# The Impact of Artificial Intelligence Tool Used on Retail Investors' Trading Frequency, Risk Appetite, and Herding Behaviour

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**Abstract.** This article aims to systematically explore the impact of the use of artificial intelligence (AI) tools on the transaction frequency, risk preference and herd effect of retail investors, and on this basis, put forward behavioural guidance and institutional optimisation suggestions. The study found that the impact of AI tools on the transaction behaviour of retail investors shows significant duality and complexity: in terms of transaction frequency, the use of AI tools reduces the transaction threshold and increases the transaction frequency of retail investors, but the rational analysis characteristics of AI tools also inhibit the excessive transaction of some retail investors; in terms of risk preference, although AI tools strive to enhance decision-making rationality, they may distort investors' income expectations and risk perception due to algorithm "black box" and automated narrative, and induce irrational risk assumption; in terms of herd effect, AI tools do not eliminate crowd behaviour, but reconstruct and strengthen the "algorithm-driven herd" through mechanisms such as model homogenisation, signal standardisation and feedback acceleration. This article further puts forward suggestions from the aspects of retail cognitive management and regulatory system design, emphasising that investors should transform into "algorithm critics", and supervision should seek a dynamic balance between stimulating innovation and preventing risks.

**Keywords:** Artificial Intelligence Tool, Retail Investors, Trading Frequency, Risk Appetite, and Herding Behaviour.

## 1 Introduction

In recent years, the microstructure of the global stock market has undergone profound changes, evolving from a traditional centralised exchange to an electronic and fragmented multi-trading venue system, in which high-frequency trading has become the core force of market liquidity and price discovery. On the one hand, high-frequency trading reduces transaction costs by providing liquidity, but the extremely low latency technology it relies on has also spurred a continuous technological arms race and even triggered market disturbances such as the 2010 "flash crash". On the other hand, while alternative trading mechanisms such as dark pools promise zero transaction costs, they

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may exacerbate information asymmetry and adverse selection, which is particularly disadvantageous to retail participants.

In addition, with the advancement of modern research, experts have made outstanding studies on stock market conditions and retail investor trading in areas such as trading frequency, risk preference, and herding effect. This research is the greatest success of modern financial markets. Meanwhile, this change has also led to a diversification of AI financial tools in these areas.

Trading frequency is a professional form of proprietary trading, whose core features include high-frequency trading cooperation, that is, traders execute short and large-scale order tasks (in seconds or minutes) according to computer programs and adjust the closing status according to specific circumstances [1]. This model not only relies excessively on delayed technologies but also affects market liquidity. Risk preference describes an individual's decision-making tendencies in the face of instability. In classical economics, risk aversion is a typical manifestation, rooted in the diminishing marginal utility of wealth, that is, the incremental satisfaction derived from each additional unit of wealth decreases. Therefore, risk-averse individuals will firmly choose a high-value bet with a clear and stable return over a risky gamble. However, reality is always more complex and volatile. Behavioral economics points out that people not only dislike risk but also have a strong loss aversion tendency—the feeling of loss is far stronger than that of an equivalent amount of gain. This can lead to some contradictory behaviors: for example, people may be more willing to take on huge risks in order to “recover” after an investment has suffered a paper loss [2].

The herding effect refers to people selectively ignoring their own private information and imitating the behavior of others [3]. According to Banerjee's inference, in a sequential decision-making process with asymmetric information, when an individual observes that predecessors (especially two decision-makers) make the same response, based on Bayesian rational inference, their optimal strategy is to completely ignore their own private signals and follow the choices of their predecessors. Once this mechanism is stimulated, it will form an information link, that is, all subsequent decision-makers will continue to ignore personal information and needs and blindly follow their predecessors, thus forming a stable and irreversible "sherd" [3]. Therefore, this article aims to study the changes of AI tools in transaction frequency, risk preference and herd effect, and give corresponding improvement measures.

