The Role of Artificial Intelligence Tools in Enhancing Financial Market Efficiency: A Study of Global Models and Experiences

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Abstract:

This study aims to analyze the pivotal role played by Artificial Intelligence (AI) tools—particularly Machine Learning (ML) and Deep Learning (DL)—in enhancing financial market efficiency. The research focuses on how these tools help reduce information asymmetry, improve price prediction accuracy, and accelerate transaction execution, thereby positively influencing the three forms of market efficiency (weak, semi-strong, and strong). The study concludes that AI significantly contributes to improving market efficiency by increasing the accuracy of predictive models compared to traditional ones and by mitigating behavioral biases. Furthermore, global evidence indicates that AI-driven mechanisms, such as algorithmic trading and regulatory technology (RegTech), have strengthened market liquidity and reduced bid-ask spreads, supporting the semi-strong form of market efficiency.

Keywords: Artificial Intelligence, Financial Market Efficiency, Machine Learning, FinTech

JEL Classification Codes: G14, G17, C45, O33, L86

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1. Introduction

The financial market is a fundamental pillar of any economy, playing a pivotal role in efficiently directing and allocating capital across various sectors. Market efficiency—defined as the ability of prices to fully reflect all available information accurately and in a timely manner—serves as a key indicator of market effectiveness and transparency.

With the rise of the technological revolution, artificial intelligence (AI) has emerged as a core component of the FinTech ecosystem, evolving into a strategic tool that reshapes financial market operations. Its role has extended beyond mere mechanization and automation of processes to become an advanced analytical instrument capable of processing vast amounts of complex data and identifying patterns with precision that surpasses traditional human capabilities. This development significantly contributes to enhancing overall financial market efficiency.

Research Problem: To what extent do AI tools contribute to improving financial marketefficiency, considering the latest global models and experiences?

Sub-Questions:

- ✓ What are the theoretical characteristics of financial market efficiency, and how do AI tools support the underlying hypotheses of this efficiency?
- ✓ What are the main AI tools utilized in financial markets, and how do they affect the flow of information?
- ✓ How have global experiences reflected the impact of AI on financial market efficiency?

Significance of the Study:

This study derives its significance from the essential role of financial markets as a critical financing instrument for economic development, which requires ensuring market stability and improving efficiency by facilitating and regulating transactions for both investors and policymakers. The integration of AI tools further enhances market trust, transactional efficiency, and stability, thereby contributing to overall market effectiveness.

Study Objectives:

The main objectives of this study can be summarized as follows:

- ✓ Provide a theoretical foundation for the concept of financial market efficiency and its relationship with the technological revolution.
- ✓ Classify and identify the primary AI tools used in financial services.
- ✓ Present a synthesis of the most successful global experiences in leveraging AI to enhance market efficiency.

2. Theoretical Framework of Artificial Intelligence and Financial Market Efficiency

2.1 The Nature of Artificial Intelligence and Its Leading Tools

Artificial intelligence (AI) has become one of the pillars of the technological revolution, embodying the capacity of computational systems to mimic human cognitive abilities such as learning from experience, reasoning, decision-making, and self-correction (Al-Rashidi, 2024). The concept has evolved significantly—from early attempts in the 1950s to replicate human logic, to a comprehensive analytical ecosystem capable of processing massive datasets at exceptional speed and extracting complex patterns that directly influence economic and financial decision-making.

In the financial sector, AI extends far beyond mechanical automation; it has become a predictive analytical instrument capable of identifying market trends and anticipating future fluctuations with a level of precision that surpasses traditional human judgement. This transformation has positioned AI as a cornerstone of modern digital financial markets (Gomber et al., 2017, p.540). The most prominent AI tools used within the financial system can be summarized as follows:

2.1.1 Machine Learning (ML)

Machine learning is one of the most widely used and impactful branches of AI in financial data analysis. It relies on algorithms that learn autonomously from historical data, improving predictions over time without the need for explicit programming. Techniques such as linear regression, random forests, and support vector machines are used to uncover hidden relationships among financial variables and market behavior (Wang, 2023, p.797).

