ISSN: 2583-9888
DOI: doi.org/10.51219/JAIMLD/shafeeq-ur-rahaman/309

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Journal of Artificial Intelligence, Machine Learning and Data Science

https://urfpublishers.com/journal/artificial-intelligence

Vol: 1 & Iss: 1

Research Article

Data-Driven Customer Segmentation: Advancing Precision Marketing through Analytics and Machine Learning Techniques

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Citation: Ur Rahaman S, Kumar S, Puchakayala PRA. Data-Driven Customer Segmentation: Advancing Precision Marketing through Analytics and Machine Learning Techniques. *J Artif Intell Mach Learn & Data Sci 2021*, 1(1), 1356-1362. DOI: doi.org/10.51219/JAIMLD/shafeeq-ur-rahaman/309

Received: 02 December, 2021; **Accepted:** 18 December, 2021; **Published:** 20 December, 2021

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ABSTRACT

This paper compares modern, data-driven segmentation techniques to traditional methods. It tests which is better for optimizing marketing and improving customer engagement. Traditional segmentation methods, like demographic and psychographic ones, provide basic insights but, they often lack the precision needed for highly personalized marketing. Advanced analytics and machine learning, like K-means and decision trees, can better analyze customer behavior. They are better than traditional methods. They allow for real-time segmentation and more targeted marketing. Case studies of Amazon and Netflix show the power of data-driven segmentation. It improves customer retention and engagement through personalized recommendations. It also addresses ethics in using personal data for segmentation. It emphasizes the need to comply with regulations like the GDPR. This is vital for maintaining customer trust and avoiding legal issues. The findings highlight machine learning and big data's power in marketing. Also call for ethics and transparency in using these tools.

Keywords: data-driven segmentation, machine learning, customer engagement, marketing strategies, k-means clustering, decision trees, personalized marketing, GDPR compliance, ethical considerations, big data analytics.

1. Introduction

Customer segmentation is key to effective marketing. It helps businesses target specific groups of customers with shared traits. Traditionally, segmentation was grounded in demographic factors such as age, income, or geography. These methods were useful but, they couldn't capture the dynamic nature of customer behavior in today's data-rich environment. Modern marketing has evolved. It now uses advanced analytics and machine learning. These tools revolutionized customer segmentation and precision marketing.

In modern marketing, customer segmentation aims to understand groups better. It seeks behavior-driven traits, beyond broad categories. In the past, demographic or psychographic segmentation led to generalized marketing. It did not account for individual preferences or behaviors[1]. However, as digital footprints have grown, so have big data analytics. Customer data from multiple sources is now invaluable. These include social media, purchase histories, and browsing patterns. Data-driven segmentation allows marketers to create more refined customer profiles, enabling highly personalized marketing campaigns.

Machine learning has been key to this change. It is due, in part, to clustering algorithms like K-means and DBSCAN. These algorithms can find patterns in large datasets. Traditional methods struggled with this[2]. In retail, companies like Amazon use clustering. It helps recommend products based on user behavior. This has boosted customer engagement and sales[3]. Also, decision tree-based models forecast customer behaviors. They help e-commerce businesses predict which customers might churn or respond to marketing[4].

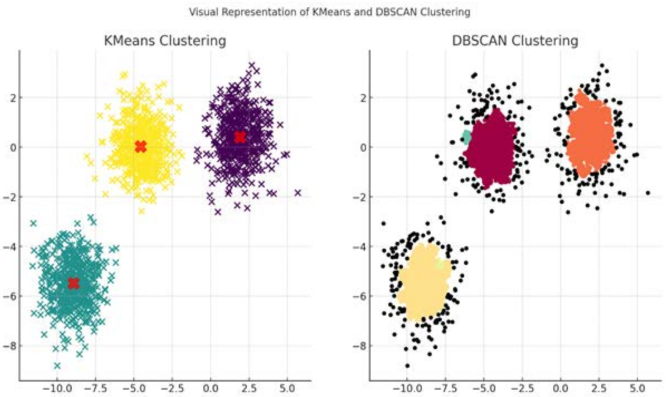

Figure 1: Visualization showing how different clustering algorithms can group similar data points based on their attributes.

