

# FinTradeSim: An AI-Driven FinTech Platform for Paper Trading, Predictive Analytics and Intelligent Financial Learning

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## Abstract

This literature survey examines recent research relevant to FinTradeSim, a Java-based FinTech platform that combines paper trading, predictive market analytics, and an AI-driven financial assistant. The reviewed works span machine learning-based stock prediction, sentiment-augmented forecasting, reinforcement learning for trading, large language model based trading agents, agentic AI for financial modeling, blockchain-enabled trading infrastructure, Java for FinTech systems, and API-centered integration architectures. Existing studies show strong progress in isolated areas such as prediction accuracy, simulation realism, explainable analytics, and scalable financial infrastructure. However, most prior systems focus on individual capabilities rather than a unified learning platform that brings together real-time paper trading, live market data, predictive analytics, retrieval-augmented AI support, and beginner-friendly decision assistance. This survey identifies the strengths and limitations of current approaches and highlights the research gap addressed by FinTradeSim: an integrated, modular, and practical environment for risk-free trading education and AI-assisted market understanding.

## Keywords

FinTradeSim, Paper Trading, Predictive Analytics, AI Agent, Stock Market Simulation, Retrieval-Augmented Generation, Financial Sentiment Analysis, Java FinTech.

## I. Introduction

Financial markets have become increasingly accessible to students, retail investors, and technology-driven traders [1]. Despite this accessibility, beginners still face substantial barriers because live trading involves real capital, fast-changing price movements, and the need to interpret technical indicators, market news, and company-level developments together [1][6]. Paper trading platforms attempt to reduce this barrier by allowing users to practice with virtual portfolios, but many existing tools either provide delayed market data, limited analytical support, or no embedded intelligence for answering finance-related questions [1].

Recent research in algorithmic trading and FinTech suggests that effective learning platforms should combine several capabilities: realistic market simulation, predictive analytics, contextual decision support, and scalable software architecture [6][7].

FinTradeSim addresses this need through a Java-based environment that integrates live market data, technical indicators, sentiment analysis, and an AI assistant into one system [10][11]. A dedicated literature survey is therefore useful to organize the surrounding research into themes, compare their contributions, and identify the open gap that such a system addresses [3][7].

This survey follows the broad academic style seen in the provided literature survey sample and reviews prior work in machine learning-based market prediction, reinforcement learning for trading, LLM and agentic-AI systems in finance, software infrastructure for trading platforms, and enabling technologies such as Java and API integration [4][7][10]. It then analyzes the strengths and shortcomings of these studies from the perspective of building an educational, AI-assisted, paper-trading platform [6][7].

## II. Literature Review

**Traditional and machine learning-based market prediction:** Early predictive trading studies established that supervised machine learning can identify stock or cryptocurrency price directions more effectively than many classical statistical baselines [1][6]. The random-forest-based stock direction study reported strong classification performance using technical indicators, showing the usefulness of ensemble learning for financial direction prediction [1]. Similarly, the sentiment-augmented random forest work expanded this idea by combining technical indicators with sentiment analysis, demonstrating that external textual information can improve predictive quality [2]. These works justify the inclusion of predictive analytics and signal generation in FinTradeSim, but they stop short of creating a complete interactive trading-learning platform [1][2].

**Large comparative ML studies:** The Bitcoin trading analysis by Jabbar and Jalil provides one of the strongest methodological foundations among the referenced works [6]. It evaluates 41 machine learning models using both prediction metrics and trading metrics such as profit-and-loss percentage and Sharpe ratio [6]. A major contribution of this study is that it shows the difference between backtesting success and real-world robustness, emphasizing that strong offline performance does not always transfer to forward testing [6]. This is especially relevant because it suggests that predictive components should be treated as

guidance aids inside a simulation environment rather than as guaranteed trading engines [6].

**Reinforcement learning for adaptive trading:** Research on reinforcement learning has pushed trading systems beyond static prediction toward sequential decision-making [4][5]. Ishikawa and Nakata proposed a deep reinforcement learning framework for Forex trading that incorporates transaction costs directly into the optimization process, making the learning objective more realistic for actual trading conditions [5]. A related quantitative trading framework compares RL agents such as DQN, PPO, and A2C using technical indicators and reward design choices [4]. These studies demonstrate that adaptive learning can improve trading decisions in dynamic environments, but they generally require careful retraining, substantial computational effort, and advanced experiment design [4][5]. This limits their immediate accessibility for beginners and supports a more practical design choice of combining simpler signals, live data, and AI explanation rather than relying only on autonomous RL execution [4][5].

