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Artificial Intelligence in Smart Finance: Applications, Challenges and Future Trends

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Abstract. The rapid development of financial technology (FinTech) has accelerated the integration of artificial intelligence (AI) into smart financial services. AI-driven technologies have significantly improved the efficiency, accuracy, and intelligence of financial decision-making processes. This study reviews and analyzes major AI applications in smart finance, including heterogeneous data fusion models for credit risk assessment, real-time intelligent algorithms for financial fraud detection, and AI-powered robo-advisory systems. A literature review and case analysis approach is adopted to evaluate the practical effectiveness of these technologies. The findings indicate that AI can substantially improve credit evaluation accuracy, enhance fraud detection capability, and support personalized investment management. Nevertheless, challenges related to data privacy, model explainability, and regulatory compliance remain significant barriers to large-scale deployment. Future developments are expected to focus on federated learning, explainable AI, and generative AI technologies. This study provides a comprehensive overview of current applications, challenges, and future directions of AI in smart finance.

Keywords: Artificial Intelligence, FinTech, Heterogeneous Data Fusion, Financial Fraud Detection, Explainable AI

1. Introduction

The rapid advancement of computing and internet technologies has accelerated the digital transformation of the financial industry. In recent years, artificial intelligence (AI) has emerged as one of the most influential technologies driving innovation in financial services. Smart finance utilizes AI-driven analytical and decision-support systems to improve operational efficiency, reduce financial risks, and enhance customer experience. AI technologies can extract valuable patterns from large-scale transaction records, customer profiles, textual information, and behavioral data, thereby supporting credit risk assessment, fraud detection, portfolio management, and regulatory compliance [1]. Recent studies have demonstrated that machine learning and data-driven approaches are particularly suitable for financial environments characterized by high dimensionality, strong noise, and rapidly changing market conditions [2]. However, the adoption of AI in financial services also raises concerns regarding transparency, fairness, accountability, and ethical governance [3]. Therefore, this study reviews the major applications of AI in smart finance, evaluates their practical

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benefits and challenges, and discusses future development trends through a literature review and case analysis approach.

2. Smart finance and artificial intelligence

Smart finance is not merely the online extension of traditional financial services. Instead, it reorganizes financial service processes through data analytics, algorithms, and automation systems. Financial institutions can use customer behavioral data for credit assessment, identify abnormal activities through real-time transaction monitoring, and reduce service barriers through intelligent customer service and robo-advisory systems. Previous research has identified AI, the Internet of Things, blockchain, and data analytics as key technological foundations supporting the development of smart finance [4]. Machine learning is widely used for classification, regression, clustering, and prediction tasks; deep learning is effective for processing images, text, transaction sequences, and complex nonlinear relationships; natural language processing supports the analysis of news, reports, and customer communications; and graph neural networks can model relationships among accounts, devices, merchants, and transactions. Compared with traditional rule-based models, AI systems can automatically learn complex patterns from data and are therefore better suited to dynamic and high-frequency financial environments.

3. Heterogeneous data fusion models for credit risk assessment

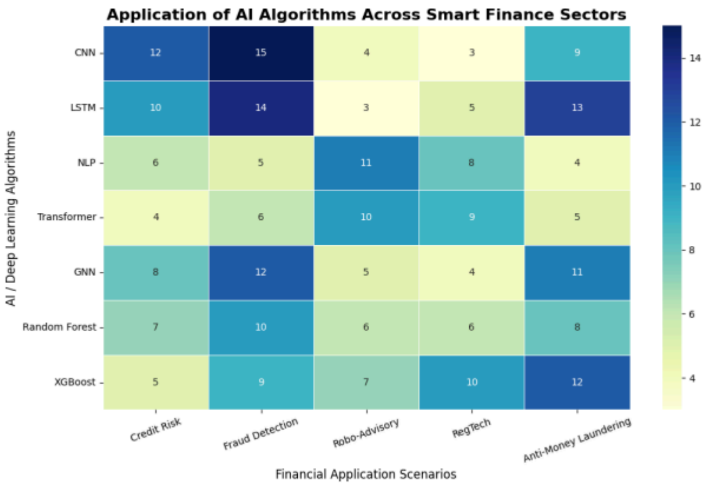

Figure 1. Integrated AI framework for smart financial systems

Credit risk assessment is one of the fundamental applications of AI in smart finance. Traditional credit scoring models mainly rely on structured data, such as income, liabilities, and repayment records. While these data are stable and interpretable, they often provide limited coverage for new customers, small businesses, and individuals with incomplete credit histories. Machine learning methods can incorporate bank transaction records, e-commerce behaviors, device information, textual materials, and social relationships into the evaluation process, thereby creating more detailed risk profiles [5]. The advantage of heterogeneous data fusion lies in its ability to evaluate repayment capacity, transaction stability, behavioral consistency, and external environmental changes simultaneously. For example, the financial statements of small enterprises may be incomplete, but order variations, tax records, supply-chain relationships, and operational cash flows can reveal their actual business conditions. Through feature engineering, ensemble learning, and deep representation

