM foundations and should shed light onto broad business aspects surrounding predictive personalization, pointing to an outside (customer-centered) view, while maximizing combining it with an inside (company-centered) viewpoint.

7.2.1. Definition and Importance

The future of Customer Engagement Management (CEM) is predicted to be shaped by predictive analytics applied to customer data assets as well as big data improvements. A significant percentage of organizations say they are competing based on customer experience, and a focus on influencing and improving their experience in the future is key for further organizations. Predictive analytics are not all that is involved, despite what the focus on this technological building block has led to our thinking. Predictive customer insights are needed to enable the next best engagement offer or action to suit an individual customer's particular stage of relationship engagement to date, or even their physical location or current customer service needs. Predictive personalization is also needed to close the experience gap – the predicted experience is delivered, or exceeded, or else disloyal customers abandon the service journey for alternative product competitors capable of delivering this experience without the wait.

Many organizations have evidence of former engaged customers who have suddenly turned negative in their published reviews of the product or service. The past behavior of customers openly discussing an offering's experience is also considered a negative experience. Micro-segmentation describes offers or actions better suited to a single individual rather than groups of customers with similar interests, longings, and intentions. Predictive personalization combined with micro-segmentation is driven by the identification of unique customers moving through various micro-slices of experience throughout their relationship lifecycle. The micro-slice transitions are detected automatically and often by machine learning algorithms analyzing internal and external data flows. At the center of these data flows are micro-moment triggers, which are events the organization should ideally be aware of; such as within the customer journey as a whole – and be monitoring for urgency.

7.2.2. Key Technologies Involved

Predictive personalization is a largely technology-enabled concept that makes use of most of the technology tools that are available to marketers today. Specifically, these tools include advanced customer decision tree models; agent-based modeling for simulation; analytical deposit and purchase-trigger event recognition; algorithms for item-affinity analysis to develop advanced shopping lists; analytic segmentation of customers and micro-segmentation of products; analytics for decision prioritization and resource allocation; forecasting and demand prediction; marketing response modeling; pattern recognition using neural nets; and propensity modeling using logistic modeling – to mention a few technologies. Predictive personalization typically requires and makes use of heavy-duty marketing analytics, advanced customer modeling, next-best-action decision logic, and sophisticated algorithmic engines for the various predictive personalization drivers. Predictive personalization can also use basic marketing tools like direct mail, telephone, and e-mail, but the predictive personalization experience is enhanced exponentially when companies deploy the latest technologies across channels, as enabled by the above list of capabilities.

Predictive personalization companies push the envelope on the experience strategy via technology. The key to enabling technology to excite the minds of marketers and driving deployable implementations today is marketing analytics. Complex models of customer choice and demand help guide and prioritize the strategy for establishing the correct experience and, importantly, deliver a clear advertisement for reservation consumer objectives like loyalty, exclusivity, and duration. To build direct commercialization channel relationships, marketers need to first invest upfront in establishing long-term customer data relationships. At micro-segment and personal levels, businesses need to observe customer behavior over time to detect patterns. Armed with the observed patterns and apparent affinities, companies can trigger-detect offer products, services, or attributes likely to increase customer share-of-wallet and share-of-time.

7.3. Micro-Segmentation Explained

Micro-segmentation refers to the practice of creating high-resolution customer segments that encompass a relatively small number of consumers with distinctive needs. While few traditional clustering techniques incorporate this functionality, many emerging AI-based clustering methods are finding favor. The customer segments can be large or small, but their defining characteristics must be based on a predicted cluster probability weighted by predicted responses for different products and channels, or CLV for specific segments. Specific segments are engaged differently and presented with different content and messaging. Micro-segmentation can effectively personalize customer engagement because products and offers are assigned on the basis of an account-specific probability. Micro-segmentation is not a simple modification of existing traditional segmentation approaches; it is a distinct method that delivers a markedly different level of granularity.

Micro-segmentation has numerous reporting and analytical advantages due to the fact that the number of micro-segments engaged is relatively small. These advantages, along with the ability to create more customized, engaging experiences, are enticing marketers to micro-segment their customer audiences. Differentiating promotions by segment is fundamental to improving response rates, customer relationships, and CLV. However, not all customer segments can be managed in a personalized manner; some are more suitable for tailored, personalized treatment than others; hence the need to prioritize and micro-segment. Proper customer micro-segmentation helps marketers make the most of the resources they have to design campaigns. Marketers can then spend the right amount of money to deliver enticing offers to the customer group most likely to respond. Micro-segmentation can allow tailored engagement that enhances product adoption and the customer's satisfaction with the product while reducing effort and risk for the customer.