## 2 Classification of AI Financial Instruments

With the daily penetration and diffusion of AI tools into the financial market, the applicability of the tools has also increased. This article divides AI tools into the following three categories according to the autonomy and core functions of the tools.

The first category is an automated execution tool, which is represented by AI execution agent, mainly including an algorithmic order system and intelligent investment system. This kind of tool aims to program and automate the investment decision-making process through preset rules and logic, so as to strip away the emotional fluctuations and subjective assumptions in human nature and realise

disciplinary investment purely based on models and data [4]. Its technical implementation relies on Reinforcement Learning and rule engines. For example, the Q-learning algorithm allows the agent to learn the best transaction action through trial and error in the simulation environment and execute it in the real-time market [5]. At the behavioural level, the impact of such tools is the most direct: through the execution of mandatory procedures, it effectively suppresses the common unplanned and emotional transactions of retail investors. For example, when the market fluctuates violently, the preset stop loss or rebalancing rules can be automatically triggered, avoiding investors' chasing ups and downs due to fear or greed. However, this may also lead to the risk of "black box dependence", that is, investors blindly trust because they do not understand the logic of the algorithm, or completely abandon the supervision and thinking of the investment process, which may lead to new systematic behavioural deviations.

The second category is decision-making-assisted tools, such as AI-driven analysis platforms (covering fundamental valuation modelling, risk dashboards, etc.), whose core function is "information enhancement". They extract market sentiment from massive texts (such as news and social media) through natural language processing (NLP) technology, and use time series models (such as LSTM, Prophet) to generate predictions, transforming complex and unstructured data into intuitive and structured decision-making input [4, 5]. The impact mechanism of such instruments on investor behaviour is more complex, showing significant two-way disturbance characteristics. Research shows that the design characteristics of such tools, such as interactivity, personalisation and algorithm transparency, can significantly alleviate behavioural deviations such as investors' overconfidence and loss aversion, thus optimising their decision-making quality [6]. They can help investors identify and correct cognitive deviations such as confirmation bias and anchoring effect by providing more comprehensive and objective data analysis, so as to optimise the quality of decision-making. On the other hand, the seemingly highly "accurate" quantitative prediction and professional visualisation interface presented by the tool may unconsciously amplify investors' overconfidence and make them overestimate their own information processing ability and prediction accuracy. This expansion of self-confidence may further lead to an irrational adjustment of risk preferences - or excessive radicalism under seemingly conclusive favourable signals or becoming irrational and conservative under complex risk warnings.

The third type is the generation of interactive tools, represented by AI investment assistants (such as integrating ChatGPT, DeepSeek and other large language model systems), marking the transformation of financial AI from "tools" to "partners".

Its core technology relies on generative artificial intelligence and large language models, which can not only automatically generate investment analysis reports, but also conduct multi-round dialogues in highly human-like natural language, explain strategies, answer questions and provide emotional companionship [5]. This high degree of anthropomorphism and ease of use makes it have the most profound impact on users' psychology and behavior. By establishing interpersonal trust, it significantly enhances users' immersion and psychological dependence and may reshape all key behavioural variables. The frequency of transactions may be stimulated or inhibited by

continuous interaction with AI; risk preferences may be systematically shifted under the personalised persuasion of AI. Learning behaviour is promoted or distorted by this low-threshold Q&A interaction. More importantly, this relationship may give rise to a new behaviour pattern, that is, "algorithm dependence"-Investors ced part or all of the decision-making power and cognitive responsibility to AI and regard it as an authoritative opinion leader, which may weaken their independent judgement ability and cause a misalignment of responsibility when negative results occur.

# 3 Analysis of the Impact of AI Tools Usage on Retail Investors' Trading Behaviors

## 3.1 The Impact on Transaction Frequency

The popularity of AI tools is significantly changing the transaction frequency of retail investors, and its core impact stems from the reshaping of tools' information acquisition efficiency, decision-making costs and market perception.

