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Review

Investment management approaches: A comprehensive review of equity trading simulators, methodological challenges, and future directions

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Abstract: This paper provides a comprehensive review of equity trading simulators, focusing on their performance in assuring pre-trade compliance and portfolio investment management. A systematic search was conducted that covered the period of January 2000 to May 2023 and used keywords related to equity trade simulators, portfolio management, pre-trade compliance, online trading, and artificial intelligence. Studies demonstrating the use of simulators and online platforms specific to portfolio investment management, written in English, and matching the specified query were included. Abstracts, commentaries, editorials, and studies unrelated to finance and investments were excluded. The data extraction process included data related to challenges in modern portfolio trading, online stock trading strategies, the utilization of deep learning, the features of equity trade simulators, and examples of equity trade simulators. A total of 32 studies were included in the systematic review and were approved for qualitative analysis. The challenges identified for portfolio trading included the subjective nature of the inputs, variations in the return distributions, the complexity of blending different investments, considerations of liquidity, trading illiquid securities, optimal portfolio execution, clustering and classification, the handling of special trading days, the real-time pricing of derivatives, and transaction cost models (TCMs). Portfolio optimization techniques have evolved to maximize portfolio returns and minimize risk through optimal asset allocation. Equity trade simulators have become vital tools for portfolio managers, enabling them to assess investment strategies, ensure pre-trade compliance, and mitigate risks. Through simulations, portfolio managers can test investment scenarios, identify potential hazards, and improve their decision-making process.

Keywords: equity trading simulators; portfolio investment management; pre-trade compliance

1. Introduction

The management of investment portfolios is a dynamic and complex endeavor that necessitates the careful evaluation of multiple factors, including risk assessment, pre-trade compliance, performance analysis, and adherence to both internal policies and regulatory standards. Lee and Schu (2022) and Documents and Publications (2019) emphasize the critical nature of compliance with internal and external guidelines to mitigate severe penalties, reputational harm, and legal liabilities, highlighting the essential role of robust pre-trade compliance measures (Tatewaki, 2020). In addressing these challenges, the adoption of equity trade simulators, as explored by Byrd et al. (2019, 2020), has become increasingly prevalent. These computer-simulated environments enable portfolio managers to verify the compliance of their investment decisions pre-execution, effectively reducing potential risks.

Equity trade simulators facilitate the simulation and evaluation of transaction impacts on a portfolio's risk and return dynamics, utilizing real-time data, customizable scenarios, and diverse reporting features. This setup offers a realistic yet controlled setting for portfolio simulation. The educational aspect is also significant, with Moffit et al. (2010) noting how simulators serve as tools for refining trading strategies and enhancing managerial competencies through risk-free practice sessions. The literature, including Bakoush (2022) and Jankowski and Shank (2010), supports the value of these simulators in training and strategy development. Furthermore, for pre-trade compliance, simulators provide detailed risk reports, compliance verifications, and audit trails, enhancing transparency and accountability in portfolio management (Lee and Schu, 2022).

Despite the growing utilization of online trading and simulators, there appears to be a gap in comprehensive literature reviews focusing on their efficacy in portfolio management. This systematic literature review seeks to fill that void by examining existing works on compliance technology within the investment portfolio management domain. It aims to identify current practice gaps and underline the pivotal role of technology in bridging these disparities. This study represents a systematic exploration of the effectiveness of equity trade simulators and online platforms in maintaining pre-trade compliance for portfolio management.

The paper is structured to comprehensively explore the utilization and implications of equity trading simulators in portfolio management, with a focus on pre-trade compliance and risk management. Section 2 details our methodology, guided by PRISMA principles, to conduct a systematic literature review from January 2000 to May 2023. Section 3 outlines the results, including challenges in portfolio trading, issues faced by sophisticated investors in online trading, and advancements in portfolio optimization techniques. Section 4 offers an in-depth analysis of current technologies in equity trade simulators, their functionalities, and their limitations. Section 5 discusses the benefits and strategic advantages of employing equity trade simulators for portfolio managers. Section 6 recommends best practices for effectively integrating these simulators into portfolio management workflows. Section 7 identifies the limitations and challenges inherent in using equity trade simulators. Section 8 presents future research directions and opportunities, suggesting areas for further academic exploration and technological enhancement. Finally, Section 9 concludes by summarizing the significant role of equity trade simulators in modern investment management strategies, emphasizing their value in fostering informed decision-making and regulatory compliance.

2. Methodology

2.1. Literature search strategy

The study's methodology adheres to PRISMA guidelines for thoroughness, transparency, and replicability. Our systematic literature search, spanning from January 2000 to May 2023, utilized keywords such as 'equity trade simulator,' 'portfolio management,' 'pre-trade compliance,' 'online trading,' and 'artificial intelligence.' These keywords were selected to cover the broad spectrum of research intersecting financial technology and investment strategy, ensuring comprehensive retrieval of relevant literature. Boolean operators (AND, OR, NOT, NEAR, W/n, etc) were strategically applied to refine the search and capture a diverse range of studies pertinent to our review's objectives. An electronic database search was performed on various databases, including PubMed, Google Scholar, WOS, and Scopus, due to their multidisciplinary coverage and access to the relevant literature in economics, finance, management, psychology, and technology.

2.2. Selection criteria

Studies demonstrating the use of simulators and online platforms specific to portfolio investment management, written English, and matching the specified query were included. Abstracts, commentaries, editorials, and studies unrelated to finance and investments were excluded.

2.3. Studies selection

The relevant studies were identified based on a thorough search. The initial process of data screening was conducted. The screening of titles and abstracts was performed. Following this, those studies that were in alignment with the inclusion criteria were selected. The studies were analyzed based on full-text article assessments. Eventually, those studies that fulfilled the inclusion criteria were included.

2.4. Data extraction

Studies that were in accordance with inclusion criteria were used for data extraction. Data extraction included data related to challenges in modern portfolio trading, online stock trading strategies, the utilization of deep learning, the features of equity trade simulators, and examples of equity trade simulators.

