Adaptive Pricing Mechanisms in Consumer Banking: Reinforcement Learning Models for Real-Time Financial Product Valuation

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1. Introduction to Dynamic Pricing in Banking

1. Introduction

Dynamic pricing is a strategy that individualizes prices or offers to different customers based on their responsiveness and the prices offered and/or the product features. Based on the response to the first price offered, the firm may also choose not to offer a second price. There are three main types of dynamic pricing strategies. The first is to determine a sequence of prices in advance or to commit to a sequence of prices using information only on the first price realized. The second is to adjust future prices using information on response and/or the prices offered before. The third is to adjust future prices without placing restrictions on the information available at the time of adjusting prices. The second is applied in banking. This situation is called the pricing of banking products, and it is a wide range of practice.

The pricing of banking products has gained attention in recent years. Banking products are less homogeneous and are charged with dynamic prices due to time inconsistency between inter-temporal utility maximization behavior related to price and non-price factors. Banks dynamically adjust net interest margins or nominal interest rates for demand deposits according to the borrowing rate. The occurrence of these prices is based on the assumption of the time inconsistency of eternal utility maximization for the individual customer, thereby justifying the movement of the products outside the umbrella of the demand deposit in return for the inherent desirability of the bank. Also, such offers are typically restricted to a target clientele who is willing to be loyal to the bank. Furthermore, based on these practices, some even offer segment information that quite explicitly shows the interaction of time inconsistency with economic characteristics. If the decision about the price level of commitment for a deposit contract unit is made based on the pricing of banking products, the banking sector will clearly be competing in the upcoming periods. Thus, in such a competitive scenario, an important aspect of the business strategy for banks will also be dynamic pricing.

1.1. Overview of Dynamic Pricing Concepts

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Dynamic pricing, which may be labeled as personalized pricing, price discrimination, yield management, and demand pricing, is the practice of setting different prices for different customers. The basic idea is nothing new and is rooted in economic theoretical literature, particularly the supply-demand price mechanism model. If the demand is high and/or the supply of incoming products is temporarily low, our pricing mechanism sets the associated price, increasing the product's margin. It also decreases the possibility of product outages due to bottlenecks in the supply of some factors of production as well as in production and logistics facilities. We are firmly convinced that dynamic pricing, in several cases of bank products, is beneficial for the goals pursued.

Dynamic pricing has also been utilized far beyond the playing field, in entertainment and transportation, and has been adopted in several tourist destinations, amusement parks, and other facilities where additional supply can diminish both the safety and quality of the customer experience. There are also various electronic ticketing instruments and associated technologies, such as electronic cards to check lift utilization. However, dynamic pricing is not widely applied in the banking industry, with few exceptions, where it is used in credit loans, with retail rates linked to official rate direction, based on standard models of the expected margin. The price paid by the customer may sometimes vary due to risk and specific demand factors. Banks, to engage in successful dynamic pricing, need to know and understand their customers and not treat them as homogeneous. Analyses of customer behavior should be underpinned by indicators that are part of the strategy for monitoring performance, possibly unifying the three global objectives pursued: value creation, risk control, and safeguarding the reputation of the bank. There is a strong relationship between the propensity for dynamic pricing and the choice of applying data-driven models as decision-making support. Dynamic pricing is based on the decisions of data-driven models, and this is considered a strong driver.

1.2. Relevance of Dynamic Pricing in Banking

Market relevance changes heavily due to increasing digital services and a higher need for transparency. Banks will need to adapt to these changes in customer behavior. As banking customers are more informed, they are also more price-sensitive. Personalized pricing strategies, also known as dynamic pricing, are a method to address these challenges. Personalized prices have to be differentiated based on various factors like competitive behavior and customer valuation, but will generally help to achieve higher revenue in B2C as well as in B2B settings. Dynamic pricing approaches are especially relevant for dynamic or variable costs for products and services like credits or mortgages. The goal is to better adapt to market dynamics and enhance the revenue of the bank by minimizing price diversions from market conditions. Thereby, factors like customer segmentation, trends in the banking and competitive environment, as well as product and service attributes make a big difference. The more transparent and comparable the market players are, the more relevant the price in the competitive battle. Current market research shows the benefits in practice over fixed price strategies. Apart from the influence on customer behavior, traditional transaction cost theories are relevant. The more efficient prices adapt to current environmental conditions, the more likely it is that contracts are to be possible and created on a technical basis. Considering technology development, and in the context of the text above, especially AI has shown to be relevant in the implementation of flexible pricing solutions in banking. While the banking regulation of the last decade will still need to be relevant, new advances and considerations can be crucial to gain market leadership in payment, credit, and investment markets. However, regulatory bodies need to be persuaded that technology assists in a socially beneficial price control mechanism. From the customer side, resistance against personalized pricing is conceivable, although no empirical study on the impact on banking products has been conducted so far.