2. Aim of the Research

This research aims to compare the benefits of traditional and modern segmentation methods. It will also assess their impact on marketing effectiveness. Traditional methods still matter in some cases. For example, they work when demographic targeting is enough. But, today's fast-changing consumer markets need more advanced, predictive models. Unsupervised machine learning algorithms have helped businesses. They can now refine their understanding of customer behaviors. They do not need predefined categories, as with traditional segmentation[5].

This paper will analyze the evolution of segmentation techniques. It will focus on the key role of data-driven, machine learning methods in precision marketing. They create actionable insights. First, we will examine the limits of traditional segmentation methods. Then, we will explore how modern algorithms analyze customer data in the real world. Case studies from e-commerce and retail will show successful uses. They will also address the ethical challenges of using personal data, especially under the GDPR.

The research aims to show that data-driven segmentation is best. It can create personalized marketing strategies that maximize customer engagement. The findings will show that, as businesses use advanced analytics, marketing will improve but, they must address the ethical issues of data use[4,1].

3. Literature Review

3.1. Traditional segmentation approaches

Demographic and psychographic segmentation methods are vital to marketing. But, their limits in precision marketing are becoming clear. Demographic segmentation groups consumers by observable traits, like age, gender, income, and education. It is popular as it provides easy-to-access, quantifiable data. For instance, Coca-Cola has used demographic segmentation. It aims to target different age groups and income brackets with distinct products[1]. A key flaw is that demographics miss consumers' behaviors and motivations. This leads to broad generalizations and inefficient marketing[6]. The approach assumes all people in age or income groups are the same. It often misses individual differences in preferences and buying habits.

Psychographic segmentation arose to fix some limits of demographics. It adds a layer of psychological insight. It segments consumers based on lifestyle, personality traits, values, and attitudes. In retail, brands like Nike use psychographics. They target consumers by lifestyle, not just age or income. They seek those who prioritize fitness and an active life[7]. Psychographic segmentation lets marketers target consumers' deep motivators. It shows why they make decisions. A study of art collectors highlighted this. Psychographic segmentation revealed unique, personality-driven behaviors. These could not be found in demographics alone but, psychographic data has downsides[8]. It's harder to obtain and analyze. It often requires more qualitative data collection. This makes it less accessible for smaller companies (Frame Health, 2021).

Demographic and psychographic approaches are valuable but imprecise for modern marketing. They can't match data-driven methods, such as machine learning-based clustering. Traditional segmentation methods place consumers in predefined groups. This can oversimplify the complexities of human behavior. As the digital economy expands, relying solely on these approaches becomes increasingly outdated. In contrast, data-driven segmentation uses real-time behavioral data. It provides insights that are both predictive and adaptive. This has revolutionized precision marketing[1,7].

4. Modern Segmentation Techniques

4.1 Clustering algorithms

Modern segmentation techniques are popular in data-driven marketing. Clustering algorithms, like K-means and DBSCAN, are among the most popular. They can handle complex, high-dimensional datasets, a key weakness of traditional methods. K-means is a popular clustering algorithm. It partitions customers into clusters based on their purchasing behavior. The marketer must specify the number of clusters beforehand. The algorithm then assigns data points to the nearest centroid, refining cluster boundaries. This method has worked in sectors like retail and e-commerce. It helps businesses optimize customer targeting by finding segments based on behavior patterns[9]. For instance, Amazon uses K-means to group customers by purchase frequency. This helps it deliver personalized product recommendations and targeted ads[10].

K-means is popular but has limitations. It is sensitive to outliers and assumes spherical clusters. This is where DBSCAN (Density-Based Spatial Clustering of Applications with Noise) comes in. It offers a more flexible clustering method. DBSCAN is great at finding oddly shaped clusters. This is useful for identifying customer segments in complex datasets with no clear behavior patterns. For example, DBSCAN was used on customer data. It found high-value segments that K-means might miss due to noise and outliers[11]. In one study of retail data, DBSCAN found outliers customers with very different buying habits. This let the business target them with interventions, boosting retention and sales[12].

These clustering techniques analyze many dimensions of customer data at once. They provide a better understanding of customer behavior than traditional methods. Using machine learning algorithms like K-means and DBSCAN, companies can find hidden patterns. These inform targeted marketing strategies. This leads to better resource use and higher ROI. This shift to advanced, data-driven segmentation is key to precision marketing. Businesses can now segment customers by complex behavior, not just demographics[9,10].

