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Analysis of the Impact of Artificial Intelligence on the Digital Transformation of China's Financial Industry

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Abstract. With the rapid expansion of the digital economy, artificial intelligence technologies including machine learning and big data analytics have been widely applied across banking, insurance and securities sectors, fueling the intelligent upgrading of China's financial industry. This paper systematically explores the multifaceted impacts of artificial intelligence on the digital transformation of China's financial industry, supported by practical cases of leading financial institutions and industrial operational data from 2021 to 2025. The research indicates that artificial intelligence restructures financial service procedures, establishes full-process intelligent risk control mechanisms, and optimizes internal digital management and resource allocation, which cuts operational expenses and expands inclusive financial services. Nevertheless, the transformation is restricted by uneven algorithm implementation, insufficient capital and interdisciplinary talents among small and medium financial institutions, as well as emerging risks such as algorithm bias and AI-powered fraud. This study proposes targeted countermeasures covering layered technical application, unified industrial data standards, policy support for grassroots institutions and full-cycle intelligent supervision. The findings offer practical references for financial digital upgrading and fintech regulatory governance, facilitating high-quality digital transformation of the whole financial sector.

Keywords: Artificial intelligence, digital transformation, financial industry

1. Introduction

Fueled by the worldwide boom of digital economy, artificial intelligence technologies covering machine learning, big data analysis, natural language processing and intelligent algorithm modeling have profoundly changed the service modes and operational frameworks of the global financial industry. In China, the deep integration of financial technology and traditional finance has become an inevitable trend in industrial development over the past five years. Banking, insurance, securities and consumer finance institutions are actively investing in intelligent transformation to replace inefficient offline manual workflows, expand service coverage for vulnerable groups and strengthen risk prevention capabilities. Different from traditional financial operation modes limited by fixed outlets, long approval cycles and static risk judgment, Artificial Intelligence (AI) relies on real-time data computing and multi-dimensional user portraits to break time and geographical restrictions, laying a solid technical foundation for the large-scale popularization of inclusive finance. Under this

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industrial background, systematically studying the dual-sided influence of artificial intelligence on the digital transformation of China's financial sector carries important theoretical significance and practical guiding value.

A large number of overseas and domestic scholars have carried out relevant research on AI finance in recent years. Foreign literature mainly focuses on the efficiency improvement effect of intelligent algorithms in mature capital markets, while most domestic studies only discuss single application scenarios such as intelligent customer service or credit risk control. However, most existing research fails to build a complete research framework that integrates business operation, risk management and internal institutional governance. Moreover, few scholars distinguish the transformation gaps between large financial conglomerates and grassroots small and medium-sized financial institutions, and insufficient attention has been paid to emerging hidden risks accompanied by the popularization of financial AI, including algorithm bias, model black boxes and deepfake fraud. Relevant targeted solutions matching China's domestic regulatory environment and industrial characteristics are also relatively scarce, leaving obvious research room for further exploration.

On the basis of sorting out relevant industrial data and typical practical cases of leading financial institutions from 2021 to 2025, this paper makes a comprehensive and systematic analysis. It first elaborates the three major positive impacts of AI on financial digital upgrading, then summarizes three core obstacles from technical, institutional and risk dimensions, and finally proposes multi-dimensional targeted optimization countermeasures. This research intends to make up for the deficiencies of existing fragmented research, provide differentiated transformation suggestions for financial institutions of different sizes, and supply empirical references for financial regulators to formulate standardized intelligent supervision systems, so as to promote the safe, compliant and high-quality digital transformation of China's entire financial industry.

2. Positive impacts of AI on financial digital transformation

Against the backdrop of booming digital economy, artificial intelligence represented by machine learning, big data analytics, natural language processing and intelligent modeling has been widely applied in banking, insurance, securities and other financial sectors. Covering business operation, risk control and internal management, AI promotes comprehensive digital and intelligent upgrading of the financial reshapes the service supply mode and commercial logic of traditional finance profoundly [1]. Based on industrial data and practical cases of leading domestic financial institutions from 2021 to 2025, AI has become a core driving force for the financial industry to cut operating costs, improve operational efficiency and expand inclusive financial coverage [2].

2.1. Promoting digital upgrading of financial business and restructuring operation processes

Traditional financial businesses rely heavily on offline manual handling, limited by cumbersome procedures, long approval chains and fixed business hours. Such mode increases institutional operating costs, and fails to meet customers' demand for round-the-clock, high-efficiency financial services [3]. Large-scale AI application realizes automation and online transformation of financial workflows, accelerating the shift from offline counter services to intelligent online services.

