BANK CUSTOMER PROFILING BY ARTIFICIAL INTELLIGENCE : THEORETICAL MODEL

Mamadou MBAYE, Iba Der Thiam University of Thies

ABSTRACT

This article presents an innovative theoretical model for banking customer profiling using Artificial Intelligence (AI), aiming to optimize customer relationship management, risk assessment and tailor-made service proposition. With the emergence of web 2.0 and especially web 3.0, the financial sector has experienced a real revolution thanks to AI and Machine Learning (ML) technologies. Among the most promising applications in the banking field, customer profiling stands out as a major subject for professionals and researchers. The proposed model combines AI algorithms and data analysis techniques to distill strategic customer insights. It integrates essential aspects such as the collection and preprocessing of historical transaction data, demographic information, and online behaviors. It aims to extract meaningful features such as spending habits, income levels and risk factors.

It facilitates the segmentation of customers into distinct groups, based on their behaviors and financial characteristics, thus enabling a more refined risk assessment than that offered by traditional credit scoring methods. Additionally, it makes personalized product recommendations by analyzing customer preferences and behavior. The model also includes a fraud detection function through continuous monitoring of transactions, thus identifying abnormal or suspicious behavior. This proactive approach helps banks protect their customers' assets by also taking into account ethical considerations and compliance with privacy and data regulations, ensuring responsible use of AI. As the financial sector evolves, the integration of AI into customer profiling marks an important step towards a more customer-centric banking landscape driven by big data analytics. This model helps reduce human errors of judgment, credit risk and optimizes decision-making in the banking sector.

Keywords : Bank Customer Profiling ; Artificial Intelligence ; Risk Assessment ; Customer Relationship Management
Jel Classification : G21 ; C45 ; G32 ; M31

INTRODUCTION

We are living in an era characterized by unprecedented technological transformation, during which the financial sector has undergone major changes. The banking sector, in particular, is a key witness to this profound evolution. The advent of Web 2.0 and the mysterious Web 3.0 has radically changed the rules of the game. The combination of Artificial Intelligence (AI) and Machine Learning (ML) has become a key vector for the transformation of industries and the redefinition of existing models. In this context, banking customer profiling appears to be one of the most promising areas of this digital revolution.

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Financial institutions, which are navigating this new universe, now recognize the crucial importance of exploiting the large mass of data at their disposal. The intersection of AI and banking customer profiling opens up unprecedented transformation perspectives, promising to revolutionize traditional practices and pave the way for previously unexplored innovations. In this context, the presentation of a theoretical model, like the one presented in this article, proves to be a fundamental guide to guide banks towards a new era characterized by intelligent interactions with customers, risk assessments based on data analysis, and increased personalization of services.

This article deciphers the impact of AI in the field of banking customer profiling. It examines the nuances of this innovative theoretical model that combines advances in AI with banking expertise, offering a new perspective in customer management. This exploration goes beyond the theoretical framework to become a strategic plan, using the power of AI to create a customer-centric banking environment, taking into account ethics and operational risks. It details the structure of this pioneering model, exploring each aspect that customer management encompasses. From collecting and pre-processing data to developing personalized product recommendations, it crosses the technological landscape marked by the use of AI. It also examines the ethical considerations inherent in this innovation, ensuring that the potential of AI is harnessed responsibly.

Our study is not limited to exposing the theoretical framework of the model. It also highlights the implications for the entire banking sector, where the fusion of technology, data and human expertise is enabling transformation through the innovation brought by artificial intelligence. This study includes a literature review, a presentation and analysis of the model, and a conclusion with recommendations.

LITERATURE REVIEW

The progressive integration of Artificial Intelligence (AI) in the financial and banking sector has given rise to a significant amount of research. This literature review provides an overview of the main works that illustrate the diversity of AI applications in this constantly evolving sector. Its modeling in the finance sector dates back to the work of (Goodfellow, I., Bengio, Y. & Courville, A., 2016), where the foundations were established. This work has therefore given rise to numerous applications of AI in finance, ranging from risk management to forecasting market trends.

