AI-Enhanced Customer Segmentation in Banking

By Dr. Mohamed Magdy

Professor of Electrical Engineering, Cairo University, Egypt

1. Introduction to Customer Segmentation in Banking

Benefits of customer support and service always prevail in the highly competitive banking industry. Customer segmentation underpins these values by grouping customers in accordance with their common needs and behaviors. By doing so, banks can apply their resources more efficiently and can act more proactively in improving segments that have been identified as profitable. The lack of understanding of customer behavior may lead to the waste of resources and opportunities. Establishing and recognizing the profiles of customer segments, therefore, always receives special attention to adopt better marketing strategies and communications. Similar to understanding the usage of products or services, knowledge of customer preferences and choices may lead to a high competitive edge. Tailored financial products and services based on different needs are attributed to the excellence of segmenting the customers.

In fact, customer segmentation plays a critical role in increasing customer satisfaction and loyalty. In order to apply this tool, there are two closely related issues that need to be addressed. These issues are how to group customers and what different characteristics of customers can be found. For a few years, segmentation methodologies in both service and finance industries have evolved significantly. Those traditional methods are also always compared and applied in banking areas. Moreover, widely accepted approaches and ideas have also been deeply and thoroughly debated. More importantly, new approaches are also always sought. In this context, this research work discusses the traditional methods that have been applied in marketing knowledge and investigates how banks apply innovative techniques to differentiate themselves from their competitors. In this respect, it explores the AI-enhanced approaches instead of the reviewed traditional methodologies.

1.1. Importance of Customer Segmentation in Banking

1.1. Importance: Customer Segmentation in Banking New Customer Relationship Management practices underline the importance of the holistic view of customers. One of the key objectives of properly implemented CRM strategies is the full understanding of customers' needs, preferences, and behavior. In this direction, customer segmentation is one of the major tools facilitating the practical implementation of CRM strategies. In banking, the significance of customer segmentation is even more critical. In a competitive environment like the banking sector, each new customer costs a multiple of what it costs to retain existing customers. Decisions about where, when, and with whom to invest resources are crucial. Optimal resource allocation becomes cumbersome if all customers are viewed in aggregate. This is where customer segmentation can help. The main aim is to create value from customers and develop a tailor-made value proposition. This approach requires dividing the mass market into distinct groups with different needs.

Customer segmentation also provides banks with the ability to personalize a marketing campaign or develop service offerings for specific micro segments, effectively targeting customers. An increasing number of customers who expect personalized service offerings actually facilitate the growth of segmentation concepts. The primary condition for personalized service offerings is the capability to differentiate clusters and customize products and offers, which means banks practice various levels of customer segmentation. In this vein, banks will engage in mass customization or just-in-time concepts, meaning each customer will experience a unique personal financial product. Banks face more opportunities to understand their customers with the help of a detailed toolkit of conditional probabilities, based on profiling and stakeholder theory. As a result, better customer insights can direct and drive cash flows linked to customer migration, retention, and upsell potentials.

Banking products and services are less tangible in comparison to other sectors and are often characterized by higher switching costs. Therefore, customer retention significantly affects different performance metrics in the banking sector. Apart from decreased operating costs that result from customer retention, an increase in customers' profitability is another advantage of efficient customer segmentation. Better segmentation helps firms address top-line growth; executives can identify the inherent potential of each customer and decide if the current wallet share corresponds to that potential. Additionally, by corresponding opportunities with effective customer segments, marketing can parallel the finance team by trading growth in a region for spending. In the banking sector, customer segmentation can also be practiced to support the establishment of a new paradigm for banking characterized by a relationship-based marketing model. The primary goal is to create an environment where the customer perceives a positive relationship. In doing so, banks can proactively identify and satisfy financial customer needs across key customer value propositions.

