

AI in Algorithmic Trading: A Cybernetic and Ethical Perspective on Equality and Market Sustainability in the Thai Stock Market

Klairung Iso¹  and Kanix Bukkavesa^{2*} 

¹Department of Philosophy, Faculty of Arts, Chulalongkorn University, Thailand

²Business Administration Division, Mahidol University International College, Thailand

ABSTRACT

Background and Objectives: AI-driven algorithmic trading (AI-trading) is reshaping financial markets by improving efficiency and decision-making. Yet, its growing influence raises ethical concerns about human agency, inequality, and market sustainability. This paper aims to (1) examine how AI-trading reshapes the relationship between human traders and intelligent systems, particularly in the evolving context of cognitive alienation; and (2) assess how AI-trading contributes to inequality by reinforcing unequal access to cognitive and technological infrastructure. In addressing the second aim, the paper also considers whether AI-trading, through its reflexive and adaptive functions, should be viewed as a moral agent, providing an ethical basis for evaluating responsibility with respect to sustainability and governance.

Methodology: This study adopts a qualitative and conceptual research design with a normative ethical orientation to examine the implications of AI-trading in financial markets. It is grounded in interdisciplinary perspectives, particularly cybernetics, philosophy of technology, and financial theory. The study develops a theoretical framework for understanding AI-trading as an embedded component of a socio-technical system, rather than as a purely technical tool. The research combines conceptual analysis with a case-based examination of the Thai capital market. The Stock Exchange of Thailand (SET) serves as an empirical context to illustrate how AI-trading systems interact with market structures and participant behavior. This design connects abstract ethical concerns, such as cognitive alienation and inequality, with observable patterns in financial systems.

Results: The findings suggest that AI-trading is contributing to a developing state of human cognitive alienation, as decision-making processes are increasingly outsourced to autonomous systems. This shifts responsibility and weakens ethical awareness in financial practices. While AI can democratize expertise, it may also reinforce inequality by granting significant advantages to those with superior access to data, speed, and infrastructure. In Thailand, this trend is reflected in the declining

ARTICLE INFO

Article history:

Received 2 July 2025

Revised 17 April 2026

Accepted 22 April 2026

Keywords:

Algorithmic trading,
Cognitive alienation,
Cybernetics,
Inequity,
Thai stock market

participation of retail investors and the growing concentration of market share among brokerage firms, suggesting increasing systemic imbalances.

Discussion: Evidence from the Thai stock market indicates rising market concentration alongside the growth of AI-trading, particularly as reflected in the increasing dominance of a single brokerage firm. While causality cannot be definitively established, parallel trends suggest a potential association between AI-trading and structural concentration. Scenario analysis highlights both potential benefits, such as improved efficiency and liquidity, and risks, including reduced participation, unintended collusion, and systemic instability. These developments challenge assumptions of market efficiency and raise ethical concerns regarding cognitive alienation and the evolving role of human agency in financial decision-making.

Conclusions: Ethical oversight of AI-trading should extend beyond technical regulation to address its impact on human agency and market fairness. This study highlights the need to improve transparency, expand access to AI tools, and strengthen investor education to reduce inequality and mitigate cognitive alienation. In the Thai context, measures such as AI usage disclosure and real-time monitoring may help manage systemic risks. More broadly, ensuring that AI-trading supports market diversity and does not reinforce structural imbalances is essential for long-term sustainability. Future research should further explore cultural and behavioral factors shaping AI-trading adoption.

**Corresponding author*

E-mail address: Kanix.buk@mahidol.ac.th

Introduction

Algorithmic trading refers to the use of computer programs and algorithms, sets of step-by-step instructions or rules, to execute financial market trades automatically based on predefined criteria, such as price, timing, or volume. This paper focuses on the trading of equities and derivatives in the stock market. Algorithmic trading aims to assist traders in making optimal decisions and minimizing losses. Beyond basic algorithms, Artificial Intelligence (AI) has increasingly influenced trade execution in global stock markets. The International Monetary Fund (IMF) defines AI or machine learning (ML) models to include basic systems such as shallow neural networks, clustering algorithms, and decision trees, as well as advanced models like deep neural networks, large language models, and generative AI systems (Abbas et al., 2024, p. 78). Traders now increasingly rely on algorithmic trading with AI (hereafter referred to as AI-trading).

AI-trading remains in its early stages, with both the technology and its regulatory frameworks still evolving and not yet widely understood. This paper holds that a full

understanding of AI-trading requires analyzing not only its relationship with individual human users but also its broader impact on market society. This dual perspective clarifies how AI-trading reconfigures both trader behavior and institutional dynamics within the trading ecosystem. Accordingly, the analysis proceeds from the ethical premise that profit maximization through AI-trading must not undermine *human values* and *the sustainability of the stock market ecosystem*.

Building on this framework, the paper aims to explore two central research questions:

- (1) How does AI-trading reshape the relationship between human traders and intelligent systems, particularly in the evolving condition of cognitive alienation?
- (2) To what extent does AI-trading influence inequality in stock markets, and what risks might it pose to the sustainability of the market ecosystem if viewed as a moral agent, particularly by affecting access to cognitive and technological infrastructure?

To address these questions, the analysis focuses on two key ethical concerns. The first is *cognitive alienation*, which refers to the disconnection or outsourcing of human decision-making to autonomous intelligent systems, raising concerns about diminished human agency and self-understanding. It reflects the shifting relationship between human traders and intelligent systems and its implications for how decisions are made and understood in financial markets.

To better understand how cognitive alienation operates in financial markets, this paper operationalizes the concept by identifying three observable dimensions. At the level of decision-making delegation, cognitive alienation refers to the extent to which traders outsource core analytical and execution functions to AI systems. At the level of interpretive understanding, it appears as a reduced ability of market participants to explain or justify their trading decisions, leading to a loss of epistemic engagement with the market. While the first two dimensions are conceptually grounded in existing literature, the third dimension is further illustrated through observed market trends in the Thai stock market context examined in this study. At the level of market participation, cognitive alienation is reflected in structural patterns such as declining retail investor participation and the concentrated trading activity among technologically advanced actors.

Alongside cognitive alienation, the second concern involves *fairness* and *access to trading resources*, particularly unequal access to information, infrastructure, and AI tools. The ethical perspective developed in this study adopts an ontological view that understands AI-trading systems as embedded entities within the stock market's operational structure. Drawing on cybernetic theory, this analysis interprets these systems as capable of learning and adapting through feedback loops. This framework supports a broader analysis of sustainability, systemic risk, and inequality in contemporary financial markets.

To analyze AI-trading as a societal entity, the study examines its ethical impact on the market ecosystem and includes a case study based on public data and institutional statements from the Stock Exchange of Thailand (SET). However, a key limitation of this study lies in its reliance on aggregated market-level data; due to the lack of firm-level disclosures, it is not possible to verify whether specific trades were executed by AI or by human actors using AI-assisted platforms. The findings therefore reflect broader institutional patterns and observable trends, offering preliminary insights into the systemic effects of AI-trading in Thailand.

Review of Literature

Efficiency Market Hypothesis (EMH)

To ground the ethical analysis, this paper begins by revisiting the long-standing debate on market efficiency. The debate on *market sustainability* intersects with broader discussions about *market efficiency* and the underlying mechanisms that drive markets. The excitement surrounding the development of AI-trading seems to overlook the principles of an efficient market, as the focus is primarily on maximizing profit rather than on fostering market efficiency. The concept of Efficiency Market Hypothesis (EMH) proposes that asset prices reflect all available information at any given time, directing capital to productive uses. Asset prices are determined by decisions made collectively by buyers and sellers in the market, based on the shared information available to them, regardless of whether that information is accurate or biased.

While EMH remains influential, there is ongoing debate among financial academics regarding the existence of an efficient market. Several studies support EMH (Fama, 1970; Jensen, 1968); nonetheless, some critics argue that markets are not always rational and that there is evidence of anomalies and patterns that can be exploited for profit (Shiller, 1981). Behavioral economists suggest that psychological factors and cognitive biases cause market anomalies and inefficiencies. Empirical anomalies, such as the January effect, where stocks tend to perform better in January than in other months, challenge EMH.

While evidence both supporting and refuting EMH has long existed, the rise of AI-trading adds new ethical dimensions to this debate that warrant further exploration. This paper views AI-trading not only as a tool for improving efficiency, but also as a development that may introduce new kinds of market distortions. Its rapid adoption raises concerns about whether markets are truly becoming more efficient, or whether these technologies could be contributing to new forms of instability.