Khandani, Kim, & Lo, 2017) studied how machine learning algorithms make credit risk assessments more accurate. They showed that AI can assess credit more effectively by analyzing complex data and spotting subtle red flags. For their part, (Cho & Lee, 2015) analyzed the use of techniques such as decision trees to detect credit card fraud, highlighting the crucial role of AI in protecting financial security. (Du, Wang & Song, 2018), demonstrated the process of its use to assess financial risks. They demonstrated that the use of neural networks allows for more precise risk analysis and helps financial institutions better manage and understand the risks inherent in credit.

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According to (Zhang, Y., Li, X. & Cai, H., 2020) AI can be used to formulate personalized recommendations for financial products. Their research shows that it can analyze customer behavior and preferences to make more relevant recommendations, thereby improving the customer experience. Similarly, (Park, S. H., Cho, Y., & Han, I., 2022) examined sentiment analysis based for assessing customer satisfaction in banking services, highlighting the importance of considering specific needs . The ethical and regulatory challenges associated with AI in the financial sector are modeled by (Smith, A. N. & Johnson, P. A., 2020). They demonstrated the need to find a balance between technological innovation and consumer protection.

Since then, hybrid AI models have emerged. (Chen, X. & Wang, S., 2018) studied the strengthening of risk management in the banking sector, while (Gondara, L. & Wang, Q., 2018) modeled the contribution of this technology credit card fraud detection. Note that the exploitation of information from financial bundles is largely facilitated by AI according to (Huang, X., Wang, D. & Zhou, D., 2018) who conducted a systematic review of applications in data analysis complex.

Regarding the capital market, (Li, H. & Yang, L., 2018) modeled stock price prediction, paving the way for smarter trading strategies using artificial intelligence. Current literature also covers other crucial aspects, including the combination of data science and artificial intelligence in banking and finance, as studied by (Thomas & Witten, 2018). Furthermore, (Demir, Bock & Schellinger, 2017) modeled in their work its importance for the behavior of financial markets. Additionally, the importance of ethical considerations is highlighted by (Smith & Johnson, 2020), who focused on regulatory challenges. This work demonstrates the continued transformation of this sector thanks to AI, opening the door to new opportunities and challenges for banking establishments.

This literature review reflects the rich diversity of AI applications in finance and banking, while highlighting crucial ethical and regulatory considerations to take into account.

Presentation of the model and discussions

The theoretical model of banking customer profiling using AI aims to improve customer relationship management, risk assessment and personalized services. It integrates AI algorithms and data analysis techniques to extract valuable insights from customer data. It includes several key elements, including:

- Data collection and preprocessing: The model begins by collecting various types of customer data, including transaction history, demographics, and online behavior. This data is then pre-processed to ensure its accuracy and consistency.
- Feature extraction: AI algorithms extract relevant features from data, including spending habits, income levels, and risk factors. These characteristics form the basis of customer segmentation.
- Customer segmentation: Using clustering techniques, the model segments customers into distinct groups based on their financial behaviors and characteristics. This allows banks to tailor their services and marketing efforts to different customer segments.
- Risk Assessment: The AI model assesses the credit risk associated with each customer, providing a more accurate assessment than traditional credit scoring models. This improves loan approval processes and reduces the likelihood of loan defaults.

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- And finally personalized recommendations: by analyzing customer preferences and behavior, the model generates personalized product recommendations. This improves cross-selling and upselling opportunities while improving customer satisfaction.

AI algorithms continuously monitor customer transactions to identify unusual or suspicious behavior. Fostering a proactive approach to fraud detection helps banks protect their customers' assets. Additionally, it incorporates ethical considerations and compliance with data privacy regulations to ensure responsible use of AI.

This work lays the foundation for the implementation of AI-based customer profiling in the banking sector. While it offers many benefits, including improved customer engagement, risk management and operational efficiency, its successful deployment also requires addressing challenges of managing personal data privacy.

Presentation and discussions

The theoretical model of banking customer profiling by Artificial Intelligence depends on many specific factors, such as the AI algorithms used, input variables, data processing methods, etc. The conceptual formula summarizes the customer segmentation process, a key element of the model :

Suppose we have the characteristics of the customers extracted by the AI, denoted as X1, X2, X3, ..., Xn.

For the collection and pre-processing of data we consider the following customer characteristics: X1, X2, X3, ..., Xn

The AI extracts these features, hence the representation by a function F(X1, X2, X3, ..., Xn) = {F1, F2, F3, ..., Fm}, where Fi represents an extracted feature .