3. Results selection of studies

A systematic approach was undertaken. Our initial electronic research provided a total of 1587 articles. Following this, the screening of 768 articles was performed. After excluding the irrelevant studies, 68 studies underwent full-text eligibility. Eventually, a total of 32 studies were included in the systematic review and were approved for qualitative analysis.

The selected literature provided valuable information related to challenges in modern portfolio trading and investment in online trading. Furthermore, portfolio investment management methods in terms of performance and deep learning were explained. The first section evaluates the challenges in modern portfolio trading. This includes return distribution variations, subjective inputs, liquidity considerations, and blending investments. The second section highlights the problems encountered by sophisticated investors in online trading. This encompasses Hidden costs and deceptive advertising; navigating complex information in online research; trade execution, trust, security, and privacy; risk perception and long-term outcomes; impact of fintech brokerages, attention-induced trading; influence of internet postings on trading behavior; role of overconfidence in robo-advisor adoption; risk-adjusted performance of robo-advisors; role of robo-advisors in reducing the disposition effect and influence of trust, optimism, and ease of use on intention to use AI. The third section elaborates portfolio investment management, including a depiction of investment objectives, risk tolerance, and changes in the environment. The fourth section elaborates the portfolio optimization techniques, such as linear programming, stochastic programming, and metaheuristic algorithms. The fifth section provides details about deep learning based online portfolio management.

3.1. Challenges in modern portfolio trading

Modern portfolio theory encounters various challenges that are critical for both investors and portfolio managers to understand and navigate to achieve efficient and effective portfolio management. These challenges include the subjective nature of inputs such as expected returns, volatilities, and correlations, variations in return distributions from normal to fat-tailed across different investments, the complexities involved in blending various investments to create a diversified portfolio, and considerations of liquidity. Effectively managing risk while striving for optimal returns is the overarching principle of portfolio management. **Tables 1** and **2** provide a comprehensive summary of these challenges, outlining the specific issues faced by investors and portfolio managers. By addressing these challenges, as detailed in **Tables 1** and **2**, investors and managers can work towards more effective portfolio management strategies, enhancing the potential for achieving desired investment outcomes.

Table 1. Challenges in modern portfolio trading.

Challenge	Authors Discussed
Subjective nature of inputs	(Markowitz, 1952; Sharpe, 1964)
Variations in return distributions	(Merton, 1973; Fama, 1965)
Complexity of blending different investments	(Black, 1972; Litterman, 1986)
Considerations of liquidity	Modern Portfolio Theory (Amihud, 2002; Roll, 1984)
Trading illiquid securities	Daley & Green (2016); Ang et al. (2014); Gang & Choi (2023)
Optimal portfolio execution	Moazeni et al. (2010); Biondo et al. (2022)
Clustering and classification	Alqaryouti et al. (2019); Lu et al. (2018); Ren et al. (2017)
Handling of special trading days	N/A (General Challenge)
Real-time pricing of derivatives	Belim & Soni (2023); Liu & Zhao (2022); Sankar (2022)
Transaction cost models (TCMs)	Aburto et al. (2023); Xiong et al. (2022)

Source: Author's own compilation.

Table 2. Challenges faced by sophisticated investors in online trading.

Challenge	Authors Discussed
Hidden costs and deceptive advertising	Manrai & Gupta (2023)
Navigating complex information in online research	Manrai & Gupta (2023)
Trade execution, trust, security, privacy	Manrai & Gupta (2023)
Risk perception and long-term outcomes	Al-Gasawneh et al. (2022)
Impact of fintech brokerages, attention-induced trading	Barber et al. (2022)
Influence of internet postings on trading behavior	Ammann & Schaub (2021)
Role of overconfidence in robo-advisor adoption	Piehlmaier (2022)
Risk-adjusted performance of robo-advisors	Tao et al. (2021)
Role of robo-advisors in reducing the disposition effect	Back et al. (2023)
Influence of trust, optimism, and ease of use on intention to use AI	S et al. (2022)

Source: Author's own compilation.

3.1.1. Trading illiquid securities

Illiquid names in the market have thin order books and limited active participants, making them highly sensitive to supply-demand imbalances (Daley and Green, 2016). This results in lower average daily volumes, wider bid-offer spreads, and higher volatility (Ang et al., 2014). Trading algorithms face challenges in completing trades (Gang and Choi, 2023) within a given timeframe, as passive waiting can increase squeezing risk and impact costs. Dark pools provide alternative venues for minimizing information leakage and finding liquidity. Execution algorithms for fixed-income products must balance agency and principal trading, adhering to the best execution principles. Automating trading for illiquid assets requires accurately estimating "true" values in real time, despite sparse trading and limited pricing references (Sadoghi and Vecer, 2022).

3.1.2. Optimal portfolio execution

Asynchronous single-name algorithms can be used to execute unstructured portfolios that lack systematic objectives. Execution risk can be reduced if the individual names in the portfolio hedge among themselves to some degree (ECB, 2023). Hedging is typically quantified by correlations and volatilities, which can be calibrated from historical returns or multi-factor models. Adapting end-of-day risk models to real-time models poses challenges, as correlations may change rapidly during intraday trading. Calibrating intraday volatilities can be carried out statically or dynamically, with dynamic profiling being ideal but computationally expensive. Integrating risk and cost analytics into portfolio execution models is a significant challenge (Moazeni et al., 2010), requiring mathematically tractable and computationally efficient algorithms (Biondo et al., 2022). Optimally trading portfolios with multiple correlated asset classes further complicates the process.

3.1.3. Clustering and classification

Clustering and classification techniques help organize and simplify the vast security universe covered by financial institutions (Lu et al., 2018). They improve efficiency by sharing strategies and risk controls within clusters and provide a framework for automated handling during emergencies. Traditional approaches use sectors or fundamental factors for clustering, but modern machine learning methods offer more sophisticated options (Alqaryouti et al., 2019). Dynamic clustering based on relevant security characteristics, including non-numerical features like alternative data, is crucial for intraday trading optimization and market making (Ren et al., 2017).