**LLMs and multi-agent trading simulation:** A major recent shift in financial AI is the move toward language-model-based trading agents [3][7]. StockAgent introduces a multi-agent framework where LLM-driven agents simulate investor behavior under changing external conditions such as news, financial events, and market sentiment [7]. This work is valuable because it goes beyond prediction and explores behavioral finance, scenario simulation, and agent interactions [7]. However, it is designed primarily as a research simulation framework rather than a user-facing educational platform with live paper trading and embedded assistance [7]. TradExpert takes another direction by using a mixture-of-experts architecture in which specialized models process different financial modalities such as market data, news, fundamentals, and alpha factors [3]. This demonstrates the value of modular intelligence in financial systems [3].

**Agentic AI for financial services:** The paper on agentic AI crews for financial modeling and model risk management extends the idea of specialized AI agents into regulated financial workflows [8]. Its contribution lies in decomposing financial tasks into coordinated expert agents with human oversight [8]. This supports the design principle that one monolithic AI assistant may be less effective than modular pipelines that retrieve, analyze, and respond using targeted components [8]. At the same time, such frameworks are more suitable for institutional settings than student-facing simulators, since they require stronger governance, validation, and human supervision [8].

**Blockchain-enabled trading infrastructure:** Beyond analytics, some literature addresses market infrastructure itself [9]. The blockchain-enabled stock trading system shows how decentralization and smart contracts can reduce intermediary dependence, improve transparency, and streamline settlement [9]. While this approach is conceptually powerful, it addresses a different layer of the trading ecosystem than a lightweight paper trading platform [9]. Its main relevance is architectural because it highlights the importance of trust, auditability, and transaction integrity in trading systems [9]. Nevertheless, blockchain complexity and deployment overhead make it less suitable for a lightweight learning-focused platform compared with a modular Java and API-based system [9][10][11].

**Java and API-centered platform design:** Two practical sources support the engineering choices behind FinTradeSim [10][11]. The Java-in-FinTech reference emphasizes Java's long-standing strengths in secure, scalable, and enterprise-grade financial applications [10]. The API integration guide highlights how modern applications increasingly depend on external services for real-time data exchange [11]. Together, these sources support a system design in which a Java web application can provide the

user-facing core while market data APIs, news APIs, and AI services extend its capabilities [10][11].

**Inference acceleration and AI deployment:** Groq's LPU-oriented inference approach is relevant for addressing latency and local deployment bottlenecks in AI-assisted financial systems [12][13]. In financial assistance systems, response speed matters because the usefulness of a contextual AI agent decreases if query handling is slow or infrastructure-heavy [12][13]. These works suggest that external high-speed inference services may be a more practical option than locally hosted large language models for student-oriented or resource-constrained deployments [12][13]. This directly supports the use of external inference combined with retrieval augmentation [12][13].

### III. Methodology

The proposed system uses real-time market data, machine learning techniques, and AI-based financial assistance for paper trading and predictive market analytics [1][2][10]. First, stock market data and financial news are collected and processed using live APIs and supporting data sources [10][11]. Then, the collected data is used for paper trading simulation, technical analysis, sentiment analysis, and predictive signal generation [1][2][6]. After data processing, the system allows users to perform virtual buy and sell operations in a risk-free trading environment [10][11].

The proposed FinTradeSim system begins with collecting live stock prices, market updates, and financial news from different APIs and online sources [10][11]. The collected data is processed using methods such as filtering, formatting, storing, and analysis to improve its usefulness for trading simulation and prediction [1][2]. After preprocessing, modules such as paper trading, technical indicator analysis, machine learning-based prediction, and AI query handling are applied for stock market learning and decision support [1][3][7]. The paper trading module helps users simulate trades using virtual money, while the analytics and AI modules provide market insights, sentiment-based understanding, and trading-related responses in real time [7][12]. Finally, the system stores user activity, transaction history, and analytical results in the database [10][11]. The generated trading signals, market trends, portfolio updates, and AI-based responses are displayed to the user for effective paper trading, market analysis, and financial learning [1][2][10].

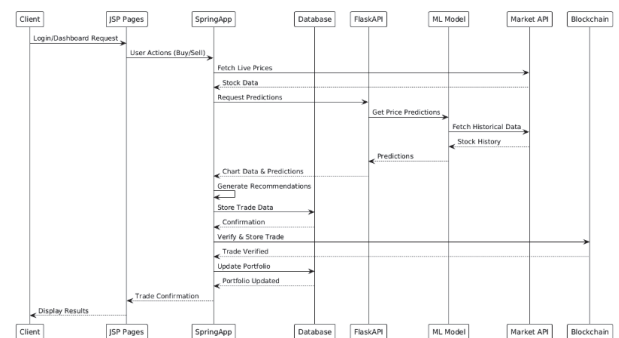


Figure 3.1 Sequence Diagram for FinTradeSim

The sequence diagram illustrates the workflow of the stock trading and prediction system. The user interacts with the JSP-based interface to access dashboard features, request stock data, and view predictions. The application coordinates communication between the database, Flask API, machine learning model, and market API to fetch live and historical stock data. The ML model processes this data and generates price predictions, which are returned to the application for visualization. When a user places a trade, the system records and verifies the transaction through the blockchain module, ensuring transparency and security. Finally, the portfolio

is updated, and the trade confirmation along with prediction results is displayed to the user.