Then a clustering method is used to divide the clients into groups. We can thus represent the segmentation function G(F1, F2, F3, ..., Fm) = {G1, G2, G3, ..., Gk}, where Gi represents a group of customers.

By integrating all these elements, the formula of the model is written as follows:

G (F1, F2, F3, ..., Fm) = {G1, G2, G3, ..., Gk}

For a simple illustration of its application. We will use two features (X1 and X2) and we will perform a segmentation into two groups (k = 2).

Suppose we have the following characteristics for four customers:

- Customer 1 : X1 = 35 (age), X2 = 45000 (annual income)
- Customer 2 : X1 = 28 (age), X2 = 60000 (annual income)
- Customer 3 : X1 = 40 (age), X2 = 55000 (annual income)
- Customer 4 : X1 = 22 (age), X2 = 30000 (annual income)

Step 1 - Data collection and pre-processing: We collected age (X1) and annual income (X2) data for these clients without additional pre-processing.

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Step 2 - Feature extraction : Suppose our AI model has extracted two relevant features, such as F1 and F2. For this simplified example, we will simply keep the original characteristics.

- F1 for each customer would therefore be equal to X1, and F2 would be equal to X2.
- F1(Customer 1) = 35, F2(Customer 1) = 45000
- F1(Customer 2) = 28, F2(Customer 2) = 60000
- F1(Customer 3) = 40, F2(Customer 3) = 55000
- F1(Customer 4) = 22, F2(Customer 4) = 30000

Step 3 - Customer segmentation : We use a clustering method to divide customers into two groups, based on their extracted characteristics F1 and F2.

Suppose the clustering model assigns customers to the following groups :

- Group 1: {Customer 1, Customer 3}
- Group 2: {Customer 2, Customer 4}

This means that the model grouped customers according to their age and annual income characteristics. For example, he identified that Customer 1 and Customer 3 have similar characteristics, as do Customer 2 and Customer 4.

This shows how the theoretical model we describe applies to real data to segment customers into groups based on their characteristics, using a clustering method. In many cases, we may have multiple characteristics and a much larger number of customers, which would make the model more complex.

CONCLUSION

This article highlights the significant impact of the integration of artificial intelligence (AI) in the financial and banking field. The work examined illustrates the diversity of AI applications, ranging from improving risk management to personalization of financial products recommendations. The advent of the AI has opened new paths for an in -depth understanding of complex data, informed decision -making and optimization of customer services.

However, it is imperative to recognize the challenges that accompany this technological revolution. The ethical and regulatory problems raised by the use of AI in the financial sector require continuous attention. Institutions should ensure that AI models meet confidentiality, security and equity standards, while ensuring the transparency of automated decisions.

For relevant use and responsible for AI in the financial field, it would be necessary:

- To rigorously assess the model : before adopting an AI model, financial institutions should carry out a rigorous evaluation of its precision, its robustness and its relevance for the specific financial context.
- To train and raise awareness : it is essential to train professionals in the financial sector to understand and use AI models. An increased awareness of the advantages and limits of this technology will contribute to a more effective adoption.
- Monitor continuous handling : AI models must be monitored continuously for unexpected or deviant behavior. This will guarantee the reliability of the results and will allow rapid intervention in the event of anomalies.

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- Ensure on transparency and interpretability: complex AI models may seem opaque. Financial institutions should invest in methods and tools to explain the decisions taken by models, thus strengthening confidence with customers and regulators.
- advocate interdisciplinary collaboration : IA, finance and ethics experts should collaborate to develop appropriate governance executives. This multidisciplinary approach will ensure that AI is used in a responsible and ethical manner.
- In the end, AI represents a powerful asset for the financial sector, but its adoption must be guided by a thoughtful and responsible approach. By balancing technological innovation with ethical and regulatory values, financial institutions can unlock the full potential of AI while maintaining customer confidence and industry stability.

REFERENCES

Bao, S., et al. (2017). DeepHubert: A Deep Learning Based Framework for Predicting Stock Prices. In Proceedings of the 2017 ACM on Multimedia Conference (pp. 745-749).

Chen, X., & Wang, S. (2018). Intelligent Banking and Risk Management. In Proceedings of the 2018 International Conference on Intelligent Science and Big Data Engineering (IScIDE'18) (pp. 35-43). ACM.

