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Research on Machine Learning Implementation and Fintech Ecosystem Construction in the Upgrade of Digital Financial Services

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Abstract: As digital finance continues to develop; many more applications of machine learning are now being rolled out. As shown in the above content, this technology is now mature, and the structure of financial institutions operating logic has changed. This article will take the application of technology and the building of an ecosystem as the two main directions for analysis, and it is argued that current machine learning has moved beyond the proof-of-concept stage and is beginning to be deeply integrated into the core business processes. The extent to which this will be realised in practice will not depend solely on technology but also on the support provided by the fintech ecosystem. The article will present the stage features of implementation, the efficiency limits in application scenarios, the basic components of the ecosystem architecture, the value creation mechanism for multi-party cooperation, and current institutional obstacles, in sequence. The purpose is to show the two-way causal empowerment effect of machine learning on the fintech ecosystem, and a delay in either will reduce the others effectiveness. The main conclusion i s that the depth of technology application depends on the completeness of the ecosystem, and continuous reconfiguration of the ecosystem relies on the incremental benefits brought by technology application to all participants.

Keywords: Digital finance; Machine learning; Technology implementation; Financial technology ecosystem.

1. Introduction

In 2025, the two main constructions of the digital finance policy system took place. In March, the State Councils General Office issued the "Guiding Opinions on Doing Well in the 'Five Major Projects' of Finance", which incorporated digital finance into the national strategy; in December, the National Financial Supervisory Administration issued the "Implementation Plan for High-Quality Development of Digital Finance in the Banking and Insurance Sectors" and proposed 33 specific tasks in terms of governance structure, technology application and risk supervision. The two documents have the same idea: Digital finance is no longer an option for financial institutions; now, all parts of the industry have begun to demand it.

The Speed of application for machine learning in finance has also exceeded expectations. According to the iResearch Financial Technology Development Insight Report in the AI Era, in 2025, Chinese financial institutions will invest 14.4 billion yuan in AI products, and this amount is expected to reach 57.92 billion yuan by 2030. An increase in investment will not lead to new technologies automatically. ICBC has finished the private deployment of the DeepSeek large model and integrated it into the business system in a few months; most small and medium-sized banks are still at the stage of external procurement and partial trial use. This difference is not due to a lack of technology but rather to systemic deficiencies in institutional environment, data foundation and talent reserve [1].

This paper starts from this point. Most of the existing research on machine learning in finance and the construction of the fintech ecosystem has been conducted separately, and few studies have integrated the two. This paper will attempt to fill this gap and puts forward the following questions: How is the progress of machine learning application? What kind of benefits have been achieved? What are the components of the ecological conditions for implementing it? How Do Technology and Ecology Interact in Practice? The stages of implementation, representative applications, ecological architecture, cooperative mechanisms and structural constraints are presented sequentially in the article to provide a causal basis for the descriptive analysis.

The Implementation Logic: From Scenario Selection to System Embedding

Application of machine learning in digital finance is not a simple problem that can be solved by building a system alone. There are multiple levels and corresponding lower bounds. The time from 2018 to 2022 can be viewed as the test period. At present, most applications of machine learning by financial institutions are concentrated in peripheral areas, such as intelligent customer service and product recommendations. They used off-the-shelf solutions for their needs; these had a low risk and did not change their core business. Everyone was uncertain, and the deployment speed was relatively slow, with a small investment scale. In 2023, the era of large models started to change. It had a lower cost and was more efficient; now, technologies have been introduced in several parts of the business, such as credit approval, anti-fraud inspection and compliance checks. Large models have been released by the lab and are now in use. As shown in the iResearch data, 80.6% of the financial institutions have added artificial intelligence to their "top-tier strategic goals". The remaining 19.4 per cent of institutions that have not included AI in their top-level plans will likely face significant competitive disadvantages in the coming years; technological iteration is happening at a high speed. If you are even slightly behind, it will be more difficult to catch up later [2].