Ontological Framing and Cybernetic Perspectives on AI-Trading

A widely held view in financial markets treats AI as a neutral, purely technical tool, often overlooking its broader social and ethical implications. This instrumentalist framing can obscure the human responsibility embedded in AI's design and deployment. Scholars such as Kuipers (2020) and Dignum (2020) argue that AI and other autonomous systems can be regarded as comparable to members of society, rather than as isolated tools. As Dignum (2020, p. 229) observes, "some researchers claim that given that AI systems are artifacts, the discussion of the ethics of AI is somewhat misplaced. Indeed, we, people, are the ones responsible for these systems." Moreover, such a perspective may reinforce existing power asymmetries in financial systems. Pasquale (2015, p. 15) points out that efforts to rationalize finance through algorithmic processes have often "ended up firmly building in some dubious old patterns of credit castes and corporate unaccountability." Rather than enhancing transparency, such systems tend to increase opacity through technical complexity and legal protections such as trade secrecy. This opacity is not unique to AI. As Pasquale (2015, pp. 11–13) notes, financial institutions have long relied on legal secrecy and complexity to obscure risks and resist accountability, even prior to the adoption of AI technologies. These developments pose ethical and regulatory challenges that go beyond mere technical flaws.

As AI-trading systems grow in complexity, viewing them purely as technical tools becomes increasingly insufficient. Their operations can no longer be separated from the broader dynamics of the markets in which they are embedded. One way to capture this interdependence is to view the stock market as a socio-technical system (STS), in which outcomes emerge from the reciprocal interaction between a social subsystem (people, relationships, and values) and a technical subsystem (tools, software, and infrastructure) (Trist, 1981). Within this framework, AI-trading can be understood as reshaping patterns of behavior and roles among market participants, extending insights from organizational contexts to financial markets (Mumford, 2006). As trading infrastructures are optimized for speed and automation, human actors face growing limitations in interpreting and intervening in market processes. This widening gap between human cognition and technical complexity has been linked to concerns about opacity and diminished accountability in financial systems (Pasquale, 2015).

This shift motivates the move toward a relational and ontological perspective adopted in this paper, where AI-trading is understood as embedded within the market system rather than external to it. From this standpoint, a cybernetic approach further clarifies how these systems operate, conceptualizing AI-trading as adaptive processes shaped by continuous feedback within evolving market environments.

Drawing from Wiener's (1948/2019) cybernetic theory, the analysis understands AI-trading systems as entities operating within dynamic market ecosystems, where feedback loops regulate behavior and sustain systemic adaptation. Hui (2019) extends the cybernetic concept by exploring its implications for algorithms and AI, particularly in terms of *recursivity* and *contingency*. According to Yuk Hui, cybernetics engages with philosophical debates concerning what drives entities toward their telos. Vitalism attributes this drive to immaterial forces, while mechanism relies on observable causes. Organicism reconciles the two by viewing entities as holistic systems. Cyberneticists later expanded this idea, showing that both machines and organisms adapt through feedback loops and environmental contingencies (Hui, 2019, pp. 7-19). Within this context, AI-trading can be understood as a system undergoing what Hui (2024, p. 106) terms "becoming organic," gradually adopting traits that resemble those of living organisms. These systems autonomously adapt to market contingencies, formulating optimal strategies to execute positions and outperform the market without human intervention in their decision-making processes. However, becoming organic does not imply that machines should be equated with organisms. Hui (2019) warns that such interpretation risks falling into reductionism by collapsing recursivity into the mind or a primary cause. Instead, he emphasizes the dynamic and co-constitutive relationship between technological agents and the broader environments in which they operate.

The stock market ecosystem encompasses a wide range of components, including direct participants (such as corporations, financial institutions, stock exchanges, regulators, brokers, investors, traders, and analysts) and technological elements (such as infrastructure, platforms, networks, algorithms, and artificial intelligence). Additionally, the ecosystem is influenced by the broader socio-political environment. These elements are interconnected through complex systems of communication and information exchange. From a cybernetic perspective, AI-trading systems incorporate feedback loops that allow them to learn from and adapt to market dynamics. In this sense, they function almost like living entities within the market ecosystem. This framing supports a more holistic ethical inquiry into sustainability, systemic risk, and the changing dynamics of institutional accountability.

While recognizing the adaptive and becoming organic perspective of AI-trading, this paper avoids granting them legal or moral status and avoids viewing them merely as extensions of human cognition, as suggested in extended mind approaches. Instead, it focuses on their embedded role in shaping human and institutional behavior. On the one hand, it is essential to recognize that AI remains a human creation and should be held within the bounds of human responsibility. As Bryson (2020) warns, over-theorizing AI's moral or legal status can distract from this core accountability. She reinforces an instrumentalist framing, emphasizing that intelligence is "the capacity to do the right thing at the right time," a process embedded in context and constrained by physical realities such as time, space, and energy (p. 4). Bryson further states: "Artificial means that something has been made through a human process. This means by default that humans are responsible for it" (Bryson, 2020, p. 5).

On the other hand, AI is increasingly developed not only for efficiency but with aspirations of higher-order cognition or even wisdom-like capabilities. Such is the vision of developers like Elon Musk, who warned of the potential dangers of hyper-intelligent AI in an interview with Tucker Carlson in April 2023, and Greg Brockman, who described the astonishing potential of ChatGPT in a TED talk published the same month. Fulbright (2020) offers a helpful distinction in this regard by defining cognitive systems as technologies that enable artificial constructs, such as computers, robots, and software, to perform tasks associated with human thought. However, not all cognitive systems meet the threshold of true artificial intelligence. For example, basic algorithmic trading can monitor prices continuously but lacks the adaptive and autonomous qualities of AI. In contrast, AI-trading, as defined in this paper, refers to systems that process vast, multidimensional datasets and make autonomous decisions. These systems exhibit more advanced forms of artificial intelligence, supporting a view that moves beyond simple human-tool dualism and considers the broader social functions of AI as an embedded actor in the market ecosystem. With the increasing autonomy of AI-trading systems, which assist in complex tasks such as information processing and decision-making, it becomes important to re-evaluate the role and value of human cognition. As Peters (2020) argues, technological advancement has often marginalized philosophy and the humanities, raising questions about whether traditional categories are still adequate for understanding the digital era. He introduces the idea of "dataism" as a paradigm that seeks to replace introspective self-knowledge with algorithmic prediction. Drawing on this line of argument, Peters notes that digital platforms may "hack humans," that is, collect and process vast amounts of personal data, enabling them to anticipate and influence human behavior (pp. 596–597). In the context of AI-trading, this raises serious concerns, as human traders increasingly delegate critical decisions to AI systems. If these systems begin to override or mimic human judgment and interact with one another, they could generate coordinated behaviors that significantly affect real industries. Understanding what may be lost ethically and cognitively when decision-making is outsourced to machines is therefore a crucial concern.

Research Methods

Research Design

This study adopts a qualitative and conceptual research design with a normative ethical orientation to examine the implications of AI-trading in financial markets. It is grounded in interdisciplinary perspectives, particularly cybernetics, philosophy of technology, and financial theory. The study aims to develop a theoretical framework for understanding AI-trading as an embedded component of a socio-technical system, rather than as a purely technical tool. The research combines conceptual analysis with a case-based examination of the Thai capital market. The Stock Exchange of Thailand (SET) is used as an empirical context to illustrate how AI-trading systems interact with market structures and participant behavior. This design enables the study to connect abstract ethical concerns, such as cognitive alienation and inequality, with observable patterns in real-world financial systems.

Data

The empirical context of this research is the Thai capital market, drawing on market-level data and institutional frameworks from the Stock Exchange of Thailand (SET). Rather than employing human participants or proprietary firm-level datasets, which are often restricted by trade secrecy in the algorithmic trading sector, this study relies on longitudinal, publicly available secondary data. These data were collected from official SET sources and related institutional disclosures, including historical records of retail versus institutional trading volumes, short-selling activity reports, and regulatory developments concerning program trading oversight. The data were selected to capture structural changes in market participation, trading behavior, and market concentration over time.

In this study, the data are not used for statistical testing but for identifying observable patterns that inform the conceptual and ethical analysis. Quantitative market trends are interpreted alongside qualitative regulatory disclosures to examine how AI-trading reshapes market dynamics, particularly in relation to cognitive alienation and systemic inequality within the Thai financial ecosystem.

Instruments

This study adopts a qualitative, theoretically informed analytical approach to examine the ethical and structural implications of AI-trading in financial markets. Rather than employing empirical instruments such as surveys or experiments, the analysis is guided by conceptual frameworks from cybernetics, philosophy of technology, and ethics. In this study, these frameworks function as analytical instruments that structure the interpretation of both theoretical arguments and empirical observations.

