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(Review Article)

A review on algorithm aversion, appreciation, and investor return beliefs

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Abstract

As artificial intelligence (AI) continues to transform financial decision-making, responses of investors toward algorithmic tools have varied from rejection to voluntary adoption. This review looks at two different behavioral outcomes: algorithm aversion, or resistance to machine-provided advice even when it has been validated, and algorithm appreciation, where investors prefer algorithmic advice under certain particular conditions. Drawing on behavioral finance, psychology, and decision theory research, the review examines how such beliefs influence investor return beliefs i.e., the subjective investment performance expectations that people have. The review also examines the cognitive and affective processes underlying such beliefs, as well as the roles of trust, control, and framing in shaping investor attitudes. Findings show that institutional investors are more likely to algorithm appreciation with experience and data processing capacity, whereas retail investors have greater aversion with emotional bias and low transparency. The discussion is wrapped up with practical recommendations for improving algorithm acceptance, including higher user control, transparency in design, and blended advisory models. Closing the technical performance-user experience gap is paramount to encouraging effective, robust AI-driven investment systems.

Keywords: Artificial Intelligence; Algorithm Appreciation; Algorithm Aversion; Investor Return Beliefs; Investor Behavior; Financial Decision-Making

1. Introduction

With the widespread integration of Artificial Intelligence into everyday life and the growing reliance on, or at least the need to consult AI technologies, it comes as no surprise that AI has found its way into the field of finance. Its entrance has been long anticipated.

Algorithms are a crutch in today's digital age even for experienced financial professionals. From robo-advisory services and trading to risk evaluation and portfolio management, artificial intelligence and data systems significantly influence personal investment decision-making.

While some may argue that algorithms offer consistency, speed, and accuracy that do better human judgment, and despite their growing integration into financial systems, many individuals still remain reluctant to accept algorithmic advice.

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This reluctance is not merely technical but deeply psychological. Investors exhibit *algorithm aversion*; a hesitancy to trust or follow advice from machines, even if accurate, as history has shown, possibly remain neutral, or even now show signs of *algorithm appreciation*; trust in, or preference for advice from AI.

Underlying this issue is a nuanced but powerful concept: *investor return beliefs*. These are the personal hypotheses individuals have regarding the success of their investments. These beliefs are not only shaped by financial knowledge or market performance but also by the source of decision-making information. Whether an investor has the willingness to accept or reject algorithmic recommendations can distort their confidence, risk appetite, and ultimately, portfolio results.

- As such, this review seeks to explore a timely and relevant question in the field of behavioral finance
- Do investors trust AI-generated financial forecasts, and how do they respond to them compared to human forecasts?

It aims to

- Consolidate the existing literature on algorithm aversion and appreciation;
- Examine the cognitive and behavioral processes involved in these reactions;
- Analyze how these perceptions influence investor return beliefs and decisions; and
- Discuss implications for investor behavior, financial technology design, and future research directions.

2. Conceptual framework

To understand how people experience and engage with algorithms, it is necessary to first untangle the root concepts underlying this review. Two interrelated but distinct phenomena-algorithm aversion and algorithm appreciation-are the focal constructs.

Algorithm aversion refers to the tendency of people to favor human judgment over algorithmic advice, even when the algorithm is objectively superior (Dietvorst, Simmons, & Massey, 2015). Such a reaction is usually triggered by discomfort with a perceived lack of control, apprehension of mistake, and lost faith in non-human deciders.

In contrast, algorithm appreciation occurs when users appreciate and recognize algorithmic benefits, particularly when algorithms are understandable, transparent, or successfully proven in the past (Logg, Minson, & Moore, 2019). Both these reactions are typically experience-dependent, stimulus-based, and perceived-stakes.

These perceptions are grounded in established psychological theories. The notion of bounded rationality from the behavioral decision theory posits that individuals employ heuristics and are prone to cognitive biases e.g., overestimation of human knowledge or anchoring on familiar approaches (Kahneman, 2011). Attribution theory explains why individuals respond differently to errors: when humans err, we attribute the mistake to perhaps a situational error, whereas algorithmic errors tend to be judged harshly and blamed more on the system's design flaw (Weiner, 1985). Trust and control theories give some explanation for why people are reluctant to cede to algorithmic systems especially when they appear opaque, unaccountable, or inflexible (Lee & See, 2004; Madhavan, Wiegmann, & Lacson, 2006).

At the heart of this controversy remains the notion of investor return beliefs: the personal beliefs, or expectations, of investors regarding the performance of their investments. Perceptions influence risk-taking, investment confidence, and asset allocation (Benartzi & Thaler, 1995). Emotional disposition, financial savviness, and experience direct the development and revision of such beliefs (Barberis & Thaler, 2003).