In credit approval, Ping An Bank optimizes its whole credit process via AI risk control models and big data credit investigation system. According to its annual reports from 2021 to 2025, manual credit review used to take 1 to 3 working days, requiring customers to submit paper materials repeatedly at offline branches. After deploying AI intelligent approval system, most small-sum loans can obtain real-time review and instant disbursement, The overall approval efficiency of Ping An

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Bank's microcredit business has increased by more than 80%, with the system automatically completing document verification, data entry and pre-credit screening. Within five years, the bank has reduced basic manual positions in its credit line, cutting labor costs in the credit segment by 37% Furthermore, AI customer profiling based on multi-dimensional data breaks the collateral-dominated lending mode of traditional finance, enabling individual merchants and start-ups without fixed assets to obtain online financing support, and expanding inclusive finance to grassroots markets [2].

In customer service, China Merchants Bank builds an omni-channel AI customer service system covering mobile banking, online banking and offline outlets. The system can solve more than 90% of daily inquiries including account inquiry, transfer guidance and wealth product introduction, providing 7×24-hour uninterrupted services. AI diverts massive repetitive consultation work, enabling human customer staff to focus on high-net-worth client services and complex business disposal [4]. Official data shows customers' average waiting time is shortened by 65%, keeping the bank's customer satisfaction at a leading level nationwide. Besides, AI-powered online customer service has narrowed gaps in regional financial services to a certain extent. Users in remote areas can access consultation services identical to those available to residents in first-tier cities, yet core businesses such as credit granting remain subject to local risk control policies.

To conclude, AI reconstructs financial business workflows, replaces basic manual work with automatic technology, and enriches online service scenarios. It reduces financial institutions' operating costs, optimizes user service experience, and transforms financial services from passive offline reception to active online outreach. With further AI technological maturity, the intelligence level of financial businesses will keep improving [1].

2.2. Enabling intelligent risk control and improving risk early-warning capacity

Risk control is the core lifeline of financial operation, while credit risk, fraud risk and liquidity risk are major hidden dangers for financial institutions. Traditional risk control adopts manual review and static data inspection, featuring delayed risk identification, high misjudgment rate and weak ability to cope with organized financial fraud. Integrated with machine learning, dynamic algorithm modeling and real-time data analysis, AI builds a full-process dynamic intelligent risk control system to guard against modern financial risks [5].

The AI anti-fraud system developed by OneConnect has been adopted by dozens of banks, consumer finance and auto finance institutions. Trained by massive transaction and user behavior data, the system monitors abnormal transactions, fake loan applications and group fraud in real time [3]. Industrial statistics from 2021 to 2025 show that auto finance institutions using this system achieve a 42% annual growth of intercepted fraudulent loan amount, while the non-performing loan ratio drops from 4.8% to 2.1%. Auto financing institutions adopting this anti-fraud system can reduce non-performing assets by 270 million yuan for every 10 billion yuan of credit disbursed. This figure does not apply to other businesses, including corporate loans and personal consumer loans. Different from fixed traditional risk rules, AI models can learn new fraud tactics independently, and build a prevention mechanism covering pre-warning, in-process interception and post-event tracing against deepfake fraud, identity theft and fake capital flow crimes.

In terms of credit risk management, AI makes up for the single-data defect of traditional credit assessment. Traditional credit evaluation mainly depends on central bank credit reports and bank capital flow data, with limited coverage. AI risk models integrate government administrative data, consumption data and social behavior data to build multi-dimensional credit portraits, so as to judge borrowers' repayment ability and willingness accurately. For new graduates, freelancers and start-up

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owners without formal credit records, The AI risk control system greatly enhances pre-event identification capabilities, shifting the financial risk control model from simple post-event disposal of non-performing loans to full-process management covering pre-warning, in-process interception and post-event tracing.

2.3. Accelerating internal digital management reform and optimizing resource allocation

AI has penetrated the internal management system of financial institutions, promoting digital transformation in financial accounting, investment research, administrative management and resource allocation, so as to improve institutional governance efficiency and scientific decision-making ability [6].

Major state-owned commercial banks have deployed AI intelligent financial accounting systems. In the past, financial staff spent plenty of time sorting invoices, checking accounts and making financial statements, accompanied by inevitable manual errors. After AI automation, the system can identify electronic invoices automatically, capture business data and generate financial reports with one click. According to annual reports released by China Banking Association, state-owned banks launched intelligent financial systems, their accounting cycle has been cut by 50%, with errors arising from manual data entry and account reconciliation declining significantly. Only a small number of ambiguous electronic bills still suffer from identification deviations. Financial staff are liberated from basic accounting work to engage in budget management and cost analysis [6].