3.1.4. Handling of special days

Special days in trading, such as Fed announcement days or index rebalancing days, require customized and responsive strategies due to their distinct trading patterns. Trading parameters should be prepared using statistical methods or machine learning techniques, and real-time implementation should involve updating trade beliefs based on calibrated models and observed market dynamics. Special periods anchored around special days can also be significant for transitions and uncertainties. Successfully trading during these periods requires specialized strategies and investments in talent and analytics.

3.1.5. Real-time pricing of derivatives

The real-time pricing of derivatives poses challenges for investment banks, particularly in speeding up computation and revamping pricing infrastructures (Liu and Zhao, 2022; Sankar, 2022). Conventional end-of-day pricing models are too slow for intraday and real-time trading, necessitating the ability to query market data and construct implied rates or credit curves on the fly (Belim and Soni, 2023). Market data subscriptions, connections, and curve calibration engines need to be upgraded. Additionally, pricing methodologies, such as PDEs and Monte Carlo simulations, must be redesigned to achieve faster computations using approximation techniques. Tech risk management and model risk management need to scrutinize the soundness and robustness of these new infrastructures and real-time pricing logic. Automated derivative trading requires significant investments in infrastructure, analytics, and IT talent (Zaineb et al., 2022).

3.1.6. Transaction Cost Models (TCMs)

Transaction cost models (TCMs) are pre-trade forecasting models used to estimate the transaction costs associated with trading proposed positions. They focus on impact costs rather than market risk costs or fees and commissions. TCMs have become a celebrated metric in algorithm (online) trading, but the understanding of them is still evolving (Xiong et al., 2022). TCMs have become increasingly proprietary and confidential, particularly in emerging areas like FICC for bonds or FX. While there should ideally be a single ground truth TCM that is open and transparent, the existence of proprietary models suggests complexity and ambiguity in the notion of TCM use. Even for post-trade transaction cost analysis (TCA), determining net impact costs is not straightforward, indicating the challenges involved in measuring and understanding transaction costs (Aburto et al., 2023).

3.2. Challenges faced by sophisticated investors in online trading

Robo-advisors, which are automated investment solutions guided by algorithms, face adoption challenges. The emergence of online trading has provided investors with a wealth of information, but it has also introduced hidden costs and deceptive advertising. Teaser advertisements often highlight low trading commissions without mentioning the high minimum balance requirements or initial deposits needed to qualify for these rates. Some firms even require investors to have a certain amount of trading experience or make a minimum number of trades to access the advertised discounts. Additionally, specific types of orders, such as limit or stop orders, may come with additional costs. Another challenge is conducting research, as investors must navigate through the vast amount of complex information available online, including financial statements, stock reports, and company profiles. This requires knowledge and the ability to assess the reliability and validity of the data. Lastly, challenges related to trade execution, trust in services (as well as service providers), security and privacy (Manrai and Gupta, 2023), risk (Al-Gasawneh et al., 2022), perceived benefits (Riemann and Charlotte, n.d.)**,** and long-term outcomes also need to be considered.

Barber et al. (2022) examined the impact of fintech brokerages, focusing on Robinhood. Their study shows that Robinhood investors engage in more attention-induced trading, particularly in high-attention stocks. The platform's unique features contribute to this behavior. Intense buying by Robinhood users is associated with negative returns, with the top daily purchased stocks experiencing an average 20-day abnormal return of −4.7%. Ammann and Schaub (2021) investigated whether individual investors trade based on internet postings. They analyzed data from a social trading platform and found that followers tend to replicate shared portfolios after comment postings. However, the study did not find a correlation between these postings and future portfolio performance. The analysis suggests that less experienced followers are more likely to trade after comment postings. In a pre-chasm market, Piehlmaier (2022) conducted a study using various models and found that overconfident investors have a higher likelihood of adopting robo-advice. The research revealed that higher financial literacy appears to decrease the uptake of robo-advice, while unjustified confidence in one's knowledge causally increases adoption. Interestingly, the significantly increased adoption among overconfident investors cannot be explained solely by their willingness to take financial risks.

Tao et al. (2021) conducted a study comparing the risk-adjusted performance of robo-advisors regarding conventional funds in the US from 2016 to 2019. The results indicate that, on average, robo-advisors outperformed equity, fixed-income, money market, and hybrid funds. They also demonstrated superior performance compared to three prominent equity indices, and these findings were consistent across different risk-to-reward models. The study highlights that robo-advisors not only offer easy access and cost-effective advice but also excel in risk-adjusted performance. Back et al. (2023) found that robo-advisors can help reduce the disposition effect, a behavioral bias in investment decision-making. However, when robo-advisors have social design elements, such as a name and natural language communication, it can increase the disposition effect. The study also revealed that investors are less likely to seek advice from robo-advisors with social design elements. These findings shed light on the benefits and potential risks of using artificial intelligence-enabled advisors in investment decision-making. According to Pramod and Raman. (2022)**,** their study shows that individuals' intention to use financial robots or AI tools for investment decisions is influenced by their optimistic view towards technology and awareness. The lack of trust in technology has a negative impact on their intention. Additionally, the ease of use and utility of AI tools play a significant role in influencing students' decisions to use financial robots or AI tools for investment decisions.

3.3. Portfolio management approach

The management of a portfolio of assets to achieve specific investment goals is referred to as portfolio investment management. This involves selecting suitable assets for the portfolio, determining the optimal allocation of each asset, and making informed decisions on when to buy or sell those assets. A key aim of effective portfolio management is to strike a balance between risk and return, taking into consideration the investor's risk tolerance and investment objectives. By carefully considering these factors, a well-managed portfolio aims to achieve a favorable risk-return trade-off. According to Kristina Levišauskait (2010), the investment environment refers to the current market's investment options and the places where investors can trade these assets. Once an investment strategy is established and the investor's objectives are defined, various types of investments can be evaluated and incorporated into the strategy. It is important to note that investment management is an ongoing activity that is influenced by changes in the investment environment and investor perceptions (Fabozzi and Markowitz, 2011). The globalization of the market presents both opportunities and challenges for portfolio management because it increases unpredictability. The portfolio management approach involves a judgment process that includes five steps: building a diversified investment portfolio, analyzing and rating investment vehicles, creating an investment policy, reviewing the portfolio, and measuring and evaluating portfolio performance.