Between "wanting to use" and "actually being able to use", at least three barriers must be surmounted: computing power, data and organisation. Computing Power is Expensive. Shanghai Pudong Development Bank (SPDB) has established a cluster of thousands of heterogeneous computing resources based on Huawei Ascend servers, and China Construction Bank (CCB) has also used its own computing resources for the adaptation training of large model financial scenarios. These investments are usually in the hundreds of millions of yuan, and small and medium-sized institutions simply cannot bear the cost; they are unable to calculate the cost and must wait and watch. The Quality and Quantity of the data used to train the model directly affect how well the model works in practice. The large bank has amassed a larger volume of organised and high-quality data compared with the regional bank. The latter have smaller data volumes and lower standardisation, and the same model may yield different results. SPDB set up an artificial intelligence centre to connect R&D with the business side of the company at the same time. In short, if the company fails to adapt at this time, the new equipment will be useless and cannot improve working efficiency. Technology is only one part of the whole in the end. Whether the organisation can understand it and adjust the process is often the deciding factor in whether it will be implemented successfully. Large institutions are constructing systems and capabilities; small institutions are still buying tools and conducting trials. The distance between the two is not decreasing; it is increasing [3].

2. The Boundaries of Efficiency: Empirical Investigation of Three Core Scenarios

The other is a division of institutions. How much value does the realised application bring to a specific business case? Machine learning is applied to a particular area of the business to determine whether it can provide tangible benefits, and which parts are still likely exaggerations.

The oldest kind of application is credit risk management. Traditional risk control is based on expert scoring cards and fixed credit indices, and thus is inadequate for handling "creditless" groups. Machine learning expands the coverage by incorporating traditional strong signals (credit history, assets and liabilities) and non-traditional weak signals (social security contributions, changes in housing provident fund, APP behaviour sequences). The research team at the University of Science and Technology of China used almost nine million credit application data from a state-owned bank to find that, after adding an AI scoring model, the loan approval rate for low-income and creditless groups was higher, and the default rate did not increase correspondingly. AI has discovered some high-impact predictors that the previous models did not. Haier Consumer Finance applies RNN, Transformer and other sequence models to analyze the time-series data of the PBOCs credit reports, accurately identifies "borrowing to repay borrowing" behaviour, and has increased the efficiency of early risk detection by 10 per cent. It is not a large number, but it shows that the risk-control logic has shifted from static profiling to dynamic behaviour monitoring [4].

Intelligent customer service and precise marketing are also areas for intensive application that have a different value logic than risk control. China Merchants Banks "AI Xiaozhao" handles more than a million conversations daily, has an accuracy rate of over 90% for common questions, and serves more than 20 million customers each month. Behind this data is the concept of "substitution" to replace human labour with machines for standardised, repetitive work to reduce operating costs [5]. Microfinance also has the same two expectations. After five months of operation of "AI Credit Expert", the consistency rate between AI and manual approval increased from 39% to 90%. When AI judgment is combined with manual review, the technical conditions for being replaced by scale have been met, and the response speed of micro-credit financing for small and medium-sized enterprises is expected to be significantly improved. This case also shows the two logical patterns of "discovery" and "substitution"—AI can find good customers that manual review would have missed, and it also has the technical foundation to replace manual review.

3. Composition of the Ecosystem: Who Supports the Implementation of Technology

A single-point scenario may be suitable in principle, but it will be difficult to implement practically without a system. If we believe that technology can answer the question of "whether it is feasible", then building an ecosystem is to address the problems of "how to keep it running" and "how to achieve it together". Fintech ecosystems are not only sets of technologies but also living systems that include banks, internet companies, regulatory authorities, universities and scholars, the general public, etc. Observing the operation of this system can be done at three levels [6].

At the infrastructure level, computing power, data and platforms provide the material support for running the ecosystem. The Peoples CCB and the National Data Bureau have jointly launched the "data element ×" pilot program and promoted the construction of financial data standards simultaneously. These efforts may not show results in the short term, but precisely because there are no standards, data circulation has been poor. Incompatible Interfaces cannot transmit models trained at other institutions, and the cost of cooperation is relatively high. The Qianyi platform of Haier Consumer Finance has added more than 12 million lines of code cumulatively. As shown in the figure, platform construction can only be realised by continuous investment; there is no shortcut.

At the level of policy and regulation, the policy deployment for 2025 has generally established the institutional system of the ecosystem. Artificial intelligence is mentioned several times in the "Implementation Plan", and "full use of the innovative leading role of new technologies such as artificial intelligence" is explicitly required. At the same time, the digitalisation of regulation is also advancing; the Shandong Regulatory Bureau has built a smart regulatory system based on machine learning, knowledge graphs and NLP technology, and the abnormal trading behaviour intelligent monitoring project of the Shenzhen Stock Exchange has been rolled out in the internal production environment. The regulatory function has changed from "external constraints" to "system components", and this is a typical feature of the fintech ecosystem compared with general technology industry ecosystems [7].