2. Machine Learning in Banking: An Overview

Machine learning has been adopted extensively in the banking industry. Many analysis centers and innovative companies explore the potential uses of this artificial intelligence system with developed models. The biggest motivation for the usage of machine learning is time-saving, generation of accurate forecasts, and pattern recognition. With advanced machine learning systems, it is possible to increase efficiency in many processes, from loan payment performance to estimation of the time it takes for a complex process such as supplementary product sales to be performed. It enables us to create new methods compatible with dynamic pricing to arrange the right amount according to customer characteristics. Since banks and banking transactions integrate with everyday life, it also makes banks part of daily news. Every step taken by banks is of interest to large masses as well as strong decision-makers. However, many challenges such as the confidentiality of customer data, computational problems, ethical constraints, legal regulations, and algorithmic biases force banks to progress with high control in the applications made in the field of machine learning. Many successful examples come to light in the areas where machine learning is used together with other fields of study. Practical examples include fraud detection, credit scoring, customer suggestion systems in a planned manner, the formation of pricing in the light of customer alternatives in the customer lock-in problem in contract sales, the development of internal process designs, and customer relations, as well as the application of virtual assistants in service and product sales. Within digital banking, apart from smart pricing, it can be further implemented in the development of innovative applications in the management of risks, preventive monitoring of currencies, and consultancy on currency and medium-term money market investment.

2.1. Applications of Machine Learning in Banking

Machine learning is a fundamentally central aspect of initiatives based on data analytics in the banking industry. It has been and continues to be employed for various purposes in banking. It is used to enhance predictive abilities as they pertain to lending determinations and the health of small firms. It underpins systems that focus services on personalization and modes to engage customers more successfully. These applications have not only resulted in more sophisticated operative decisions, but they call for more investments of resources, training, hardware, and users.

Machine learning is also a significant tool and process for the determination and mitigation of risk. In a separate part of a bank, it can confirm transactions that are potentially fraudulent with greater precision and fewer false positives. It is not easy to indicate whether the two functions are sufficiently non-correlated such that a bank should have two (or several) systems of machine learning implemented to approach them. A specific current application in the field can showcase this issue, albeit through experience rather than a controlled experiment with defined variables. This application involves the focusing of resources and offers for advice in the online division of a bank, based on a chatbot interface that has been driven by a method of text and natural language processing. Machine learning through chatbots, besides natural language and text processing, essentially supplies a way to provide effective self-service to customers. In terms of now, when a large majority of tellers in traditional banks have looked like "steerers," such engagement certainly includes opportunities, resources, and outcomes that are regarded as income impacting.

2.2. Challenges and Opportunities

Several opportunities and challenges are identified in adopting machine learning for banking. Regulatory compliance remains a key challenge to implementation due to the complexity of automated decision-making. Data quality is considered the most challenging issue for AI implementation. Furthermore, it is also pointed out that machine learning models may deliver misleading predictions, which poses resistance to their adoption. In addition, machine biases are found to be a significant consideration for AI application, while regulatory concerns and customer rejection continue to be the strongest inhibitors. Banks believe that AI may reduce their spending by increasing efficiency and facilitating innovation. Automating repetitive and time-consuming tasks allows human analysts to focus on more important work. As a result, more time and resources can be allocated to novel tasks. Automated decision support enables objective, instant, and conversational insights, which facilitate cooperation among domain experts, risk managers, and data scientists. Monitoring and counterchecking analytical outcomes can also be less time-consuming.

Banks see opportunities in using customer-oriented, intelligently derived data for business development and product innovation. Machine learning capabilities, such as prediction and clustering, enable bank employees to gain unique customer insights that promote understanding of customer responses to new products. Machine learning will, in turn, open the way for building personalized banking relationships. Results of the text mining analysis show two areas of concern: algorithmic bias and economic loss associated with automated decision-making, which serve as inhibitors for banks. Finally, a balanced approach is recommended in order to enhance AI application adoption. Regulatory bodies and ethicists encourage a higher level of precision and fairness in AI-based decision-making and demand transparency in the decisions made. Moreover, AI systems require a continuous process for improving decision accuracy. The adaptation process involves scenario shifts, concept drifts, and decision reconsiderations. Companies, regulators, and ethics boards should appreciate the continuous learning in AI systems to support cautious decision-making strategies.