4.2. Decision trees and machine learning

Decision trees and machine learning are now vital. They automate and improve customer segmentation. This is true for large, complex datasets. Unlike traditional methods, which rely on fixed categories, decision trees are flexible. They learn from data to create rules that define customer groups. These models help businesses find actionable insights. They do this by identifying patterns in customer behavior. They improve segmentation and enhance marketing personalization.

One of the key advantages of decision trees is their interpretability. They work by recursively splitting datasets. They use the features that best separate data points. This makes them highly transparent. This is valuable for sharing results with non-technical stakeholders. They can easily understand and visualize the model's decision-making process. In retail, companies use decision trees to segment customers by purchase history. This helps them create targeted marketing campaigns.

Decision trees are more than just transparent. They handle both categorical and numerical data. This makes them versatile across many domains. In marketing, they apply to not just traditional customer demographics. They also apply to more dynamic data, like website interactions and buying habits. These models work well in ensemble methods, like Random Forest or Gradient Boosted Trees. They boost accuracy by combining the outputs of multiple decision trees. These methods can greatly improve customer segmentation. They capture non-linear relationships in complex data that single decision trees might miss.

Decision trees are also robust in handling missing data, a common issue in real-world datasets. Techniques like surrogate splits help decision trees perform well with missing data. This makes them suitable for finance and healthcare, where missing data is common. Also, decision trees can handle high-dimensional datasets, like those in genomics and e-commerce. They let companies segment customers by many variables without using too many resources.

These strengths make decision trees a powerful tool for refining segmentation strategies. E-commerce companies can use decision trees to predict customer churn. They can analyze indicators like purchase frequency and product return rates. This ability lets businesses find at-risk customers. They can then use targeted strategies to retain them before they churn. Decision trees are scalable and adaptable. When paired with ensemble methods, they are even better. Their effectiveness in automating customer segmentation is growing across industries.

Decision trees and machine learning models are better than traditional segmentation techniques. They are essential in marketing today, which demands precision and personalization.

5. Role of Data Science in Precision Marketing

5.1 Advanced analytics

Data science now plays a vital role in precision marketing. Advanced analytics have transformed how we refine customer segments. Machine learning models are key to finding insights in buying behaviors, CLV (Customer Lifetime Value), and engagement patterns. They enable personalized marketing strategies that traditional methods can't achieve.

Predicting CLV is now key to resource allocation and targeted marketing. By using machine learning, companies can better estimate their customers' long-term value. These models use historical data to predict future behavior. This includes purchase history, engagement patterns, and frequency. This lets marketers find high-value customers. They can then optimize retention and spend marketing money more efficiently. A study on customer lifetime value in a B2B SaaS company showed that a hierarchical ensemble model improved CLV predictions. It did this by using behavioral and transactional data[13]. This model gave insights for better customer segmentation. It helped tailor marketing campaigns. As a result, customer retention and ROI improved.

Also, there's a rise in using machine learning models, like Random Forest and Gradient Boosting Machines, to predict buying behaviors. These models assess factors like product preferences and purchase gaps. They also consider engagement metrics. They segment customers by their likelihood to repurchase or churn. Found that neural networks surpassed traditional models[14]. They were better at predicting e-commerce customers' future purchases. The machine learning approach provided a better understanding of customer behavior. These insights help companies to launch targeted campaigns. They can also anticipate future needs and improve engagement with tailored recommendations.

Machine learning can use data from many sources. This includes social media, browsing history, and purchase data. This ability boosts its predictive power. This analysis lets marketers refine segments. It uses both past behavior and real-time engagement metrics. An airline used a model that combined social network data with purchasing behaviors. It improved CLV estimates. This led to better-targeted loyalty programs and retention strategies[15]. This approach shows that diverse data sources make customer profiles more accurate.

Machine learning has made customer segmentation more precise. It shows the potential for highly personalized marketing campaigns. Companies should move beyond broad customer categories. They should focus on micro-segments. This will ensure that every interaction meets each customer's specific needs and behaviors. This level of personalization enhances customer satisfaction, boosts engagement, and ultimately increases revenue. Machine learning is now vital in marketing. Its predictive power uncovers deep insights into customer behavior and value.

5.2 Predictive and prescriptive analytics

Predictive and prescriptive analytics are vital for marketing. They use data to predict customer behavior and recommend actions to improve results. Predictive modeling is a key part of data-driven marketing. It lets businesses forecast future behaviors, like finding high-value customers and predicting churn. For instance, predictive models can analyze purchase history and engagement patterns. Such insights help companies to allocate marketing budgets. They can target the segments with the highest ROI.

