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# *The Research Progress and Challenges of Intelligent Data Analytics in the Financial Industry*

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***Abstract.*** As the financial industry experiences rapid growth in data volume and increasing complexity, traditional analytical methods find it challenging to fulfill the requirements for efficient and accurate decision-making. Intelligent data analysis technologies like machine learning and big data analytics have been widely applied in the financial sector, enhancing data processing capabilities and decision-making efficiency in areas including financial forecasting, credit evaluation, and investment decisions. In addition, these technologies are instrumental in enhancing risk management, optimizing resource allocation, and fostering innovation within financial services. This paper reviews the research progress in this field, analyzes the theoretical foundations, technical approaches, and key achievements of various methods, and summarizes the current critical challenges, including data quality and privacy protection, model interpretability, algorithmic bias, and regulatory adaptation. The results indicate that despite the improvements in accuracy and automation brought by intelligent data analysis in financial operations, issues concerning transparency, security, and effective deployment remain major challenges. Future efforts can advance the effective application of these technologies in finance by optimizing data governance, improving model robustness, fostering interdisciplinary collaboration, and refining regulatory frameworks.

***Keywords:*** Intelligent data analysis, Machine learning, Big data, Financial forecasting, Risk management

## 1. Introduction

Amid the wave of digital transformation, the financial industry is undergoing profound changes, with computer technology serving as the core driving force. The rise of machine learning, big data, and digital finance has not only driven innovation and transformation but also enabled precise risk assessment and investment decisions by uncovering hidden patterns in vast financial data through complex modeling. Leveraging advanced data processing, big data enables financial institutions to enhance customer insight and operational efficiency. Meanwhile, digital finance utilizes internet and mobile technologies to break through the temporal and spatial constraints of traditional financial services, broadening service boundaries while also enhancing efficiency and accessibility. The widespread adoption of these technologies has significantly improved financial efficiency and competitiveness, promoted market stability and innovation, and deeply influenced the global

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economy. The paper examines the multifaceted applications of computer technology in the financial domain, focusing on its specific influence on financial forecasting, risk management, educational reform, and sustainable finance development. It analyzes the advantages, limitations, and challenges of various technologies, while reviewing current research progress, controversies, and existing gaps. By reviewing diverse literature, this paper highlights key gaps in current research and provides insights to advance financial applications of computer technology and drive sustained innovation.

## 2. The evolution of intelligent data analysis in finance

### 2.1. Rule-driven stage and early applications

The adoption of computer technology in finance began in the mid-20th century, initially aimed at straightforward data processing and transaction tracking. In the 1960s, automated banking was revolutionized by IBM's System/360 mainframe through its centralized transaction processing [1]. In the 1970s, Barclays Bank introduced a SQL-based relational database system, enabling real-time, cross-regional account integration [2]. As computing power and algorithms improved, applications increasingly incorporated intelligence. In the 1980s, Fair Isaac's FICO model introduced statistical credit risk assessment and continues to be widely used today [3]. In the early 1990s, Citibank used neural networks to predict stock volatility. Though limited by data scale and computational power at the time, this validated the potential of nonlinear models in financial forecasting. The large-scale application of big data technology emerged more recently following technological breakthroughs. Post-2010, Goldman Sachs used Hadoop to process petabytes of trading data, enabling real-time high-frequency trading and improving market response [4]. During this phase, mining unstructured data such as social media sentiment and satellite imagery began impacting industry research and credit assessment. Digital finance developed alongside the internet's growth, with the 1995 launch of Security First Network Bank in the United States marking the start of purely online financial services offering basic account management and transfers. The rise of third-party platforms such as Alipay in 2005 accelerated mobile payments and inclusive finance, creating a diverse payments, lending, and investment ecosystem [1].

### 2.2. Data-driven stage and technological breakthroughs

Multi-Layer Perceptrons (MLPs), with their strong nonlinear modeling capabilities, have become increasingly prominent in financial applications. For instance, an eight-layer TensorFlow-based MLP model achieved 85% accuracy in forecasting the Shanghai Composite Index one year ahead, significantly outperforming traditional ARIMA models [5]. In credit scoring, MLPs automatically capture complex feature interactions without assuming linearity, outperforming logistic regression by 37% in KS value based on commercial bank deployment data [6]. Similarly, in financial fraud detection, MLPs surpassed SVMs in both accuracy (85% vs. 72%) and computational efficiency [6]. Compared with Random Forests (RF), MLPs exhibit stronger performance in scenarios requiring nuanced feature interaction modeling. While RF reduces feature space to 15% using Gini-based pruning, it may miss key indicators such as shell company counts, whereas MLPs preserve such features through dense connections, boosting the F1-score by 4.2% [6,7]. However, RF remains more efficient in handling ultra-high-dimensional sparse data like credit card transactions, training over three times faster than MLPs [7]. Despite these advantages, MLPs face challenges such as overfitting in small datasets and the need for regularization and early stopping [5]. They also require tailored attention mechanisms to extract key features from multimodal financial data like text and

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transactions [6]. Moreover, in low-dimensional scenarios, geometric-aware RF (RF-GAP) rivals MLP's accuracy (82% vs. 85%) while reducing training time by 60% [8].