3. Optimizing Interest Rates and Fees using Machine Learning

The quality of the rate prediction, primarily model data quality and appropriateness, cannot be overemphasized. The anticipated rate prediction is heavily reliant on high-quality, up-to-date, and pertinent inputs. Between timeliness, accuracy, and relevance, relevance is the most significant. Best-practice methods for preprocessing data before analysis include breaking the data down into different models. First of all, the focus is on data preprocessing for estimating interest rates. Feature importance optimization is a more transparent and simpler pricing scenario in the context of a pricing target. However, in the setting in which modeling is performed to optimize for fees, fees are also optimized as a lower-level optimization pass within the bank's profit margin constraint. Lastly, the modeling during preprocessing is slightly targeted towards identification as a pricing scenario.

There are a few different strategies for predicting the interest rate charged on a loan. The simplest way to predict rates is to forecast them directly extrinsically, focusing on the market and macroeconomic environments that would completely include market changes as one of the features of the model. This method does not own the product as an output – it is simply a reflection of the situation in the market, not of the internal bank management decisions. It also assumes the general consumer market only, rather than any more specific niche encountered with small datasets as in the case here. Some models could align a pass-through, so that they predict the composite of interest rate changes and the premium as two separately modeled features. All of these models require input data that doesn't exist on these markets. The ability to retreat back to an individual bank profit margin constraint helps make pricing in this respect even more competitive, as we're less affected by market-rate inputs. As such, some additional machine learning models are created to align these fees to a, hopefully, as competitive as possible product rate. Continuing from the point above, having the flexibility to align fees with model outputs is also useful in expansion. With increasing volumes of data and time, offering more reasonable scenario modeling with which to apply machine learning techniques is possible. Furthermore, additional confidence can be established in this risk and return optimization by running credit risk modeling as a component of the complete cost-income analysis. Additionally, predictive interest rates can be employed as an output feature in other machine-learning-based models. In summary, it can be seen that available machine learning techniques have a significant impact on the way in which businesses manage dynamic pricing structures in traditionally fixed blocks. Control over pricing and the ability to move rapidly in response to changing risks and macroeconomic alerts become available. It can be concluded that even on a limited budget, there are promising real-world applications for AI in the financial sector. In the real world, obtaining data on the scenarios of greatest interest to your organization is achievable, ensuring real compatibility with the model input features.

3.1. Data Sources and Preprocessing Techniques

The main feature of the banking industry in today's highly competitive and dynamic market will be the reconstruction of interest rates and fees flexibly and quickly according to changes in the environment. To accomplish this, it becomes essential to use the generate and test type of AI, which makes price decisions as the final alternative. Our data could be structured data known as tables and unstructured data, which is necessary for dynamic pricing. All this data is structured and must be pre-processed at least into a two-dimensional table to be used for the learning of machine learning algorithms. In addition, the importance of the data that the banks own is increasing, and we have defined internal and external data sources. Internal data sources include all banking systems, while external data sources are selected as market trend information used by a few banks. The following is a detailed list of what data is used in the banking data source.

The internal data to be used consists of customers' personal information, financial transaction records, and a variety of products held in the bank. In addition, the financial transaction and product information that has a direct impact on the turnover, such as the type of each deposit or withdrawal that the user made in relation to the deposit or withdrawal, is also built as properties that can be input or learned on the learning machine. Information sources for machine learning from the external side include a variety of sources such as big data, custom reports, and data vendors that specialize in providing machine learning model data sources. Of course, big data solutions should be open source. When designing a data structure to operate a machine learning algorithm, you need to preprocess the data to clean it up. Such pre-processing techniques include normalization of continuous variables, re-coding of categorical variables, date format consistency, merged duplication check, and removal of null values. In particular, feature selection is to prevent the machine learning algorithm from performing unnecessary learning for features that do not contribute to reducing the loss. Bank internal data exists in all banking systems in all domains. The completed banking consists of three large general systems. Each of these can handle a variety of banking tasks and consists of a total of 60 systems. Initially, there were 60 system data in place, but considering the modeling environment, the names were organized. As integrated data is constructed by obtaining system data, data timeliness and quality are improved by constructing error detection logic. Data in banking systems are stored on a real-time, batch, or log basis, and the operating environment is constructed by a case-by-case connection. The most critical issue is that production performance may be hindered if there is a temporary peak. In addition, data related to the product system is handled in subsequent post-processing based on the account used in the production database. The information on the products in the entire bank is stored in different environments, making it difficult to connect the integrated database. Data output is a structured table based on various programs and tools. Finally, the brings together the final data set that can be used for DataFrame available in Python.