7.3.1. Concept and Benefits

What if a shoe brand knew which of its loyal customers might be tempted to switch to a competitor? Or a beverage company know which of its occasional buyers could be turned into regular customers at their convenience, with little effort, and with inexpensive strategies? Or a bank know which of the few clients who determined regulations to open new accounts were also their most important business clients? Much money is wasted on "everyone" email campaigns and promotion strategies. With micro-segmentation, decision-makers can detect which are their important segments, or their segments of one, and decide what strategy to use for each special segment. With personalization, marketers try to give one-to-one experiences with little effort. The clearer it is who the buyer is, the easier it is for both communities to offer and get what they want. So, marketers should try to pursue micro-segmentation. Technology is key. In a world where customers are in different networks and have their profiles, social media, and browsing experiences, the difficulty is not in the capacity of computers to provide up-to-date micro-segmentation, but in the craving to offer special segments –segments of one– what they need and how to desire it. Moreover, with mobile phones, the proximity of the networks allows the use of instant technology, real-time technology, that shows the right ad for the right person at the right time. Micro-segmentation is the new holy grail. It enables tomorrow's intelligent shopping, which is about discovering what is visible at the lowest cost, independently and contactless, thanks to augmented reality and artificial intelligence.

7.3.2. Techniques for Effective Micro-Segmentation

While there are many sophisticated methods of segmentation, many of the most common approaches to customer micro-segmentation can usually be placed into at least one of seven main buckets, including demographics, geographic, psychographic, behavioral, value-based, or predictive. Demographic: These are typically the simplest methods of dividing customers into segments – based on more basic descriptors such as age, gender, or income. However, such demographic segments ignore individual preferences, habits, and loyalties. Geographic: Geographic segmentation can range from as simple as breaking customers into city or state groups to as in-depth as segments that target neighborhoods down to specific block levels. While it is a powerful method of segmentation, geographic results usually still only scratch the surface of specific targeting objectives. Psychographic: Psychographic segmentation allows marketers to create segments based on customer personalities, lifestyles, interests, or opinions that are more closely correlated to product or service preferences. Psychographics can help brand builders position new product extensions more accurately by appealing to the lifestyles of the segments they are targeting. Behavioral: Behavioral segmentation is built on prior customer actions, buying habits, and propensities. Insights derived from these prior actions help marketers make better future predictions. Like big data systems oriented around predictive analytics, behavioral segmentation improves targeting by predicting future actions based on what a customer has previously done, such as purchase frequency, buying cycle, or churn. Of all the segmentation methodologies available, behavioral methods are generally regarded as providing the most useful insights, because they are often the most accurate and customer-specific. Value-Based: Value segmentation goes one step further than behavioral approaches by segmenting customers based on potential economic values, such as conversion probability, likelihood to respond to an upcoming campaign or future profitability. Value-based segments are the lifeblood of sales and marketing organizations, and when appropriately used, are critical components of all marketing efforts.

7.4. Data Collection Methods

Customer engagement is a long lossy journey that begins with tossing a baited hook on the wide-open waters of the market to attract a customer to the purchase process. Today companies are using every possible medium conceivable for promotion from traditional media advertising to social networks for baiting potential customers like storing bait to attract them toward the engagement journey. But all the endeavors are either losing significantly converting potential customers or spending extravagantly to ensnare them. Real IT advancements in statistical modeling to explore the possible ways that can be employed for reducing these costs of customer engagement have practical realization in many firms. Such advancement leads to a prediction-driven marketing strategy wherein key customer response rates are modeled based on finely segmented through-the-line customer data, to optimize expenditure by matching suitable spend to the likelihood of response of each customer.

Customer engagement becomes possible only through the exploration of customer data originating from different sources. The variety available on the data, and the choices of what to collect are immense. Yet, the critical step in improving customer engagement for any organization is the collection of raw data. Any errors, or shortcuts in this step will ensure that the best models that are built will never improve customer engagement. Serious marketers who wish to use database marketing modeling to improve their results need to be aware of how the kind of data required, and the sources of data to be collected for it. Different stages of customer engagement may demand different types of data from different possible sources. It then becomes imperative to clearly understand these workings, especially with the costs and potential destruction of relationships involved.

