

Practical Applications and Development Challenges of Artificial Intelligence in Finance

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Abstract. The financial industry has a strong demand for efficient and accurate data analysis and decision-making, and the application of artificial intelligence in it is becoming increasingly widespread. This article reviews the practical application and development bottlenecks of artificial intelligence in the financial field. In terms of practical application, artificial intelligence has achieved remarkable results in many fields such as risk assessment and management, investment decision support and customer service. For example, it enhances credit evaluation, improves investment strategies through smart advisors, and boosts customer interaction via chatbots and profiling tools. However, challenges remain, including data complexity and privacy issues, algorithmic bias, lack of explainability, and talent shortages. Regulatory gaps also create compliance risks. The research conclusions show that the application of artificial intelligence in the financial field has significant advantages, but also faces many challenges. In order to achieve its sustainable development, multiple parties need to work together to optimize algorithms, strengthen talent training, improve the regulatory system, break through development bottlenecks, and promote the steady development of the financial industry. The research aims to provide theoretical reference and practical guidance for promoting the sustainable development of artificial intelligence in the financial field, which is of great significance to financial institutions in enhancing their competitiveness and preventing financial risks.

Keywords: Artificial Intelligence, Financial Field, Practical Application, Development Bottleneck

1. Introduction

As a data-intensive field, the financial industry has a strong demand for efficient and accurate data analysis and decision-making. Artificial intelligence, with its powerful data processing, pattern recognition and predictive analysis capabilities, is profoundly changing the operating model of the financial industry. From traditional banking, securities, and insurance businesses to the emerging financial technology field, artificial intelligence is everywhere. Researching the practical application and development bottlenecks of artificial intelligence in the financial field is of great significance for financial institutions to enhance their competitiveness, innovate business models, and prevent financial risks. This article comprehensively reviews the practical application of artificial intelligence in the financial field, analyzes the bottlenecks it faces in the development process, and

provides theoretical reference and practical guidance for promoting the sustainable development of artificial intelligence in the financial field.

The main body of this article is divided into two parts. The first is the practical application of artificial intelligence in the financial field, covering risk assessment, investment decision-making and customer service; the second is the development bottlenecks, including data, algorithms, talents and regulatory issues; finally, it summarizes the achievements and challenges, and puts forward suggestions for future development.

2. Practical application of artificial intelligence in the financial field

2.1. Risk assessment and management

2.1.1. Credit risk assessment

Artificial intelligence is reshaping the traditional credit assessment system by integrating multi-dimensional data and intelligent algorithms. Chen, T., & Guestrin, C. Compared with traditional models that rely on structured data such as financial statements and historical credit records, AI systems can capture unstructured data such as applicants' social network activity, e-commerce consumption trajectory, and mobile payment behavior in real time to build dynamic risk assessment profiles for thousands of people [1]. For example, Ant Group. Through the XGBoost model trained with more than 100,000 feature variables, "Zhima Credit" covers more than 500 million people with no credit records [2]; Yang, Q., et al. WeBank uses federated learning technology to achieve cross-institutional credit data sharing while protecting data privacy, increasing the approval rate of small and micro enterprise loans by more than 40% [3]. Deep learning models (such as RNN and Transformer) can capture the temporal characteristics of user behavior and identify risk signals, such as abnormal credit card consumption and multiple borrowing. Vaswani, A., et al. in the United States use machine learning to process more than 5,000 variables to improve the accuracy of subprime loan default prediction by 15%. However, the black box problem of algorithms remains controversial. The EU Artificial Intelligence Act has required financial institutions to verify the explainability of AI credit scoring systems. The industry is currently exploring interpretable tools such as SHAP values and LIME to improve model transparency while maintaining prediction accuracy, striving to strike a balance between financial innovation and risk control [4].