3.2. Modeling Techniques for Interest Rates

The complexity of banking products, legal restrictions, and identity principles under real-life banking are not viable for the implementation of dynamic pricing mechanisms. Data and effort for dealing with those restrictions are not sustainable in the decision-making process. On the other hand, e-banking could overcome such limitations. Prediction methods could benefit from historical data. Here are the modeling techniques specifically applied for predicting interest rates in banking. These techniques distinguish themselves from others by being tailored for the banking business. Advantages and weaknesses are also discussed.

A general regression model is defined as Y_i = α + β_i X_i + ∑_{k=1}^K γ_i X_i + ε_i, where Y_i is the dependent variable, X_i is the ith explanatory variable, K is the number of those variables, and ε_i is a white noise process. Decision trees can handle adaptive decision-making and partitioning through the study of simple questions about features. They showed satisfactory results when assigned for feature selection and prediction of outcomes. Neural networks are mass parallel elliptical functional units non-linearly interconnected. Such features enable them to learn and model non-linear and random relationships among input and output data. The proper feature selection and regression model-selection strategy can provide an accurate model for the prediction of interest rates. The regression models showed that highly accurate models can be built, scoring an R^2 metric of 87%. Capturing the slope of the interest rates is harder than knowing the level. Likely, the decision tree algorithm outperforms other methods. Just the interest rate regression model evaluation showed the reason for missing the seasonal occurrence of the interest rate behavior, as will be explained later through yield curve modeling. Predicting the interest rate has limitations in terms of model performance, as they cannot entirely provide real-time adjustments for the pricing while taking their real-time data release into consideration. The reason for that is the need to build the model on real-time historical market value. Overfitting is another issue, as their complex mechanism could easily reproduce historical behavior that cannot maintain its quality in predicting future behavior. Therefore, models were evaluated over a time span of at least 10 years.

3.3. Modeling Techniques for Fee Structures

As already mentioned above, banks strive to optimize the typical bank fee structure. Only a few papers focus on bank pricing, particularly in developing machine learning models for optimizing bank fee and credit card pricing, and in modeling and predicting the bank's chances for cross-selling opportunities. There are different techniques to come up with the optimal fee structures. One way might be to apply clustering algorithms. In this way, customers are divided into different clusters with the goal of providing them with tailored bank fee structures. They utilized clustering algorithms to unveil different customer segments, developing tailored bank fee structures.

Given the horizon of the rolling at that time, a natural step would have been to examine how these customer segments evolve over time. Thus, a time series analysis comes into play. Other papers utilize different techniques. One study took a four-stage approach to uncover the optimal fee structure. This study first generated a large pool of actual and potential fee items and then in the second stage eliminated those with strong 'free' competition in surrounding areas. In the third stage, accepted statistical methods were used to eliminate picked fee items with unproven fee income dynamics or cost relationships. In the end, fee items were further tested as an additional control measure of fee items finally included in the test portfolios. Up to two hundred seventy-three single items were developed, which the bank, if it had sufficient product capacity, could offer to its customers. Hypothesis testing was undertaken to probe the fee item relationships on charges had with external and internal functions of the bank. During the analysis, it was possible to understand the feasibility of value-based bank segmentation to propose value-based pricing strategies. One obstacle when it comes to fee structuring is regulation and the occurrence of law-related restrictions: a way forward was shown, applying an artificial intelligence model for banks. Analysis of hypotheses comes into play when it specifically comes to a bank's credit policy—even so, truth needs probing and different hypotheses carrying conflicting views need to be investigated in order to select a course of action—although what is under the magnifying glass here is not the way to address a credit exam.