The Third Level is Cooperative Incentives. Infrastructure and policy frameworks are necessary but not sufficient conditions. The ecosystem will only work if all the parties are willing to cooperate proactively without having to be reminded. China UnionPay, in cooperation with the Bank of Communications, Fudan University and Shanghai Artificial Intelligence Laboratory, has launched the national artificial intelligence application pilot base. Ant Digital Technology has led more than a dozen enterprises to establish a "Financial Intelligent Body Application Joint Creation Alliance". The reasons for the above collaborations are that each party has gained something it could not have achieved on its own: large institutions have gained an all-over view of the situation; technology companies have learned about financial business; and academic institutions have encountered real-life problems. Only when this two-way or multiple ways of value flow are the norm will the ecosystem be able to self-reinforce.

4. The Dilemma of Collaboration: Incentive Compatibility and Capability Differentiation

The two structural problems that have yet to be addressed to unlock the full potential of machine learning are insufficient incentive compatibility and the deepening division of capabilities. These two problems are intertwined and work together to increase the risk of a complete failure.

First, we have incentive compatibility. McKinsey published the "Global Banking Annual Report 2025" and presented the data. After the full-scale implementation of AI in banking, some cost items fell by 70%, but the technology investment itself added to these costs; furthermore, there were continuous operating and maintenance expenses that reduced the net saving to about 15% - 20%. Although the large institutions deemed this investment-to-output ratio reasonable, smaller institutions could not afford it; the initial threshold was too high, the return was uncertain, and they could not compete in terms of budget, so they were unable to make such a decision [8]. According to iResearch data, 75 per cent of the financial institutions that have introduced AI list "cost reduction and efficiency improvement" as the main reason. Everyone was concerned about saving money, but no one was taking the lead to drive cooperation among organisations in the ecosystem. For the cooperation in technology output, data sharing and joint modelling to be effective, all parties need to feel that it is worth doing. The problem is that such a situation of "everyone can manage" is not yet widespread.

Capability differentiation is shown below. Large banks and leading fintech companies have already completed the entire chain of computing power, models and business. Small and medium-sized institutions are still buying off-the-shelf systems and using external suppliers. Moreover, differentiation will occur spontaneously; the data generated by the operation of the business will drive model optimisation independently. The data of large banks are accumulating more and more, and the models are becoming more accurate with their use; the business volume of small and medium-sized institutions is relatively small, and a data loop cannot be formed, so the gap will only widen further. Over time, they will no longer have the will to fight. There have been some policies at the top level. The large institutions are to provide technical support for the small institutions in the "Implementation Plan for High-Quality Development of Digital Finance in the Banking and Insurance Sectors". The direction is correct, but the market-based mechanism has not been realised. Technology output is not only a collection of software but also includes adaptation and maintenance, personnel training, cost allocation, and revenue sharing, none of which have been clearly specified in the current system [9].

5. Structural Constraints and Possible Breakthrough Directions

The above problem is not a local technical issue but is due to its stage characteristics. With the rapid development of technology and applications, systems and cooperation mechanisms have not kept up, and as a result, several deficiencies have arisen that need to be addressed [10].

The first reason for the lack of data circulation is an obstacle. Financial data contain private information and business secrets, and due to security and compliance reasons, cross-institutional data sharing has high institutional costs. The "data element ×" pilot program organised by the PBOC and the construction of a financial data standards system are both to reduce circulation costs at the institutional level. Standardisation is only the first step; problems of data ownership, revenue sharing and responsibility division have not been addressed at the execution level either.

If the data is an obstacle at the circulation level, then model explainability will be lacking in the decision-making stage. Deep learning models are "black boxes", so it is difficult to explain why a particular decision has been made to customers in certain scenarios, such as credit approval; when a model declines a loan application, the financial institution needs to provide a specific reason, but the decision path of a neural network cannot be easily converted into human-readable rules. The financial industry is relatively open, and thus does not have the same high demand for traceability, auditability and accountability in its decisions.

There is a shortage of cross-disciplinary talents at all times. Those who are accustomed to financial business are unfamiliar with algorithms, and those who know algorithms do not know financial situations and regulatory requirements; thus, there is often a mismatch in the structure of knowledge that results in a disconnection between technology procurement and business needs [11]. The cycle of talent cultivation is much longer than the speed of technological iteration; therefore, the talent gap cannot be addressed through traditional education in the short and medium term and a continuous re-training mechanism for the institution needs to be established. Finally, more basic than data and models is the question of people.