7.4.1. Types of Data Required

Organizations gather data for many reasons, including salary, debt load, health, and credit history. Each of these variables has some predictive value, and it is the goal of the predictive model to consider them in combination. Predictive modeling uses data such as demographics, business and household information, and lifestyle attributes. Profile variables that describe customers and contacts are important to target prospecting. For loan underwriting and receivables management, businesses focus on credit risk scores and financial indicators. For sourcing, modeling is used to determine where an organization's customers come from and how they physically move.

Predictive modeling can pull in all manner of data, including direct marketing responses, complaints history, claim history, digital footprints, financial data, insurance coverage, credit rating data, demographic history, internal organization cues, order history, risk information, social networks, payment data, and loyalty program data. Of that data, there are four that are highly indicative of model performance: demographics, engagement, historical behavior, and account payment history data. Demographic data are useful as a supplement because they can provide a starting point for targeting certain offers when behavioral data are sparse or exist only for certain subpopulations. Additional bumps in performance are found with the inclusion of engagement data, such as account usage and whether the account is currently active, and past behavioral history, such as a history of past purchases or online visits. Finally, if available, the best-performing variable in the model is historical payment behavior across all payments, along with the time trend of change over the past several months.

7.4.2. Sources of Customer Data

To present personal recommendations and selections to customers or prospects, companies must first identify the data they will collect and the methods for doing so. The data must indicate what is desired in a real-time context but must also measure the intent of the user or customer. After exploring the types of data needed, we present the sources of data according to whether it is internal data or external data. Internal data examines current activities, such as transactions and interactions. External data can enhance internal data by measuring what is happening externally.

Part of the promise of big data and predictive and prescriptive algorithms is the ability to lessen the quantities of data collected through the transformation of functions such as collaborative filtering. There are a multitude of sources of information that companies may use to better understand customers. Data can come from the three main activity vectors employed in seeking or optimizing sales: transactions, interactions, and products. When conducting transactions or interactions, functions such as commerce add to the data collected about customer intent. In collaboration with product functions, commerce creates meta-data on products, such as their category, brand, and descriptions, which in turn allows customers to share and evaluate ratings and reviews among themselves or through digital agents acting on behalf of customers.

External sources of data can lend additional context to interpreting the signals relating to intent present in internal data. While these external data sources are often not available, free, at the level of granularity, or having the resolution of internal data, it is often beneficial to incorporate data from these data sources into predictive and prescriptive analytics model implementations to augment and improve these models.

7.5. Data Analysis Techniques

A variety of statistical and machine learning-based techniques are available to analyze the massive amount of customer data. On the statistical side, there are traditional customer lifetime value models that help predict customer behavior at the macro level, such as recency, frequency, or monetary value. These models use historical data to identify profiles of potentially good or bad customers and predict future behavior based on these profiles. In terms of machine learning and artificial intelligence, clustering techniques help with the micro-segmentation of customers to identify unique groups based on behavior and transaction characteristics. Predictive models at an individual customer level can help predict behavior using a combination of social, behavioral, emotional, and transactional data, which can identify the effects of marketing interventions and help with the targeting of future messaging and other triggers. The text also presents advanced methods of causal inference that can identify the average treatment effect and frame the response model in a predictive causal manner to improve uplift modeling. Near-Real-time Analysis: Many companies are attempting to analyze customer interaction data such as web browsing, email opens, and clicks. If the data is structured and cleaned, and the models are simple, online analysis of the data can help identify unique customers and how they interact with the web, mobile, and other channels, a very helpful tool to drive web design and marketing strategies. More advanced neural network models require batching data for compute-heavy backpropagation processing. It requires advanced techniques to identify the parameters that lead to improved prediction results associated with their uniqueness from customer intent and experiences.

7.5.1. Statistical Methods

When discussing data analysis techniques, we generally refer to statistical methods and machine-learning approaches. Statistical methods such as correlation analysis, regression analysis, and factor analysis have existed for decades and are well-defined. They assume that data comply with specific distributional and structural assumptions that can be statistically tested. When these conditions are fulfilled, statistical methods allow for an unambiguous interpretation of the results. For some analyses, such as regression analysis, statistical methods contrast dependent and independent variables and hence allow for causal inference. However, statistical methods are not always applicable; not all data fulfill the conditions of statistical methods. For instance, modeling dependencies between variables or predicting specific outcomes is not possible for large sets of categorical variables using statistical methods. In that case, machine-learning approaches must be applied.