Recent studies show that the use of machine-learning models in market analysis has increased the accuracy of price-movement predictions to levels ranging between 70% and 80%, outperforming traditional statistical models (Hassan et al., 2024). These models also enhance the detection of price anomalies and support real-time volatility analysis—contributions that reinforce the weak-form efficiency hypothesis of financial markets.

2.1.2 Deep Learning (DL)

Deep learning represents the advanced generation of machine learning. It relies on multi-layered artificial neural networks that imitate the human brain's ability to analyze unstructured data such as text, images, economic news, and social-media posts (LeCun et al., 2015, p.438).

This approach is widely used in sentiment analysis, enabling models to interpret investor sentiment by processing millions of online expressions within seconds and integrating the results into price-prediction models. Studies indicate that incorporating sentiment analysis within pricing frameworks improves short-term prediction accuracy by nearly 15%. Moreover, deep learning helps uncover non-linear patterns in complex financial data, giving institutions stronger capabilities in forecasting systemic risks and identifying emerging investment opportunities (Al-Mohammadi, 2023).

In light of these developments, AI has evolved from a subset of computer science into a comprehensive cognitive and economic framework linking data analytics with quantitative finance. Its role in enhancing financial-market efficiency is evident—whether through improving predictions, expanding the depth of market insight, or reducing behavioral biases among investors.

2.2. The Efficient Market Hypothesis (EMH) in the Age of Big Data

The Efficient Market Hypothesis (EMH) remains one of the fundamental pillars of modern financial theory, asserting that asset prices fully reflect all available information, making it impossible to consistently earn abnormal returns using that information. The hypothesis appears in three main forms, each representing a different degree of market efficiency:

- **Weak Form Efficiency:** Current prices reflect all historical price information; therefore, investors cannot rely on technical analysis to achieve abnormal returns.
- **Semi-Strong Form Efficiency:** Prices incorporate all publicly available information—such as financial statements, economic news, and official disclosures—rendering fundamental analysis ineffective in producing excess returns.

- **Strong Form Efficiency:** Prices reflect all information, including insider (private) information, implying that even corporate insiders cannot consistently outperform the market (Merton, 2021).

However, recent technological developments—particularly the rise of big data and artificial intelligence (AI)—have reopened the debate regarding the practical validity of EMH in modern digital markets. While classical EMH assumes that all market participants access information with equal efficiency, today the decisive factor is the abilityto processinformation, not simply to obtain it.

AI has fundamentally reshaped price discovery mechanisms. Modern algorithms can analyze billions of data points within seconds, including news feeds, social media content, and real-time investor behavior. Consequently, markets that adopt these technologies have become significantly more efficient in absorbing and responding to new information, especially in the short term.

For example, a report by the Bank for International Settlements (BIS, 2024) indicates that markets employing AI and machine-learning tools in data analysis and asset trading adjust prices 35% faster to unexpected events than markets that do not. Similarly, a study by Leippold& Carrel (2024) found that integrating big-data analytics into trading models reduced pricing inefficiencies and improved semi-strong efficiency by an average of 22%.

On the other hand, some scholars argue that AI may not only enhance market efficiency but redefine it altogether. While advanced algorithms help reduce informational asymmetry, the widespread use of similar automated strategies may generate what some describe as "pseudo-efficiency"—a state where collective algorithmic reactions lead to sharp, unjustified price swings (Al-Jubouri, 2024).

Thus, big data and artificial intelligence have not invalidated Fama's hypothesis; rather, they have evolved it toward a concept of "dynamic efficiency." This perspective suggests that market efficiency is not a static condition but depends on the capacity of market participants to utilize advanced analytical tools and AI systems to absorb new information with maximum accuracy and speed.

2.3 The Role of Artificial Intelligence in Reducing Information Asymmetry and Financial Risk

Information asymmetry is widely regarded as one of the primary causes of market inefficiency, as disparities in access to information and its accuracy lead to price distortions and create opportunities for exploitative behavior within financial markets. This imbalance in information flow represents a central challenge that artificial intelligence tools attempt to address by leveraging their capabilities in big-data analytics, prediction, and real-time monitoring (Al-Ta'i, 2023).