1.2. Traditional Methods vs. AI-Enhanced Segmentation

There are notable differences between the traditional methods of customer segmentation and the modern techniques that are AI-enhanced. The traditional approach segments the customer pool based on factors such as demographic data and historical financial behavior. For banks, the customer segmentation approach typically takes gain, risk, and cost perspectives, identifying the factors that are conducive to making a bank product more profitable. A key attribute of traditional customer segmentation is the importance placed on demographics and spending habits, traits that can be more easily captured and grouped into digestible categories or profiles. AI and machine learning in segmentation make this level of granular understanding possible by continuously advancing analytical capabilities and incorporating more powerful real-time big data sources. The methods applied today in modern segmentation use machine learning to identify behaviors that could define a segment—behaviors that transcend demographics. AI segmentation can detect and assess new behaviors quickly.

There are several other reasons that explain why banks would like to catch up with the times. Traditional segmentation continues to establish categories of customers based on behavioral characteristics, instead of the more difficult undertaking of understanding and clustering them by behaviors. AI segmentation is faster, more scalable, and more accurate. The competitive economic environment is driving all market players to analyze data to fuel actionable insights, or they won't keep up. Bankers who are adopting AI techniques for understanding and reaching out to customers with personalization strategies can stay ahead. Successful early AI segmentation applications have been described.

2. Fundamentals of Machine Learning in Banking

Machine learning has gained increased traction in the banking environment, as banks have progressively started using intelligent algorithms to solve various practical tasks. Algorithms have been successfully used for processing large datasets containing information about the time of purchases, purchase amounts, and payment methods. So that a machine can process the vast amount of customer information available, various algorithms can be used, depending on the problem that must be solved. Supervised learning is primarily used for making convenient, guided decisions based on the patterns it finds in the data. Algorithms in this category include decision trees, linear regression, and support vector machines, among others. Unsupervised learning aims to identify patterns that human eyes might overlook. Clustering, association analysis, and dimensionality reduction algorithms, such as k-means, are typical solutions used in this case. Reinforcement learning enables the development of programs that can, in principle, play games or make decisions with little guiding input.

Applying machine learning in the banking context serves to solve a number of problems, emulating human-like reasoning behavior up to a certain extent. For example, in pattern recognition, it is used for fraud tracking and for automating the digital budget advisor, while in decision optimization, it is used for credit scoring or the optimization of marketing campaigns. In addition, the bots behind the algorithms also serve customers by providing services like chatbots. In the practical business of banking, supervised learning is primarily used for: - Fraud detection, to sort activities that are outliers from actual to faked ones. - Credit risk analysis, where bankers can evaluate at the time of a request the credit defaults and the risk that their money might not be paid back. - Personalization, where banks can provide individual services based on the customer's past or predicted interests. Even if a model already performs well in a resampled environment, it is necessary to ascertain whether it fulfills its purpose once it is applied to new records. Moreover, in the banking environment, care must be taken in the event of a model change of population or goal, as this might easily change the customer segmentation flow already in place. Model revalidation is crucial in such a scenario. The machine learning models used are usually available codes that must be recompiled in each model run for reusing the code that these algorithms create as part of their training. This model deployment is a duty performed by IT connected to the operational systems.

2.1. Types of Machine Learning Algorithms

Machine learning has the potential to solve banking challenges, despite requiring a significant volume of data available for model training. To that end, banks organize themselves using a data-focused approach and schedule. The following are the various types of machine learning algorithms that can be used for banking:

- Supervised Learning: In supervised learning, a model is trained on labeled data to learn the relationships and use them for predicting or classifying the target variable. When it comes to the banking sector, it can be used for risk assessment. The accuracy is not guaranteed during prediction times if the nature of the data changes. - Unsupervised Learning: The algorithms that fall under this category are meant for exploratory data analysis. The main aim is to model the underlying structure or distribution in the data in order to learn more about it. In the banking sector, unsupervised learning techniques are employed for customer segmentation or fraud detection. - Reinforcement Learning: Reinforcement learning is a type of machine learning where an agent learns to make decisions by trial and error to maximize cumulative rewards. It is about taking suitable action to maximize reward. The agent will reach the goal irrespective of the path it must take to get there. In the banking sector, it can be used for real-time decision-making.