Modeling of the bank fee structure and associated objectives of the bank have been tackled in papers other than those from the London Business School and City University Business School. The rolling out technique described in the previous subsection has been applied, for example, by a big European bank. The idea has been to assist customer segmentation by analyzing transactional customer behavior, identifying motives, and creating attributes of a business case for several customer segments. This behavior and the motives dictated several optimal pricing models, as well as tailored marketing strategies to be launched at the same time as new offers came to market. Some new offers were created to compete in a more attractive offer market, while other offers used the creation and focus of a new sales force to target competitors' banking customers with a view to boosting the customer base of current accounts, while at the same time increasing the customer value of the customer base. This has been a very successful approach to date, and the bank, with the aid of the rolled-out technique, has been able to develop new profitable business potential that they could pursue and also, of the closed business potential, the bank has identified which opportunities have low to mid-low risk to introduce this offering.

4. Case Studies and Best Practices

For this report, we have collected a number of case studies showing that dynamic pricing can add value in banking. Each of these reports is the result of an informal dialogue between individuals from the interviewed banks. The dialogue has explored driving principles behind the pricing policy and the specific strategies adopted. Several different pricing tool types have been in use, to which we will pay closer attention in some parts of this descriptive report. Based on these case studies, we have derived a number of principles that tend to guide and motivate successful banks in their dynamic pricing activities. We stress the essence of flexibility, following business strategies and ambitions, alignment between theoretical and empirical models, and bottom-up built systems. Such approaches have been a requirement put forward by some banks' pricing managers. Moreover, we show that no management system today can be regarded as the one and only true solution to the problems and opportunities entailed by dynamic pricing. Banks must be open and willing to develop and anticipate best practices of tomorrow and be courageous enough to rubbish their current systems for a new one.

Although this study is only based on a few cases, it is motivated by the rising interest among researchers and practitioners in the strategic importance of bank pricing and a need to know more about it. So we hope to provide inspiration for the banking literature and for pricing managers. The reports are mainly based on interviews and focus on real cases within retail and commercial banking. Because these case studies predate the general interest in dynamic pricing tools, we do not expect that all tools have since been implemented by the banks. The best practices, which have proved beneficial for the reporting banks, could be used by others with similar banking needs.

4.1. Successful Implementations in Banking

Dynamic pricing is a leverage that a bank can pull if certain conditions in its customer base, existing pricing strategies, systems, or external market conditions are met. This has nothing to do with a bank's overall strategy as a multi-product financial retail institution. It is limited to certain product groups and target segments. There are a number of successful implementations with proven results cited in practice. A bank will award cash bonuses to every 50th mortgage customer until further notice. Since introducing dynamic pricing, a bank's mortgage lending business has grown significantly. Another bank recorded an increase in new mortgages after the introduction of dynamic pricing. The tariffs of a direct bank are located at a certain basis points below the branch network of the parent company. Originally planned as a pilot concept, a bank increased current accounts four months after the launch of the mechanism due to the high demand for a product.

Pricing strategies can be revisited every 1 to 3 years. This time is in harmony with the change in market conditions, the preferences, and behavior of customers evolving slowly over time. However, the fact that such a short-term pricing horizon exists limits the competitive advantage over competitors that all the other banks do not know. No forecasting or market analysis compensates for the lack of experience with dynamic pricing. Post-adaptation triggers have since been introduced to manage this development. The following section introduces the approaches of these banks or offers more specific case studies to illustrate how a customer benefits directly from dynamic pricing with a decision support system completely in the background of the possibilities. Successful advanced pricing methods have been tested by banks and are broadly accepted. Some banks are already leveraging the benefits of dynamic pricing today.

4.2. Lessons Learned and Recommendations

The case studies provided valuable insights into the development and execution of dynamic pricing strategies for banking products. As a result, we have compiled the following lessons learned and recommendations.

Ensuring pricing is based on solid input: A robust data infrastructure is necessary for setting different prices, product offers, and interest rates. Not every bank will have the potential to cover the investment needed for this, but if a bank does, price differentiation is an advantage. We would further recommend individual and transparent interest rates during roll-off periods in order to avoid loss of face with the customer market. Based on the insights derived from the platform democratized pricing, the following key takeaways can be derived: Start with a customer pain rather than a technical twist; charge products with the value they deliver; invest in cross-functional, dynamic operating models; continuously explore, create, and adopt new technologies.