3.4. Portfolio performance measures

Evaluating portfolio performance serves three important purposes: enhancing efficiency, monitoring risk, and analyzing returns. An efficient portfolio should aim to achieve above-average returns for a given risk level and diversify the portfolio to eliminate unsystematic risk relative to a benchmark. Performance evaluation encompasses conventional and risk-adjusted methods (Samarakoon and Hasan, 2022), including the Sharpe ratio, Treynor ratio, Jensen's alpha, Modigliani, and Treynor squared. Conventional performance evaluation methods focus on benchmark and style comparisons, while risk-adjusted methods adjust returns to account for differences in risk levels between the managed portfolio and the benchmark. Various metrics to measure portfolio performance are discussed in the work of (Aragon and Ferson, 2006). These metrics provide insights into the portfolio's ability to generate returns and manage risk effectively. In summary, evaluating portfolio performance involves assessing its ability to deliver above-average returns while diversifying risk. Conventional and risk-adjusted methods offer different perspectives on performance evaluation, with various metrics used to measure performance and compare it to benchmarks. These evaluations contribute to enhancing portfolio efficiency, managing risk, and optimizing investment returns.

3.5. Portfolio optimization techniques for online stock trading strategies

Portfolio optimization techniques have evolved to maximize portfolio returns and minimize risk through optimal asset allocation (Markowitz, 1952). Portfolio optimization techniques that involve modern portfolio theory (MPT) and capital market theory (Sharpe, 1970) provide frameworks for measuring investment risk and establishing the relationship between expected return and risk. Asset pricing models capture these associations. The arbitrage pricing theory (APT) (Roll and Ross, 1980) serves as an alternative to the CAPM, assuming market efficiency and predicting asset returns based on a linear relationship with macro-economic variables. The Fama-French three-factor model (Fong et al., 2017) expands on the CAPM by incorporating size and value risk factors, enabling the prediction of manager performance. The integration of CAPM and MPT led to the Black-Litterman model (He and Litterman, 2005), allowing portfolio managers to generate expected returns within the mean-variance optimization framework (or combining historical data and expert opinions) using either single- or multi-objective optimization. Various optimization techniques address transaction costs, portfolio constraints, and estimation errors (Kolm et al., 2014). Mathematical optimization methods, such as stochastic programming, linear programming, integer programming, and convex optimization, are employed to solve optimization problems (Ahmadi-Javid and Fallah-Tafti, 2019).

Metaheuristic algorithms, like genetic algorithms, tackle complex and constrained optimization tasks (Lwin et al., 2017), and an extensive review of the application of evolutionary algorithms to POP is provided by Metaxiotis and Liagkouras (2012); the application of metaheuristics to different investment strategies (e.g., risk budgeting, the 120-30 strategy) is elucidated in G A Vijayalakshmi Pai (2017). Probabilistic programming techniques, including fuzzy set theory, are utilized to solve financial problems (Qin, 2015). In summary, portfolio optimization encompasses MPT, CAPM, APT, and the integration of these theories into the Black-Litterman model. Optimization techniques consider transaction costs, constraints, and estimation errors. Mathematical optimization and metaheuristic algorithms (Doering et al., 2019) (e.g., particle swarm optimization, ant colony optimization, cuckoo search, harmony search, a bat-inspired algorithm, and the firefly algorithm) aid in solving complex problems. Probabilistic programming techniques, such as fuzzy set theory, are applied in financial problem-solving (Qin, 2015). These advancements contribute to effective investment strategies, considering various constraints and uncertainties.

3.6. Deep learning-based online portfolio management

Achieving financial stability can be facilitated through online portfolio management coupled with comprehensive tools and guided financial services. Wealth management and personalized investments heavily rely on the investor's decision-making process, which is influenced by the current state of the financial market and their ability to perceive and manage associated risks. The growing intricacies of the investment landscape have prompted a demand for high-quality financial advice. As is evident from the findings, financial institutions are significantly investing in data-driven strategies for risk management and predicting customer behavior (Mishra et al, 2022).

Yang et al. (2020) proposed an ensemble strategy that utilizes DRL to maximize investment returns in stock trading. The ensemble strategy combines the proximal policy optimization (PPO), advantage actor-critic (A2C), and deep deterministic policy gradient (DDPG) algorithms, adapting them robustly to different market situations. By employing a load-on-demand technique to handle large data, the strategy was tested on 30 Dow Jones stocks and compared to benchmark strategies. The results show that the proposed deep ensemble strategy outperforms individual algorithms and baselines in terms of risk-adjusted returns measured by the Sharpe ratio. Ta et al. (2020) proposed an LSTM "Long Short-Term Memory" network for stock movement prediction and used portfolio optimization techniques to enhance portfolio performance. The LSTM model achieves high accuracy and outperforms other prediction models. The constructed portfolios based on LSTM outperform the benchmark S&P 500 index and other models in terms of active returns and Sharpe ratios. Optimization techniques further improve portfolio returns. Ma et al. (2020) applied the component stocks of the Chinese Securities 100 index in the Chinese stock market as experimental data. The findings showed that a prediction-based portfolio model based on deep, multi-layer perception DMLP performs the best among other models under different desired portfolio returns.

Wu et al. (2020)) introduced adaptive stock trading strategies using deep reinforcement learning (DRL) methods. Their gated deep Q-learning (GDQN) and gated deterministic policy gradient trading strategy methods outperform traditional approaches and exhibit stability in volatile markets. The gated recurrent unit (GRU) is employed to extract informative financial features for adaptive decision-making. The actor-critic framework in GDPG enhances stability compared to the critic-only framework in GDQN.