From the perspective of improving transaction frequency, AI tools have greatly reduced the information asymmetry and decision-making threshold of retail investors through real-time data capture and intelligent analysis functions. Traditional retail investors need to spend a lot of time screening market data and interpreting policy signals, while AI tools can quickly integrate multi-dimensional market information, generate recommendations and trend predictions for trading objects, so that retail investors can more conveniently capture short-term market fluctuation opportunities, thereby stimulating the increase of transaction frequency. In addition, the "real-time early warning" and "intelligent monitoring" functions of some AI tools strengthen the sensitivity of retail investors to market changes and induce short-term trading behaviour of frequent trading, especially in the market environment where hot plates rotate quickly, this impact is more prominent [7].

However, on the other hand, the rational analysis characteristics of AI tools also inhibit the excessive transactions of some retail investors. High-quality AI tools will provide rational trading advice in combination with retail investors' risk tolerance and asset allocation goals. Through risk tips, position control reminders and other functions, it will reduce the ineffective transactions caused by retail investors' emotional impulses or blindly following the trend. At the same time, the refined accounting of transaction costs (such as commissions and slippage losses) of AI tools can allow retail investors to more clearly perceive the implicit costs of high-frequency transactions, thus actively reducing the transaction frequency and turning to medium- and long-term value investment.

## 3.2 The Impact on Risk Preference

They may mistakenly believe that AI tools have discovered "patterns" or "loopholes" in the market, leading to unrealistic fantasies about future returns and a greater tendency to pursue higher-risk assets, ultimately falling into the behavioral trap of "distorted return expectations - increased risk exposure". However, some studies have pointed out

that if the design of AI tools pays enough attention to interactivity, personalization and algorithm transparency, it can effectively reduce investors' overconfidence and loss aversion bias, thereby optimizing their risk decisions [8].

Secondly, accompanying the distorted expectations of returns is a false perception of "controllable risk" fostered by automation. AI tools, with their automated trading, dynamic rebalancing, and even stop-loss settings, often give users the illusion that risks have been completely managed and hedged by sophisticated algorithms in their interface design. However, Eichler and Schwab point out that the core limitation of robo-advisors lies in their inability to eliminate systemic market risk or predict real market volatility caused by complex interactions and nonlinear relationships. What algorithms can do is primarily to make ex-post, reactive adjustments based on historical data and established models (such as modern portfolio theory). This creates a profound paradox: the "multi-dimensional risk assessment" (such as volatility and drawdown analysis) and automated protection provided by tools at the micro level may cause users to ignore the fundamental and uncontrollable market uncertainties at the macro level [7]. Users are willing to try high-risk asset allocations that they would not normally venture into because they trust the "safety net" of algorithms, mistakenly equating "algorithm-managed risk" with "risk has been eliminated". This cognitive misalignment means that while retail investors enjoy the convenience and initial profits brought by AI tools, they may unknowingly be exposed to tail risks far exceeding their actual capacity to bear. Therefore, while AI tools improve investment efficiency, they may also subtly weaken investors' respect for the inherent risks of the financial market and their independent judgment by shaping a narrative that technological rationality is omnipotent. This creates a tension that is worth being wary of, which is contrary to the original intention of behavioral finance to "understand the limitations of human nature". What the algorithm can do is mainly make post-and reactive adjustments based on historical data and established models (such as modern asset portfolio theory). This gives rise to a profound paradox: the "multidimensional risk assessment" (such as volatility, pullback rate analysis) and automated protection provided by the tool at the micro level may make users ignore the fundamental and uncontrollable market uncertainty at the macro level [7]. Users dare to try to allocate high-risk assets that would not have been involved because of the "safety net" of the trust algorithm, and mistakenly equalising "algorithm management risk" with "risk has been eliminated". This cognitive misalignment makes retail investors unknowingly exposed to tail risks that far exceed their actual ability to bear when enjoying the convenience and initial profits brought by AI tools. Therefore, while improving investment efficiency, AI tools may also subtly weaken investors' awe and independent judgement of the inherent risks of financial markets by shaping a narrative of technical rationality, which is consistent with the original intention of "understanding the limitations of human nature" advocated by behavioural finance, which constitutes a kind of cautionary tension.