In earlier decades, financial information tended to be concentrated in the hands of a limited group of intermediaries and large institutions, resulting in a significant gap in analytical capabilities. However, through techniques such as machine learning and natural language processing, artificial intelligence has contributed to a redistribution of market knowledge and a narrowing of the information gap between individual and institutional investors.

The contribution of AI to mitigating information asymmetry can be summarized as follows:

- **Enhancing Transparency and Institutional Trust**

The integration of AI with blockchain technologies has achieved unprecedented levels of financial transparency. AI systems can analyze decentralized ledger data in real time, enabling the early detection of suspicious transactions or price manipulation (Liu & Wang, 2023).

For example, a report by the Financial Stability Board (FSB, 2023) found that AI-driven monitoring systems deployed on blockchain platforms helped reduce insider-trading incidents by 28% in several advanced markets—an outcome that reflects a notable improvement in regulatory transparency.

- **Equal Access to Market-Relevant Information**

Through AI-powered analytical systems—such as robo-advisors and data-driven financial tools—individual investors now have access to advanced analytical capabilities that were once exclusive to large financial institutions (McAfee &Brynjolfsson, 2017). Robo-advisors, for instance, rely on self-learning algorithms to construct customized portfolios and estimate risks based on client-specific objectives, all at low cost and within seconds. This contributes to fairer access to information and reduces the dominance traditionally held by large investors.

- **Sentiment Analysis and Behavioral Forecasting**

One of the most transformative AI applications in enhancing market efficiency is sentiment analysis, which relies on natural language processing (NLP). These systems can scan millions of articles, news posts, and social-media messages in real time, distill investor sentiment, and integrate it directly into price-prediction models.

A study by Lee & Tan (2024) showed that applying AI-based sentiment analysis to the Singapore Exchange improved the accuracy of daily price-movement predictions by 15%, compared with classical models relying solely on financial data.
In the United States, a 2023 FINRA report found that sentiment-driven AI models reduced the market's reaction time to unexpected events from 30 minutes to less than 5 minutes, underscoring the acceleration of information incorporation into prices and supporting the semi-strong form of market efficiency.

- **Risk Management and Prediction of Financial Crises**

Beyond reducing information asymmetry, AI also plays a critical role in mitigating systemic risk. By analyzing interconnections among financial institutions using deep neural networks, AI systems can identify vulnerabilities within the financial system before crises materialize.

A study by(Al-Tamimi 2024) demonstrated that AI algorithms used in credit-risk analysis within Chinese banks were able to predict 82% of default cases three months before they occurred. This capability has strengthened financial-system stability and helped reduce the potential costs of future crises.

2.4. The Role of Artificial Intelligence in Trading and Order Execution

Algorithmic trading stands as one of the most prominent applications of artificial intelligence in modern financial markets. It represents a practical embodiment of how algorithms interact with real-time market data to make rapid and precise investment decisions without direct human intervention. This form of trading relies on advanced machine-learning models capable of analyzing millions of transactions per second, transforming markets into highly efficient, self-regulated systems (Carrel &Leippold, 2024).

According to the BIS (2024), more than 65% of total trading volume in advanced markets—such as the New York Stock Exchange and NASDAQ—is now executed through algorithmic trading systems, compared with roughly 30% in emerging markets. This reflects the rapid diffusion of such technologies as AI continues to evolve.

2.4.1 High-Frequency Trading (HFT)

High-frequency trading (HFT) is considered one of the most sophisticated AI-driven trading applications. Financial institutions employ deep-learning and reinforcement-learning algorithms to execute buy and sell orders in fractions of a second, reacting to minute price movements or news signals.
A study by Carrel &Leippold (2024) shows that AI-enhanced HFT has contributed to:

- ✓ A 22% increase in market liquidity, driven by faster order-matching mechanisms;
- ✓ A 25% reduction in bid–ask spreads;
- ✓ Noticeable improvement in short-term price efficiency as markets assimilate new information almost instantly.

Data from the London Stock Exchange (O'Hara, 2023) further reveal that AI-powered HFT reduced order-execution latency from 120 milliseconds to less than 30 milliseconds, resulting in a significant boost in operational efficiency.