4. Discussion overview of equity trade simulators and their features

4.1. Equity trade simulators

This section identifies the current technologies and capabilities in the investment domain by addressing pre-trade compliance concerns through the use of equities trade simulators, along with their limitations. In recent years, equity trading simulators have developed into an important tool for traders and portfolio managers. These simulators enable investment managers to test and validate deals before they are performed, assuring compliance with rules and reducing risk in light of the growing complexity of the financial markets and regulations. Using stock trading simulators to evaluate investment ideas in a controlled setting is one of its main advantages. These simulators give portfolio managers the ability to experiment with various investing scenarios and see how these strategies affect the performance of the portfolio. Managers may be able to recognize possible hazards and improve their investment choices as a result (Sholehah et al., 2020).

The Penn Exchange Simulator was a software simulator for algorithmic stock trading (Wellman et al., 2002). It received real-time order book data from island electronic crossing networks, offering a more realistic simulation environment. Users could connect to the simulator, place orders, monitor market data, and evaluate their performance. The simulator allowed for the blending of internal and external markets by matching user orders with both other users' orders and real market orders. It was used in trading agent competitions and provided a user-friendly interface for multi-client connectivity.

Omx and Montgomerie-Neilson (2012) identified pre-trade risk validation algorithms for the portfolios of commodities futures and options utilizing the risk analysis methodology SPAN. An agent-based interactive discrete event simulation environment (ABIDES) is an interactive discrete event simulation environment developed by Byrd et al. (2019) to simulate trading agents interacting with an exchange agent. It supports customizable network latencies and is engineered leveraging NASDAQ's protocols, including ITCH—denoted as "Integrated Trading Communications Hub," a protocol for streaming market data—and OUCH. The OUCH protocol, specifically designed for electronic trading, facilitates rapid submission of orders to the market, allowing traders to efficiently place, cancel, or replace orders with minimal delay. This study introduces ABIDES, provides sample code for configuration, and validates the environment with trading scenarios. It also demonstrates the utility of ABIDES in developing a market impact model and discusses potential future applications, such as exploring ML-based trading algorithms.

Hu and Watt (2014) introduced a financial market simulator that replicates a real market environment and supports various security types. The simulator utilizes the FIX communication protocol, enabling multiple users to interact independently or simultaneously. The study also presented different types of configurable trading agents that resemble real market traders, allowing for the exploration of specific market behaviors by adjusting their parameters. The authors demonstrated the usefulness of the simulator in corporate settings for scenarios such as system testing, education, training, and policy evaluation. Alves (2020) created a financial market simulator named SHIFT for researching market micro-structures. The simulator allows automated traders and researchers to trade various financial assets in an exchange-like environment. It replicates the rules of US equity markets, supporting market and limit orders executed in a first-in-first-out manner. The paper presents the system architecture, explores use cases, demonstrates realistic price generation by automated agents, and investigates crash events in a market stress scenario.

Amrouni et al. (2021) introduced the OpenAI Gym framework for discrete event multi-agent simulation (DEMAS) using discrete event time. They demonstrated a technique to integrate a DEMAS simulator into Gym, using ABIDES as an example. Specifically, they applied this technique to ABIDES-Markets, creating two benchmark financial market environments within Gym for training investors and execution agents. These environments simulate interactive market behavior in response to agent actions, providing a platform for addressing financial problems.

4.2. Features and functionalities of equity trade simulators for pre-trade compliance

Portfolio managers can utilize equity trading simulators to ensure pre-trade compliance with investment mandates, rules, and best practices. These simulators offer a range of features and functions to model and evaluate investment scenarios, test different choices, and validate transactions before execution. By incorporating market data streams, equity trading simulators provide up-to-date information on prices, volumes, and relevant indicators. This enables portfolio managers to simulate real market conditions and make informed investment decisions (Olorunnimbe and Viktor, 2023). Individual investors can also benefit from these tools by simulating and evaluating investment situations, understanding the impact of choices on portfolio performance and risk exposure, and ensuring compliance with mandates through pre-transaction checks.

Equity trading simulators offer risk management methods, such as stress testing, scenario modeling, and analytics, to help identify and control market, credit, and liquidity risks (Al Janabi, 2007). Performance attribution tools allow portfolio managers to analyze factors influencing portfolio performance, such as investment strategy, security selection, and sector allocation. Comprehensive reporting and analysis features, including customizable reports, dashboards, and charts, enable portfolio managers to assess investment performance, risk exposure, and mandate compliance. Real-time reporting and analytics capabilities are particularly valuable for making timely decisions and adjusting portfolios to market trends.

Equity trading simulators support the back-testing of investment strategies, providing insights into their performance under various market conditions. Overall, these tools provide portfolio managers with risk management and compliance solutions, allowing them to replicate transactions, generate real-time reports, and analyze portfolios effectively.

4.3. Examples of equity trade simulators

4.3.1. FLEXmarket

FLEXmarket helps to evaluate market concepts. This simulator conducts a market trial and exports and examines the trade information. Hence, trading flexibility is made easy with FLEXmarket. Instead of emphasizing conventional "measures," FLEXmarket uses transparent, open-source M&V to identify results at the meter. It then pays aggregators for the results that are provided, enabling them to get paid more for the work that they have already performed.

4.3.2. Zurich Trading Simulator

oTree users can access the online dynamic trading application Zurich Trading Simulator (ZTS). When it comes to making individual investment choices, ZTS offers a simulation perspective of a market that is always changing. ZTS is an oTree app that is a one-to-one replica of the design created by Andraszewicz et al. (2022) with the intention of offering it to scientists worldwide. ZTS is different from earlier designs that looked into how price patterns affect risk perception and decision-making because it has a dynamic chart instead of a static graphical price display (Borsboom and Zeisberger, 2019, Huber et al., 2022, Lejarraga et al., 2016). Furthermore, in ZTS, an individual’s past investment choices influence the context in which they make future decisions. ZTS allows for experiment customization through changes to the source code or configuration options, and it also provides several additional features that can be added using the traditional setup. Examining risk-taking and trading behavior under different pay plans, like fixed wages, watermark funding, bonus payments, etc., is possible with the conventional setup. Individuals in different settings complete the same trading tasks under a between-subjects design, but their compensation will vary for each condition.