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learning, AI models can improve the sensitivity of default probability prediction. However, the use of diverse data sources also introduces challenges related to privacy protection, authorization boundaries, and model interpretability. If loan applicants cannot understand why a decision was made, trust in financial services may be weakened. Therefore, AI applications in credit risk assessment should maintain human oversight and provide explainable decision mechanisms.

To provide an overall understanding of the relationship between AI technologies and smart financial applications, Figure 1 presents an integrated framework illustrating the distribution of major AI algorithms across different financial service scenarios. The framework demonstrates how machine learning, deep learning, graph neural networks, and natural language processing contribute to financial decision-making, risk management, and service optimization.

As shown in Table 1, AI applications in smart finance can be compared across credit risk assessment, fraud detection, robo-advisory services and regulatory technology, with each scenario relying on different data sources, methods and value contributions.

Table 1. Comparison of artificial intelligence applications in major scenarios of smart finance

Application scenarios	Key data	Common methods	Core Values
Credit risk assessment	Credit records, bank statements, documents, and transaction behavior	Ensemble learning, deep learning, heterogeneous data fusion	Improve the accuracy of credit scoring and expand the coverage of financial services
Transaction fraud detection	Transaction sequence, device fingerprint, account relationship, geolocation	Anomaly detection, graphical models, real-time classification algorithms	Identify unusual behavior and reduce fraud losses
Robo-advisor	Risk appetite, asset prices, news text, portfolio performance	Combinatorial optimization, NLP, reinforcement learning	Lowering investment thresholds and supporting personalized asset allocation
Regulatory Technology	Report data, compliance documents, and operation logs	Text mining, knowledge graphs, and automated censorship	Improve compliance efficiency and reduce human error.

4. Real-time intelligent algorithms for financial fraud detection

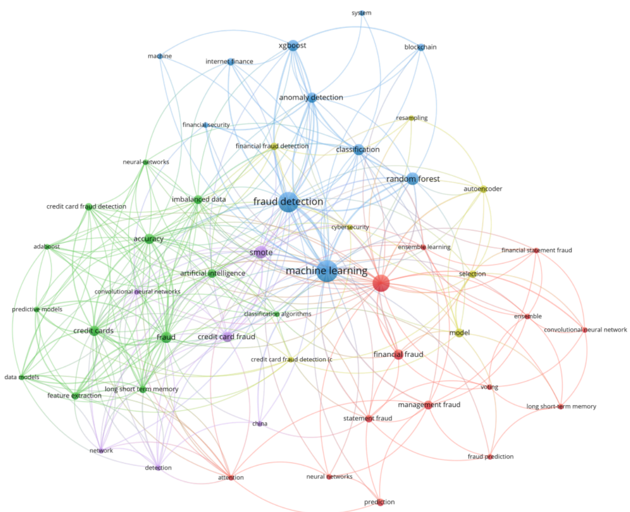

Figure 2. Keyword network of AI research in financial fraud detection

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Figure 2 illustrates a keyword co-occurrence network of AI-related research in financial fraud detection. The visualization reveals major research clusters, including anomaly detection, graph learning, risk management, and deep learning. The network structure indicates the increasing importance of intelligent data-driven approaches in modern fraud detection systems. As shown in Figure 2, financial fraud is characterized by concealment, sudden occurrence, and rapid diffusion. Traditional rule-based systems are often insufficient to identify sophisticated fraudulent activities, whereas AI-driven methods can capture complex behavioral patterns from real-time transaction streams [6]. Real-time fraud detection systems typically include data collection, feature updating, risk scoring, and response management. Features are generated from transaction amount, time, location, device information, merchant characteristics, and account relationships. When a transaction is identified as high risk, the system may trigger SMS verification, manual review, or temporary account restrictions. Graph-based models are particularly important because many fraud schemes involve coordinated activities among multiple accounts, devices, phone numbers, and merchants. Graph neural networks can analyze network structures to identify organized fraud rings, money-laundering chains, and fake transaction networks. Nevertheless, excessive sensitivity may increase false positives, while overly lenient settings may miss high-risk transactions. Financial institutions therefore need layered thresholds and differentiated response strategies [7].