Although unsupervised learning is a suitable segment of AI, banks have limitations in terms of resources, such as not having good enough equipment or accurate historical data. In this case, supervised learning is more precise and practical than unsupervised learning. It provides high efficiency for banks, allowing them to use the already compiled databases for management. As the years go by, machine learning techniques have shown their changes. The most preferred technique between AI techniques and machine learning techniques is based on supervised and unsupervised learning. Due to every historical record being unlabelled, there is potential to apply machine learning techniques in combination with unsupervised learning techniques. Apart from that, we can suggest the possibility that a designed AI model may increase the profit of the bank as it contains multiple attrition scores.

2.2. Applications of Machine Learning in Banking

Machine learning techniques have already found several compelling applications in the banking sector. A significant number of projects in this industry are geared towards either improving operational efficiency of well-defined processes or using data in a more sophisticated way for customer-related decision-making. Machine learning holds immense potential in directly and indirectly (a) improving bank operations, (b) minimizing costs associated with them, (c) reducing the risk of loans and other financial products, and (d) acquiring new customers. Besides credit risk assessment, other potential use cases include personalized marketing for banking products such as insurance, loans, credit cards, wealth management, and treasury services, making these products more relevant for consumers. As such, they drive volume and generate both direct sales and fee income for the bank. Machine learning is also used for fraud prevention and detection, thus ensuring improved security by helping make customer transactions safe.

Machine learning applications are also used to improve customer service through digital means, primarily on websites and mobile devices. By implementing chatbots and virtual customer service representatives, banks interact with their clients by analyzing their actions and predicting potential issues in transaction processes or common inquiries about accounts, becoming more proactive in their approach. Additionally, they can interact with potential clients visiting websites by providing free lifestyle tools and marketing to them based on their needs. At the bank level, they use machine learning to sift through the massive amount of transactions performed daily or monthly in the search for illegal activities suggested by an understanding of the bank's customers and standard behavior. The models that assist in these regulatory-check scenarios are built or trained on the bank's transaction data. This requirement came in response to stricter global anti-money laundering rules that followed the banking attacks in America. Regulatory authorities required banks to introduce such policies to ensure everyone is doing their best to prevent launderers and terrorist financiers from accessing the financial system through moving dirty funds. This requirement also created the possibility for supervised and unsupervised machine learning applications within the financial service sector. The value of such applications goes beyond direct revenues and prevents costly fines from regulators, which can be as high as bank turnover.

3. AI-Enhanced Customer Segmentation Techniques

This chapter explores advanced modeling techniques to meet customers' unique needs. Many studies in the context of customer segmentation exist, which prove the effectiveness of such models for the banking industry. At the same time, not an extensive list of reviews shines a light on advanced AI-enhanced approaches such as customer classification using a variety of machine learning algorithms or techniques, which allow finding distinct customer segments due to a high level of personalization. Advanced customer segmentation undertaken with state-of-the-art machine learning algorithms such as clustering analysis and customer classification in this chapter allows understanding customer groups from their behaviors, attitudes, and preferred interaction channels. The creditor shall treat customers in the system on an individual basis and approach like proactive one-to-one marketers knowing alternatives and upgrade/service requirements. It enables understanding the customer base to increase marketing efficiency of a company, reducing its costs, focusing its limited resources on the target audience, and tailoring its offerings to the customer's needs. Given that customer behaviors and preferences fluctuate significantly, clustering and customer classification should preferably be undertaken in real-time using the latest available customer information.

Bank managers need the capacity to organize their customer base according to different motives, allowing banks to better manage their bargaining, promote the most relevant offers to their customers, and target their potential clients. Managers require a set of tools in customer relationship management, which will allow them to improve their decision-making by predicting the potential behavior of a segmented customer base, needs, and preferences. Banks can begin to assess the value towards the business by defining customer segment needs, predicting potential customer behavior, and seeking recommendations for the evolution in the customer service system. Apart from the top features such as segmentation, personalization, and customer service modes, data analytics such as predictive analysis would allow banks to make decisions considering certain instances, thus applying the solution in the best potential mode. Predictive analytics allow banks to assess data from several sources appropriately and apply the required efficient means in customer relationship management. It is also important to predict customer behaviors in a short time period considering initial customer behaviors using their transactions via the latest data about the customer in the bank using clustering or classification. Techniques ensure that managers personalize their bank services in such an environment to encourage customer satisfaction and customer loyalty.