### 2.3. Intelligence-driven stage and financial transformation

The integration of deep learning and natural language processing (NLP) has transformed financial analytics, especially in market forecasting via sentiment analysis. By extracting emotional signals from social media, news, and reviews, these models improve the prediction of market fluctuations, consumer trends, and public opinion risks. Recurrent Neural Networks (RNNs) with LSTM or GRU units effectively model long-term text dependencies, enabling systems like Azure Text Analytics API to achieve over 95% accuracy in multilingual sentiment analysis [9]. Leveraging localized perception and pooling, Convolutional Neural Networks (CNNs) are adept at short-text feature extraction. NLP-Fast enhances this with multi-scale convolutions for sentiment keyword extraction, boosting inference speed by 1.5 times [10]. Meanwhile, Transformer-based models such as BERT capture global context via self-attention, reaching 97.3% accuracy in complex sentiment tasks [11]. Sentiment analysis has become a key tool in financial forecasting. For instance, the Google Cloud Natural Language API detects tone shifts in earnings calls to support investment decisions [9], while BERT-enhanced Twitter sentiment models predict S&P 500 movements with 78% accuracy within 24 hours. In e-commerce, NLP-Fast aids e-commerce by analyzing user reviews [10], while VADER-based systems detect early industrial risks through sentiment analysis [12]. Despite its potential, sentiment analysis struggles with fine-grained distinctions, such as separating constructive feedback from malicious content. Advances like multi-task learning in NLP-Fast improve F1-score by 12% while reducing model size by 80% for edge deployment [10]. Azure Cognitive Services supports over 100 languages via zero-shot transfer with under 3% accuracy loss, and DistilBERT achieves 92% accuracy with only 50ms latency for real-time monitoring [9,12]. Future research targets multimodal sentiment analysis and causal reasoning, aided by tools such as Google Cloud Vision for image-text fusion [9].

## 3. Key applications of intelligent data analysis

### 3.1. Financial prediction and decision management

The financial industry increasingly relies on deep learning and data mining to meet growing data complexity and business demands, exceeding traditional models in accuracy and decision-making. This is particularly evident in financial forecasting, where deep learning excels in crowdfunding, market analysis, and risk assessment by capturing complex patterns efficiently.

In the context of big data, data mining enables financial institutions to conduct in-depth analysis of customer behavior and business data. By incorporating dimensions such as time, geography, and departments, institutions can identify customer statuses, predict demands and churn risks, and boost targeted marketing and service personalization. In enterprise risk management, data mining helps monitor abnormal transactions, detect fraudulent activities, and deliver real-time risk warnings, thus boosting financial security. For financial markets, the completeness and diversity of data enable the identification of patterns, price trends, and shifts in customer demand, providing valuable market insights. Traditional models such as ARIMA and moving averages remain popular for short-term investment forecasting due to their speed and interpretability. However, deep neural networks built with integrated multi-source data, such as historical price movements and logistics indices (e.g., BDI, RFTI), can effectively capture nonlinear relationships, reducing prediction errors from 3.356 to

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1.542 [13]. Leveraging their automatic feature extraction and long-term dependency modeling, neural networks achieve superior multi-series forecasting performance in complex domains such as e-commerce sales [14]. Fraud detection, a critical area of financial security, demands models that are both real-time and adaptive. Rule-based systems, while fast and interpretable, struggle to detect emerging fraud patterns and often suffer from high false positive rates (35%-50%) [15]. Random forest models achieve a high accuracy rate of 99.95% through feature selection but only 75.68% recall. To address class imbalance, generative adversarial networks are used to generate synthetic samples, improving the F1 score to 88.97%. Using ten performance metrics to evaluate 16 models, the comparative analysis showed that machine learning excels at detecting complex fraud patterns. The hybrid model integrating particle swarm optimization with self-organizing maps particularly stood out, achieving an AUC score of 0.93 in specific scenarios [16].