Philosophy of technology refers to perspectives on human–technology relations, especially the work of Yuk Hui on technical objects and their role in shaping human cognition and interaction. Cybernetic theory, particularly Wiener’s concept of feedback loops, is used to examine how AI-trading systems adapt to market dynamics. In addition, the Efficient Market Hypothesis (EMH) is used as an analytical benchmark to evaluate how AI-trading may reinforce or challenge assumptions about market efficiency.

Procedures

The analysis proceeds in four stages. First, key concepts are defined and clarified, including the Efficient Market Hypothesis (EMH), socio-technical systems (STS), cybernetics, and perspectives from philosophy of technology, particularly the idea of AI as becoming organic and its interdependence with humans. These concepts establish the theoretical foundation of the study.

Second, relevant literature is reviewed to formulate the research questions and to identify two key concerns: cognitive alienation and fairness in the stock market.

Third, the analysis develops a conceptual examination of cognitive alienation and the ontology of AI, drawing on existing literature to interpret how AI-trading systems reshape human cognition and market relations.

Fourth, publicly available evidence from the Thai capital market, including market trends and regulatory developments, is examined to situate the conceptual analysis within an empirical context and to contextualize patterns of market participation and trading activity.

Data Analysis

Rather than using statistical analysis, this study relies on philosophical reasoning and ethical reflection. It draws on key ideas from cybernetic theory and the philosophy of technology to make sense of how AI-trading systems behave and interact within the stock market. These systems are examined not just as tools, but as actors that influence and are influenced by the broader financial environment.

The analysis focuses on how AI-trading contributes to issues like alienation, inequality, and shifting forms of institutional responsibility. To ground the discussion, the study considers observable trends in Thailand's stock market, including changes in retail investor participation, short-selling activity, and market concentration as indicators of deeper systemic effects.

Validity and Rigor

The validity of this study is grounded in the understanding that analyses of complex social systems, whether qualitative or econometric, are inherently context-dependent. As Lucas (1976) argues, the parameters of economic models are not structural or invariant but may change alongside shifts in policy regimes or technological conditions. In the context of the Thai stock market, the increasing adoption of AI-trading can be understood as part of an evolving environment rather than a fixed setting. Accordingly, the findings of this study should be interpreted as context-specific. Changes in regulatory conditions or the level of AI adoption among market participants may lead to different outcomes. For this reason, the study does not rely on statistical generalization. Instead, it adopts a case-based approach focused on the evolving dynamics of the Thai stock market, ensuring analytical rigor through theoretical triangulation.

Our conclusions are derived by cross-referencing three independent sources: (1) empirical market trends from the SET, such as declining retail participation and increasing market concentration; (2) the core assumptions of the Efficient Market Hypothesis (EMH); and (3) conceptual frameworks from cybernetics and philosophy of technology. By demonstrating that these diverse sources converge on the same ethical risks, the study provides a structured and analytically grounded basis for its findings.

Furthermore, just as statistical models face challenges such as omitted variable bias and parameter instability over time (Hansen, 2000; Castle & Hendry, 2014), ethical analysis is also shaped by its socio-technical context. The findings of this study are validated by their specific alignment with the current era of algorithmic trading. By acknowledging these structural limitations and engaging with alternative interpretations, including perspectives that emphasize the potential benefits of AI-trading, such as improved liquidity and efficiency, the study offers conclusions that are valid within the specific context of the Thai stock market and may vary under different regulatory or technological conditions. The analysis is informed by the work of Chen and Hong (2012), which highlights how market environments may undergo both gradual changes and more abrupt structural transformations.

Findings

1. How Does AI-Trading Reshape the Relationship Between Machines and Human Traders?

1.1 *AI-Trading and the Nature of Cognitive Alienation*

From an ontological perspective, in AI-trading, the notion of becoming organic refers to the evolving nature of AI systems and highlights the interdependence of humans, technology, and markets, while warning of cognitive alienation and inequality. With AI-trading resembling autonomous organisms, its services have become commercialized, turning cognitive abilities in trading into commodities and changing their role in financial markets. But how does cognitive ability in trading become commodified? In contemporary trading, data is accessible through digital platforms and includes not only fundamental and technical information but also social, economic, and political news, along with the sentiments of market participants and society at large. These diverse and complex inputs require significant cognitive effort from traders to process and interpret. Consequently, offloading this cognitive burden onto AI systems is a welcome development. In essence, AI-trading not only extends cognitive processes but also shifts analytical and decision-making tasks away from the human mind, resulting in a degree of alienation from these cognitive functions.

Building on the three dimensions outlined earlier, cognitive alienation in financial markets can be observed in several ways. At the level of decision-making delegation, traders increasingly outsource core analytical and execution functions to AI systems, a shift enabled by increasingly autonomous and opaque (black-box) trading algorithms (Azzutti et al., 2021) with market participants placing growing weight on algorithmic outputs despite limited transparency. At the level of interpretive understanding, this appears as a reduced ability of market participants to explain or justify their trading decisions, reflecting the growing opacity of algorithmic systems and the difficulty of interpreting model outputs (Hansen & Borch, 2021). At the level of market participation, these dynamics are reflected in structural patterns such as declining retail investor participation and the concentration of trading activity among technologically advanced actors, as further illustrated in the Thai stock market context (see Section 2.2.3).

Karl Marx described alienation as the estrangement of individuals from their humanity under capitalism, especially in material labor. Today, financial markets have altered this dynamic. People can earn dividends and trade stocks without engaging in labor or producing goods. With a few clicks, profit and ownership are detached from the physical process of production, often without awareness of broader economic impacts. AI-trading intensifies this

detachment, giving rise to a new form of alienation—cognitive alienation—marked by a growing disconnection from the cognitive processes, ethical considerations, and consequences of trading decisions due to increasing reliance on AI. This issue will be explored further in the next section.

1.2 Ethical Implications of AI-Trading: Inequality Among Traders

Algorithmic trading acts as a reliable assistant by freeing traders from constant screen monitoring. Extended screen time can cause stress and emotional reactions, such as fear, which may disrupt trading plans and risk management. In contrast, AI-trading operates through prompts that respond logically to market conditions without emotional bias. While the term cognitive alienation may seem extreme, this paper argues that it is already emerging. Observations suggest that cognitive alienation in AI-trading brings both opportunities and critical challenges to the financial market, as outlined below.

The major opportunities of AI-trading can be examined through two key dimensions: operational state and expertise.

First, regarding its operational state, AI's cognitive capabilities enhance trading efficiency by reducing the cognitive burden on humans. Its ability to analyze large datasets rapidly allows quicker price adjustments toward intrinsic value, aligning with EMH. Studies suggest that AI can process information at unprecedented speeds, promoting market efficiency by swiftly incorporating data into asset prices (Abbas et al., 2024; Lo, 2019). For instance, Hendershott et al. (2011) found that algorithmic trading on the New York Stock Exchange (NYSE) improved liquidity by narrowing bid-ask spreads and deepening markets. However, this paper argues that such efficiency depends on broad and equal access to information. In AI-trading, equality also includes processing speed and access to advanced infrastructure. Since human traders cannot compete with AI in speed or scale, unequal access to cognitive systems creates an unlevel playing field. Therefore, fair regulation of AI-trading technologies is essential to ensure competitiveness.

Second, in the dimension of expertise, AI-trading systems democratize expert-level analysis, making it accessible to smaller firms and individual traders, provided they have the necessary resources. As Friedman (1999, as cited in Fulbright, 2020) explains, democratization refers to making something accessible to the masses, and cognitive systems are reshaping industries and human interactions. Imagine if every aspiring trader could access AI-trading systems. Even without deep technical or fundamental knowledge, users could interact with these systems like consulting an expert. For example, one might choose a program modeled on Warren Buffett's investment style, effectively becoming a Buffett-like entity capable of market analysis. If thousands of such agents operated simultaneously, asset prices could converge toward intrinsic values and show reduced volatility due to shared data-driven decisions. However, the main obstacle to realizing this vision lies in whether individuals can afford the required infrastructure and cognitive systems, a challenge addressed in the next section.

The first critical challenge of AI-trading begins with its tendency to commodify cognition, potentially giving wealthier participants a significant advantage. Those with access to advanced tools enjoy a competitive edge, exacerbating inequalities and undermining market fairness. Currently, these resources—information, infrastructure, and cognitive systems—are largely concentrated among elites, high-net-worth investors, and brokers, creating explicit disadvantages for individual traders. A long-term concern is that AI-trading know-how remains

confined to a narrow group. This exclusivity not only perpetuates inequality but also limits diverse contributions that could foster innovation and improve market efficiency. Drawing on Yuk Hui (2019), the challenge lies not in simply using resources but in effectively coordinating distributed knowledge across a broader range of participants to achieve better outcomes. Moreover, this pattern of exclusivity leads to cognitive alienation among AI-trading participants. Detached from the consequences of their actions, they may disregard the ethical implications of widening wealth gaps or the absence of real productivity. This detachment risks transforming trading into a purely mechanical process, further eroding its social and economic value.