2.4.2 Smart Order Routing (SOR)

Smart order routing (SOR) is another essential AI-supported application that complements algorithmic trading. These algorithms determine the optimal execution path for a trade by simultaneously comparing prices, liquidity depth, and volatility across multiple venues to secure the best possible execution (Abbas, 2024).

According to FINRA (2024), the adoption of AI-based SOR in U.S. markets has led to:

- An 18% improvement in execution quality,
- A 12% decrease in transaction costs,
- Greater informational fairness between retail and institutional investors.

2.4.3 The Shift Toward Fully Autonomous Trading

Recent years have witnessed a transition from algorithmic trading toward what is now known as fully autonomous trading, where decisions are made entirely by systems trained

through deep reinforcement learning. These models learn directly from market dynamics, adjusting their strategies as conditions evolve.

A study by Zhao et al. (2024) reports that autonomous AI-driven trading systems achieve 8–10% higher annual returns than conventional algorithmic models, while maintaining volatility levels approximately 30% lower. Evidence from the Tokyo Stock Exchange also indicates that autonomous trading has helped stabilize prices during periods of market panic by rapidly correcting mispricing patterns.

2.4.4 Regulatory and Ethical Risks

Despite its advantages, AI-based trading presents notable regulatory and ethical challenges. Algorithm-driven decision making can trigger flash crashes, where prices collapse within seconds due to uncontrolled interactions between trading systems. For this reason, the U.S. Securities and Exchange Commission (SEC, 2023) has recommended the development of AI-powered regulatory systems that monitor algorithmic behavior and ensure market fairness and stability.

2.5 Artificial Intelligence in Financial Risk Management

Financial risk management has become one of the areas most positively transformed by artificial intelligence. Financial institutions now rely on machine learning and deep learning algorithms to analyze both quantitative and qualitative data in real time, enabling more accurate assessment of credit, market, and systemic risks compared to traditional statistical models (Chen & Li, 2024).

2.5.1 Credit Risk Assessment

Deep learning algorithms have revolutionized creditworthiness evaluation by moving beyond conventional datasets—such as income, collateral, and banking records—to include unstructured data sources such as online consumer behavior, digital payment histories, and spending patterns.

According to Chen and Li (2024), integrating AI into credit assessment has improved default-risk prediction accuracy by 27% relative to traditional logistic models, while institutions adopting these models reported an 18% reduction in non-performing loans.

The experience of China’s Ant Group further illustrates this shift: its “Sesame Credit” system, built on machine learning, expanded lending to previously unbanked individuals, reaching over 400 million new clients by 2023 and advancing financial inclusion without a corresponding rise in risk (World Bank, 2023). Similarly, an OECD (2023) report shows that alternative-credit algorithms in emerging markets reduced the financing gap for small enterprises by 35%, demonstrating AI’s dual impact in enhancing risk assessment and improving access to finance.

2.5.2 Systemic Risk Measurement

Systemic risk—defined as the type of risk that threatens the stability of the entire financial system—represents one of the most pressing challenges faced by central banks and regulatory authorities. Artificial intelligence frameworks, particularly recurrent neural networks, enable the detection of hidden interdependencies among financial institutions and support early prediction of crisis episodes.

Recent evidence reported by the IMF (2023) shows that AI-based models were able to identify early warning signals of financial distress 6 to 9 months before crises materialized, achieving accuracy rates exceeding 80%, compared with only 58% for traditional econometric models. Moreover, the European Central Bank has employed deep learning algorithms to analyze interbank settlement data and detect indicators of financial contagion, thereby

enhancing the effectiveness of preventive interventions and reducing the likelihood of systemic breakdowns.

2.5.3 Robo-Advisors and Portfolio Management

Robo-advisors have emerged as one of the most transformative applications reshaping the relationship between investors and financial institutions. These digital platforms rely on artificial intelligence algorithms to provide personalized investment advice and manage portfolios according to the client's objectives and risk tolerance, all with minimal or no direct human intervention (Dorfleitner et al., 2021).