5. Robo-advisors and personalized financial services

Robo-advisory represents an important application of AI in personal finance. These systems analyze questionnaires, transaction records, and risk preferences, then combine asset prices, macroeconomic indicators, and market sentiment to provide portfolio recommendations. Compared with traditional human advisory services, robo-advisors generally offer lower costs, wider accessibility, and more efficient portfolio monitoring [8]. Technically, robo-advisory systems require three core capabilities: customer profiling, asset allocation, and market perception. Customer profiling identifies investors' risk tolerance, investment horizon, and liquidity needs. Asset allocation constructs portfolios across stocks, bonds, funds, cash, and other assets. Market perception analyzes news, reports, and social media information to evaluate market sentiment. Natural language processing and sentiment analysis can provide additional insights for short-term market forecasting and event-driven investment decisions [9]. The value of robo-advisory extends beyond automated product recommendation; it also translates professional investment processes into understandable services for ordinary investors. By explaining risk exposures, concentration levels, and portfolio suitability, these systems can improve customer trust and financial literacy.

6. Comprehensive benefits and challenges of AI in smart finance

Overall, AI brings significant value to smart finance in three main areas: operational efficiency, risk management, and personalized services. First, AI can automate repetitive tasks such as document review, customer segmentation, anomaly screening, and compliance reporting, thereby reducing labor costs. Previous studies have shown that AI and machine learning can improve the efficiency of regulatory reporting and reduce delays and omissions in manual processing [10]. Second, AI enhances financial risk management by shifting risk identification from ex-post analysis to real-time warning systems, particularly in credit risk, fraud risk, and market risk management [11]. Third, AI enables more personalized financial services. Smart finance systems can provide tailored product recommendations and risk alerts based on customer lifecycle characteristics, preferences, and service history. Despite these benefits, large-scale AI adoption also introduces important challenges.

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Data privacy and security become critical when financial data is shared across institutions. Complex AI models often lack interpretability, making it difficult to explain credit decisions, risk controls, and investment recommendations. Algorithmic bias may inherit historical inequalities from training data, while regulatory accountability remains unclear when AI systems cause financial losses. Table 2 summarizes major AI application scenarios in smart finance, and Table 2 outlines key governance challenges and corresponding response strategies.

Table 2. Major challenges and countermeasures of artificial intelligence in smart finance

challenge	Specific manifestations	Response direction
Data privacy and security	Financial data is highly sensitive, and sharing it across institutions and training models can easily cross the boundaries of authorization.	It employs data minimization, federated learning, data anonymization, and access auditing.
The model lacks interpretability.	Complex models struggle to explain the key reasons behind loan rejections, risk controls, or investment recommendations.	Introduce interpretable AI, model documentation, and human review processes.
Algorithmic bias and fairness	Historical biases in the training data may be inherited and amplified by the model.	Conduct deviation testing, cluster assessment, and fairness constraints.
Division of Regulatory Responsibilities	When model errors cause losses, the boundaries of responsibility among institutions, developers, and users are unclear.	Establish a model-based governance system, a record-keeping mechanism, and a regulatory sandbox.

7. Conclusion

Overall, AI brings significant value to smart finance in three main areas: operational efficiency, risk management, and personalized services. First, AI can automate repetitive tasks such as document review, customer segmentation, anomaly screening, and compliance reporting, thereby reducing labor costs. Previous studies have shown that AI and machine learning can improve the efficiency of regulatory reporting and reduce delays and omissions in manual processing [11]. Second, AI enhances financial risk management by shifting risk identification from ex-post analysis to real-time warning systems, particularly in credit risk, fraud risk, and market risk management [12]. Third, AI enables more personalized financial services. Smart finance systems can provide tailored product recommendations and risk alerts based on customer lifecycle characteristics, preferences, and service history. Despite these benefits, large-scale AI adoption also introduces important challenges. Data privacy and security become critical when financial data is shared across institutions. Complex AI models often lack interpretability, making it difficult to explain credit decisions, risk controls, and investment recommendations. Algorithmic bias may inherit historical inequalities from training data, while regulatory accountability remains unclear when AI systems cause financial losses.

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