The above constraints suggest that the deep application of machine learning technology in digital finance has reached the stage of "institutional adaptation". The technology is no longer the bottleneck; the problems are now about how to ensure the smooth flow of data within the compliance system, how to explain the decision-making logic of the model to regulators and customers, and whether there are sufficient personnel to grasp both the potential and the constraints of the technology for financial business simultaneously.

6. Conclusion

Based on the discussion in the above sections, a basic judgment can be made: the application of machine learning in digital finance and the construction of the fintech ecosystem are not two independent paths but rather the two ends of a two-way causal chain. The depth of technology application is limited by the completeness of the ecosystem; if the supporting infrastructure, such as computing power, data and talent, is not solid, then the technology will only remain at the stage of point-based applications, lack an ecosystem for support, and the investment in technology will be wasted. At the same time, the restructuring of the ecosystem also needs continuous additions of tangible benefits from technology in real-world business operations; otherwise, cooperation will lack a reason.

From the perspective of industry practice, at present, this causal chain is mainly driven by "technology pulling". In recent years, the development of machine learning has indeed led financial institutions to increase the speed of deployment and, in turn, have required regulators and industry organisations to improve institutional supply. However, the "ecosystem pull" end has not been realised yet. Transaction costs of data circulation, capability output and collaborative innovation are still relatively high. Strengthen the technology side as well, or there will be some bottlenecks in the future. This is a serious defect that has been reported in many places by the industry.

In the 15th Five-Year Plan period, it is necessary to change the focus of policy from promoting the introduction of technology to reducing the institutional costs of ecosystem cooperation. Data standards need to be introduced more rapidly; at the same time, an operational plan should be established for pricing and revenue-sharing of technology outputs, and whole-industry talent cultivation requires comprehensive coordination. Only when the technology side and the ecosystem side work together continuously will digital finance be able to move from an investment-driven stage to an efficiency-driven and value-creation model. Of course, this article is mainly based on public industry reports and institutional practice cases, and does not delve into the different demands of various types of institutions in ecosystem cooperation sufficiently. In the future, some detailed classifications will be added in this direction.

References

[1] Fenwick, M., & Vermeulen, E. P. (2020). Banking and regulatory responses to FinTech revisited—Building the sustainable financial service "ecosystems" of tomorrow. Singapore Journal of Legal Studies, 165-189.

[2] Farboodi, M., & Veldkamp, L. (2021). A model of the data economy (NBER Working Paper No. w28427). National Bureau of Economic Research. https://doi.org/10.3386/w28427

[3] Guo, Y., Liu, X., & Zhang, M. (2025). From advantage to disadvantage: How FinTech impacts small banks? Financial Innovation, 11, Article 124. https://doi.org/10.1186/s40854-025-00714-1

[4] Bhatore, S., Mohan, L., & Reddy, Y. R. (2020). Machine learning techniques for credit risk evaluation: A systematic literature review. Journal of Banking and Financial Technology, 4, 111-138. https://doi.org/10.1007/s42786-020-00022-3

[5] Grennan, J., & Michaely, R. (2021). FinTechs and the market for financial analysis. Journal of Financial and Quantitative Analysis, 56(6), 1877-1907. https://doi.org/10.1017/S0022109021000305

[6] Lee, I., & Shin, Y. J. (2018). FinTech: Ecosystem, business models, investment decisions, and challenges. Business Horizons, 61(1), 35-46. https://doi.org/10.1016/j.bushor.2017.09.003

[7] Colaert, V. (2018). RegTech as a response to regulatory expansion in the financial sector. SSRN, 2677116. https://doi.org/10.2139/ssrn.2677116

[8] Begenau, J., Farboodi, M., & Veldkamp, L. (2018). Big data in finance and the growth of large firms. Journal of Monetary Economics, 97, 71-87. https://doi.org/10.1016/j.jmoneco.2018.05.002

[9] Arner, D. W., Barberis, J., & Buckley, R. P. (2017). FinTech, RegTech, and the reconceptualization of financial regulation. Northwestern Journal of International Law & Business, 37(3), 371-413.

[10] Alt, R., Beck, R., & Smits, M. T. (2018). FinTech and the transformation of the financial industry. Electronic Markets, 28(3), 235-243. https://doi.org/10.1007/s12525-018-0312-7

[11] Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. Journal of Management Information Systems, 35(1), 220-265. https://doi.org/10.1080/07421222.2018.1440766