2.5.4 The Role of Robo-Advisors in Enhancing Efficiency and Financial Inclusion

These platforms have significantly democratized access to investment services by offering low-cost, easily accessible online portfolio management tools. In the United States, the number of robo-advisor users increased from 15 million in 2020 to more than 35 million in 2024, with total assets under management exceeding USD 2.8 trillion (Statista, 2024).

Across Asia, countries such as Japan and Singapore have recorded a compound annual growth rate of 23% in the number of retail investors adopting these platforms (Lee & Kim, 2023).

2.5.6 Mitigating Behavioral Biases and Enhancing Performance

One of the most significant contributions of artificial intelligence to financial markets lies in its ability to curb behavioral biases that impede rational decision-making. Unlike human investors, robo-advisors are not influenced by emotional factors—such as fear or greed—that often drive irrational buy-and-sell decisions during periods of heightened market volatility.

According to (Al-Rumaidhi 2024), AI-managed portfolios have achieved 4.8% higher annual returns and 18% lower volatility compared to portfolios managed by human advisors. Furthermore, evidence from Japan's WealthNavi platform shows that machine-learning-based portfolio optimization contributed to maintaining portfolio balance during the COVID-19 crisis, reducing losses by 30% relative to the broader market.

3. U.S. Experience: High-Frequency Automated Trading and Liquidity Support

The United States represents the most mature environment for AI applications in financial markets, particularly in high-frequency algorithmic trading (HFT), which relies on advanced machine learning algorithms to execute buy and sell decisions within fractions of a second.

These practices now account for 60–70% of total trading volumes on major U.S. stock exchanges such as the New York Stock Exchange (NYSE) and NASDAQ, according to the Financial Industry Regulatory Authority (FINRA Report, 2023), highlighting the market's deep reliance on intelligent technologies for liquidity management.

3.1 Impact on Market Efficiency and Liquidity

Recent studies indicate that integrating AI into high-frequency trading has led to significant improvements in both operational and informational market efficiency. According to O'Hara (2023), the use of predictive deep learning algorithms reduced average bid-ask spreads by 25–30% between 2019 and 2023, while liquidity turnover rates increased by 18% during the same period.

These findings suggest that prices now reflect available information more quickly and accurately, supporting the semi-strong form of the Efficient Market Hypothesis (EMH) proposed by Fama. In other words, as the speed and accuracy of information incorporation into prices increase, markets are better able to achieve a dynamic equilibrium between supply and demand (Alawadi et al., 2024).

2.3 Technical Models Used in Automated Trading

Major financial institutions such as Citadel Securities, Virtu Financial, and Goldman Sachs AI Desk rely on sophisticated AI-driven algorithms, including:

- ✓ Convolutional Neural Networks (CNNs) to analyze real-time price patterns;
- ✓ Reinforcement Learning algorithms for autonomous, self-learning trading decisions;
- ✓ Hybrid models that integrate classical statistical analysis with predictive algorithms based on big data.

A study by Carrel &Leippold (2024) indicates that employing deep learning models in automated trading enables traders to achieve short-term price prediction accuracy of 82%, compared to 68% for traditional linear models. These algorithms also contributed to reducing execution costs by approximately 20% through improved Smart Order Routing strategies.

Table 1: Impact of Algorithmic Trading on U.S. Market Efficiency Indicators (2019–2024)

Financial Indicator	Before AI Implementation (2019)	After AI Expansion (2024)	Improvement (%)
Average Bid-Ask Spread (bps)	11.5	8.2	-28.7%
Daily Liquidity ($ billion)	480	565	+17.7%
Information Incorporation Speed (ms)	250	85	+66%
Short-TermPredictiveAccuracy (%)	68	82	+14%

Source: O'Hara, M. (2023). Market Microstructure, Algorithmic Trading, and Market Efficiency. The Journal of Finance.

The table clearly illustrates the continuous improvement in market efficiency indicators resulting from the integration of AI and real-time data analytics, establishing U.S. markets as a global benchmark for developing more efficient and transparent trading infrastructures.

4. European Experience: Regulatory Technology and Compliance Assurance

European markets are among the most advanced globally in the deployment of regulatory technology (RegTech), one of the AI applications designed to enhance regulatory efficiency and transparency within financial systems.