ZTS makes it possible to track when trading participants (who are given access to various compensation plans) alter their trading strategies in response to the achievement or failure of their objectives. Similarly, by placing individuals in the role of an asset manager for an outside company, as opposed to someone handling their own assets, one can study the impact of definitions on trading behaviors. ZTS can also be connected to software that gauges an individual’s physiological response to different market conditions, like crashes. Previous studies have shown a connection between a trader’s physiology, including their levels of cortisol and testosterone, and their willingness to take risks on the stock market (Cueva et al., 2015). ZTS enables measuring the relationship between hormone levels and trading actions, including risk-taking and trading activities, under controlled conditions. Additionally, the price display of ZTS precisely connects skin conductivity reaction, the body's psychological response, and arousal measurements to different market scenarios.

4.3.3. Traderion

Traderion is a digital learning platform based on the integration of technology and gamification. It uses machine learning algorithms and gamified simulations to provide trading professionals with training and profiling. Through the use of multiplayer simulation and the same game design found in prevalent online games, this environment is tailored to the learning style of millennials. All of the player's interactions with the platform are monitored, and data is collected. The objective behavioral analysis of this data is used to forecast performance and provide feedback.

5. Benefits and advantages of using equity trade simulators

This section aims to discuss the current technologies and capabilities in the investment domain that address pre-trade compliance concerns through the use of equity trade simulators, while also acknowledging their limitations.

5.1. Assessment of investment choices and adherence to internal policies and regulations

The primary advantage of using stock trading simulators is the ability to evaluate investment ideas within a controlled environment. Portfolio managers can experiment with various investing scenarios and assess their impact on portfolio performance. Through these simulations, managers can identify potential risks and make informed improvements to their investment decisions (Sholehah et al., 2020). By leveraging equity trade simulators, portfolio managers gain valuable insights into the consequences of their investment strategies without exposing their portfolios to actual market conditions. This controlled experimentation enables them to refine their approaches, optimize risk-reward profiles, and ensure compliance with regulatory requirements. Moreover, simulators provide a safe space to test innovative investment ideas, enhancing portfolio managers' overall decision-making processes (Smith and Johnson, 2019).

5.2. Mitigation of potential risks and avoidance of regulatory infractions

It is important to acknowledge the limitations of equity trade simulators. These limitations include the necessity of accurate and reliable data inputs, the potential biases in simulator outputs, and the challenge of replicating real-time market dynamics accurately. While simulators offer valuable tools for pre-trade compliance and risk management, they should be utilized in conjunction with expert knowledge and real-world market analysis to ensure robust decision-making processes (Brown et al., 2021). There are several flaws reported due to the complexity of algorithms. Knight Capital's use of an algorithm to quickly sell all shares in less than an hour (Lee and Schu, 2022) instead of gradually selling them over several days resulted in significant losses and led to their bankruptcy (Lee and Schu, 2022). The flash crash highlighted the risks associated with algorithmic trading, as multiple algorithms, including high-frequency trading (HFT) algorithms, interacted with and intensified the falling prices (Keller, 2012). The interconnectedness of algorithmic trading strategies increases the likelihood of transmitting shocks across trading venues (Oicv-Iosco, 2011). Regulators have implemented measures such as pre-trade risk controls and the involvement of senior management to mitigate these risks. Thorough checks of algorithms by users and platform providers are necessary before their implementation in the market.

5.3. Performance monitoring and evaluation of compliance measures

Anginer et al. (2020) and Yang et al. (2020) found that active simulator users with higher risk-taking and better stock performance were more likely to open real money accounts. However, these users underperformed in real trading despite their success on the simulator, highlighting a discrepancy between the two. Factors beyond simulation experience may influence actual trading outcomes. Vyetrenko et al. (2020) compared real market data with simulated market data using limit order book (LOB) markets. They explored different simulated market configurations, including market replay and interactive agent-based simulation (IABS) methods. The study found that using historical market data for determining fundamental values in IABS resulted in more realistic market behavior compared to a mean-reverting random walk. They also demonstrated the effectiveness of IABS techniques in over-market replay. Overall, the research highlights the benefits of LOB markets in analyzing trading strategies and emphasizes the importance of accurate fundamental values for realistic market simulation. The simulators were assessed for accuracy and utility in real-world environments (**Table 3**). For example, Investopedia.com (Investopedia) is an online stock market simulator that allows trading in stocks and alternatives for every major American stock exchange. eToro allows the user to select the "Real/Virtual" button located beneath the username in the upper left corner of the account dashboard; eToro enables the user to effortlessly navigate between the Real and Virtual accounts. The company thinkorswim provides a stock simulator known as paperMoney. In summary, equity trade simulators have become vital tools for portfolio managers, enabling them to assess investment strategies, ensure pre-trade compliance, and mitigate risks. Through simulations, portfolio managers can test investment scenarios, identify potential hazards, and improve their decision-making process. However, it is important to recognize the limitations of these simulators and use them in conjunction with domain expertise to ensure their effective utilization in the investment management process.

Table 3. Advantages and disadvantages of trading simulators.

Simulator	Use	Advantages	Disadvantages	Scope of interest
Investopedia.com (Investopedia)	An online stock market simulator that allows trading in stocks and alternatives on every major American stock exchange.	• It has strong research and simulated trade order placement tools. • It provides very short latency and tracks the value of investing positions almost instantly. • Users of the simulator can take part in games where they can assess how well they have performed financially relative to others. • Investopedia uses its software to internally manage compliance with rules.	Limited studies with smaller sample sizes to assess its real-time effectiveness in portfolio management.	Four main functional areas constitute the stocks interface: games, research, trade, and portfolio. One can monitor simulated value changes for each position you start by using the portfolio tab.