Prescriptive analytics goes further. It suggests marketing actions based on predicted outcomes. For example, predictive analytics may flag some customers as likely to churn. Prescriptive analytics goes further. It suggests actions to retain these customers. For example, offer personalized discounts or loyalty rewards. This integration of optimization algorithms helps businesses decide not only who to target but how to target them. A telecom case study showed that prescriptive analytics works. It predicted customer churn. Operators used it to engage customers with retention offers. This reduced churn rate[16].

Predictive and prescriptive analytics create a feedback loop. Businesses can predict what might happen. They can also adjust strategies to achieve desired outcomes. Prescriptive models use business rules and constraints. They can recommend things like product pricing and personalized marketing. Syriatel, a telecom company, used predictive analytics to foresee customer churn. Then, it applied prescriptive analytics to adjust pricing and improve customer engagement[17].

Predictive and prescriptive analytics are a powerful toolkit. They help businesses optimize their marketing. Predictive analytics finds trends and future behaviors. Prescriptive analytics turns these insights into actions. It guides businesses to make data-driven decisions that maximize customer value and engagement.

5.3 Automated segmentation models

Automated segmentation models are vital for marketers. They help deliver personalized customer experiences at scale. These models use advanced data mining and machine learning. They let businesses automatically segment large datasets. This is based on a range of customer behaviors, preferences, and purchase histories. This automation boosts precision. It also cuts the time and effort needed for segmentation.

A common method for automated segmentation is clustering. It uses algorithms like K-means and self-organizing maps. These models segment customers by similar behaviors, like purchase frequency or browsing habits. They don't need predefined categories. For example, K-means clustering has been used in e-commerce. Businesses use it to categorize customers for targeted marketing campaigns. By automating segmentation, Amazon and Alibaba can scale personalized recommendations. This greatly improves customer engagement.

Moreover, automated segmentation models go beyond simply grouping customers. They show which segments are most likely to respond to certain marketing efforts. For instance, businesses can use neural networks or decision trees in their segmentation models. They can predict future customer behaviors, like repeat purchases or churn risk. These capabilities let marketers automate, in real time, the delivery of personalized messages and offers. This ensures each customer interaction is relevant and timely[18].

Another benefit of automated models is their ability to refine segmentation with new data. As customer behaviors evolve, the models can adjust the segments. This keeps marketing strategies aligned with current consumer trends. This flexibility is vital in fast-moving sectors like retail and digital services. In these fields, customer preferences can shift quickly. A study showed that automated models helped a telecom firm.

6. Case Studies and Industry Applications

6.1 Retail sector

Amazon is known for its use of customer data. Its personalized product recommendations have changed retail marketing. The company uses advanced machine learning, like Amazon Personalize. It offers very personalized recommendations based on each customer's preferences and behaviors. This personalization starts with collecting vast customer data. It includes past purchases and browsing behavior. Then, it processes this data in real-time to create targeted product suggestions.

A key example is how Amazon segments its customers. It uses K-means clustering and other advanced algorithms. These models let Amazon divide its customers into segments. It can do this based on purchase frequency, spending habits, and engagement with the platform. By automating this segmentation, the company can recommend relevant products at the best moment. This will boost customer satisfaction and conversion rates.

The scale and effectiveness of Amazon's recommendation engine are unmatched. It processes billions of customer interactions each month. It gives millions of users worldwide personalized recommendations. A key example of this capability is seen in the collaboration between Amazon Web Services (AWS) and Segment, a customer data platform. Segment uses Amazon Personalize to unify user data. It then deploys machine-learning recommendations for its clients. This improves marketing precision without needing an internal ML pipeline.

Personalized recommendations have a big impact. They improve the customer experience and drive sales. Amazon can predict what each customer will buy based on their behavior. This leads to better marketing and higher customer retention. Personalized strategies boost e-commerce conversion rates. Amazon is a leading case study in using data-driven customer segmentation and recommendation systems[19].

6.2. E-commerce

E-commerce platforms have used behavior-based segmentation to boost conversion rates. They applied advanced machine learning to analyze customer data and deliver personalized experiences. This data-driven approach helps businesses predict what users will like and buy. It improves targeting and marketing efficiency.