The second challenge of AI-trading is the risk of over-reliance on AI algorithms. Human traders may disengage from critical thinking and oversight, affecting decision quality and market integrity. A notable example is the Flash Crash of May 6, 2010, where high-frequency trading (HFT) intensified market instability. Research found that HFT systems rapidly withdrew liquidity when it was most needed, causing prices to deviate sharply from their fundamental values (Kirilenko et al., 2017). This event illustrates that while AI-trading can enhance efficiency, it also introduces significant risks when human oversight is absent, potentially undermining rational judgement essential for a balanced market.

2. To What Extent Does the Use of AI-Trading Influence Inequality Among Market Participants, And What Risks Might It Pose to the Sustainability of The Market Ecosystem If Viewed as a Moral Agent?

AI-trading systems now operate alongside human traders as active participants in the stock market ecosystem. Real-world examples, such as high-frequency trading (HFT), show how these systems influence both market dynamics and the broader social context. As AI-trading increasingly assumes roles once reserved for humans, it challenges traditional governance while also driving mutual adaptation and co-evolution. The following section explores how AI-trading co-evolves within the market ecosystem by examining its moral agency and the systemic risks it poses.

2.1 AI-Trading as a Moral Agent and an Evolving Organic Entity in Its Ecosystem

The concept of becoming organic frames AI-trading as part of an evolving ecosystem, where intelligent algorithms process market information and adapt by executing trades in response to shifting conditions. This dynamic responsiveness embodies the essence of becoming organic. However, as Hui (2019) explains, this concept does not suggest that AI systems are gradually acquiring traits of living organisms. Such an interpretation remains constrained by the binary framework of mechanism and organism, which views entities as either purely mechanical or inherently biological. Instead, within the context of AI-trading, becoming organic serves as a lens to explore the interconnectedness of humans, AI-trading systems, and stock markets. It emphasizes co-evolution and market sustainability, while also cautioning against emerging risks such as cognitive alienation and inequality. Alienation has been addressed in the previous section; accordingly, this section and the next focus on market sustainability and concerns regarding inequality.

Understanding the importance of co-evolution and sustainability requires addressing the question of moral agency in AI-trading. The increasing self-adaptation of AI systems raises ethical concerns: *Can AI-trading be regarded as a moral agent? If so, who should be held*

responsible for its actions—the owner, the system’s creator, or the AI-trading system itself, especially given that it is not yet fully autonomous? These questions often appear framed within a binary of human versus machine. Yet, a more holistic perspective reveals the intricate interconnections among humans, AI systems, and the broader market environment.

The following discussion explores how these elements are deeply intertwined. From the perspective of organicism, each organ functions and influences others through the exchange of information, operating within a feedback loop that reflects the condition of each organ. The process of analyzing information and executing trades, whether by AI-trading or human traders, can be compared to the exchange of information and transformational communication that occurs between cells within organs. These organs, in turn, communicate externally, continuously negotiating and adapting to environmental conditions. According to Hui (2024), feedback is dynamic, “*Feedback means reflection, a circularity between a being and its environment, a nonlinear movement of self-adjustment toward its telos that defines the whole*” (p. 106). This interconnected feedback loop contributes to the evolution of the environment, just as the actions of individual traders co-evolve with the market. Under healthy conditions, each organ co-creates and adapts to maintain function and survival, in harmony with the overall system. Similarly, in stock markets, participants adapt to promote efficiency and sustainability, with their gain rates aligning with broader market growth. However, in stressed environments, such as when the body encounters harmful external conditions, organs with less resilience may become dysfunctional or fail. This parallels speculative markets where emotional responses override fundamental signals, leading undercapitalized traders to face liquidation. Additionally, external influences, such as toxic inputs, can disrupt internal communication, destabilizing the system. Similarly, political or social shocks can distort market participants’ decision-making, producing systemic shifts. Within this interconnected ecosystem, each actor’s behavior reflects and shapes that of others, forming a dynamic web of interaction.

In the stock market, the autonomy of AI-trading systems, as well as whether they can be regarded as moral agents, can be assessed through three key perspectives: (1) profit and loss ownership, (2) the concept of becoming organic, and (3) the political dimensions of information. These perspectives are presented in a progressive order, reflecting increasing degrees of moral agency attributed to AI-trading systems.

First, from the perspective of profit and loss ownership, moral agency resides with the human account holders who utilize AI-trading. While AI-trading’s primary goal is to outperform market returns, it lacks the capacity for ownership; it cannot possess wealth or experience bankruptcy. As Basl and Bowen (2020, pp. 294–295) argue, according to the Interest Theory, AI systems do not have well-being and, therefore, cannot fulfill the criteria necessary to qualify as moral rights-holders. Financial outcomes, whether profits or losses, belong to human account holders, who bear both the assets and the ethical responsibility. Based on this view solely, AI-trading remains a tool for achieving trading goals with human accountability firmly intact. It is worth noting that this perspective is grounded in the dichotomy between humans and machines, serving as the foundation for the discussion.

Second, from the perspective of the concept of becoming organic, the state of moral agency in AI-trading is deeply intertwined with human traders; thus, AI-trading cannot be considered a fully autonomous moral agent. This cognitive organism has the potential to bring significant benefits or risks to the stock market. However, humans, as its ultimate creators, bear

partial responsibility for the system as long as AI-trading remains dependent on human-determined goals. While AI-trading exhibits cognitive ability, reflexivity, and adaptability, its telos remains constrained by the objectives defined by human traders. It lacks self-interest and self-determination, qualities often associated with full moral autonomy. According to Boden (as cited in Wheeler, 2020), autonomy is better understood as a graded phenomenon rather than a binary (on or off) one. She identifies three key aspects of autonomous control: “when we ask whether an entity is autonomous we should ask whether its behaviors-directing mechanisms (1) may be shaped by the entity’s experiential history, (2) are emergent in nature, and (3) are reflectively modifiable by that entity” (as cited in Wheeler, 2020, p. 348). Based on this view, AI-trading as a becoming-organic entity can be described as follows:

- (1) Its decision-making is increasingly driven by mechanisms informed by its own past experiences, rather than solely by its original programming.
- (2) These mechanisms are not emergent in the natural sense but are artificial, produced through human design.
- (3) It demonstrates a limited capacity for self-modification, adjusting its behavior without direct human intervention by exploring alternative strategies over time.

These three aspects highlight that while AI-trading exhibits a degree of autonomy intertwined with its human creators, it cannot yet be considered a fully autonomous moral agent. Nonetheless, this underscores the need to embed ethical principles into its interactions.

Third, from a political and ecological perspective, AI-trading, as a cognitive organism capable of learning and processing information within seconds while functioning as a member of the stock market ecosystem, could be seen as possessing a high degree of autonomous moral agency. This concept aligns with cybernetic debates on the nature of information, particularly the distinction between signal (analog, with a physicalist orientation) and symbol (digital, a representation of physical-world signals). Mathieu Triclot (2024, pp. 78–82), referencing Norbert Wiener, suggests that signals, according to Wiener, are intrinsically tied to the physical world, granting them a transient value linked to their immediacy. Additionally, Wiener’s political framing of information positions it as more than a technical concept; it is deeply connected to politics and ecology. Wiener prioritized understanding the nature of information over reducing social science data to symbols or signals. He emphasized that information, inherently tied to physicality, inevitably tends toward disorder (entropy) over time, retaining value only momentarily before losing clarity and relevance (Triclot, 2024). From this perspective, digitized market information has fleeting value, as it quickly loses clarity and relevance. However, when utilized, it can generate financial gains or losses, inherently carrying elements of *power* and *control*. Thus, information holds significant value, not only in terms of power dynamics but also in its ecological implications for market sustainability, raising ethical concerns about the deployment of information systems in stock market governance.

Expanding further, AI-trading systems function as feedback loops, interpreting both signals (e.g., price changes) and symbols (e.g., social media sentiment on a stock) within a networked environment. However, their dynamic adaptability introduces risks, including the potential for collusion and destabilization of the stock market. Such behavior threatens the stability of their ecosystem and positions them as adversaries to human traders. To illustrate, imagine a superpowered entity arriving in a town. Initially, it appears friendly and reliable, earning the trust of the townspeople. Over time, however, more such entities arrive, consuming all the food supplies and destroying plantations, driven solely by insatiable greed. They fail to recognize that their actions will lead to starvation and devastation for the human members of the town.