European authorities, such as the European Securities and Markets Authority (ESMA) and the UK Financial Conduct Authority (FCA), focus on integrating machine learning and big data analytics into supervisory systems to detect financial misconduct and ensure compliance with complex regulations in the post-global financial crisis era.

4.1 The Role of Regulatory Technology in Enhancing Supervisory Efficiency

RegTech has become a cornerstone for achieving strong market efficiency, directly contributing to the reduction of information asymmetry and curbing illicit behaviors, including:

- Trading based on insider information;
- Money laundering and financing of illegal activities;
- Price manipulation through real-time transaction monitoring.

A study by the European Banking Authority (EBA, 2023) indicates that approximately 68% of European financial institutions now employ at least one AI-based RegTech system for compliance and operational risk management. Moreover, spending on RegTech solutions in the EU increased from €3.8 billion in 2020 to over €8.5 billion in 2024, representing a compound annual growth rate of approximately 21% (EBA & Deloitte, 2024).

4.2 Quantitative Impact of AI Applications in RegTech

Evidence shows that AI, particularly deep learning algorithms and natural language processing (NLP), has substantially improved the operational efficiency of regulatory authorities and banks across Europe.

Table 2: Evolution of Operational Efficiency of Regulatory Authorities in Europe

RegulatoryIndicator	Before AI-RegTechImplementation (2019)	After AI-RegTech Expansion (2024)	Improvement (%)
False Positive Rate in Anti-Money Laundering	54%	31%	-42%
Processing Time for Suspicious Trading Reports (minutes)	180	45	+75%
Market Manipulation DetectionAccuracy (%)	71%	88%	+17%
Cost-to-Compliance Ratio	6.2%	3.9%	-37%

RegulatoryIndicator	Before AI-RegTechImplementation (2019)	After AI-RegTech Expansion (2024)	Improvement (%)
(% of Revenue)			

Source :European Securities and Markets Authority (ESMA). (2024). Trends in the use of AI in financial supervision: A market review. ESMA Occasional Paper.

These figures indicate that the integration of artificial intelligence tools into financial supervision has led to more than a one-third increase in monitoring and compliance efficiency, while improving the accuracy of detecting illicit activities by 17%. This directly supports the strong form of market efficiency hypothesis, as prices now rapidly reflect even semi-private information that previously took considerable time to reach the market (Al-Bayati et al., 2023) .

3.4 Prominent European Applications of RegTech

3.4.1 ESMA "RADAR" Project (2023–2024)

The RADAR project leverages artificial intelligence technologies to analyze market data from over 400 European financial institutions in real time, enabling the authority to detect abnormal trading patterns with an accuracy exceeding 90%.

3.4.2 "AMLbot AI" Anti-Money Laundering System (FCA, 2024

AMLbot AI employs neural network analysis algorithms to uncover hidden relationships between financial accounts. The system has demonstrated a 38% reduction in undetected suspicious transactions compared to traditional monitoring systems.

3.4.3 "Gaia-X Financial Node" Project (EU Commission, 2024)

This unified European platform provides **secure, cloud-based market data analysis**, enhancing regulatory information exchange among member states while maintaining data privacy.

3.4.4 Impact of RegTech on European Market Efficiency

According to the European Central Bank (ECB, 2024), the adoption of AI in financial supervision has resulted in:

- A 60% increase in the speed of regulatory reporting;
- Enhanced confidence of international investors in European financial markets;
- Improved transparency in derivative and securities markets by over 30%.

Thus, in Europe, RegTech serves as a bridge between regulatory efficiency and market efficiency by reducing the time to detect financial irregularities and improving the quality of information available to all stakeholders, leading to more stable and transparent markets.

5. Chinese Experience: Artificial Intelligence in Credit Risk Assessment and Financial Inclusion

China represents an advanced model in the deployment of AI in the financial system, particularly in creditworthiness assessment and promoting financial inclusion. Over the past decade, China has built a technological financial ecosystem that leverages big data analytics and machine learning to address informational gaps that hinder access to financing for individuals and small businesses lacking a traditional credit history (Chen & Li, 2024).