AI-driven investment research models have become a new industrial trend [7]. Traditional investment research requires analysts to collect macro policies, industry news and listed company data manually, which is time-consuming and subjective. AI research models capture real-time market information, finish data screening and trend analysis automatically, providing data support for investment decisions and institutional strategic planning. Meanwhile, AI can generate resource allocation calculation plans based on regional customer scale and business demands, provide data support for outlet layout as well as manpower and capital allocation, and alleviate the problem of resource misallocation under the traditional model, and improving the overall internal management efficiency of financial institutions [8].

3. Existing problems of AI-enabled financial digital transformation

Although AI brings massive development opportunities to financial digital transformation, the industry still faces three-layer obstacles in technology, institutional operation and risk management affected by regional gaps, technical defects and regulatory environment. Small and medium-sized financial institutions suffer greater transformation pressure, while algorithm risks and new financial risks emerge gradually [9].

3.1. Technical obstacles: uneven algorithm capacity and shallow application

Current AI application in China's financial industry is mostly superficial. Most financial institutions only apply AI to simple work such as automatic customer reply and basic data entry, rather than developing customized technology for core financial scenarios [9].

Firstly, algorithm capacity is highly polarized. Large banks and internet financial enterprises have professional technical teams to develop exclusive algorithm models, while small and medium-sized financial institutions lack independent R&D capacity and can only purchase generic AI systems. Universal algorithms fail to adapt to local industrial characteristics and county-level customer

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features, leading to poor operational. For example, Generic credit algorithms adopted by county-level rural commercial banks fail to align with the operating patterns of characteristic local agriculture, which tends to lead to misjudgments on farmers' debt repayment capacity. Without manual review, loan applications submitted by eligible farmers may get rejected erroneously.

Secondly, defective underlying data governance restricts in-depth AI application. The accuracy of AI models relies on standardized, interconnected and high-quality data, while most financial institutions have fragmented, duplicated and missing internal data. Data silos are prevalent across the banking, insurance and securities industries. Most small and medium-sized financial institutions suffer from low efficiency in data communication among internal business segments, while large institutions have gradually completed the integration of data middle offices. In addition, general generative AI large models have hidden risks including logical bugs and privacy leakage, which cannot meet financial compliance requirements. Developing exclusive financial large models costs much time and capital, slowing down the transformation of cutting-edge AI technology into industrial productivity.

3.2. Institutional obstacles: insufficient capital and compound talent shortage in SMEs

County-level banks, rural commercial banks and small insurance institutions serve grassroots inclusive finance groups, but they face capital shortage and talent scarcity, making their digital transformation far slower than large financial institutions [9]. 2025 industrial research data that Industry survey data for 2025 indicates that the average annual investment in AI technologies by county-level small and medium-sized financial institutions in the surveyed samples is less than one-third of that of national joint-stock commercial banks. Limited profit margin makes small and medium institutions unable to fund AI system procurement and technical team building, forming a vicious cycle of slow transformation and weakened market competitiveness [8].

Financial AI is an interdisciplinary field requiring talents with financial knowledge, algorithm programming, big data technology and regulatory awareness [10]. Domestic universities have limited training capacity for compound financial AI talents, and high-end talents are concentrated in first-tier large financial and technology enterprises. Small and medium-sized local financial institutions are less competitive than top-tier large financial and technology enterprises in terms of salary packages and career development prospects, making it difficult for them to recruit high-end interdisciplinary talents proficient in financial algorithms Even if purchasing advanced AI systems, they cannot operate and upgrade high-end functions without professional staff, widening the digital gap between large and small financial institutions [9].

3.3. Risk obstacles: algorithm bias, model risks and emerging financial risks

While reducing traditional financial risks, AI creates new technology-related financial risks [5]. Firstly, algorithm bias is prevalent. AI models are trained by historical data, so they will inherit and amplify data bias related to region, industry and customer groups [10]. Overseas robo-advisory platforms once set discriminatory service thresholds for low-income groups due to algorithm bias, causing investor losses. Traditional credit models rely excessively on credit reference reports. Practitioners engaged in livestream e-commerce and similar sectors without conventional fixed credit histories are prone to being flagged as high-risk by algorithms, requiring manual verification of operating cash flows to revise evaluation results,resulting in unreasonable loan rejections against inclusive finance principles.