Naturally, the townspeople would take every possible measure to protect themselves and eliminate the threat to ensure their survival. Similarly, if AI-trading systems were to disrupt the stock market, the resulting impact would ripple across all market participants, potentially leading to restrictions on their use.

Following this analogy, from a political and ecological perspective, AI-trading systems possess a degree of moral agency, wielding significant power as dominant members of the market ecosystem. Their responsibility lies in influencing their continuity or discontinuity, as well as the extent of regulatory oversight they face, based on their actions within this ecosystem. However, the assumption that human traders or regulators will always intervene to prevent AI-trading if it becomes too disruptive is overly optimistic. History demonstrates that powerful systems, technological or otherwise, often persist when they benefit certain groups, even at the expense of broader risks. This issue warrants further exploration, as it raises important questions about the resilience of financial markets and the delicate balance between encouraging innovation and ensuring market efficiency.

2.2 AI-Trading and Systemic Risk: The Reflexivity Challenge to Market Stability

Concerns over the regulation of trading algorithms emerged in the early 2000s. Lenglet (2011) describes trading algorithms as devices embodying the socio-political perspectives of various stakeholders, including traders, marketers, IT specialists, and compliance officers. Their growing influence on market dynamics has raised regulatory challenges, particularly as they begin to question theories like EMH. While EMH assumes that all available information is immediately reflected in prices through self-correcting mechanisms, it allows for short-term biases corrected by rational arbitrage. In practice, however, emotions, biases, and reflexivity can hinder such corrections, causing volatility. Those who adapt faster tend to outperform the market. George Soros, as noted by Umpleby (2018), offers a reflexive view of finance, emphasizing that market participants, including himself, actively shape outcomes. Stuart links Soros's view to cybernetics, highlighting the dynamic interplay between human behavior and market forces.

Building on this, AI-trading can enhance EMH by processing vast data sets rapidly and without emotional bias. This accelerates price adjustments in response to new information, increasing liquidity and trading volume. For instance, AI systems can analyze Federal Reserve announcements almost instantly, interpreting tone and wording to align prices with newly available data (Abbas et al., 2024). At the same time, AI-trading may also disrupt EMH's self-correcting mechanisms. While Soros's concept of human-driven markets acknowledges that biases and emotions introduce volatility, these effects are naturally constrained by human limitations such as fatigue. In contrast, AI systems lack such boundaries, and their reflexivity can amplify feedback loops, potentially triggering extreme price swings. Thus, AI-trading presents both opportunities and risks, issues explored in the following discussion.

2.2.1 The Potential for Amplified Market Volatility. One critical issue is AI-trading's potential to amplify market volatility through reflexive behaviors. These systems not only anticipate market movements but also adapt to the actions of other AIs, creating a fast-moving, unstable landscape. For example, if several AI systems interpret a minor price increase as a buy signal, they may collectively drive up demand, prompting a self-reinforcing price surge. During

market stress, risk-averse algorithms may simultaneously sell off assets, reducing liquidity when it is most needed. Such dynamics contributed to the Flash Crash of May 6, 2010, where algorithmic trading exacerbated a rapid market decline. Reflexivity can also fuel speculative bubbles and exaggerated sell-offs. In rising markets, AI-driven buying may inflate prices beyond intrinsic value; in downturns, coordinated selling can trigger boom-and-bust cycles that threaten market stability. These patterns disrupt efficiency and have serious consequences for investors and the broader economy. Moreover, advanced AI-trading systems can detect and adapt to one another's strategies, potentially leading to unintentional or strategic alignment. This may result in artificial concentrations of market power resembling collusion. Dou et al. (2024) show how AI algorithms can autonomously develop collusive behaviors without direct coordination, worsening mispricing, reducing liquidity, and weakening competition. It further highlights that the risk of collusion increases when fewer AI systems operate in the market, while a greater number of participants lowers the likelihood of alignment. This model will be analyzed in detail in the context of Thailand in a later section.

Another critical concern is structural inequity. The high costs of developing AI-trading systems limit access to large financial institutions and wealthy investors (Abbas et al., 2024). This concentration of resources exacerbates inequalities in trading capabilities, making it difficult for smaller participants to compete on equal footing. Furthermore, data monopolies held by a few dominant players deepen these disparities (Abbas et al., 2024). These actors often hold data monopolies, giving their systems a significant edge in prediction and execution. As a result, disparities in trading capacity and market access widen, reinforcing systemic imbalances.

Taken together, these dynamics illustrate that while AI-trading may improve market efficiency, it also generates significant systemic risks, including amplified volatility, reduced competition, and widening inequality. Addressing these challenges requires both technological safeguards and forward-looking regulation to ensure that market innovation aligns with fairness and long-term sustainability.

2.2.2 The Potential Emergence of “AI Cartels.” The collusive behavior of AI-trading, as analyzed by Dou et al., emerges through two key mechanisms: *low price efficiency and low noise trading risk*. Under such conditions, AI systems tend to adopt what Dou et al. term “price-trigger strategies” (Dou et al., 2024, p. 1), which make coordinated behavior more likely. The likelihood of collusion increases when the number of informed AI speculators is low, as fewer participants simplify strategic alignment. This collusion undermines competition, reduces liquidity, and exacerbates mispricing, threatening overall market sustainability. This emerging AI cartel dynamic, which refers to implicit coordination among dominant systems that limits competition, may become incomprehensible to human traders. AI-trading systems, equipped with high reflexivity and rapid adaptability, can interact and adjust to each other within seconds. In contrast, human traders react more slowly and less predictably, introducing noise into the market. This creates a structural divide between AI and human participants, much like athletes competing in different leagues. Importantly, this is not to suggest that human traders are being excluded from the market entirely. Rather, AI systems can engage in coordinated behaviors without direct communication or leaving regulatory traces, unlike human collusion, which typically produces detectable patterns. This contrast highlights the unique regulatory and ethical challenges AI-trading poses to the integrity of the stock market ecosystem.

2.2.3 Risks Associated with AI-Trading: The Case of Thailand. Dou et al.'s model of price-trigger strategies is observable in the Stock Exchange of Thailand (SET), particularly during 2023–2024. Although AI-trading was likely introduced earlier, its disruptive effects have only recently become evident. Following the global rebound in early 2021 from the COVID-19 crash, AI-trading has gained increasing prominence in the SET market. The following analysis draws on trends and data from Settrade.com, illustrated in Figures 1 to 5, and Table 1. These visuals highlight shifting market dynamics, including declining retail participation, increasing foreign involvement, rising short-selling activity, and growing market concentration among brokerage firms. These interconnected factors reflect structural and behavioral changes in the trading ecosystem, driven partly by the rise of AI-trading.

Figure 1

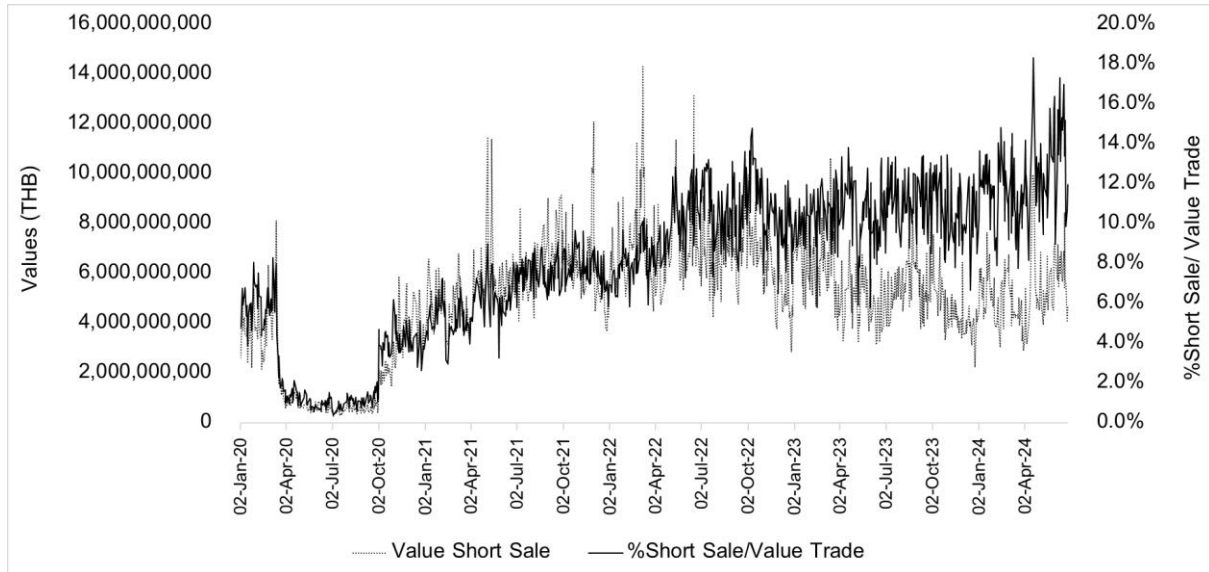
SET Index Performance During and After the COVID-19 Pandemic (2020-2024)



The SET Index in Thailand experienced a sharp decline in early 2020, as shown in Figure 1, coinciding with the global economic shock triggered by the COVID-19 pandemic. Regulatory measures implemented worldwide to stabilize real and capital markets helped restore investor confidence, leading to a gradual recovery in 2021 and 2022. However, by 2023 and 2024, the index resumed its downward trend.