### 3.2. Intelligent transformation in financial education

The emergence of big data and intelligent technologies is driving a transformation in financial education toward more innovative, tech-oriented, and interdisciplinary approaches. As the financial industry undergoes digital transformation, educational systems must respond by cultivating talents who not only possess solid foundational knowledge but exhibit strong data literacy, technological proficiency, and innovation capacity. Traditional financial education, especially in fields such as accounting, faces several structural challenges. These include narrowly defined training objectives focused on theory over practice, limited integration of emerging technologies into the curriculum, a shortage of faculty with both domain expertise and technical skills, and outdated evaluation methods that fail to reflect student development in data-driven contexts. Financial education must pivot toward nurturing applied and cross-functional professionals to stay aligned with the sector's rapidly changing demands. This involves embedding big data and intelligent finance concepts into the curriculum, hence encouraging cross-disciplinary learning that bridges finance, data science, and information systems. Teaching content should be continuously updated to reflect real-world applications, such as intelligent auditing, algorithmic trading, digital financial reporting, and fintech risk management. Faculty development is also a cornerstone of this transformation. Building a diverse teaching team that combines academic strength with technical capability is key. This may involve industry-university collaborations, joint training programs, or technical upskilling for current educators, ensuring that teaching keeps pace with technological progress. In addition, assessment systems need to evolve accordingly, as traditional exam-based methods fall short in evaluating complex competencies like data analysis, systems thinking, and collaborative problem-solving. An intelligent, networked evaluation system, leveraging digital platforms, real-time feedback, and input from multiple stakeholders including peers, instructors, and industry mentors, can provide more comprehensive, dynamic insights into student performance and readiness for industry demands.

### 3.3. Sustainable finance and green growth

By improving efficiency, reducing costs, and enhancing risk management, digital finance facilitates green growth, though its influence varies with technology use and market dynamics. The level of application of technologies like blockchain and big data plays a critical role in stabilizing these effects. The adoption of distributed ledger technology in digital finance platforms effectively lowers default rates in green supply chain financing. However, when the technology penetration rate falls below a certain threshold, it may increase information asymmetry risks. Similarly, in supply chain

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finance, every 10% increase in the coverage of Internet of Things (IoT) technology improves the accuracy of green project identification by 8%. Nonetheless, significant regional disparities exist, eastern regions demonstrate 19% higher efficiency in releasing technological dividends compared to western regions. This shows that technological maturity and the regional digital infrastructure jointly determine the technological threshold for stable performance [17].

The complementarity between digital finance and the traditional financial system is also dynamic. In financially repressed regions, digital finance strongly promotes green transformation among SMEs. However, once the concentration of traditional credit markets exceeds a certain threshold, a crowding-out effect may occur. For instance, for every unit of traditional trade credit replaced by digital finance, the cost of green supply chain financing decreases. Yet, if the banking sector lags in its digital transformation, there may be risks of liquidity mismatch. This highlights the need for structural fit in a changing financial system [18]. The sustainability of digital finance's impact depends on how enterprises respond to green innovation. Quantitative analysis based on Chinese provincial panel data reveals that under digital finance incentives, the intensity of green R&D investment by state-owned enterprises increases significantly, while private enterprises tend to experience a strategic delay of 6 to 12 months. Furthermore, when the yield of green financial products falls below the market average, corporate willingness to pursue green transformation drops by 15% to 20%. These behavioral lags and preference shifts result in phased fluctuations in the green impact of digital finance [19]. Geopolitical risks and economic cycles introduce differentiated effects. During economic upturns, digital finance significantly enhances cross-border financing in the new energy sector, while its effectiveness tends to decline amid external uncertainties. Besides, extreme climate events may amplify the risk transmission effects of digital finance through supply chain disruptions. For instance, following floods, the volatility of green bond interest rates increases markedly. These variations in sensitivity to external shocks highlight the necessity of building a more resilient digital green finance system [20].

## 4. Key challenges and future prospects

Though increasingly applied in finance, computer technologies remain limited in effectiveness and adaptability. The lack of research across varied markets, institutions, and regulatory contexts stems from an overemphasis on specific regions, scenarios, or time periods. Technically, while machine learning and big data excel in solving complex financial problems, their black box nature hinders interpretability, making it hard to meet transparency demands. Methods like LIME and SHAP offer partial solutions, yet their computational cost and instability limit real-time use. Data security and privacy also pose challenges. Techniques like federated learning and differential privacy reduce leakage risks but require high computation and remain vulnerable to attacks, limiting scalability in distributed systems. Imbalanced data leads to algorithmic bias, which in turn restricts AI's role by disadvantaging specific groups in credit evaluations. Though fairness techniques exist, they often reduce model performance and lack standardized metrics. Moreover, multi-technology integration is underexplored. Most implementations target isolated use cases, and combining ML with smart contracts still faces execution, privacy, and compliance issues. Meanwhile, the systemic impact on institutions, regulators, and investors is still insufficiently understood. For instance, AI-driven credit scoring improves efficiency but lacks a clear framework balancing interpretability and privacy. Addressing these challenges requires not only technical solutions, but also coordinated policy and cross-sector collaboration.