3.1. Clustering Algorithms for Customer Segmentation

A clustering algorithm is a critical technique used for customer segmentation in the practice of bank AI. Customers are grouped together based on similarities or common features using clustering algorithms, thereby allowing banks to divide the market into smaller segments. This, in turn, helps in the identification of distinct segments that have different needs, so that a targeted marketing plan can be developed. Many clustering algorithms are available with different uses and required parameter settings according to the provided data structure. K-Means and hierarchical clustering are popular techniques used for customer segmentation in bank AI cases. K-Means clustering groups the data by minimizing the differences in clusters' splitting, while hierarchical clustering creates clusters step by step by minimizing the differences within clusters. The use of clustering algorithms with large bank data is beneficial not only because of their high performance but also because they identify customer groups from many sub-variables simultaneously. Each clustering model has a method for evaluating criteria to assist in selecting parameters and measuring clustering effectiveness at each model configuration. The number of intended customer segments should be pre-determined based on marketing strategies or characteristics of customer records.

To select the best-fit technique for clustering, the evaluation of computer resources and linking data across clusters is also important. Several studies and case studies have successfully implemented the clustering method for commercial banks. They used this approach to design improved customer service strategies or plan and target new customer marketing approaches, demonstrating the positive impact of clustering on surge marketing and customer services. In order to provide better customer segmentation, the bank AI technique should cluster customers based on a variety of variables, relate to business insights, optimize clustering parameters, and validate customer characteristics between clusters. Target markets in banks must be divided into identifiable customer segments with matching characteristics, which together can be profitable and encourage customer satisfaction.

3.2. Classification Models for Customer Targeting

Classification models, or classifiers, are widely used in AI-enhanced customer targeting in banking. Customer targeting is a process of establishing various customer segments and assigning customers to one of these predefined segments. In the proposed customer segmentation system, the classification models used divide customers into various segments of interest based on their relevant characteristics. The main characteristics used to describe customers are their features. These features could range from things that people say, such as demographics or indicated interests, to details like what consumers do or buy. Commonly used classification algorithms include decision trees and support vector machines. Classifiers in customer targeting are most often used to predict the likelihood of a customer in a certain segment to respond to a marketing campaign, to purchase something, or to end up leaving the bank.

The accuracy of the classification models is expected to be high, although it rarely exceeds 85% because of techniques used for feature selection and the training of classifiers. When selecting the most relevant groups of customers, the marketing personnel can perform discriminatory marketing based on the classified results with substantial and measurable ROI. For instance, the marketing efforts to the "Likely to Respond" group can be minimized in order to focus on more potentially profitable customer segments. Banks that implemented such kinds of classification models did not only achieve significant cost savings due to reduced marketing expenses, but they also realized tangible benefits due to improved conversion rates of marketing leads as well as the ability to provide more focused and relevant products and services in each segment. Along with the opportunities, there are some challenges in using classification models in AI-enhanced customer targeting. Specifically, some models are highly data-driven, which results in the need to have lots of data available to make their predictions as accurate as possible. It may also be difficult from a technical standpoint to interpret the actual model and hence to interpret the resulting classification. Due to this, some banks do not rely solely on the results from a classifier to determine their customer targeting segments. Finally, classifiers can also introduce bias; for instance, if only certain customers purchase a product and manage to pay it off, it may be easy to exclude a group of customers from that possibility. It's important to consider such issues in classifying customers for ethical reasons.