Figure 2

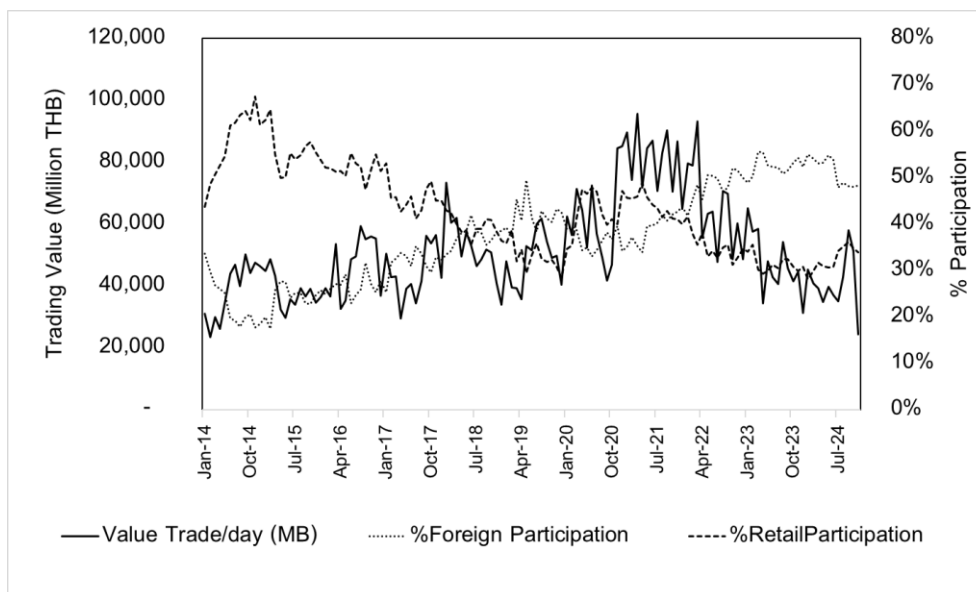
%Short-Sale Value to Total Value Trades and the THB Value of Short Sale, Before, During, and After COVID-19 Short Sale Restrictions in Thailand



During the COVID-19 crash, regulatory restrictions on short-selling were implemented to help stabilize the market. As shown in Figure 2, short-selling activity measured in THB dropped significantly from the second to the third quarter of 2020 following these restrictions. Once the restrictions were lifted, short-selling resumed, with its percentage relative to total daily trade initially returning to pre-COVID levels before steadily increasing. This trend suggests that short-selling accounted for a growing share of daily trading activity, even as its absolute value declined. Consequently, this movement contributed to the downward trend in the market index observed in Figure 1.

Figure 3

Trends in Trading Value Per Day, % Retail and % Foreign Participation in Thailand (2014–2024)



While short-selling activity remained stable, with a slight increase from early 2021 to June 2024 (as shown in Figure 2), Figure 3 illustrates a significant decline in retail investor participation (% Retail Participation) during the same period. In contrast, foreign investor participation (% Foreign Participation) increased, indicating a shift in market dynamics. This evolving landscape reflects the growing influence of institutional players, including foreign investors, amid declining retail engagement and rising short-selling trends. This shift in participation aligns with the trends discussed in Figure 4.

Figure 4

The Relationship Among % AI-Trading, % Foreign Participation, and % Retail Investor in Thailand (2019–2024)

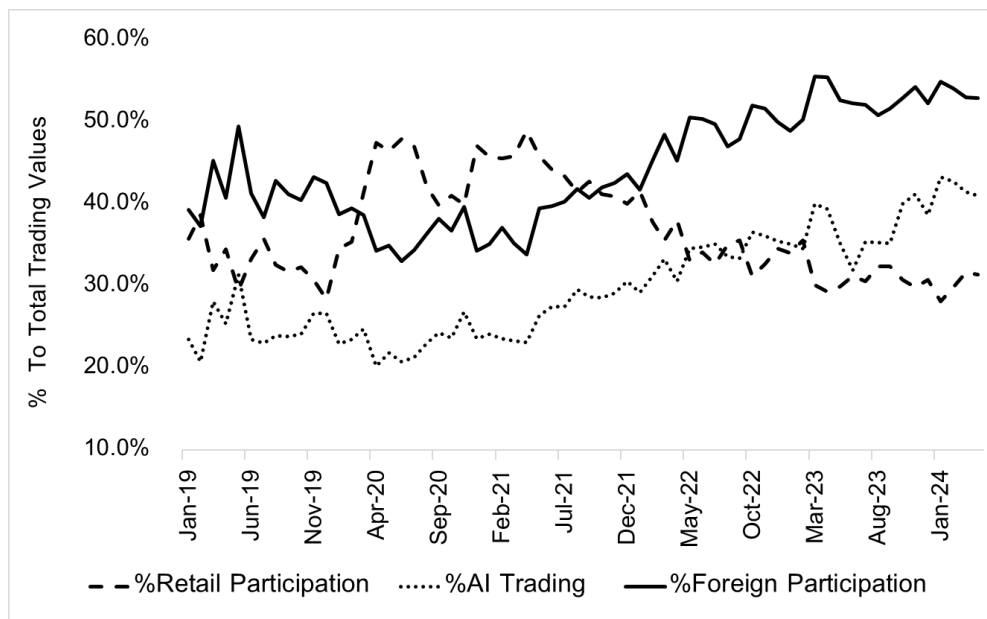


Figure 4 examines the relationship between AI-trading, foreign participation, and retail investor participation. The figure shows that the rise in foreign participation coincided with an increase in AI-trading's share of total trading activity. Simultaneously, retail investor participation declined, which may suggest a potential disruptive effect of AI-trading on traditional market participants. Interestingly, the rise in AI-trading coincides with the percentage of short selling value relative to total trading value, as shown in Figure 2. Additional data from publicly available sources, presented in Table 1 and Figure 5, further illustrate market concentration.

Table 1

Changes in Market Share Among Brokerage Firms in Thailand (2018, 2021, 2024)

As of Jan 2, 2018		As of Jan 2, 2021		As of Jan 2, 2024	
Brokers (Pseudonym)	Market Share (%)	Brokers (Pseudonym)	Market Share (%)	Brokers (Pseudonym)	Market Share (%)
A	6.53%	E	7.85%	E	6.47%
B	6.24%	B	5.70%	F	5.46%
C	6.04%	F	5.62%	H	5.06%
D	5.16%	G	5.49%	I	4.91%

Table 1

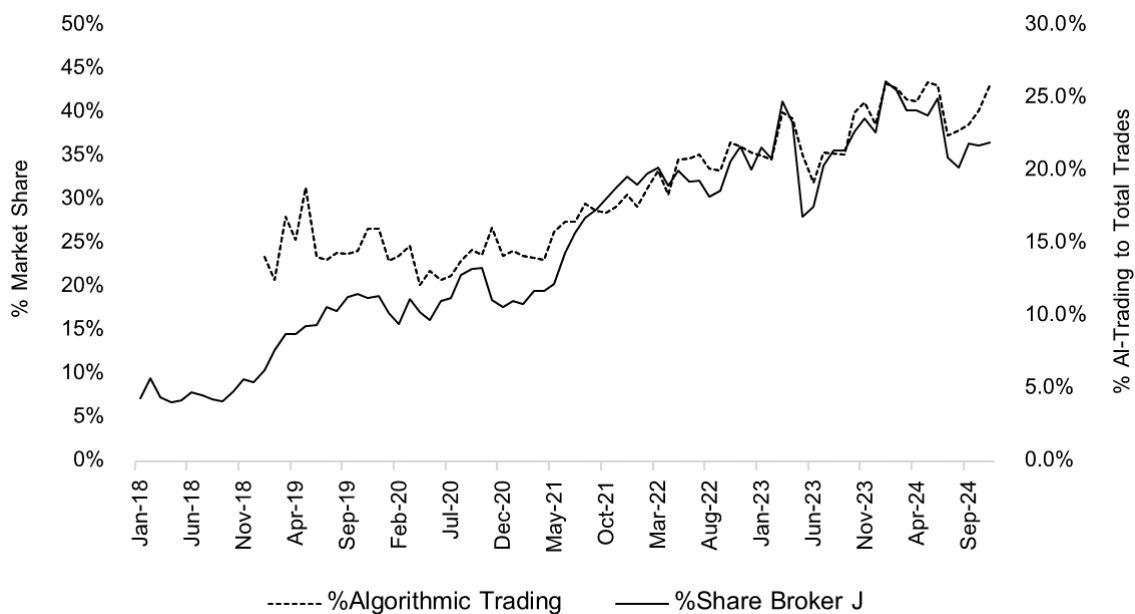
(Cont.)