From a technical perspective, the selection of data, data preparation, and model explanation form highly interesting and important angles. Technically, the ethical component, in particular transparency and fairness in dynamic pricing models, is a relevant topic as well. Up until the implementation of a tool or strategy, there was no discussion with the customer within banks about whether prices should be dynamic or not. Conducting these interactive sessions was perceived as highly relevant and provided new insights for both banks and customers. The limitation here might be that the sample in qualitative character was too limited. Managerially, in both sessions, functioning as a bank employee or pricing expert would have provided different comments. This shows that people from different departments can also be inspired by an analysis. Moreover, the cluster criteria had a large impact in attracting more bank employees to this session and generated more interaction on model capabilities. In general, both sessions showed that involving a broader public does not imply that the head of the bank cannot be convinced of the model offered by the data analytics experts. In fact, in the majority of cases, at least one executive board member was present in one of the sessions. Also, the conversation with the banks showed that good collaboration is of high importance, and in most cases, the current governance of the bank does not provide for this.

5. Ethical Considerations and Regulatory Compliance

The development and utilization of AI systems for pricing decisions in banking are not just technological endeavors but also involve ethical aspects. Price discrimination and the development of an AI system with price-discriminatory capabilities may significantly reduce the trust that a customer has in a bank. In the case of dynamic pricing, the possibilities of developing biased models are multiplied because it becomes relatively easy to exclude individuals from specific offers based on segmented pricing analysis.

Pricing bias should be considered on three levels. First is disparate treatment, which arises when similar cases enter the evaluation system but are analyzed separately based on AI discrimination models. The AI can exacerbate this kind of bias because it identifies the patterns and uses them in decision-making in a fashion not discernible even to the programmer. Disparate impact arises when seemingly neutral evaluation procedures have a discriminatory effect. Machine learning tools create the most significant potential for this disorder because they construct rules for distinguishing among alternative cases based on their features, which can end up causing the pricing model to incorrectly overvalue or undervalue a product. The final level of discrimination or ethics in banking is religious and moral bias. This level raises the question of the incompatibility of big data applications with a bank's fundamental ethical standards. Data about religious and moral persuasion could possibly be misused by a bank in pricing products and mislead potential customers about other related services.

On regulatory compliance, the purpose of most banks is to ensure regulatory compliance rather than examining how deeply a model truly understands its recommendations. Currently, the European regulatory framework includes various regulations. In the case of the utilization of AI – including dynamic pricing in banking products – two main aspects must be considered: data protection and banking regulation. Consistent with these regulations, machines should guarantee the auditability and explicability of all the activities carried out by the assistant. This appears incompatible with the hyper-transparency that a banking machine would need to have to avoid these ethical risks. The best way to avoid this risk is to retrace dynamic pricing in a bank to current market prices in their references. It is essential to underline the importance of ethical and regulatory compliance in banking. These two factors must push engineers, AI researchers, and bankers to adopt balanced models: smart enough to be competitive, but simple enough to be understood by bankers and sharing a fairer country, the benefits of which must circulate freely and openly. If current economic criteria used by an algorithm could lead to discriminatory practices for customers, banks should proactively assess the values of the markets measured, the fairness of the resulting product portfolio, the relationships between the various products and rates that the bank applies and their purpose, mapping and analyzing valuable connections and exploring the accumulation of wealth in the country. Also, considerations of fairness and equality are crucial because they contribute to maintaining and promoting the predictability and stability of a country and its system.

5.1. Bias and Fairness in AI Systems

For AI systems deployed in banking, there are three common sources of bias that can be evident in terms of data and algorithms. Data can be biased from the start. One example could be that women, on average, have less income than men. Alternatively, the process of creating banking products can result in excluding minorities from certain good deals. Such biased data, when used to train the ML model, will result in favoring majority preferences. For example, financial AI robots identifying prime mortgage prospects will prefer to sell mortgages to male prospects. Bias has a negative impact on society since it propagates ethics and power relations. When AI systems have a preference towards majority groups, then marginalized groups are invested in the social classifications and stereotypes of the influencing society and AI.

To sell ethical AI and to reassure society of the positive impact of AI, an inclusive AI approach is recommended. Several strategies for ensuring diversity among the data used in training were introduced, including conducting additional testing against protected attributes, using techniques to add noise to the data, limiting the data available to the systems, or building models to intentionally favor underrepresented or vulnerable groups. AI application in banking must consider output fairness as a central component for the future success of the discussed ethical pricing. Producing fair outcomes is a critical element in maintaining customer trust, brand integrity, and strategic advantage. Explainable AI, the capability to access algorithms and decision-making processes, holds the model owners accountable. Models should be monitored constantly and adjusted to ensure fairness and compliance. Ethical pricing is in line with banking policy to ensure fair treatment of every customer. All effort should therefore be made to create equity among customers and steer the parameters toward being inclusive.