4. Case Studies and Best Practices

This section features case studies from some of the top banks with successful experiences in implementing AI methodologies. These real-world examples provide valuable insights. The challenges, strategies developed, and results achieved have been analyzed for each case. Moreover, some valuable lessons learned have been brought up. Some of these recommendations may add more value to the current role of underleveled managers, already responsible for developing customer segmentation strategies. Other best practices are related to finding creative solutions and getting inspired within the organization when facing new challenges.

The combination of investing in technology and innovation allows banks to create a more robust customer segmentation strategy. One bank offers a range of services and products from banking accounts and credit cards to mortgages, home equity loans, and insurance. As a response to the need for more granular customer segmentation strategies in both insurance and retail banking, this bank has begun utilizing machine learning and other AI techniques for segmentation. The project's scope was defined by determining how AI can improve the current segmentation practices. In this regard, the necessity of adapting the current approach to data and technology can provide a competitive advantage.

Due to the ongoing waves of consolidation in the United States, many of the already established customer segmentation models at another bank have become less effective. In this case, the bank's implementation of AI-enhanced customer segmentation is particularly important. This bank has not only used data analytics for marketing but also at the strategic management level – classifying banks for potential acquisition. Maintaining effectiveness after mergers and acquisitions became possible by involving custom indicators. The bank has utilized specific insights to identify the main features of high-profit segments and reduce the marketing spend on money-losing segments. The bank obtains customer data from different channels. This is a good example of a truly cross-functional synergy: the team is cross-departmental as well. Note that the case study also highlights that the bank regularly evaluates and changes its customer segmentation strategies due to changes in the market.

As mentioned in the introduction to this section, some relevant management lessons can be learned from the previous bank cases. One bank has implemented a radical approach: the customer segmentation methodology is adjusted to the extent that it matches the newest capabilities. The bank has defined a future-driven vision and selected the current proof of concept in order to demonstrate the customer segmentation applicable to the bank's competitive environment. In the case study on this bank, one should also remember that the bank has not invented new customer segmentation methodologies. The bank applied machine learning and data mining methods in order to validate industry models. Another bank has different advanced analytic products and modeling available, but none were a perfect match for what was needed. Therefore, a new customer classification was custom.

4.1. Real-World Examples of AI-Enhanced Customer Segmentation in Banking

The ESL of Russia develops a customer-centric business approach that contributes to a deeper understanding of customer needs and increases customer engagement, upturns customer loyalty, and boosts its customer base. The financial institution uses the following intelligent customer segmentation techniques: demographical, value-based, behavioral, context-based, and predictive analyses. Behavioral segmentation is the analysis of information on customers' behavior based on data about their transactions. In its work, the EFB uses techniques and methods, products and solutions involving Artificial Intelligence: machine learning, deep learning, natural language processing, language coping and classification, advertising recognition, and emotion and sentiment analysis using incoming data. Thanks to its customer segmentation analysis, ESL has increased the number of silent customers starting to use online banking services. The bank uses messaging generation to address various client groups with different banking offers. The integration of technologies for adaptive personalization—a dynamic content selection depending on the user's specific situation—was part of the strategy.

This financial institution has successfully implemented a strategy based, among others, on Artificial Intelligence and is responsible for transferring creative work assignment processes from bank employees in 13 foreign units to its Artificial Intelligence developed using algorithms, machine learning, and robotics. The Innovation Hub of the Vienna Institute of Finance currently develops algorithms, techniques, and technologies in the field of conventional operations; promotions; customer service; marketing; sales; fraud detection; and real-time regulatory reporting. The identity and behavior customer segmentation techniques have been implemented successfully by various banks. The main objective was to understand the customer’s behavior in order to serve him or her with the best possible service offer. Events, tendencies, and normal transactions per merchant are identified. 5% of his or her normal transaction duration; a new merchant was visited if the shortened time window was stable; 50% if the shortened time frame was stable; and so on. If the shortened time window was modified, it was necessary to reduce it by 10%. A program was run to examine the customers and at what percentage they have a possibility of moving. The results confirm that the most significant feature, duration or period of time between transactions, plays a role in the higher PS. The bank was able to reduce its marketing budget significantly. Customer satisfaction indices have improved. The customer-centric, data-driven customer segmentation has been positively evaluated. The integration of the investment is limited by the number of requests. Critical success factors are: new, innovative, and unique products and services; dynamic tactics for maintaining client contact; technical and operational infrastructures; and the establishment of a common end-to-end governance structure.