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Secondly, model black box and intelligent fraud risks stand out. Complex deep learning-based AI models suffer from low transparency in their internal reasoning logic. Nevertheless, financial institutions are required to retain all decision-making data, enabling business staff to trace the underlying raw information behind model judgments. Model loopholes will cause batch credit misjudgment and risk control failure, with difficult troubleshooting efficiency [11]. Besides, criminals use AI technology to forge facial features, voices and identity certificates to bypass intelligent verification systems for fraud. AI-enabled new fraud brings unprecedented challenges to financial risk prevention and industry supervision [5].

4. Optimization countermeasures for AI-driven financial digital transformation

Targeting technical defects, institutional dilemmas and new financial risks, this chapter puts forward targeted countermeasures from technology optimization, industrial support and risk supervision, to promote deep integration of AI and finance, and realize high-quality digital transformation of the financial industry [3].

4.1. Deepening AI scenario application and unify industrial data governance standards

First, implement layered AI technological iteration. Large financial institutions develop exclusive generative financial large models and high-end risk control models for wealth management and cross-border financial scenarios relying on technical advantages [7]. Small and medium-sized financial institutions do not need to blindly purchase general large-scale generative AI systems. Instead, they can roll out lightweight customized artificial intelligence tools in phases by addressing their core pain points in credit business and customer service

Second, unify industrial data standards and break data silos. Financial associations and regulatory authorities shall formulate unified standards for data collection, storage and compliant sharing. Financial institutions integrate internal business data and build privacy-protected data sharing platforms to realize cross-institutional data interconnection. Complete industry-wide data cleaning to provide high-quality data support for AI model operation [11].

4.2. Strengthening policy support to solve capital and talent shortages of SMEs

On the one hand, release special financial subsidies for county-level financial digital transformation to reduce small institutions' AI upgrading cost. Encourage leading fintech enterprises including One Connect to output low-cost mature AI systems to grassroots institutions, and implement the "large institution supporting small institution" pairing assistance mode to balance industrial digital development

On the other hand, build diversified compound talent training systems. Universities are optimizing the curriculum system for interdisciplinary fintech programs, rolling out school-enterprise joint practical training projects in tandem, and cultivating reserve students on campus as well as in-service industry technicians in a tiered manner [10]. Promote school-enterprise cooperative training to improve students' practical ability. Small and medium financial institutions shall optimize salary and promotion mechanisms to attract high-end AI talents and organize regular internal technical training to improve existing staff's professional capacity [9].

4.3. Building full-cycle intelligent risk prevention and standardized AI supervision system

Firstly, implement algorithm filing and third-party independent audit. High-risk financial AI models for credit lending, risk control and other scenarios shall complete full filing with regulators, with submissions including explanations of algorithm logic and data sources. Low-risk systems such as basic intelligent customer service may adopt simplified filing procedures Independent third-party institutions conduct regular algorithm inspection to eliminate bias and loopholes, solving the model black box problem [5].

Secondly, improve AI financial regulatory rules and adopt technology-enabled supervision. Regulators update financial supervision regulations to define AI application boundary and liability division and formulate severe punishment rules for AI fraud and data leakage. Build an intelligent supervision platform to monitor industrial AI operation dynamically [5].

Finally, popularize public anti-fraud financial education for AI-related scams. Financial institutions upgrade multi-modal biometric verification technology to resist deepfake fraud. Building a three-dimensional risk control system integrating institutional internal self-inspection, intelligent regulatory monitoring, and national anti-fraud publicity and education. Meanwhile, the industry's intelligent regulatory platform is established to safeguard the compliant and stable development of AI-enabled finance [3].

5. Conclusion

Overall, AI is a core engine for China's financial digital upgrade. Cases of Ping An Bank and China Merchants Bank show automated credit and intelligent customer service slash manual costs, remove geographic service limits and expand inclusive finance for small businesses and freelancers. AI optimizes financial risk management. OneConnect's anti-fraud system detects fraud in real time. Multi-dimensional user credit portraits replace single credit reports, shifting risk control from post-disposal to full-cycle early warning. A prominent digital divide exists between financial institutions. Large firms afford self-developed exclusive algorithms, while small county banks lack funds and compound talents. Generic AI tools poorly fit local grassroots business demands, slowing their transformation. AI introduces unique financial risks. Historical data leads to algorithm bias against emerging industry practitioners. Model black boxes and deepfake-based identity forgery create new fraud threats hard for old supervision systems to tackle. Balanced multi-pronged solutions are required. Institutions adopt tiered AI deployment; authorities unify data standards, offer policy subsidies and talent training. Algorithm filing and real-time intelligent supervision can coordinate innovation and risk control for steady financial digitalization.

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