### 3.3 Impact on Herding Effect

The popularity of AI tools does not eliminate the herd effect in traditional financial behaviour. Instead, it reconstructs its formation path, amplifies its market impact, and

presents more complex systemic risk characteristics through algorithmic mechanisms. In AI-driven social trading platforms, multiple users relying on similar algorithm models will lead to convergent behavior, which in turn triggers market contagion and liquidity shocks, confirming the formation mechanism of the 'algorithm-driven herd' proposed in this paper [8]. Although the personalised analysis function may in theory alleviate individuals' dependence on market consensus by providing customised suggestions, in reality, the underlying logic of AI tools represented by robot investment, social copy platforms and quantitative signal services is often based on model convergence, signal standardisation and feedback acceleration, which actually exacerbates the convergence of retail behaviour and the vulnerability of the market. This has a similar mechanism to the phenomenon of information cascading in traditional social networks, that is, users' crowd behaviour is highly dependent on the source of information (friends vs. Volkswagen) and product popularity, and AI tools may amplify the homogeneous transmission of such signals through algorithms, thus giving rise to a more efficient 'algorithm flock' [9]. Specifically, the "algorithm herd" mechanism of AI tools is reflected in a triple path: First, the homogenisation of the model leads to a high degree of convergence of investment suggestions. Most AI tools are trained based on similar historical data sets, open-source frameworks and optimisation goals. Their output asset allocation or transaction signals are essentially standardised products, resulting in different users receiving highly consistent investment suggestions and forming a structured flock [10]. Second, information processing and signal amplification have accelerated the formation of consensus. AI analyses news, public opinion and market data in real time through natural language processing and converts them into executable trading signals. This process not only compresses the information digestion time, but also strengthens the market hotspots through algorithm screening, prompting retail investors to focus on the same batch of "hot targets", thus forming an information waterfall at the cognitive level and triggering collective action. Third, transaction execution and market feedback form a self-reinforcing cycle. The convergence trade held by retail investors based on AI signals will be quickly captured by the market microstructure, causing price fluctuations; The price fluctuation itself is recognised by the AI system as a new input signal, further strengthening the original trading direction and forming a recursive cycle of "buying triggering more buying, selling triggering more selling" [10]. This mechanism is particularly typical in the GameStop event in 2021: the consistent bullish sentiment formed by retail investors on social media is interpreted by algorithms as a strong momentum signal, which attracts quantitative funds and market makers to join, and finally amplifies local consensus into market-wide fluctuations through derivatives mechanisms such as option hedging. It can be seen that AI tools do not achieve "personalisation" in the true sense. Instead, they cover up the collective behaviour logic behind them through the technical shell, so that retail investors are unconsciously involved in a more efficient and hidden "algorithm-driven herd" in seemingly autonomous decision-making. This prompts people to see that in the absence of effective supervision of algorithm model diversity, transparency of information recommendation mechanisms and system feedback loops, AI tools may also become implicit amplifiers of systemic risks while improving investment efficiency.

# 4 Comprehensive Recommendations

## 4.1 Advice for Individual Investors

In the use of AI tools, retail investors often fall into a "technology-dependent illusion" - mistakenly thinking that algorithms can replace the entire complexity of human decision-making. However, the real problem is not the tool itself, but whether the user has "algorithm criticality". It is recommended that retail investors should not only be satisfied with the execution of AI-generated transaction signals, but also take the initiative to establish the habit of "algorithm audit": regularly examine whether the output of the tool is in line with market common sense, whether it is consistent with their own risk preferences, and whether there is a suspicion of overfitting historical data. In addition, retail investors need to be wary of the "interface-friendly trap". The more concisely designed and interactive the AI tool is, the more likely it is to cover up the complexity of its decision-making logic, causing users to relax their vigilance. Therefore, in addition to the basic principles of learning tools, retail investors should also cultivate the ability of "anti-factual thinking" - in addition to AI advice, take the initiative to build alternative investment situations to test the robustness and adaptability of algorithms. In the end, retail investors should realise that AI is not the object of "decision-making outsourcing", but a tool for "cognitive extension"; the real investment wisdom still lies in human control of uncertainty and awareness of their own behavioural deviations.