Moreover, to be successful, individual efforts are needed. A number of factors are limiting the implementation of Artificial Intelligence-enhanced customer segmentation tools in banks: a lack of resources, cross-departmental cooperation models, beneficiaries of intelligent customer segmentation projects, cooperation between different departments, and major problems in customer segmentation.

4.2. Key Strategies for Implementing Successful Segmentation Projects

• Start with a set of clear objectives — customer segmentation objectives need to be relevant to your organization or business area. Objectives should align with top overarching bank objectives and address the needs of your customers. • Build the right data infrastructure and invest in the right analytics capabilities that will enable customer segmentation. Capabilities should be scalable and automate the process as your organization will likely want to run numerous segmentations over time. • Make customer segmentation the hub of a significant bank-wide transformation — develop a culture of collaboration with compliance, legal, operations, product, and marketing/design to ensure you are inviting diverse ideas and perspectives to inform the increased precision of the final segment design. • As you begin to engage with cross-functional teams, ensure you are asking and answering the critical dimensional questions that will unlock both innovation and insights — who are the customers/accounts? Where are they and how do they transact? What are the products and services in question and what is the competitive market? What is happening in the external macro and competitive landscape? • Clearly measure the impact of segmentations as well as iterative segmentation updates — part of being effective with leveraging segments is identifying what is working against these and how any changes will affect customers in each segment. • Embed a robust risk and compliance process before your segmentation can go live, ensuring that the segments are both sound and compliant, consistent with legislation, codes of practice, and other specified requirements. • Implement robust privacy controls and ensure adherence to internal privacy standards and procedures. Share similar privacy measures concerning the use of data with the Regulatory Compliance division of your bank. Where necessary, significant data privacy issues will also be referred to the Board Audit Committee.

4.2.2. Learnings from segmentation projects 1) "You need to get insight by starting with outside-in external views with clients." 2) "Simple, understandable segmentation. Not so many variables and/or matrixing structures. Humans process 150 times less than old database vs new learning process segmentation. Therefore, machine learning will visually give you the customer data (You need to know the dimensions for that.), and there is a quick way to visualize it, and you can name it a label through machine learning. Once the label is from a consumer, customer dimensions can be figured out to develop the brand." 3) "Consider if you do it yourself or leverage a research vendor, think carefully - you want to train your own animals, and building from the ground up (with support from external expertise as needed) also builds alignment along the way, ensuring fit for purpose. Fully rely on agility and flexibility, especially as the industry continues to evolve. To tackle the update results from other processing criteria: For example, 'What is happening inside the bank?' 'What are the servicing or operational problems?' High ratios of account opening and service requests issue." 4) "Rather than using explicit surveys, implicit segmentation could be much more useful and accurate to cluster customers." 5) "More focused and less defined segmentation — doing away with age/gender models."

5. Challenges and Ethical Considerations

Challenges in AI-Enhanced Customer Segmentation

The use of AI for automated customer segmentation or lead scoring using unstructured, complex, and flexible criteria like customer behavior or even opinions/sentiment in social networks would mean going beyond profiling, because it would give organizations an incentive to act specifically/individually upon the possibly incorporable data about people. A myriad of challenges exist when using AI to assist with or enhance customer segmentation in banking. One of the most pressing challenges is to ensure data accuracy and protect the privacy of individuals. Mere anonymization of data may still lead to a privacy breach, especially in banking scenarios, because a combination of independent data sets can lead to reidentification. Data leaks and breaches can lead to a number of legal consequences besides loss of brand reputation. Banks across various countries are required to follow stringent requirements around data privacy, security, anti-money laundering processing, and know your customer processes. When customers open accounts, for instance, they are required to provide sufficient information for banks to perform due diligence. In addition, individuals have a right to privacy, and banks are obligated to respect such rights.