One prominent example is the use of K-means clustering to segment customers based on their shopping habits. By grouping customers into clusters with similar behaviors, platforms can tailor their marketing. They can use factors like purchasing frequency and product preferences. This personalized approach has been shown to increase conversion rates significantly.

Additionally, deep learning-based recommendation systems are increasingly being adopted by e-commerce platforms. These systems use neural networks to analyze real-time customer interactions. They can recommend products that are highly relevant to each user. A case study of a large e-commerce site showed that personalized recommendations increased click-through rates and conversions. Amazon and similar platforms use user behavior to adapt. It boosts customer satisfaction and sales with hyper-personalized shopping[20].

Also, a system that uses decision trees and other machine learning algorithms has been used to predict customer repurchasing behavior. This system allows platforms to target users who are most likely to return and make additional purchases. For example, an e-commerce platform using such models saw a big boost in conversion rates. It identified and nurtured high-potential customer segments (Liu et al., 2020).

6.3. Subscription models

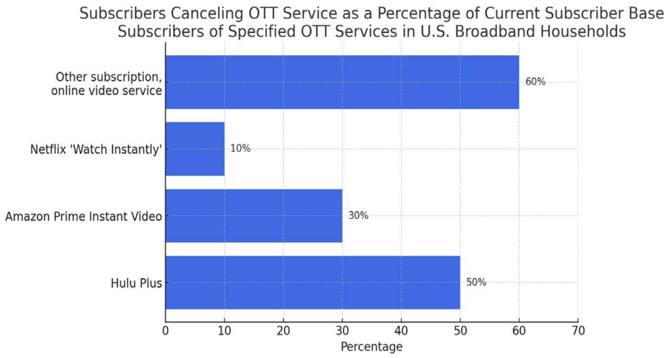

Figure 2: Bar chart visualizing the percentage of subscribers canceling OTT services.

In subscription models, Netflix uses advanced segmentation to boost user engagement and retention. Netflix uses advanced analytics and machine learning to segment its users. It does this using behavioral data, like viewing patterns, genre preferences, and binge-watching. This lets Netflix customize its content for each user. It ensures they see shows and movies that match their tastes. This boosts user satisfaction and loyalty.

For example, Netflix's recommendation engine accounts for 80% of the content that users watch on the platform. It does this by analyzing not just the genres users like. It also looks at deeper metrics. These include how often a user watches, when they are most active, and how long they watch before pausing or exiting a show. These insights help Netflix predict what users will watch next. It can then push relevant content to keep them engaged

Netflix personalizes the user interface. It adjusts content display based on what it thinks will appeal to each user. For instance, the platform customizes thumbnails and content rows. It does this based on a user's past interactions. This makes it easier and more enticing for users to discover new content. These micro-personalizations have helped Netflix reduce churn. They keep a constant flow of relevant, engaging content for its users.

Also, Netflix uses models to find users at risk of unsubscribing. This lets the company use targeted strategies to retain them. For example, it can send personalized content offers or reminders of unfinished series. This approach keeps Netflix a leader in customer retention in the competitive streaming industry[21].

Netflix has set a global benchmark for subscription services. It did this by refining its segmentation models and adapting to user behavior. This has kept its engagement high and churn rates low.

7. Comparative Analysis

Category	Traditional Segmentation	Modern Data-Driven Approaches	Examples & Outcomes
Methodology	Primarily based on static demographic data like age, gender, and location	Uses advanced algorithms (e.g., K-means, decision trees) to analyze behavioral data	Traditional methods often fail to capture behavioral nuances. Data-driven techniques, such as machine learning, enable more dynamic customer segmentation and predictive analytics (Qadadeh, 2020).
Precision	Limited precision; generalized customer groups	Highly precise; personalized customer experiences based on real-time data	Netflix's recommendation engine provides personalized content suggestions, increasing user engagement by predicting preferences based on viewing history
Outcome	Broad marketing campaigns, lower personalization, higher marketing costs	Targeted campaigns, improved personalization, better resource allocation	E-commerce platforms using machine learning models have seen an increase in conversion rates through behavior-based segmentation
Churn Rate	Higher, due to lack of personalized engagement strategies	Lower, through targeted retention efforts such as predictive churn models	Netflix's churn prediction models have helped reduce subscriber attrition by identifying at-risk users and offering personalized content or promotions[21].
Scalability	Limited scalability; manual data analysis often required	Scalable with automated processes and real-time analysis	Amazon's data-driven segmentation scales effortlessly across millions of users, enabling real-time product recommendations that account for individual preferences.
Flexibility	Rigid and slow to adapt to changing consumer behavior	Highly adaptable; models continuously update based on new data inputs	Netflix's adaptive segmentation helps it remain relevant by constantly updating user recommendations based on real-time interactions, ensuring high engagement (Whitelabel Loyalty, 2020).
Resource Allocation	Suboptimal; marketing spend is spread across broad segments	Optimal; marketing resources are focused on high-value or at-risk customer segments	Data-driven platforms like Amazon improve ROI by focusing marketing efforts on customers with the highest likelihood of engagement and conversion (Qadadeh, 2020).