Fig 7 . 2 : Statistical Methods vs. Machine Learning

Statistical methods or analyses apply a two-sample t-test, the Kruskal–Wallis test, ANOVA, correlation analysis, and regression analysis. Detecting differences between groups is usually done by applying either a two-sample t-test or the Kruskal–Wallis test. The t-test detects differences between two groups when the independent variable is strictly binary, and the dependent variable is normally distributed and metrically scaled. In contrast, the Kruskal–Wallis test can be applied to more than two groups, and the dependent variable can either be ordinally or metrically scaled. Factor analysis, multivariate regression, and canonical correlation analysis help to reduce data dimensions by discovering patterns of relationships within the data. For more than 80 years, it has seemed to be common practice to conduct exploratory factor analysis using a nonorthogonal rotational procedure such as rotation. The goal is to discover the latent, nonobvious factors of a scale. One significant advantage of factor analysis is that the scale's number of factors is lower than or equal to the test's items, which simplifies multiple statistical analyses of reliability.

7.5.2. Machine Learning Approaches

Customer demands for personalization and real-time engagement require novel approaches. Predictive analytics, which leverages a rich set of advanced data mining and predictive modeling tools, is expected to be a game-changing solution for organizations to enhance customer engagement. Using predictive analytics, organizations employ advanced statistical models to anticipate demand changes or customer behavior at the individual level, enabling highly targeted, proactive, and timely actions. In the marketing context, predictive models unlock the power of organization-held data and internal or external Big Data to predict various marketing-relevant variables and enhance predictive performance. By targeting marketing communications and business decisions by predicting model outcomes, organizations can optimize business objectives such as customer return, loyalty, and retention, or action decisions such as cross-selling or upselling.

In this era of Big Data, organizations have unprecedented amounts of customer data and sophisticated predictive tools. Five megatrends – machine learning, data science, deep learning, automation, and artificial intelligence - are propelling the adoption of advanced models to push the boundaries of predictive analytics in customer engagement. These megatrends are in the cross-section of the above two dominant marketing concepts – data-enriched customer engagement and advanced predictive analytics. Utilizing novel, advanced predictive models, organizations can not only keep pace but exceed customer expectations for personalizing relationships with the right message at the right time. These megatrends provide a rich set of machine learning tools readily available for organizations to enhance customer engagement through predictive analytics.

7.6. Implementation Strategies

Organizations today have opportunities to build competitive advantages by identifying and addressing customers' specific needs even better than the customers can identify or articulate them. Businesses increasingly rely on predictive models to solve business problems. Such models leverage historical behavioral data to classify customers into different segments or to derive expected outcomes for individual customers. Predictive modeling not only improves the personalization of customer engagement but also contributes to improved overall customer metrics, including acquisition and retention, response rates, lifetime value, and profitability.

The company must engage in nine steps to efficiently create and execute a predictive personalization strategy using predictive modeling. Steps 1–5 outline an Implementation Path and steps 6–9 lay out an Execution Path for Customer Engagement Tasks. The five-step Implementation Path outlines the stages involved in developing predictive models and the customer outcome-focused Execution Path outlines the customer engagement tasks using the implemented models and their outputs. Predictive models can be used for engagement in one or more than one downstream activity of response prediction, micro-segmentation, personalization of engagement, focusing communications, and influence to create or shape expected outcomes. The nine steps will allow a company to design a customer experience that is optimized for each customer based on their unique combinatorial predictive profiles across multiple engagement and outcome dimensions.

From a marketing manager's viewpoint, the predictive modeling process is a series of clearly defined, straightforward steps, executed in order. However, this definition conceals the underlying complexities, challenges, and decisions faced by both model developers and the marketing manager at various points in the predictive modeling process. These challenges vary from the actual model development and implementation to the need to work closely with the marketing managers to create a common understanding of how predictive modeling can dovetail with marketing and to establish the organization-wide processes and systems required to implement predictive modeling successfully.