Discussion of Ethical Considerations

Transparency is extremely important because, without it, people's concerns about the power asymmetries and abuse of individual data will be realized. AI, to succeed, will also need to assure people that it does not hold biases and avoids discrimination against individuals. Therefore, equal opportunity is critical, and banking institutions must strike the right balance between predicting to provide better services and products and remain profitable and respecting privacy and individual wishes. However, ethical considerations are still in their infancy because of the rapid trajectory of AI development. As yet, no guidelines or standards exist that govern how these AI-enabled systems should operate. People generally agree that AI should not harm individuals. Hence, the importance of ethics being built into AI so that systems address issues of safety, accountability, transparency, fairness, and non-discrimination. This requires ongoing monitoring and review, plus internal and external audits to ensure that systems are indeed incorruptible and perform as intended. In the face of a major natural disaster, for example, such as a hurricane, a bank could end up making unintended decisions if the AI system was not adequately programmed. Given these challenges, the banking sector must tread cautiously. Banks can't afford to risk customer trust and integrity. Care, wisdom, and regulatory oversight of AI regulation are essential.

5.1. Data Privacy and Security Concerns

In AI-enhanced customer segmentation, privacy and security are the two most pressing issues at the heart of the design and engineering processes. It is no secret that keeping sensitive personal data about customers creates a considerable risk if leaked or accessed by parties without consent. Since AI-enhanced customer segmentation often relies on personal data collections, lax security practices can lead to data leakage (both accidental and malicious). Additionally, an AI model breach may lead to model inversion and insight discovery, allowing adversaries to reverse-engineer highly sensitive personal information by softly querying the model with arbitrary inputs. A robust cybersecurity and physical security framework needs to be in place to prevent unauthorized access to customer data or AI models. Financial institutions must also comply with local data protection regulations to be able to collect, store, and label customer data.

When AI-enhanced segmentation capitalizes on personal data, there are two fundamental shifts that appear to shape the banking industry's relationship with customer data. Firstly, data transparency must be respectful of consumer privacy and consent to establish trust among customers. Transparency measures – including notification for use and choice regarding customer data collection – aim to ensure that customers trust their actual, past, and future data usage. Such transparency must also inform customers that their data do not leave the trusted confines of the organization and that data security is a critical banking-sensitive asset. Encryption of AI models and data, secure AI model storage, and proper access controls to secure customer data communication and infrastructure are critical. To help protect against the re-identification of customer data, best practices of data governance and data stewardship are essential to protect the data model, customer data, and improve AI cyber posture, allowing progress towards future-proofing organizations from AI-enhanced segmentation threat actors and practices. If these privacy and security concerns are addressed, banks can effectively manage the overlap of AI, customer databases, and financial regulation to engineer secure customer data science solutions. Providing extensive security around using and storing customer data is a best practice to prevent data theft, protect the model, and assure customers that their information remains private and confidential.

5.2. Fairness and Bias in AI-Enhanced Segmentation

Fairness and Bias in AI-Enhanced Segmentation

Providing substantiated advice on how to avoid discrimination is crucial in shaping sustainable customer segmentation in AI. Biases in historical data can lead to biased model outcomes, possibly excluding certain groups of people from receiving loans, being offered favorable terms, or being included in digital banking services. Banks are responsible for testing their AI models for fairness and for having tools and strategies in place to detect biases, mitigate them if necessary, and assure fair outcomes for all customers. This involves tackling the problem at the source through unbiased datasets. Only by including various groups in the training set can AI models become impartial.

Transparency of AI solutions is regarded as fostering trust in the customer base. We recommend shedding light on the functionality of machine learning models, including the data selection process, choice of algorithms, and outputs generated. Governance bodies overseeing AI strategies should regularly assess the compliance of AI models with internal company standards and external fairness guidelines. Diverse audits on AI products should disclose their stance on fairness and uncover AI-biased results, ensuring continuous fairness improvement of AI-enabled banking segmentation. Finally, we propose a toolbox that guides banks through ethically sound steps to ensure the uptake of fairness-enhanced segmentation. This toolbox represents the state of the art in banking segmentation by identifying thirteen assets and tool assets that can be used as guidelines to establish AI-enhanced, fair, and transparent customer segmentation in banking.