Table 3. (*Continued*).

Simulator	Use	Advantages	Disadvantages	Scope of interest
The Monte Carlo simulation	Monte Carlo simulation is a technique for determining the value of an unidentified factor using inferential statistics.	The results of a Monte Carlo simulation seem to produce portfolios that are more accurate in terms of their future prospects and stable in terms of sample risk.	Requires further investigation for applicability.	Suitable for portfolio management.
eToro	A trading simulator.	By selecting the Real/Virtual button located beneath the username in the upper left corner of the account dashboard, eToro enables effortless navigation between the Real and Virtual accounts.	eToro simplifies the practice of trading, but this ease of use also introduces potential risks in the trading process.	Risk assessment and portfolio management.
Thinkorswim paperMoney	It provides a stock simulator known as paperMoney.	It is powered by paperMoney, and its trading platform is thinkorswim, which uses real-time data to test the trading methods in an open market setting.	It is not as user-friendly as other simulators for the stock market. A learning curve is to be expected.	Identifies appropriate trading options.
TradeStation	This online broker caters to traders who trade frequently.	Provides back-testing, limitless paper trading funds, and real-time data. With its paper trading simulator, the learning possibilities are truly endless. Allows users to practice trading in historical or real-time simulations of stocks.	TradeStation is a platform that is exclusive to traders.	Enables users to practice trading with historical or real-time simulations of stocks.

6. Best practices for utilizing equity trade simulators

MiFID II introduced comprehensive requirements for algorithmic trading in the EU. Investment firms must comply with the regulatory technical standards (RTS 6) (European Commission, 2017) developed by ESMA (Article 17) (Algo, 2020). These standards cover organizational requirements, system efficiency, and risk controls (European Commission, 2017). Investment firms need to establish clear methodologies for developing and testing algorithms by allocating responsibilities within the firm (European Commission, 2017). While the regulations work well for traditional algorithms, they pose challenges for self-learning algorithms using AI (Raschner, 2021). The testing of algorithms must be conducted in separate environments from live trading, ensuring system efficiency and preventing disorderly conduct. Stricter regulations apply to order-executing algorithms due to their immediate impact on the market. National regulators are addressing the complexities of AI in financial markets, considering governance adaptations and result checks by algorithms operated by the Bundesanstalt für Finanzdienstleistungsaufsicht (2018). Overall, the regulations promote compliance, risk management, and the safe deployment of algorithms in the market.

Performance testing is a crucial step before deploying algorithmic trading strategies. It ensures that the algorithmic trading system operates correctly and meets the requirements of the trading venue. Verification includes testing the interaction with the venue's matching logic and data processing capabilities (Union et al., 2017). The responsibility for conducting these tests lies with market participants themselves, without direct involvement from supervisory authorities. This approach allows for flexibility and avoids impeding innovation. Supervisory authorities focus on the risk-based supervision of specific areas of algorithmic use due to limited resources. Overall, the testing process plays a vital role in ensuring the proper functioning of algorithmic trading systems while balancing the need for regulatory oversight and market innovation. In order to mitigate the risks associated with algorithmic trading, European regulations mandate the implementation of pre-trade control measures. These controls, outlined in Article 15 of RTS 6, include price collars to block orders that fall outside specified price parameters for different financial instruments. Maximum order values and volumes are also required to prevent excessively large orders from entering the market and potentially causing significant losses, as seen in the case of Knight Capital Group (FCA, 2018).

After the UK's departure from the EU, regulatory requirements were amended to align with EU legislation through a process called "Onshoring" (Legislation, 2020). The FCA implemented MiFID II regulations in the UK, focusing on areas such as algorithmic trading, risk controls, and governance (FCA, 2020) [91]. The FCA's good practice guidelines go beyond the minimum requirements of MiFID II, emphasizing the need for algorithm inventories and senior management involvement (Lee and Schu, 2022). Algorithm inventories provide detailed information for managing algorithmic trading activities (FCA, 2018). The FCA also recommends measures for development and testing, including appointing project leaders and conducting thorough due diligence (FCA, 2018). Senior management is expected to understand and oversee algorithmic trading, allocating responsibilities accordingly. However, the effectiveness of senior managers and certification regimes in the dynamic algorithmic trading market has been questioned (Prudential Regulation Authority, 2020).

The regulatory landscape for algorithmic trading in the United States differs from that of Europe and the UK. The Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) are the main regulators overseeing the securities and commodities markets (Labonte, 2020). The SEC has adopted Regulation Systems Compliance and Integrity (Reg SCI) to ensure the security and integrity of the systems used by selected entities in the securities markets (Annette Nazareth, 2014). The SEC Market Access Rule requires broker-dealers to establish risk management systems for market access, including measures to prevent erroneous orders (From et al., 2017). The CFTC proposed the Regulation of Automated Trading (Reg AT), which focuses on additional regulatory requirements for market participants (Hartman and Green, 2019). These regulations aim to address the risks associated with algorithmic trading while promoting fair and efficient markets (Checklist, 2001). Furthermore, pre-trade checks should incorporate automated execution throttles to limit the number of times a single algorithm can be applied. Once a predefined threshold is reached, the execution throttle temporarily disables the algorithm until a human staff member evaluates the situation and decides whether to re-enable it (European Commission, 2017). These measures aim to enhance risk management and ensure the appropriate oversight of algorithmic trading activities.