8. Challenges and Ethical Considerations

Integrating data from various sources, like CRM systems, social media, and purchase histories, is a major challenge. It affects the accuracy of customer segmentation. Siloed systems often block data flow between departments. This leads to incomplete customer profiles and weakens segmentation strategies. CRM systems may have valuable customer data. But, without real-time social media and purchase data, segmentation is suboptimal. To fix these silos, we need data integration tech and APIs. They will create a central data flow. This will give marketers access to accurate, complete customer info.

Ethical issues related to data use are another key concern. As businesses use personal data for targeted marketing, privacy concerns have grown. People worry about the misuse of sensitive information. Predictive models used in segmentation may raise ethical issues. They might target individuals based on hidden, unwanted traits. A well-publicized case involved a U.S. retailer. It used data on buying habits to predict pregnancies. The store then sent related ads before the customers had told anyone. This raised ethical questions about predictive advertising[22].

Also, new laws like the GDPR require strict privacy rules in data collection and segmentation. Companies must comply with them. GDPR requires companies to get explicit consent before collecting personal data. Users must control how their data is used. This challenges businesses. They must balance data-driven marketing with privacy laws. Non-compliance with GDPR can incur heavy fines and harm a brand's reputation. So, companies must adopt transparent data practices. They should also invest in secure, compliant data management systems.

To navigate these challenges, companies must create a strong framework for ethical data use. They should integrate privacy and transparency into their segmentation efforts. By doing so, they can maintain customer trust while benefiting from the insights offered by modern data analytics.

9. Discussion

The debate on customer segmentation shows a sharp contrast. It is between traditional and modern, data-driven methods. Traditional methods, like demographic and psychographic segmentation, are still relevant. Their simplicity and ease of use make them useful in some contexts. For example, they still work for targeting broad customer groups. Here, individual behaviors are less relevant. An example is targeting young adults for student loans or seniors for retirement plans. However, these methods lack the precision for highly personalized marketing. They rely on static, surface-level traits like age and gender. This often leads to less effective campaigns.

On the other hand, AI and machine learning drive modern segmentation. They analyze a vast range of real-time behavioral data. This provides deeper insights. Algorithms like K-means clustering and decision trees help marketers. They can find complex patterns in customer behavior. This allows for highly targeted and personalized marketing. More advanced methods, like neural networks, are also used. For example, Amazon and Netflix use machine learning to recommend products or content based on a user's past behavior. This greatly boosts engagement and retention. A key advantage of modern techniques is their ability to update and refine customer segments based on changing behaviors. Traditional methods lack this.

A key trend is the growing use of AI and big data in customer segmentation. AI enables real-time analysis of customer behaviors, facilitating immediate adjustments in marketing strategies. PepsiCo and others are using AI in their marketing. They want to improve product development and customer engagement. As businesses seek to automate and personalize customer engagement, they will likely use AI more to predict future customer behaviors. This includes tasks like churn prediction and lifetime value estimation.

For marketers, the implications of this shift are profound. Traditional segmentation methods are still useful, especially in low-resource settings but, to stay competitive, companies must use advanced, data-driven techniques. This involves investing in machine learning. Also, their data practices must be transparent and comply with regulations, like the GDPR. We must prioritize ethical concerns about data privacy. It includes the risks of re-identifying anonymized data and exploiting personal info. Companies must balance personalization with ethical standards to keep customer trust.

10. Conclusion

This paper shows that data-driven methods are far better than traditional segmentation methods. Machine learning algorithms, like K-means and decision trees, help marketers. They can now segment customers with unmatched precision. These advanced models adapt to customer behavior in real time. They make marketing strategies both highly personalized and scalable. Amazon and Netflix show the power of these techniques. They improve customer engagement and retention.