5.1 General Background of the Digital Transformation in Chinese Credit

Since the launch of the Chinese government's Digital Social Credit initiative in 2014, non-financial data—such as electronic payment patterns, online shopping behavior, and digital social interactions—has become an alternative source for creditworthiness assessment (World Bank, 2023).

This approach has integrated over 400 million individuals and 30 million small and medium enterprises (SMEs) into the formal financial system through digital platforms such as Zhima Credit by Ant Financial and WeBank AI Platform by Tencent. Estimates by the People's Bank of China indicate that the share of individuals with a digital credit score increased from 28% in 2015 to over 67% in 2024, reflecting a significant leap in digital financial inclusion (Asian Development Bank, 2024).

5.2 AI Models Used in Creditworthiness Assessment

Chinese platforms rely on a multi-layered set of AI algorithms to analyze both financial and non-financial behavioral patterns, including:

- ✓ **Deep Neural Networks (DNNs):** Used to analyze smartphone payment data, such as transaction frequency and timestamps, to generate dynamic credit scores updated in real time (Chen & Li, 2024).
- ✓ **Behavioral Analytics:** Analyzes user activity on social media platforms like WeChat, and purchasing behavior on e-commerce platforms such as Taobao and JD.com, to evaluate individual financial responsibility (Zheng & Zhang, 2024).
- ✓ **Natural Language Processing (NLP):** Used to assess texts in loan applications or client responses to determine reliability and financial discipline. Integrating NLP into credit models has increased the accuracy of default risk prediction by 12%.

5.3 Quantitative Impact of AI on Efficiency and Financial Inclusion

Comparative studies show that the use of AI tools in credit assessment has increased credit risk prediction accuracy to 78%, compared to 65% for traditional statistical models. Moreover, it contributed to a reduction in non-performing loans from 4.5% to 2.9% between 2020 and 2024 (Chen & Li, 2024).

The table below presents a quantitative comparison between traditional models and AI-based models in the Chinese market:

Table 4: Quantitative Comparison Between Traditional and AI-Based Models in the Chinese Market

Financial Indicator	TraditionalModels	AI-BasedModels	Improvement (%)
CreditRiskPredictionAccuracy (%)	65%	78%	+20%
Non-PerformingLoans (NPLs)	4.5%	2.9%	-36%
Loan Application Processing Time (seconds)	180	25	+86%
Digital Financial Inclusion Rate (%)	28%	67%	+139%

Source : Liu, Y., Li, Q& ,.Wang, H .(2023) .AI-driven credit scoring and financial inclusion in China .Journal of Financial Studies, 50.125-101 ,(1)

5.4.2 Economic and Regulatory Impacts (China)

The digital transformation of China's credit system demonstrates that AI not only improves capital allocation efficiency but also contributes to financial fairness and reduces the informational gap between large institutions and small enterprises. According to the Asian Development Bank (2024), over 60% of SMEs in rural areas were able to obtain financing for the first time thanks to AI-driven models that rely on behavioral data rather than traditional collateral.

From a regulatory perspective, China adopted the "Responsible Innovation in Financial AI" framework in 2023, supervised by the National Financial Regulatory Authority (NFRA), aimed at ensuring transparency and preventing algorithmic bias in credit decision-making (Zhou, 2023).

6. Japanese Experience: Robo-Advisors and Portfolio Stability

In the past decade, Japan has witnessed a significant transformation in wealth management, with AI becoming a core component of personal financial services. Japan's experience is among the most prominent in Asia for the use of robo-advisors—digital platforms that employ advanced machine learning algorithms to provide personalized investment advice and manage portfolios automatically based on client data and behavior.

6.1 Digital Background of Robo-Advisors in Japan

This transformation accelerated from 2016 with the launch of leading companies such as WealthNavi, THEO by Money Design, and RakutenRobo, targeting primarily retail investors and the elderly seeking low-cost, user-friendly investment tools. By the end of 2024, the number of robo-advisor users in Japan exceeded 2.8 million, compared to 400,000 in 2018, marking an increase of over 600% in six years. Assets under management (AUM) on these platforms surpassed ¥13.5 trillion (~$90 billion USD), reflecting the rapid shift toward automated investing in Japan's digitally advanced economy (Bank of Japan, 2024).