7.6.1. Integrating Predictive Models

Our approach requires that you have lists of prospective customers (typically with past behavior variables) and multiple predictive models that each predict a single outcome or response variable relevant to a marketing program. A model could predict who will be a lead generation respondent, who will sign up for a newsletter, who will later purchase a specific product line, or what types of products one wishes to purchase. To perform the segmentation and allow for easy exportation of the resulting score files, the models need to be developed using a custom branch of R. This custom R environment includes new packages that have been developed for expanding datasets beyond their original size so that every customer record matches to the same distribution defined in the original dataset. The model solution outputs the probability, odds ratio, and chi-squared gain table, along with an explanation of the model parameters, for each marketing response predictive model.

The data processing tools take original customer datasets and augmentation datasets and merge them so that for each record in the augmentation dataset there are all of the records in the original customer data file. The tool then creates an augmented dataset for each file in the group of augmentation files that will be usable for both training the prediction model and scoring it against the original dataset. The primary function of the pipeline is to create the datasets that will be usable for generating a predictive model in the original customer datafile, and then running the resultant model on the same datafile to create the same distribution of predicted values as in the training data, but which will not alter any prediction variable values.

7.6.2. Developing Customer Profiles

To perform effective micro-segmentation of customer data and build predictive models, predictive personalization solution providers recommend developing detailed customer profiles or "customer DNA". These profiles should be developed in parallel with data preparation, exploratory data analysis, and the development of predictive models to create feedback loops between the modeling work, data selection, and predictive model performance evaluation. The idea is that feedback loops help improve the accuracy of predictive models and the overall predictive personalization effort by ensuring that the most relevant variables are selected and profiles are aligned with the predictive analytics modeling work.

In the plasticity model, customer attributes included in profiles are additional attributes not required for predictive analytics modeling work or predictive model performance implementation. A plasticity model achieves this objective by making use of demographic, psychographic, and geographic information enrichment through data appends and business intelligence databases. Digital identity management systems also help fill in the missing customer behavior and identity profile gaps through cookies and other software application solutions. These profile development efforts engage specialists and work with customer service. Product design, sales, marketing, online interactions, and other departments owning customer interactions must all have their say and input into what information must and can be captured in the databases used to compute customer profiles.

Micro-segmentation involves analyzing customer activity data and identifying behavioral differences among customers. Once differences are found, data mining tools can be used to filter customer activity data. Using this filtered data set, predictive modeling solutions can identify customers with similar behaviors. Clustering techniques help organize customers into internally homogeneous segments or clusters based on behavior. These segments can help target market offers more effectively and identify high-potential customers for churn, sale, and win-back marketing strategies.

7.7. Customer Engagement Channels

Implementing micro-segmentation and predictive personalization can require intensive effort, time, and investment, which means organizations need to choose the 'right' customer engagement channels where they target to maximize success. In many B2C environments, this means choosing from a range of digital marketing channels and platforms, which offer marketers sophisticated targeting tools. These include paid search, display advertising, personalized web content, remarketing, and increasingly mobile advertising. Despite the sophisticated targeting mechanisms, many digital channels require a minimal investment before useful feedback is gained in terms of engagement and conversion from the targeted segments. Digital marketing channels do, of course, provide potential avenues for facilitating engagement through earlier and later selling stages. Personalized email campaigns in particular are often the first step in direct selling in establishing a one-to-one dialogue with a customer, and brands and retailers develop specific customer audience segments with tailored email offerings to create interest and drive conversion. Re-targeting prospects who have visited websites, or dynamic remarketing, continues to be widely adopted in search and display campaigns; and demographic, customer, and interest information is used in preference to a click or conversion history to reach relevant prospects. It is expected that investment will continue to grow in data-driven digital marketing. Brands and retailers are already using and are set to increase spending on cross-device targeting, utilizing both demographic and behavioral data to link devices, in recognition that multiple device usage is vital for digital ad effectiveness and that any privacy concerns are effectively managed. However, while digital channels are gaining share at the expense of traditional channels, they tend to be used more as enhancements alongside traditional channels, such as direct mail and telephone. While lifting response rates from one-off direct mailings, both channels are still seen as valuable to convert new traditional and digital customers; many organizations initially use personalized email offers followed by catalog or direct mailings in subsequent customer lifecycles.