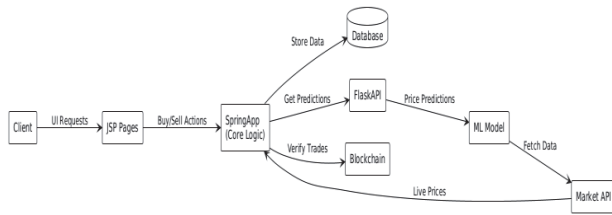


Figure 3.2 Workflow

#### IV. Comparative Analysis

Across the reviewed studies, several comparative patterns emerge [1][4][7]. Prediction-focused models such as Random Forest, sentiment-augmented learning, and broad comparative ML studies offer measurable trading insights and strong empirical evaluation, but they typically operate as standalone research models [1][2][6]. Reinforcement learning systems add adaptability and realism through sequential decision-making, yet they tend to be computationally heavier and harder to explain to novice users [4][5].

LLM-based systems such as StockAgent and TradExpert expand the scope from numerical prediction to reasoning, multi-factor interpretation, and interaction across heterogeneous financial signals [3][7]. However, these systems are often designed as research frameworks or institutional intelligence layers rather than accessible beginner platforms [3][7][8]. By contrast, the practical infrastructure sources on Java, API integration, and inference acceleration do not provide trading intelligence on their own, but they make an integrated real-time platform feasible [10][11][12].

From a platform design viewpoint, no single reviewed work combines all of the following in one educational environment: risk-free trade execution, real-time market feeds, predictive analytics, financial news understanding, retrieval-augmented query answering, and a modular web-based implementation suitable for incremental development [3][7][10]. This comparison supports the positioning of FinTradeSim as a synthesis-oriented system rather than a narrow contribution in only one research area [1][7][10].

#### V. Research Gap

The most important research gap is fragmentation [3][7][8]. Existing literature usually isolates one dimension of intelligent trading systems: prediction accuracy, reinforcement learning, multi-agent simulation, infrastructure security, or AI deployment efficiency [1][7][8]. Very few studies attempt to integrate these capabilities into a single platform intended for hands-on learning and low-risk experimentation [7][8][10].

A second gap is usability for beginners [6][10][11]. Many research papers assume advanced users, offline experimentation, or institution-grade computational resources [4][7][8]. They do not focus on how students or novice traders can practice trades using live data, inspect their decisions, receive contextual market explanations, and improve gradually inside one environment [6][10][11].

A third gap is the absence of unified AI support within paper trading [2][3][7]. Several papers show that market prediction improves when technical signals are combined with sentiment or contextual data, and that LLMs can assist with complex financial interpretation [2][3][7]. Yet most systems still separate simulation, analytics, and user assistance into different tools [7][8][11]. FinTradeSim addresses this by combining paper trading, predictive analytics, and an AI query mechanism inside a common Java-based architecture [10][11].

Finally, deployment practicality remains a challenge [8][12]. Research prototypes often demand specialized frameworks, heavy computation, or non-trivial operational setups [7][8][12]. There is clear value in a modular architecture that uses mainstream web technologies, external APIs, and efficient inference services to make intelligent trading support more deployable and maintainable in academic and prototype settings [10][11][12].

#### VI. Conclusion

The reviewed literature shows that major advances have been made in machine learning-based market prediction, reinforcement learning for trading, multi-agent financial simulation, and intelligent financial assistance [1][4][7]. Each of these lines of research contributes an important idea: predictive models improve signal generation, RL improves adaptivity, LLM systems improve contextual reasoning, and modern software infrastructure enables real-time scalable deployment [1][4][7].

At the same time, the literature also reveals a persistent gap between isolated research advances and an integrated user-facing learning system [6][7][10]. FinTradeSim is well positioned within this gap because it combines live paper trading, predictive analytics, and AI-assisted financial support in a single modular platform [10][11][12]. A literature survey grounded in the reviewed papers therefore supports the novelty of FinTradeSim not by claiming entirely new algorithms, but by showing the practical importance of unifying complementary advances into one coherent FinTech application [1][3][7].

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