Future research in financial technology can advance in several important directions. In particular, expanding the diversity of research samples by including data from different countries, institutions

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of various sizes, and a broad range of financial services can improve the generalizability of findings across global markets. Besides, improving model interpretability is essential. To boost transparency and build trust, research should focus on making machine learning decisions more understandable through novel or refined methods. Moreover, further work is needed on data privacy, algorithmic fairness, and cybersecurity. Establishing relevant technical standards and regulatory frameworks will help ensure the safe and responsible application of computer technologies in finance. And more focus should be placed on technology integration. To foster innovation and real-world impact, research should examine how multiple technologies function together in financial environments. In addition, it is crucial to study interactions among financial institutions, regulators, and technology providers. The understanding of coordination mechanisms will support the sustainable and balanced development of technology in the financial ecosystem.

## 5. Conclusion

The integration of computer technology into finance has driven significant advances in predictive analytics, risk management, fraud detection, and financial education. Identifying complex financial patterns, enhancing decision-making, and increasing operational efficiency are effectively achieved through machine learning, deep learning, and big data analytics. However, challenges like model interpretability, data privacy, algorithmic bias, and multi-technology integration remain critical barriers to widespread adoption. Future research should focus on explainable AI, cross-border studies, and strong regulatory frameworks to ensure transparency, generalizability, and ethical use. As such, collaboration across finance, technology, and policy is crucial for addressing systemic challenges. In this context, as digital transformation advances, the financial sector must balance innovation with accountability to drive sustainable, inclusive growth.

## References


[1] Zhou, L., et al. (2020). An analysis of the application of computer technology in internet finance. Satellite TV and Broadband Multimedia, 04.

[2] Song, J. (2017). Research on the relationship between financial information management and modern computer technology. Science & Technology Communication, 23, 110-111.

[3] Chamberlin, D. D. (2012). Early history of SQL. IEEE Annals of the History of Computing, 34(4), 78-82.

[4] Ren, Z. (2010). Solving business problems with SQL Server 2005 Analysis Services. Innovative Computing and Communication and Asia-Pacific Conference on Information Technology and Ocean Engineering, International Conference on, 79-82.

[5] Gong, S., et al. (2021). An empirical analysis and research on the prediction of stock trends based on the MLP neural network model. International Conference on Artificial Intelligence and Blockchain Technology , 28-33.

[6] Yuan, F., et al. (2025). Money laundering risk prediction in financial transactions based on the multilayer perceptron model. Financial Technology Era, 3.

[7] Ziegler, A., & König, I. R. (2014). Mining data with random forests: Current options for real-world applications. WIREs Data Mining and Knowledge Discovery, 4(1), 55-63.

[8] Rhodes, J.S., Cutler, A., & Moon, K.R. (2023). Geometry- and accuracy-preserving random forest proximities. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(9), 10947-10959.

[9] Pais, S., Cordeiro, J., & Jamil, M.L. (2022). NLP-based platform as a service: A brief review. Journal of Big Data, 9, 54.

[10] Kim, J., et al. (2021). NLP-Fast: A fast, scalable, and flexible system to accelerate large-scale heterogeneous NLP models. International Conference on Parallel Architectures and Compilation Techniques, 75-89.

[11] Zhang, W.J., et al. (2018). On definition of deep learning. In 2018 World Automation Congress (WAC), 1-5.

[12] Ma, Y. (2025). Analysis of software development systems based on natural language processing. Network Security Technology and Application, (3), 69-72.

DOI: 10.54254/2753-8818/2025.GL25964

[13] Muanchang, S., et al. (2024). Diesel price prediction models with traditional time-series algorithms and neural networks. International Joint Conference on Computer Science and Software Engineering, 246-252.
[14] Garnier, R. (2021). Concurrent neural network: A model of competition between time series.
[15] Akouhar, M., et al. (2024). A deep learning and resampling approach to credit card fraud detection. International Conference on Wireless Networks and Mobile Communications, 1-6.
[16] Arora, S., & Kumar, D. (2017). Selection of optimal credit card fraud detection models using a coefficient sum approach. International Conference on Computing, Communication and Automation, 482-487.
[17] Yao, S., Li, T., & Li, Y. (2023). Promoting sustainable fossil fuels resources in BRICS countries: Evaluating green policies and driving renewable energy development. Resources Policy, 85(Part A), 103990.
[18] Liu, T., et al. (2022). Supply chain finance and the sustainable growth of Chinese firms: The moderating effect of digital finance. Frontiers in Environmental Science, 10, 922182.
[19] Zhou, M., & Li, X. (2022). Influence of green finance and renewable energy resources over the sustainable development goal of clean energy in China. Resources Policy, 78, 102816.
[20] Li, R., Liu, Z., Li, S., Geng, J., Shi, G., & Gu, X. (2023). Geopolitical risk, green finance and natural resources: A novel analysis of China's national level data. Resources Policy, 86(Part B), 104221.