7.7.1. Digital Marketing Platforms

Digital marketing refers to marketing through any digital channels, including websites, search engines, social media, email, mobile devices, and others. Advances in digital technology have created a highly connected world, offering marketers infinite possibilities to reach their target audiences and send personalized messages directly to them. Almost all businesses, regardless of size, need to be visible on a variety of online platforms. While visibility is important for any business, especially small businesses, what is more important is to maintain constant, meaningful engagement with customers. Online digital marketing channels help keep potential customers engaged, build relationships and trust, and encourage them to convert and become repeat customers. Different customer segments, niches, and personas have their preferred platforms for digital engagement. Businesses need to identify and leverage the right mix of platforms based on their offerings and target audience profiles.

Digital marketing has evolved into a highly effective strategy for establishing target brand visibility, delivering personalized customer engagement, driving customer lead acquisition and conversion, and strengthening customer loyalty at lower cost. Using an integrated multi-platform strategy, customers can be engaged at each stage of the buying cycle. With advances in data collection, aggregation, and analytics, marketers can leverage predictive personalization to deliver relevant, timely messages more and more directly to their audience members on the right platforms through the right channels. Marketers need to build powerful digital marketing platforms that facilitate continuous monitoring of customer behavior patterns across multiple channels. All marketing messages should convey a consistent brand identity and image across platforms and channels. The type of engagement differs with each stage in the buying process. Digital marketing platforms help businesses streamline and optimize their customer engagement.

7.7.2. Personalized Email Campaigns

Email marketing remains one of the dominant tools in the digital engagement playbook. It allows brands to engage with customers directly, under the brands' control, without having to negotiate the rules of the game with an external platform. Email enables a deeper level of one-on-one engagement and creates real dialogue opportunities. And you can also use email to build external social networks to facilitate a brand community. With email, you're not at the mercy of algorithms that decide whether or not your content is served to customers, as is the case with social channels. You can also measure results to determine how well your content is doing to create higher response rates than what you'll find on social channels.

The checklist for email campaign personalization includes that the subject line of the email must include the recipient's first name. The salutation should again include the recipient's name. Transactional emails and product recommendations, either during checkout or in a follow-up email, must be personalized. The emails must also be sent based on customer behavior, not limit engagement to just one type and one-time offer. Instead, the emails must cover multiple product categories or services, based on lifecycle or anniversary triggers, or communicate an emotional call to action in addition to any expected promotional offer. Finally, it's best to avoid generic email placements, which treat all customers the same, by instead segmenting email placement by customer profiles.

7.7.3. Social Media Engagement

However, like with all engagement strategies, the trick lies in trying to get it right. For businesses, the struggle often lies behind trying to decipher the social media behavior of their consumers. Gone are the times when businesses could put out generic ads and statements and assume the user base would respond favorably. Nowadays there are millions of businesses trying to catch the attention of the millennial and Generation Z crowd through sponsored social media advertisements. Because consumers notice such activities one or two times and quickly tend to ignore all such ads, businesses must think more creatively to drive better results. More often than not, businesses pay high amounts in sponsored promotional advertisements and drive traffic to their homepage with little to no conversion. The solution lies in curtailing and polishing the social media engagement strategy around using existing social media presence and influencing engaged consumers to work their marketing for them.

By 2025 almost three-quarters of customers will prefer to purchase goods and services through digital channels. As a result, businesses need to be ready not only to have adequate capabilities in place but an efficient method of communicating with customers throughout. One such solution would be personalized SMC engagement where up to 70 percent of customers are willing to share relevant brand information via social media platforms. Additionally, the more personalized SMC engagement is to the individual, the more responsive the consumer will be. By creating an emotional bond with the consumer, businesses can influence brand loyalty throughout their lifetime, allowing communication during both positive and negative experiences. Furthermore, when consumers share their experiences such as expressing satisfaction with the service or product, the business's internal team must seamlessly weave that into their social media engagement strategy. Doing this effectively has a long-lasting effect of positively influencing fellow consumers without any cost of advertising.

7.8. Conclusion

Although widely used for many years, mass marketing techniques seem to be experiencing a resurgence in popularity. With large amounts of analyzable consumer data, companies are embracing customer-market segmentation and attempting to influence specific groups of consumers with personalized approaches. However, for larger organizations with geographically dispersed customers, implementing personalization initiatives can be complicated. One approach practiced by these larger organizations, primarily in the service sector, revolves around developing an understanding of customer preferences that involves developing consumer segments or targets of convenience. A wider group of people receive similar treatment; only the individuals can choose to opt in or out. Unfortunately, organizations that use such approaches are constrained in their delivery of personalized services. Therefore, true personalization is generally the domain of smaller organizations that interact and engage privately with individual consumers using costly or labor-intensive methods but which can result in in-depth, rich relationships that deliver enhanced customer lifetime value.