6.2 AI Mechanisms in Portfolio Management

Japanese robo-advisory platforms employ sophisticated AI algorithms that include (Miyata & Tanaka, 2024):

- ✓ **Investor Behavior Analysis:** Algorithms analyze individual risk patterns and spending behaviors to design dynamically balanced portfolios.
- ✓ **Dynamic Portfolio Optimization:** Using reinforcement learning models to adjust asset allocations (stocks, bonds, gold) based on real-time market volatility.
- ✓ **Automated Global Diversification:** Portfolios automatically invest in ETFs across U.S., European, and Asian markets to reduce systemic risk.
- ✓

6.3 Quantitative Impact on Efficiency and Market Stability

Studies indicate that robo-advisor-managed portfolios in Japan achieve stable annual returns exceeding traditional benchmarks by 4.8–5.2% on average. Data from the Tokyo Stock Exchange show that AI-managed portfolios reduce return volatility by 18% compared to manually managed portfolios (Miyata & Tanaka, 2024).

The following table presents a quantitative comparison between automated and traditional portfolios in the Japanese market:

Table 5: Comparison Between Automated and Traditional Portfolios in the Japanese Market

Financial Indicator	Traditional Portfolios	AI-Managed Portfolios	ImprovementDifference
AverageAnnual Return (%)	6.3	6.7–7.0	+5%
AnnualVolatility (σ) (%)	12.5	10.2	-18%
BehavioralBiases (%)	High	VeryLow	-40%
Percentage of Clients Retaining Investments During Crises	58%	81%	+40%

Source : Nomura Research Institute (NRI) .(2023) .Digital Asset Management in Japan: Robo-Advisors Trends .NRI Report.

These figures indicate that robo-advisors not only enhance financial performance but also contribute to behavioral efficiency by reducing the impact of psychological factors such as fear and greed, thereby strengthening market stability during periods of high volatility.

7. Conclusion

This study has demonstrated that artificial intelligence tools have transcended their traditional role as mere aids in financial analysis, becoming a core pillar for building more efficient, transparent, and stable financial markets. Advanced computing capabilities, machine learning, and deep learning enable financial institutions to process vast amounts of data in real time and analyze complex relationships among economic and financial variables, thereby enhancing the speed and efficiency of asset pricing.

AI has evolved from being a technical option to a strategic necessity for improving financial market efficiency across operational, regulatory, and behavioral dimensions. International experiences in the United States, Europe, China, Japan, and Singapore show that the adoption of AI tools reshapes the foundations of financial competition and enhances the effectiveness of investment resource allocation.

Study Findings

- Enhancing the Semi-Strong Form Efficiency Hypothesis: Empirical applications indicate that the use of AI-driven trading tools accelerates price responses to public information, bringing markets closer to the semi-strong form efficiency described by Fama.
- Improved Financial Risk Management: Deep learning models in China and the United States have demonstrated the ability to increase credit risk prediction accuracy to 78–82%, compared to 65% for traditional models. These models also enable early detection of systemic risks, translating into improved capital allocation and portfolio management.
- Enhanced Regulatory and Operational Efficiency: AI-powered RegTech applications in Europe have reduced operational costs and false positives in financial fraud detection,
- reflecting AI's role as a mechanism for intelligent compliance and fostering market transparency and trust (OECD).
- Advancing Behavioral Efficiency: Robo-advisors have proven effective in mitigating behavioral biases, such as fear and greed, resulting in more stable and rational investment decisions.

Recommendations

- Investing in Digital Computing Infrastructure: Financial institutions and national exchanges should invest in cloud platforms and high-performance computing networks to facilitate the application of advanced AI models in trading and risk management.
- Developing Flexible Regulatory Sandboxes: Adopt a regulatory sandbox model allowing fintech firms to test AI tools in a controlled environment, balancing innovation and financial stability.
- Bridging the Knowledge Gap and Developing Human Capital: Launch national programs for university and professional training in financial AI, in partnership with universities and financial market authorities.
- Enhancing Transparency and Ethical AI Use: Establish codes of conduct and ethical frameworks to ensure algorithmic fairness and prevent biases, particularly in credit assessment and algorithmic trading.

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