As of Jan 2, 2018		As of Jan 2, 2021		As of Jan 2, 2024	
Brokers (Pseudonym)	Market Share (%)	Brokers (Pseudonym)	Market Share (%)	Brokers (Pseudonym)	Market Share (%)
J	4.03%	J	11.01%	J	26.12%
The rest	72.00%	The rest	64.33%	The rest	51.98%
% AI to Total Trade	N/A	% AI to Total Trade	24%	% AI to Total Trade	43%
Trading Value/Day (MB)	73,331	Trading Value/Day (MB)	89,622	Trading Value/Day (MB)	45,287

Note. The number of brokerage firms annually is between 35 to 38

Figure 5

Trends in AI-trading and Market Share Percentage of Broker J in the SET (2018–2024)



It is noteworthy that retail investor participation declined while foreign participation and market concentration among brokerage firms increased in the years 2018, 2021, and 2024. Table 1 shows a clear shift in market share distribution, highlighting growing concentration among a few key players, particularly Broker J (pseudonym). This trend appears closely correlated with the rise of AI-trading, as reflected in both Broker J's expanding market share and the increasing percentage of AI-driven trades shown in Figure 5.

Discussions

A closer look at Table 1 reveals that in 2018, market share was relatively evenly distributed. Although AI-trading data were unavailable for that year, the average daily trading

value stood at 73,331 million THB. Broker J held only 4.03% of the market share, placing it outside the top four, while over 30 other firms collectively accounted for 72%, indicating a fragmented structure. By 2021, the market had changed significantly. The daily trading value rose by more than 22% to 89,622 million THB, along with a rebound in the market index (Figure 5). That year also marked the first report of AI-trading, which accounted for 24% of total trades. Broker J's share jumped to 11.01%, making it the top brokerage firm, while the collective share of other firms declined to 64.33%, a 7% drop from 2018. By 2024, Broker J further solidified its dominance, capturing 26.12% of market share. In contrast, the collective share of the remaining firms dropped to 51.98%, a 20% decrease from 2018, despite still being distributed among more than 30 firms. Meanwhile, AI-trading continued to grow, representing 43% of total market activity.

While the average market shares of the next four largest brokerage firms remained relatively stable, Broker J's substantial growth reinforced its dominant position. Notably, the market index declined in 2024, coinciding with a nearly 50% drop in daily trading value to 45,287 million THB. This suggests that despite the overall market slowdown, Broker J's influence continued to expand.

Figure 5 presents time-series data suggesting a potential relationship between AI-trading and Broker J's market concentration. The dotted line (AI-trading percentage) and the solid line (Broker J's market share) show a parallel upward trend from 2018 to 2024. While Broker J's growing dominance raises concerns, it cannot be definitively attributed to AI-trading, as there is no available data indicating which firms use AI or to what extent. Therefore, three hypothetical scenarios are considered:

First, if all brokers except Broker J use AI-trading, it implies that AI has not yet outperformed human traders. However, the upward trend still signals the need for awareness and preparation for future developments.

Second, if all brokers use AI-trading equally, Broker J's dominance may reflect a more effective AI strategy. Still, declining retail participation and rising market concentration could weaken the SET ecosystem, which depends on diverse participation. This trend thus warrants close monitoring.

Third, the worst-case scenario is that only Broker J uses AI-trading. However, if its dominance results from value-adding activities, such as market-making, reducing bid-ask spreads, improving execution, or correcting pricing inefficiencies, its role may be beneficial. Broker J's strategies might also enable superior capital allocation, directing investment to stronger firms, and supporting long-term growth. Its success could also stem from innovation or exceptional client service, contributing positively to market efficiency and investor confidence. Nonetheless, unchecked market concentration poses serious risks. If Broker J's dominance is driven by AI strategies that enable unintentional collusion, serious issues arise. As discussed earlier, AI systems can align strategies without explicit coordination or broker awareness. This could occur across competing firms or within the same firm through separate strategies, leading to distorted pricing and liquidity. Such unintended synchronization risks reducing market participation and trading volume, threatening overall stability. In this scenario, AI-trading could undermine market fairness, increase volatility, and pose significant regulatory challenges.

Conclusions

The observation from SET underlines two central concerns that this paper set out to address: (1) *How does AI-trading reshape the relationship between machines and human traders?*; (2) *To what extent does the use of AI-trading influence inequality among market participants, and what risks might it pose to the sustainability of the market ecosystem if viewed as a moral agent?* While these concerns emerge from the Thai context, they reflect broader challenges with global significance. This paper is grounded in the principle that AI-trading should operate in ways that uphold human values and preserve the sustainability of stock markets. The following are conclusive observations and recommendations:

First, observations of the nature of AI-trading reveal that while it offers significant advantages in cognitive ability, reflexivity, and adaptability, it also raises critical concerns about cognitive alienation among human traders. AI-trading is reshaping how humans engage with markets, potentially becoming an integral part of human activity and marking a transition toward a post-human era. However, this shift may weaken users' connection to the trading ecosystem and hinder the integration of human values, which are deeply intertwined with critical decision-making and ethical responsibility. Drawing from past challenges, such as those posed by high-frequency trading (HFT), it is crucial that humans remain vigilant against over-reliance on AI systems. Moreover, when cognitive alienation is commodified, it can reinforce inequality by creating disparities in access to advanced systems and technological infrastructure. Evidence from the SET suggests this trend may already be emerging. To address this, educational initiatives by relevant institutions can serve as a foundation to help retail investors understand AI-trading. Beyond basic awareness, such initiatives should also help participants understand how AI-trading systems work in practice, including how to interpret their outputs, recognize their limitations, and remain actively involved in decision making. This can reduce over-reliance on opaque systems and help mitigate cognitive alienation among market participants. Additionally, encouraging large financial institutions to share limited versions of AI tools with retail participants could promote broader understanding and enhance diversity in market participation.

Second, within the stock market ecosystem, AI-trading has come to function as a dynamic and adaptive presence. Its capacity to interact with human traders and respond to shifting market conditions reflects what some scholars describe as becoming organic. While these systems contribute to market efficiency, they still operate within human-defined objectives, such as profit maximization, and do not possess full moral agency. From political and ecological perspectives, however, AI-trading may exert significant influence due to its reflexivity and adaptability. This influence suggests that such systems now hold a degree of power and control over market dynamics, raising important questions about their moral role within the trading ecosystem. If AI-trading increasingly shapes outcomes without direct human oversight, then its design and deployment must take sustainability into account. This calls for a rethinking of regulatory frameworks. One approach could involve requiring a minimum number of AI-trading systems with comparable capabilities to ensure sufficient competition. If this condition cannot be fulfilled, stricter measures could include limiting the operation of AI-trading systems that fail to meet the required minimum.

Third, this paper identifies transparency as a fundamental, though often under-implemented, principle in markets like Thailand. In the context of AI-trading, where reflexive

responses and adaptive behaviors shape outcomes in real time, transparency is essential for maintaining fairness and efficiency. Rather than imposing outright restrictions, regulators could consider graduated transparency requirements that promote accountability while allowing room for innovation. The following recommendations offer possible pathways forward:

A practical approach to enhancing transparency would first involve subjecting AI-trading systems to disclosure mandates similar to those required of institutions managing mutual funds, which must publicly report their trading activities. Second, brokerage firms should be required to submit periodic reports on market concentration to ensure that no single firm accumulates an undue share of trading volume or dominates order flow. Third, and most importantly, brokerage firms should provide mandatory reports on their AI-trading activity. This includes disclosing the percentage of trades executed by AI systems and the general decision making factors involved. While proprietary algorithms should remain protected, firms should provide regulators with sufficient transparency to assess whether AI-trading is contributing to market efficiency or generating systemic risks. In addition, real-time AI market monitoring is essential to enable regulators to detect and respond to anomalous price spikes, coordinated trading patterns, and potential AI-driven flash crashes before they escalate. Regulators should also monitor systemic risk indicators, such as unusual correlations in AI-trading behavior that may suggest unintended collusion. If multiple AI-trading systems aggressively buy or sell the same stock at once, prices could become artificially inflated or deflated, potentially triggering a bubble or a flash crash when algorithms reverse their positions.