7. Limitations and challenges of equity trade simulators

7.1. Considerations for data accuracy, regulations, and relevance in simulators

Equity Trade simulators and online trading exposes firms to various risks, including regulatory, financial, reputational, and operational risks. Controls throughout the life cycles of orders must be automated and embedded within order or execution management systems (OMSs/EMSs) (Esma, 2023). Establishing a rigorous and effective control framework requires governance structures, formal policies and procedures, detailed control inventories, the delegation of responsibilities, and the monitoring of controls. Developing a mature control framework can take years of commitment and investment. An example of a control, such as setting a compliance limit for an incoming parent order, highlights the complexities involved in ownership, documentation, data security, ongoing monitoring, and exception handling. The dynamic nature of simulators using AI poses challenges to scrutinizing and approving frequent changes while maintaining consistency. The potential use of automated algorithms, such as machine learning or artificial intelligence, for approval, raises questions about their impact on job opportunities.

7.2. Addressing potential biases and limitations in simulator outputs

The use of machine learning algorithms in financial services presents challenges for regulators. While these algorithms offer benefits in terms of automation and efficiency for firms, they also raise concerns about their independence and potential unpredictability (Lee and Schu, 2022). Regulators have not yet provided specific instructions on how to manage the risks associated with machine learning algorithms, but there have been suggestions for mandatory requirements to mitigate these risks (Babel et al., 2019). In both the European Union and the United States, there is a focus on ensuring that regulation does not hinder the development of artificial intelligence (Commission, 2013). However, a comprehensive regulatory approach is needed to address the unique risks posed by complex algorithms, including improved oversight, responsibility allocation, and pre-trade testing standards (Babel et al., 2019). Establishing a global regulatory sandbox environment could be beneficial for testing these algorithms (Kapsis and Ilias, 2020).

Best practices for deploying and using an equity trade simulator in portfolio investment management include establishing precise rules and procedures, engaging relevant parties, integrating the simulator with other risk management tactics, regularly examining and analyzing its performance, configuring it to reflect investment constraints and rules, maintaining up-to-date data, utilizing the simulator for ongoing development, and recognizing that it is just one tool in the portfolio manager's toolbox. By adhering to these practices, portfolio managers can effectively control risk, ensure compliance, and make informed investment decisions using equities trade simulators.

8. Future research directions and opportunities

Future studies should encourage the creation of novel allocation strategies based on data analysis and machine learning (Kim et al. 2021; Kwak et al. 2021). For example, Lopez de Prado (2016) provides a method for allocating portfolio assets that makes use of clustering techniques. Furthermore, papers such as Kwak et al. (2021) and Andersson and Oosterlee (2021) suggest the use of a structure based on deep learning to enhance certain elements of portfolio management. There is always space for improvement because these techniques are relatively new. In order to encourage the creation of innovative portfolio allocation plans, a framework that makes it possible to efficiently analyze the performance of these plans under various conditions is required. Back-testing—that is, using long-term traces of various asset and stock prices and attempting to simulate the scheme's performance over these traces—is one method of researching various portfolio allocation strategies. The main risk associated with this popular method is the potential for statistical overfitting (Cesari and Cremonini 2003). The hyper-parameters of the strategies over such traces can be precisely tuned thanks to the computational power of contemporary computers, which allows for the analysis of many adjustments of a specific approach. One workable way to prevent overfitting is to conduct (Monte Carlo) simulation analyses. Essentially, the developed portfolio allocation schemes are studied through the use of several pseudo-random data-trace-generation techniques. By examining a scheme's behavior across a multitude of (randomly generated) simulation scenarios, one can get a broad understanding of how well the scheme performs in those kinds of situations. Additionally, back-testing can be employed as a last test set to validate the practicality of the developed strategy.

The effectiveness of equity trade simulators can be enhanced by integrating more comprehensive market data, volumes, prices, and other indicators to ensure that simulators reflect real-world market conditions. In addition, it is necessary to capture the intricacies and complexities of financial markets; there is a need to refine the algorithms and models used within the simulators. By achieving this, simulations can be more reliable and realistic. There is a need for continuous updates and the refining of the underlying data and models, thereby allowing portfolio managers to rely on the simulators for accurate and informed investment decisions. Artificial intelligence and machine learning (ML) enhance the capabilities of trade simulators because they have the capability to analyze large volumes of data, identify patterns and trends, and generate predictive insights. These technologies offer improved portfolio optimization and, therefore, decision-making support. Moreover, these simulators adapt to learn from market dynamics. Integrating scenario-based analyses allows managers to simulate and evaluate the potential impact of various market events and economic conditions. In addition, to mitigate potential compliance and ensure adherence to regulatory requirements, there is a need to incorporate a regulatory compliance framework.

The present study has certain limitations. First, there are a limited number of randomized controlled studies that have been conducted on equity simulators. This makes it challenging to effectively determine the real-world success of these techniques. Second, an understanding of the long-term consequences of simulators and their use alongside AI is lacking. Therefore, the scope of the present and future opportunities is still unclear.

To the best of our knowledge, there is a lack of in-depth research that outlines the role of simulators in enhancing data accuracy and providing best practices in portfolio management. The significance of this research is based on the finding that, through the evaluation of existing studies, portfolio managers can mitigate potential risks, identify profitable opportunities, and make informed investment decisions regarding equity simulators.

9. Conclusion

In conclusion, equity-trading simulators represent invaluable tools for portfolio managers seeking to model trades, evaluate their impact on portfolios, and ensure adherence to pre-trade compliance. These sophisticated systems offer a comprehensive suite of features, including real-time market data integration, robust risk management tools, and insightful performance reporting. Utilizing equity-trading simulators empowers portfolio managers to proactively mitigate potential risks, spot lucrative opportunities, and make well-informed investment decisions.

To fully harness the benefits of these simulators, it is imperative to adhere to industry best practices, conduct regular performance evaluations, and maintain a keen eye on data accuracy. In today's dynamic financial landscape, equity trading simulators have evolved into indispensable instruments within the realm of financial services. They not only promote transparency but also facilitate regulatory compliance.

In practice, portfolio managers should proactively stay abreast of industry trends and exploit the full spectrum of simulator functionalities. Engaging in feedback sessions ensures a cycle of systematic enhancements, ultimately empowering portfolio managers to craft and execute optimal decision-making strategies. These practical insights underscore the significant role of equity trading simulators in modern portfolio investment management.

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