However, with these benefits comes a need to address the ethics of data use in segmentation. Advanced analytics must be applied transparently. It must protect customer privacy and comply with regulations like GDPR. Not upholding these standards could harm customer trust and lead to legal issues. Data-driven segmentation has great potential but, we must use it ethically. We need to balance tech innovation with this. It will ensure sustainable, long-term marketing strategies.

11. References

1. Jílková P. Customer Behaviour and B2C Client Segmentation in Data-Driven Society. International Advances in Economic Research. 2020;26:325-326
2. Qadadeh, A. (2020). Customer Profiling, Segmentation, and Sales Prediction Using AI in Direct Marketing. Neural Computing and Applications 2020
3. Davenport T, Ronanki R. Artificial Intelligence for the Real World: Business Benefits of AI Cognitive Technologies. Harvard Business Review. DOI: https://hbr.org/2018/01/artificial-intelligence-for-the-real-world 2018
4. Vlacic B, Qian J, Jung S. The Role of AI and Customer Experience in Modern Marketing. European Journal of Marketing 2020
5. Ma W, Sun X. Machine Learning and Artificial Intelligence Use in Marketing: A General Taxonomy. Italian Journal of Marketing 2022;3
6. Chintagunta PK, Haldar S. Investigating Purchase Timing Behavior in Two Related Product Categories. Journal of Marketing Research 1998;35(1):43-53
7. Samuel, A. Psychographic Segmentation: A Lever for Precision Population Brain Health. Frontiers in Psychology 2016
8. Pitt CS, Bal AS, Plangger K. New Approaches to Psychographic Consumer Segmentation: Exploring Fine Art Collectors Using Artificial Intelligence, Automated Text Analysis, and Correspondence Analysis. European Journal of Marketing 2020;54(2):305-326
9. Ahmed M, Seraj R, Islam SMS. The K-means Algorithm: A Comprehensive Survey and Performance Evaluation. Electronics 2020;9(8):1295
10. Oussous A, Benjelloun FZ, Ait Lahcen A, Belfkih S. Big Data Technologies: A Survey. Journal of King Saud University-Computer and Information Sciences,DOI: https://doi.org/10.1016/j.jksuci.2017.06.0012020;30(4):431-448
11. Hossain S. A Comprehensive Study of K-means and DBSCAN Clustering Algorithms for Customer Segmentation. International Journal of Computer Applications. DOI: https://doi.org/10.5120/ijca20209199412020;177
12. Turkmen O. Evaluation of Clustering Algorithms for Retail Customer Segmentation. Journal of Retail Analytics 2020
13. **Çavdar AB, Ferhatosmanoğlu N.** Airline customer lifetime value estimation using data analytics supported by social network information. Journal of Air Transport Management,DOI: https://doi.org/10.1016/j.jairtraman.2017.10.007 2018;67:19-33
14. Pollak, Z. (2021). Predicting Customer Lifetime Values – E-commerce use case. arXiv.org, DOI: https://doi.org/10.48550/arXiv.2102.05771
15. Dahana, W. D., Miwa, Y., & Morisada, M. (2019). Linking lifestyle to customer lifetime value: An exploratory study in an online fashion retail market. Journal of Business

Research, 99, 319–331. DOI: https://doi.org/10.1016/j.jbusres.2019.02.0492019;99:319-331

16. Ahmad E. Improve profiling bank customer's behavior using machine learning. IEEE Access 2019;7:109320-109327.
17. Zaubi M. Predictive analytics using big data for increased customer loyalty: Syriatel Telecom Company case study. Journal of Big Data 2020;7(1)
18. Christy J. A review on customer segmentation methods for personalized customer targeting in e-commerce use cases. Information Systems and e-Business Management 2020
19. Chen D, Sain S, Guo K. Data mining for the online retail industry: A case study of RFM model-based customer segmentation. Journal of Database Marketing & Customer Strategy Management. DOI: https://doi.org/10.1057/dbm.2012.17 2020;19:197-208
20. Deldjoo Y, Schedl M, Cremonesi P, Pasi G. Recommender systems leveraging multimedia content. ACM Computing Surveys 2020
21. Neil Patel. How Netflix Maintains a Low Churn Rate by Keeping Customers Engaged & Watching. Retrieved from Neil Patel 2020
22. Mühlhoff R. Predictive privacy: towards an applied ethics of data analytics. Ethics and Information Technology 2021;23:675-690