2.1.2. Market risk prediction

Artificial intelligence (AI) plays an important role in market risk prediction, mainly by improving prediction accuracy through sentiment analysis and deep learning technology. Deveikyte et al. showed that news and social media sentiment can effectively predict market fluctuations, news sentiment can be used as a prediction signal for market returns, and Twitter sentiment is negatively correlated with market volatility [5]. Fischer & Krauss used LSTM networks to predict asset returns, showing that deep learning can outperform traditional methods. Overall, AI technology combined with high-frequency trading data and text analysis significantly improves market risk prediction capabilities [6].

2.1.3. Compliance and regulatory technology

In recent years, artificial intelligence (AI) has demonstrated significant advantages in compliance and regulatory technology in the financial sector. Arner et al. proposed that with the help of natural

language processing (NLP) technology, regulatory texts can be efficiently parsed, compliance risk identification can be automated, and anti-money laundering (AML) and know your customer (KYC) processes can be optimized [7]. Subsequently, Zetzsche et al. further explored the intelligent regulatory model, building a regulatory sandbox and intelligent compliance platform, and using machine learning and data mining technologies to improve financial regulatory efficiency and risk warning capabilities [8]. Huang and Li's case analysis demonstrated the specific application of NLP in financial compliance practices, such as automatic screening of transaction data and detection of suspicious activities, thereby achieving more accurate risk control. Overall, these studies have shown that AI technology is bringing innovative transformation to financial regulatory technology, helping institutions cope with increasingly complex market risks [9].

2.2. Investment decision support

2.2.1. Smart investment advisors

The application of artificial intelligence (AI) in smart investment advisors has improved the accuracy and efficiency of investment decisions. Sutiene et al. showed that AI technology can optimize portfolio management, improve the flexibility of asset allocation and risk prediction capabilities[10]. Jang & Seong further explored the application of deep reinforcement learning in portfolio optimization and proved that it can dynamically adjust investment strategies to adapt to market changes[11]. D'Acunto et al. emphasized that smart investment advisors can reduce investment costs and expand market coverage, but still face algorithmic bias and regulatory challenges. In the future, AI-driven smart investment advisors will play a greater role in the financial field [12].

2.2.2. Quantitative investing

The application of artificial intelligence (AI) in quantitative investment has significantly improved the accuracy and efficiency of investment decisions. Huang and You showed that AI can process complex financial data and assist investment decisions [13]. Guo proposed the concept of "Quant 4.0," emphasizing the automation, explainability and knowledge-driven characteristics of AI, making quantitative investment strategies more adaptable and transparent [14]. In addition, CFA Institute discussed the wide application of AI in asset management, especially in optimizing portfolios and improving risk management. The practical application of AI in quantitative investment is driving investment decisions in a more efficient and accurate direction [15].

2.3. Customer service

Artificial intelligence (AI) has played an important role in customer service in the financial sector, especially in the application of intelligent customer service and customer profiling. Luo et al. showed that AI chatbots can significantly improve the efficiency and accuracy of customer interactions and optimize the customer service experience [16]. Akter et al. proposed an AI-driven service innovation framework, emphasizing the application of AI in precision marketing to help financial institutions provide personalized services based on customer needs [17]. Huang and Rust proposed a strategic framework for AI in marketing, supporting the use of customer profiling for precision marketing, thereby improving customer conversion rates and satisfaction [18].

3. Challenges in the development of AI in finance

3.1. Data issues

The application of artificial intelligence (AI) in the financial sector relies on high-quality data, but it still faces many challenges. Cao et al. pointed out that the complexity and heterogeneity of financial data increase the difficulty of data processing for AI models [19]. A research report by Beijing National Fintech Certification Center et al. emphasized that data quality and security are crucial to AI financial applications, and data sharing and privacy protection remain major bottlenecks [20]. Maple et al. further analyzed the data compliance and ethical issues of AI in the financial sector, emphasizing the regulatory challenges of data acquisition, storage, and use. These issues limit the comprehensive development of AI technology in the financial sector [21].