With consumer participation online increasingly apparent, engaging personalized relationships between consumers and the organization can be achieved irrespective of their relative size. Organizations are increasingly delivered by technology-enabled processes and data-rich consumer inquiries. Personalized tools are needed to efficiently and effectively service consumers within the increasingly experienced and demanding marketplace. The advent of a new pipeline of online technology services will help deliver personalization and micro-segmentation capabilities that were previously only the province of smaller customer-oriented organizations. These technological enhancements will directly address the issues of scale and responsiveness with larger consumer bases, as well as the zooming-out effects of technology increasingly removing people from the individual service, suggestive, and advisory process.

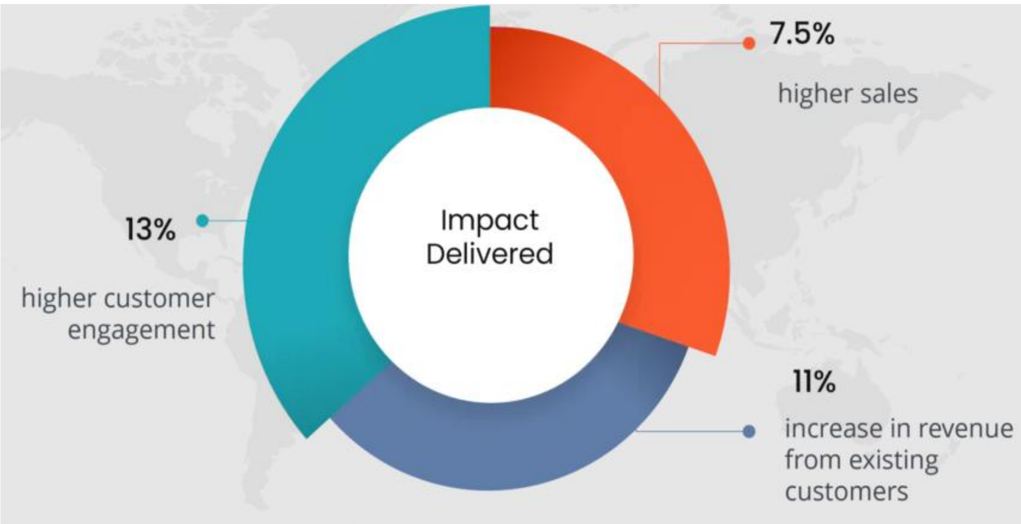

Fig 7 . 3 : Customer Micro-Segmentation

7.8.1. Key Takeaways and Future Directions

Aiming to realize sustainable competitive advantage models, organizations are implementing advanced Customer Relationship Management strategies that guarantee the ideal management of the marketing and sales functions. It is based on the relationships with the most profitable customers and the effective and efficient use of technological infrastructures to support interactions with customers, that organizations can optimize their market share on the one hand and strengthen customer loyalty on the other. This paper has proposed a Predictive Personalization strategy for customer engagement actions based on an advanced data mining technique, the so-called Micro-Segmentation, supported by the technological infrastructure of big data processing. Predictive Personalization performs the definition of market segments to support the innovation of marketing campaigns based on marketing cluster and campaign characteristic-level information as a complement in defining market segments. The proposed approach has been tested on two practical business cases concerning real data belonging to two organizations operating in different markets. Test results suggest that ahead personalized treatments are especially efficient in stimulating customer behaviors that contribute to company revenues and profits. The academic and managerial implications of the results obtained are finally highlighted.

Motivated by the results obtained through our study, we believe that researchers interested in the area of marketing activities can carry out interesting future work. In particular, we are going to suggest some directions for future research. First of all, we believe that methods that allow anticipating marketing campaign results from the implementation of Marketing Micro-Segmentation could help improve marketing campaign planning in terms of resource optimization. Moreover, researchers may be interested in deepening the idea of making Marketing Micro-Segmentation even more efficient and effective for all those kinds of marketing activities that require a reduced time to implement results in the market. Finally, we think that researchers interested in the area of marketing could use our proposal, Predictive Personalization, to interest in diversifying marketing campaigns for both products and services, aimed at stimulating the exploratory behavior of consumer choice.

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