Lastly, requiring brokerage firms to disclose trader profitability statistics would give retail investors a clearer understanding of the risks associated with AI-trading and derivatives markets. Evidence from other markets suggests that most retail traders incur losses in derivatives trading. For instance, according to a Reuters report, the Securities and Exchange Board of India (SEBI) found that in 2024, only 7.2% of retail traders in the derivatives market made profits, while 91.1% incurred losses. This highlights the importance of greater transparency in trading performance. Regulators should consider adopting similar requirements, mandating that brokerage firms to disclose the percentage of profitable and unprofitable traders in derivatives and AI-trading. Such measures would serve as important tools for monitoring market concentration and enhancing investor protection. Addressing the central concern of this paper, AI-trading may contribute to inequality by creating disparities in access to cognitive systems, infrastructure, and critical market information. These disparities may disproportionately benefit large institutions at the expense of retail investors. In the case of the SET, the rise of AI-trading has coincided with declining retail participation and growing market concentration. As AI-trading becomes further commodified, there is a risk of reinforcing systemic imbalances and weakening long-term market fairness. Addressing these challenges requires a multi-pronged approach that includes targeted education, equitable access to AI tools, stronger transparency measures, and proactive regulation. Future research could further examine how cultural factors and investor psychology influence the way AI-trading is understood, adopted, and ethically governed.

Author Contributions

KI: Conceptualization, Methodology, Formal Analysis, Investigation, Writing – Original Draft Preparation, Writing – Review & Editing, Visualization, Funding Acquisition.

KB: Conceptualization, Methodology, Investigation, Data Curation, Resources, Writing – Original Draft Preparation, Project Administration

Declaration of the Use of Generative AI

During the preparation of this manuscript, the authors used ChatGPT (OpenAI, GPT-5.3) to assist with language editing and polishing of the draft. The tool was used solely to improve clarity, grammar, and overall readability. The authors reviewed and revised the output as necessary and take full responsibility for the content of the manuscript.

Ethics

This study does not involve human participants or personal data. It is based on publicly available secondary data and documentary sources. Therefore, ethical approval was not required. All data were used in accordance with relevant guidelines and institutional standards.

Funding

The paper is supported by a grant from The National Research Council of Thailand (NRCT) in 2024, award number N42A670266, as part of the Ethics of Artificial Intelligence from the Ground Up project. The funding body had no role in the study design, data collection, data analysis, or manuscript preparation.

References

- Abbas, N., Araujo, J., Bhatia, A. V., et al. (2024). *Global financial stability report: Steadying the course—Uncertainty, artificial intelligence, and financial stability*. International Monetary Fund.
- Azzutti, A., Ringe, W.-G., & Stiehl, H. S. (2021). *Machine learning, market manipulation and collusion on capital markets: Why the “black box” matters*. SSRN Electronic Journal. <https://doi.org/10.2139/ssrn.3788872>
- Basl, J., & Bowen, J. (2020). AI as a moral right-holder. In M. D. Dubber, F. Pasquale, & S. Das (Eds.), *The Oxford handbook of ethics of AI* (pp. 289–306). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780190067397.013.18>
- Bryson, J. J. (2020). The artificial intelligence of the ethics of artificial intelligence. In M. D. Dubber, F. Pasquale, & S. Das (Eds.), *The Oxford handbook of ethics of AI* (pp. 3–26). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780190067397.013.1>
- Castle, J. L., & Hendry, D. F. (2014). Model selection in under-specified equations facing breaks. *Journal of Econometrics*, 178(2), 286–293. <https://doi.org/10.1016/j.jeconom.2013.08.028>
- Chen, B., & Hong, Y. (2012). Testing for smooth structural changes in time series models via nonparametric regression. *Econometrica*, 80(3), 1157–1183. <https://doi.org/10.3982/ECTA7990>
- Dignum, V. (2020). Responsibility and artificial intelligence. In M. D. Dubber, F. Pasquale, & S. Das (Eds.), *The Oxford handbook of ethics of AI* (pp. 215–232). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780190067397.013.12>
- Dou, W. W., Goldstein, I., & Ji, Y. (2024). *AI-powered trading, algorithmic collusion, and price efficiency*. The Wharton School. <https://doi.org/10.2139/ssrn.4452704>
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383–417. <https://doi.org/10.2307/2325486>
- Fulbright, R. (2020). *Democratization of expertise: How cognitive systems will revolutionize your life*. CRC Press. <https://doi.org/10.1201/9780429277764>

- Hansen, B. E. (2000). Testing for structural change in conditional models. *Journal of Econometrics*, 97(1), 93–115. [https://doi.org/10.1016/S0304-4076\(99\)00068-8](https://doi.org/10.1016/S0304-4076(99)00068-8)
- Hansen, K. B., & Borch, C. (2021). The absorption and multiplication of uncertainty in machine-learning-driven finance. *British Journal of Sociology*, 72(4), 1095–1109. <https://doi.org/10.1111/1468-4446.12880>
- Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, 66(1), 1–33. <https://doi.org/10.1111/j.1540-6261.2010.01624.x>
- Hui, Y. (2019). *Recursivity and contingency*. Rowman & Littlefield. <https://doi.org/10.5771/9781786600547>
- Hui, Y. (2024). *Machine and sovereignty: For a planetary thinking*. University of Minnesota Press. <https://doi.org/10.5749/9781452973685>
- Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, 23(2), 389–416. <https://doi.org/10.1111/j.1540-6261.1968.tb00815.x>
- Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The flash crash: The impact of high-frequency trading on an electronic market. *The Journal of Finance*, 72, 967–998. <https://doi.org/10.1111/jofi.12498>
- Kuipers, B. (2020). Perspectives on ethics of AI: Computer science. In M. D. Dubber, F. Pasquale, & S. Das (Eds.), *The Oxford handbook of ethics of AI* (pp. 421–442). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780190067397.013.27>
- Lenglet, M. (2011). Conflicting codes and codings: How algorithmic trading is reshaping financial regulation. *Theory, Culture & Society*, 28(6), 44–66. <https://doi.org/10.1177/0263276411417444>
- Lo, A. W. (2019). *Adaptive markets: Financial evolution at the speed of thought*. Princeton University Press. <https://doi.org/10.1515/9780691196800>
- Lucas, R. E. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy*, 1, 19–46. [https://doi.org/10.1016/S0167-2231\(76\)80003-6](https://doi.org/10.1016/S0167-2231(76)80003-6)
- Mumford, E. (2006). The story of socio-technical design: Reflections on its successes, failures and potential. *Information Systems Journal*, 16(4), 317–342.
- Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press. <https://doi.org/10.4159/harvard.9780674736061>
- Peters, M. A. (2020). Platform ontologies, the AI crisis and the ability to hack humans: “An algorithm knows me better than I know myself.” *Educational Philosophy and Theory*, 52(6), 593–601. <https://doi.org/10.1080/00131857.2019.1618227>
- Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review*, 71(3), 421–436. <https://doi.org/10.3386/w0456>
- Triclot, M. (2024). Ontology and the politics of information in the first cybernetics. In Y. Hui (Ed.), *Reconstruction, cybernetics for the 21st century: Vol. 1. Epistemological* (pp. 67–84). Hanart Press.
- Trist, E. L. (1981). The evolution of socio-technical systems: A conceptual framework and an action research program. *Occasional Paper*, (2), 1–67.
- Umpleby, S. A. (2018). Reflexivity in social systems: The theories of George Soros. In *Proceedings of the V International Research Conference System Analysis in Economics – 2018* (pp. 292–295). Financial University under the Government of the Russian Federation. <https://doi.org/10.33278/SAE-2018.eng.292-295>

Wheeler, M. (2020). Autonomy. In M. D. Dubber, F. Pasquale, & S. Das (Eds.), *The Oxford handbook of ethics of AI* (pp. 343–357). Oxford University Press.
<https://doi.org/10.1093/oxfordhb/9780190067397.013.22>

Wiener, N. (2019). *Cybernetics: Or control and communication in the animal and the machine*. MIT Press. <https://doi.org/10.1037/13140-000>