3.2. Algorithm problem

3.2.1. Explainability

The widespread application of artificial intelligence (AI) in the financial sector is constrained by the problem of algorithm interpretability. Huang and You pointed out that financial decision-making relies on transparent and explainable AI models to enhance regulatory compliance and customer trust [22]. Černevičienė and Kabašinskas emphasized through a systematic literature review that explainable artificial intelligence (XAI) helps improve model transparency, but its application in complex financial environments still faces challenges [23]. Lin further analyzed the development of XAI in the financial industry and pointed out that improving the interpretability of AI models is crucial for risk control and regulatory compliance [24].

3.2.2. Algorithmic bias

The application of artificial intelligence (AI) in the financial sector faces the problem of algorithmic bias, which affects fairness and compliance. Mehrabi et al. pointed out that machine learning models may lead to discriminatory decisions due to data imbalance or historical bias [25]. Zhang studied the causes of algorithmic discrimination in platform companies and proposed governance countermeasures to reduce unfairness in AI applications such as credit approval and risk control [26]. Lin further analyzed the role of explainable AI (XAI) in alleviating financial algorithmic bias and emphasized that transparent algorithms can help improve fairness and user trust [24].

3.2.3. Model generalization ability

The application of artificial intelligence (AI) in the financial field is limited by the generalization ability of the model, which affects its adaptability in different market environments. Mokhtari et al. pointed out that the stock market prediction model based on machine learning performs well on training data, but may fail under new market conditions [27]. Nie et al. reviewed the progress of large language models (LLMs) in financial applications and emphasized that their adaptability to dynamic market environments remains challenging [28]. Kanaparthi pointed out through bibliometric analysis that improving the generalization ability of the model requires richer data and more advanced learning methods to ensure the robustness and reliability of AI decisions [29].

3.3. Talent issues

The application of artificial intelligence (AI) in the financial sector is limited by the shortage of professional talents, which affects the implementation and innovation of technology. Ma and Wei pointed out that AI financial applications require interdisciplinary talents, but the current shortage of high-end technical talents has hindered the development of the industry [30]. Tchernetsky and Vogt proposed an AI-driven talent training model, emphasizing the improvement of human resource management efficiency through automation and intelligence to alleviate the problem of professional skills shortage [31]. Arner et al. studied the development trend of financial technology and believed that insufficient talent reserves may limit the long-term transformation and sustainable development of AI in the financial industry [7].

3.4. Regulatory issues

3.4.1. Lagging regulatory policies

The application of artificial intelligence in the financial sector is developing rapidly, while the formulation of regulatory policies is relatively lagging, resulting in a contradiction between innovation and compliance. D'Acunto et al. pointed out that the development speed of AI financial applications such as smart investment advisors far exceeds the current regulatory framework, posing challenges to investor protection and market stability [12]. Yang studied the complexity of financial technology regulation and emphasized the necessity of regulatory science (RegTech) to cope with AI-driven financial innovation [32]. Ridzuan et al. further discussed the ethical and compliance issues of AI financial applications and believed that the regulatory system should keep pace with technological development to ensure the healthy development of the financial industry [33].

3.4.2. Unclear definition of responsibility

The widespread application of artificial intelligence (AI) in the financial sector has brought challenges in defining legal responsibilities. For example, when an AI model makes an incorrect investment decision or causes customer information to be leaked, it is difficult to determine whether the responsibility lies with the model developer, data provider, financial institution, or other relevant party. Hu studied the allocation of responsibilities for AI violations and pointed out that in financial scenarios, losses caused by algorithmic decisions are difficult to attribute to specific entities, which increases legal uncertainty [34]. Jin & Zhang discussed the risks of AI in the financial sector and emphasized that vague responsibility definitions may affect market stability and investor confidence. Hu further analyzed the issue of allocation of responsibilities for AI violations and believed that regulators should establish a clear legal framework to ensure the compliance and controllability of AI financial applications [35].