## 4.2 Recommendations to Regulatory Authorities

The core contradiction facing the current regulatory framework is that excessive strictness may inhibit technological innovation and market efficiency, and excessive relaxation may condone algorithm homogenisation and systemic risk accumulation. It is recommended that the regulatory department adopt the idea of "hierarchical supervision": for low-risk and high-transparency auxiliary AI tools (such as fundamental analysis platforms), the filing system and post-event monitoring can be adopted; For high-risk, low-transparency automated trading systems (such as high-frequency arbitrage algorithms), access review and real-time risk control intervention should be implemented. At the same time, supervision should go beyond the traditional "information disclosure" model and turn to "mandatory requirements for algorithmic interpretability" - requiring service providers not only to disclose algorithm logic, but also to provide their stress test results in extreme market situations to assess whether their behavioural consistency exacerbates market vulnerability. In addition, regulators need to be alert to the phenomenon of "regulatory arbitrage": some institutions may avoid local regulatory constraints by deploying AI systems in offshore markets or dark pools with weak supervision. Therefore, building a cross-jurisdictional collaborative monitoring mechanism and promoting the docking of global regulatory standards have become an urgent task to prevent cross-border systemic risks caused by AI tools. In the end, the goal of supervision should not be to "prohibit innovation", but to guide the

evolution of AI tools to the track of improving market resilience and protecting the long-term interests of investors through institutional design.

## 5 Conclusion

This article systematically analyzes the impact of AI tools on retail investor trading behavior and its market effects. Research has found that AI tools have a dual effect on trading frequency: the convenience of AI tools increases the trading frequency of retail investors, but overly rational analysis can also inhibit trading behavior. In terms of risk appetite, while AI tools claim to improve decision-making rationality, they may create irrational expectations of returns and misperceptions of risks through "black box" narratives and automated functions. Notably, AI tools have not eliminated the herding effect; instead, through model homogenization, signal standardization, and feedback acceleration mechanisms, they have created a more covert and efficient "algorithm-driven herding," potentially amplifying market vulnerabilities.

This study also has several limitations. First, existing empirical studies are mostly based on specific market environments and limited samples, and the generalizability of their conclusions needs to be further tested under different market structures and regulatory environments. Secondly, the analysis of the behavioral mechanisms by which AI tools affect people still largely relies on theoretical deduction and indirect evidence, lacking empirical data that provides a micro-level and longitudinal tracking of the cognitive processes of retail investors and the interaction mechanisms with algorithms. Furthermore, the study mainly focuses on the direct impact of AI tools, and the analysis of the complex system effects resulting from the interplay of multiple factors such as algorithms, market microstructure, institutional behavior and macro policies is still insufficient.

Looking ahead, research should be deepened in the following directions: There is an urgent need to adopt experimental economics and digital tracking technology to directly observe and quantify changes in the cognition and behavior of retail investors in their interactions with AI tools. Also, cross-market comparative studies should be expanded, with particular attention paid to the heterogeneity of the impact of AI tools in emerging and developed markets. Apart from that, the research perspective needs to be extended from individual behavior to the system level, theoretical and computational models that can simulate the dynamic feedback between algorithmic homogenized trading, market liquidity and price discovery should be constructed to assess potential systemic risks. Finally, the governance of AI financial instruments requires a multidisciplinary approach that integrates insights from behavioral finance, computational social science, and regulatory technology to build a dynamic and adaptable governance framework that balances incentivizing innovation with maintaining market stability.

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