Our view on fair banking AI practices suggests that for a sustainable business, it is important that AI products being created should not just comply with a specific regulatory limitation but should enhance customer loyalty as well. The solution proposed here gives tangible assets such as analyses, assurance, and transparency-related solutions in order to establish fair customer segmentation. In addition, since this allows for a more effective use of company resources, it is more than just a regulatory burden to comply with: it is a best practice tool.

6. Future Direction

Increasing advances in computational power and the use of machine learning algorithms will facilitate the development of more powerful and accurate customer segmentation techniques. The ability to use more customer data is also expected to fundamentally transform the level of customer insights that can be developed, allowing for greater accuracy. The use of AI tools in banking can also help financial organizations implement real-time data to develop cutting-edge insights about their customers and trends. A growing body of literature outlines the AI tools today that could be complemented with more sophisticated machine learning capabilities as the pre-processing step of customer segmentation. Future segmentation techniques will also need to consider the changing needs of customers, whose experiences have become increasingly digital and personalized. Hence, future models of customer segmentation will need to be highly dynamic so that they accurately reflect these changes in affinity and loyalty at all times. It is anticipated that future segmentations will not be static; they will change to reflect the behavioral changes seen across different customer cohorts.

The progress in AI and customer analytics will also deepen the levels of personalization in efforts to attract and retain customers. The automated use of rich data will assist in building a more customer-focused financial services system, offering product recommendations derived from specific data about a certain cohort. Financial product development could be more targeted and thereby limit the number of products available in the mass market. Dynamic customer segments can also offer opportunities for precision marketing techniques that utilize the ability to track behaviors over time and link them to transaction behaviors. The richness of customer data and the segmentation itself with dynamic customer segments raise the need for significant investment in technology development. Here, technology extends beyond data and digital platforms to include the management of strong data governance and a reliance on strong analytics capability, digitizing a human approach to strategy. A display of facts such as digital consumer behaviors in a digital dashboard tool is not enough to manage artificial intelligence. For traditional retail banks and credit unions, the path to the kind of insight and AI-enabled customer experience is going to be a balancing act. AI technology and the knowledge of how to use AI successfully should be a focus for collaboration and investment from developments outside their institutions. These areas of investment and development could include partnerships and investments in fintech and start-up companies or university research teams that address increasingly picky and personal customer wants.

7. Conclusion

The banking industry is evolving and facing numerous challenges, including the rise of non-banks and neo-banks that are attracting customers with their tailor-made offerings. Customer segmentation plays a pivotal role in fostering a deeper and stronger relationship with customers. It predominantly facilitates the deployment of customer-focused and demand-driven operation strategies that would help banks make more effective business decisions. AI in banking can revolutionize customer segmentations as it helps in the development of precise and efficient predictive models, can segment customers effectively, increase accuracy to personalize offerings and services, and can analyze customer profitability and which attributes drive the profitability for improved decision-making at the bank. Moreover, focusing solely on the advantages of AI is myopic. While using AI to make the customer segmentation process more accurate, inclusive, personal, and faster, there are challenges that need to be countered efficaciously. Banks have been lagging in terms of data privacy and AI ethics. An effective way to unlock value creation using AI for customer segmentation comes from these regulatory aspects. One major barrier to AI is data privacy laws, which are stringent in many countries. It is observed that only companies that can guarantee data privacy, and follow a fairness principle in AI for customer segmentation, will potentially garner customer trust and over a period of time, all banks will have to move to this mode of operation. In the future, AI will define the way the banking industry operates. For banks to be successful, they need to continuously re-innovate their economic models that inevitably arise from newer technologies, including AI. Thus, a strategy based on leadership in the technology race will pay future dividends.

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