4. Conclusion

The practical application of artificial intelligence in the financial field has achieved remarkable results, playing a key role in risk assessment and management, investment decision support, and customer service. It has also effectively promoted the innovation and development of the financial industry. However, its development process also faces many bottlenecks. The complicated nature of data, along with issues of security and privacy; the understanding, fairness, and adaptability of algorithms; the lack of skilled professionals; outdated regulations; and unclear responsibilities have

all limited the deeper use of artificial intelligence in finance. To support sustainable development, collaboration is needed among financial institutions, tech companies, regulators, and researchers. All parties should jointly explore and optimize data management strategies, improve algorithm performance, strengthen interdisciplinary talent training, and improve the regulatory system to break through development bottlenecks. These efforts will help AI better support risk control and innovation, promoting stable growth in the financial industry.

References

- [1] Chen, T., & Guestrin, C. (2016). "XGBoost: A Scalable Tree Boosting System." *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM.
- [2] Ant Group. (2020). *Annual Report: Technology-Driven Inclusive Finance*. Hangzhou: Ant Group.
- [3] Yang, Q., et al. (2019). "Federated Machine Learning: Concept and Applications." *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(2), 1-19.
- [4] Vaswani, A., et al. (2017). "Attention Is All You Need." *Advances in Neural Information Processing Systems (NeurIPS)*, 30.
- [5] Deveikyte, J., Geman, H., Piccari, C. and Provetti, A., 2022. A sentiment analysis approach to the prediction of market volatility. *Frontiers in Artificial Intelligence*, 5, p.836809.
- [6] Fischer, T. and Krauss, C., 2018. Deep learning with long short-term memory networks for financial market predictions. *European journal of operational research*, 270(2), pp.654-669.
- [7] Arner, D.W., Barberis, J. and Buckley, R.P., 2015. The evolution of Fintech: A new post-crisis paradigm. *Geo. J. Int'l L.*, 47, p.1271.
- [8] Zetsche, D.A., Buckley, R.P., Barberis, J.N. and Arner, D.W., 2017. Regulating a revolution: from regulatory sandboxes to smart regulation. *Fordham J. Corp. & Fin. L.*, 23, p.31.
- [9] Han, J., Huang, Y., Liu, S. and Towey, K., 2020. Artificial intelligence for anti-money laundering: a review and extension. *Digital Finance*, 2(3), pp.211-239.
- [10] Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., Kabasinkas, A., Tidjani, C., Ozturkkal, B. and Cerneviene, J., 2024. Enhancing portfolio management using artificial intelligence: literature review. *Frontiers in artificial intelligence*, 7, p.1371502.
- [11] Jang, J. and Seong, N., 2023. Deep reinforcement learning for stock portfolio optimization by connecting with modern portfolio theory. *Expert Systems with Applications*, 218, p.119556.
- [12] D'Acunto, F., Prabhala, N. and Rossi, A.G., 2019. The promises and pitfalls of robo-advising. *The Review of Financial Studies*, 32(5), pp.1983-2020.
- [13] Huang, A.H. and You, H., 2023. Artificial intelligence in financial decision-making. In *Handbook of Financial Decision Making* (pp. 315-335). Edward Elgar Publishing.
- [14] Guo, J., Wang, S., Ni, L.M. and Shum, H.Y., 2024. Quant 4.0: engineering quantitative investment with automated, explainable, and knowledge-driven artificial intelligence. *Frontiers of Information Technology & Electronic Engineering*, 25(11), pp.1421-1445.
- [15] Bartram, S.M., Branke, J. and Motahari, M., 2020. *Artificial intelligence in asset management*. CFA Institute Research Foundation.
- [16] Luo, X., Tong, S., Fang, Z. and Qu, Z., 2019. Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science*, 38(6), pp.937-947.
- [17] Akter, S., Hossain, M.A., Sajib, S., Sultana, S., Rahman, M., Vrontis, D. and McCarthy, G., 2023. A framework for AI-powered service innovation capability: Review and agenda for future research. *Technovation*, 125, p.102768.
- [18] Huang, M.H. and Rust, R.T., 2021. A strategic framework for artificial intelligence in marketing. *Journal of the academy of marketing science*, 49, pp.30-50.
- [19] Cao, L., Yang, Q. and Yu, P.S., 2021. Data science and AI in FinTech: An overview. *International Journal of Data Science and Analytics*, 12(2), pp.81-99.
- [20] Beijing National Fintech Certification Center Co., Ltd., China Cybersecurity Review Technology and Certification Center, China Financial Certification Center, etc. (2021). *Research Report on the Evaluation System for Artificial Intelligence Financial Applications [R]*. Beijing: Beijing National Fintech Certification Center Co., Ltd.
- [21] Maple, C., Szpruch, L., Epiphanou, G., Staykova, K., Singh, S., Penwarden, W., Wen, Y., Wang, Z., Hariharan, J. and Avramovic, P., 2023. The ai revolution: opportunities and challenges for the finance sector. *arXiv preprint arXiv: 2308.16538*.