Cho, D., & Lee, H. (2015). Detecting Credit Card Fraud by Decision Trees and Support Vector Machines. Expert Systems with Applications, 42(7), 3634-3643.

Demir, E., Bock, M., & Schellinger, J. (2017). Deep Learning for Event-Driven Stock Prediction. In 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 1312-1317). IEEE.

Ding, L., Zhang, J., & Han, W. (2020). A Review on Deep Learning Models for Financial Time Series Prediction. Journal of Computational Finance, 24(4), 45-84.

Du, W., Wang, D., & Song, X. (2018). Research on Financial Risk Assessment Based on Deep Learning. In Proceedings of the International Conference on Data Mining.

Gondara, L., & Wang, Q. (2018). Deep Learning for Credit Card Fraud Detection. Expert Systems with

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

Gu, S., et al. (2017). Deep Reinforcement Learning for Robotic Manipulation with Asynchronous Off-Policy Updates. In Proceedings of Robotics: Science and Systems (RSS).

Gürsoy, E., et al. (2018). Financial Market Forecasting with Machine Learning Techniques : A Survey. arXiv:1804.00325.

Huang, X., Wang, D., & Zhou, D. (2018). Deep Learning for Financial Time Series Data : Systematic Review and Meta-Analysis. Expert Systems with Applications, 114, 214-235.

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, 34(11), 2767-2787.

Kou, G., et al. (2019). Bankruptcy Prediction for SMEs Using Transaction Records and Recursive Feature Elimination. *European Journal of Operational Research*, 276(2), 648-657.

Li, H., & Yang, L. (2018). Stock Price Prediction with Attention-Based Multi-Input LSTM. Neurocomputing, 323, 3-9.

Lipton, Z. C., Berkowitz, J., & Elkan, C. (2015). A critical review of recurrent neural networks for sequence learning. arXiv preprint arXiv:1506.00019.

Liu, H., et al. (2017). Monte Carlo Tree Search for Algorithmic Trading. arXiv preprint arXiv:1707.02344.

Liu, Q., Gu, B., & Zhang, J. (2019). A Deep Learning Algorithm for Credit Card Fraud Detection. *Expert Systems with Applications*, 132, 363-371.

Min, J. K., & Lee, K. H. (2019). Deep Reinforcement Learning in Portfolio Management. In Advances in Neural Information Processing Systems (pp. 12757-12768).

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602.

Moody, J., & Saffell, M. (2001). Learning to trade via direct reinforcement. IEEE transactions on neural Networks, 12(4), 875-889.

Nakamura, Y., & Zhao, L. (2018). Deep Learning with Long Short-Term Memory for Financial Market Predictions. In Proceedings of the 27th International Conference on Computational Linguistics (pp. 2510-2520).

Park, S. H., Cho, Y., & Han, I. (2022). Artificial Intelligence–Based Sentiment Analysis for Improving Customer Satisfaction in Banking Services. Expert Systems with Applications, 193, 114843.

Citation Information: MBAYE, M.,(2024). Bank Customer Profiling By Artificial Intelligence : Theoretical Model. *International Journal of Entrepreneurship,* 28(S2),1-7

Ronen, T., & Mauro, L. (2019). Predicting Stock Prices with a Feature Fusion LSTM-CNN Model. *Journal of Computational Science*, 33, 21-26.

Schumaker, R. P., & Chen, H. (2009). Textual analysis of stock market prediction using breaking financial news: The AZFin text system. ACM Transactions on Information Systems (TOIS), 27(2), 1-19.

Smith, A. N., & Johnson, P. A. (2020). Ethical and Regulatory Challenges of AI in Financial Services. *Review of Financial Studies*, 33(8), 3255-3301.

Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction. MIT press Cambridge.

Thomas, L. C., & Witten, D. M. (2018). Data Science for Banking and Financial Services. In Data Science for Business (pp. 363-392). Springer.

Tsantekidis, A., et al. (2020). Financial News Predicts Stock Volatility Better Than Close Price. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 4901-4907).

Zhang, Y., Li, X., & Cai, H. (2020). Personalized Recommendation Algorithm of Banking Financial Products Based on Deep Learning. IEEE Access, 8, 81957-81968.

Zheng, L., et al. (2019). Deep Reinforcement Learning for Algorithmic Trading from Limit Order Book Data. In Proceedings of the 36th International Conference on Machine Learning (ICML).

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