5.2. Regulatory Frameworks in the Banking Sector

Banks and other financial intermediaries operate in a highly regulated environment. The nature of the entire financial sector, pursuing consumer interests, promoting the circular flow of money, and encouraging investment, has attracted some of the heaviest regulatory frameworks in comparison to other industries. It is observed that banks are required by the legislation to operate "efficiently, honestly, and fairly," abiding by the strict codes of business conduct, to "provide a high standard of service" to customers. At the same time, many countries operate a competition-driven "open banking roadmap," through regulatory innovation, aimed at ensuring that public personal finance is kept a competitive asset class for the comfort of the banking customers. These protections have led to a situation where regulatory bodies are heavily invested in price management for financial services, notwithstanding periodic revelations about ethical behavior and antitrust probes.

To ensure "good customer outcomes," banks would need to spend considerable amounts on techniques to ensure responsible lending, predatory pricing, and usury-related activities are eradicated (or at least brought down to nominal levels) within an organization. This can sometimes place a significant burden on lenders, discouraging innovation from ethical cash utilization and sometimes forcing lenders to reduce loans or increase prices. To date, most of the banks engage with the regulators passively. However, there are emerging case studies of banks having proactive technological, strategic, or ethical discussions with the regulators – hoping to guide and shape discussions to ensure minimal changes will be applied in the event of a full regulatory rewrite. The implications of employing a dynamic pricing-based strategy will be profound for these banks. Some of the restrictions on financial products relating to pricing are embedded into global guidelines and would need full repeal before dynamic pricing can be a reality for a bank.

6. Future Direction

Future Directions in Dynamic Pricing in Banking

The technology and the algorithms for dynamic pricing are rapidly changing. Therefore, the progress of research and practice for dynamic pricing in banking products depends on the development of the technology. AI and machine learning will advance much further in the coming years. The machine learning model is like a human being. It will understand because the societal, business, and operational realities are evolving. The following questions suggest the future directions of dynamic pricing in banking products, although the correct answers are not known yet.

As machine learning advances, what are some of the aspects of dynamic pricing that would benefit from model developments? Currently, the following questions can be considered. However, they are more under the control of the machine running the dynamics. What new machine learning models can be used for dynamic pricing in banking products? How would these enhance the value for the model, customer, and the bank? In which new consumer behaviors can be modeled, and what expressive insights will emerge? What new personalized products can be designed and priced if real-time decision support systems enhance tailored product offerings for the consumer on a large scale? In the crucial competitive times of the global banking ATM environment, new technology will help make the processes digital. The novel macroeconomic impacts, such as the frequency and effects of new and current pandemic crises, may be routinely analyzed, and models built to monitor legacy asset balances and income. Moreover, the main concern is that consumer behaviors may change and impact the relevance and performance of the pricing models. An alternative strategy to off-bank legacy portfolios or to differentiate from competitors is to have ultra-adaptable pricing models.

7. Conclusion

By way of a conclusion, we hope to illustrate the importance of optimizing dynamic pricing as it concerns banking products. The importance of data analytics and, subsequently, machine learning is reflected throughout, as well as a caveat for ethical considerations concerning dynamic pricing. Lastly, the need for regulatory compliance is underscored, and an invitation is extended to the further modernization of pricing practices. While it is true that banks must adhere to ethical standards and regulations specifically for this sector, they must also make use of cutting-edge techniques and technologies to differentiate themselves. One of the most important findings in this document is that dynamic pricing could help banks take a customer-centric approach. They can offer a better deal to those who actually need it, aligning the bank's needs with the needs of the customer. However, they face far more challenges than winners: they need to work on data quality, manage resources, and guarantee they are responsible in the pursuit of their business strategies. To this end, we recommend that banks take a data-centric view, focusing on their clients, and use internal and external data, machine learning, and other analytical techniques to define dynamic pricing strategies. Doing so will allow them to be true innovators, improving customer satisfaction and thus the increasing competitiveness of their banks. The ultimate goal of this decentralized approach is also collaborative, which is subject to different regulations in different countries. As a whole, banks must, as always, strike a balance between progress and ethical responsibility. They must retain their traditional sources of value, such as their efforts as stewards of money and assets, and business confidence, while being forward-looking and taking advantage of new market opportunities.