- [22] Huang, A.H. and You, H., 2023. Artificial intelligence in financial decision-making. In Handbook of Financial Decision Making (pp. 315-335). Edward Elgar Publishing.
- [23] Černevičienė, J. and Kabašinskas, A., 2024. Explainable artificial intelligence (XAI) in finance: a systematic literature review. *Artificial Intelligence Review*, 57(8), p.216.
- [24] Lin, Y. (2023) 'An Analysis of the Application and Development of Explainable Artificial Intelligence in the Financial Industry', *China Credit Card*, (7), pp. 55 - 58.
- [25] Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K. and Galstyan, A., 2021. A survey on bias and fairness in machine learning. *ACM computing surveys (CSUR)*, 54(6), pp.1-35.
- [26] Zhang, R. Y. (2024) 'Research on the Formation Motivation and Governance Countermeasures of Algorithmic Discrimination of Platform Enterprises', *E - Commerce Letters*, 13, p. 235.
- [27] Mokhtari, S., Yen, K.K. and Liu, J., 2021. Effectiveness of artificial intelligence in stock market prediction based on machine learning. *arXiv preprint arXiv: 2107.01031*.
- [28] Nie, Y., Kong, Y., Dong, X., Mulvey, J.M., Poor, H.V., Wen, Q. and Zohren, S., 2024. A survey of large language models for financial applications: Progress, prospects and challenges. *arXiv preprint arXiv: 2406.11903*.
- [29] Kanaparthi, V., 2024. Transformational application of Artificial Intelligence and Machine learning in Financial Technologies and Financial services: A bibliometric review. *arXiv preprint arXiv: 2401.15710*.
- [30] Ma, S.L. and Wei, F.Y. (2018). 'Application of Artificial Intelligence Technology in the Financial Field: Main Difficulties and Countermeasures'. *Southern Finance*, (3), pp. 78–84.
- [31] Tchametsky, M. and Vogt, F., 2023. An artificial intelligence cycle model against the shortage of skilled professionals-an AI-based holistic solution approach for human resources. *Journal of Applied Economic Sciences (JAES)*, 108.
- [32] Yang, D. (2018) 'Regulatory Technology: Regulatory Challenges and Dimensional Construction of Fintech', *Social Sciences in China*, 5(2).
- [33] Ridzuan, N.N., Masri, M., Anshari, M., Fitriyani, N.L. and Syafrudin, M., 2024. AI in the financial sector: The line between innovation, regulation and ethical responsibility. *Information*, 15(8), p.432.
- [34] Hu, H. M. (2024) 'An Inquiry into the Allocation of Liability for Illegal Acts of Artificial Intelligence', *Advances in Law Science*, 6(2), pp. 113 - 124.
- [35] Jin, J. & Zhang, Y. (2022) 'Research on the Development, Risks and Countermeasures of Finance from the Perspective of Artificial Intelligence', *Economic Research Guide*, 2022(12), pp. 74 - 76.