Importantly, the origin of decision-making information, human or algorithmic, might have a large effect on perceived decision validity and, thus, set return expectations.

These concepts collectively make up a theoretical framework for explaining the evolution of investor psychology when dealing with new technology in the field of finance. The dynamic between how individuals view algorithms and what they think of their investments is at the core of contemporary behavioral finance.

3. Literature review

The use of algorithms in financial decision-making has grossly expanded over the past few decades (Sargeant, 2022). In the past, studies on the use of algorithms in finance focused primarily on their comparative efficiency and predictive accuracy as opposed to human analysis (Broby, 2022; Gupta et al., 2024). This involves key areas such as financial risk assessment, fraud detection, and portfolio management (Gupta et al., 2024).

Owing to the ability of these algorithms to analyze large datasets, studies have demonstrated their potential to identify risks and detect anomalies at impressive speeds (Kumar & Singh, 2024). Their application has also been shown to significantly reduce the probability of financial risks over time (Kumar & Singh, 2024; Adhikari et al., 2024). Moreover, data analysis offered by systems driven by algorithms occurs in real time. Hence, enabling proactive decision-making and ultimately shortening institutions' response time in the event of a crisis (Eide et al., 2025; University of the Cumberlands, 2023).

Despite the potential of these algorithms to improve financial processes, some investors are still reluctant to use them. This reluctance is termed "algorithm aversion" and has been well documented. Previous authors have defined algorithm aversion in different ways. These differences in understanding of the term are reflected in the arguments put forward.

Authors like Commerford, Dennis, Joe & Wang (2019), Ku (2020), and Dietvorst, Simmons & Massey (2015) viewed it from the standpoint of the preference of humans over algorithms in decision-making despite overwhelming evidence that the latter triumphs the former. The preference for human over algorithm input is also demonstrated in the definition by authors like Yeomans, Shah, Mullainathan & Kleinberg (2019) and De-Arteaga, Fogliato & Chouldechova (2020). These authors, however, attributed this preference to the awareness that algorithms could be erroneous. Consequently, the potential for algorithmic errors has been shown to primarily drive human aversion to these systems.

Building on these perspectives, this review defines algorithm aversion as the human reliance on humans over algorithms in decision-making, despite evidence that algorithms outperform humans, driven primarily by distrust for algorithmic tools.

Notwithstanding the evidence for aversion, other studies point to situations where humans choose algorithms over other humans in decision-making. This occurrence is termed algorithm appreciation.

Mahmud et al (2024) defined algorithm appreciation as "an individual's reliance or tendency to rely on algorithms in decision-making." Algorithm appreciation tends to occur when individuals are made aware of the statistical superiority of predictions made by algorithms over those of humans. It could also occur when the task is perceived as highly objective (e.g. in forecasting market trends) or when users are allowed some degree of control over the algorithm's parameters (Logg et al., 2019).

For instance, in a study by Logg et al. (2019), the authors found that participants' trust and reliance on algorithms in decision-making increased when they were given some degree of control over the algorithm's parameters. In line with these drivers, it is not surprising that algorithm appreciation is more likely among tech-savvy investors and institutional managers who have witnessed previous successes with automated systems (Mahmud et al., 2022).

While some studies suggest distrust towards algorithms, others demonstrate rapid shifts in attitudes based on framing, context, or prior experience with algorithms. As such, there is no clear consensus in the literature about whether algorithm aversion or appreciation dominates. Moreover, several gaps in the literature still remain. For instance, little is known about how investor return beliefs (i.e. expectations about future performance) influence attitudes towards algorithms. Similarly, only a few studies have systematically investigated demographic or psychological moderators such as financial literacy, risk tolerance, or trust in institutions.

4. The role of algorithm perceptions in investor behaviour

Even while algorithmic systems are designed to facilitate decision-making based on speed, accuracy, and neutrality, their performance is also very much dependent on how they are viewed. In investment contexts, investor perception determines investor behavior. Investors tend to make decisions not merely on the basis of objective performance but also on subjective factors such as trust, perceived control, and emotional comfort.

Algorithm aversion is typically the result of a perceived loss of control. The majority of investors prefer human participation because it creates a sense of agency in financial decisions, even where human judgment is demonstrably less accurate (Lee & See, 2004).

Human error also tends to be more forgivable than algorithmic error. A mistake on the part of a human advisor may be pardoned, whereas the same mistake by an algorithm can result in outright rejection (Dietvorst, Simmons, & Massey, 2015; Madhavan, Wiegmann, & Lacson, 2006).

On the other hand, algorithm appreciation occurs when algorithms are viewed as being neutral, correct, and reliable. This occurs when algorithms produce consistent results or are presented in clear, user-friendly ways. Logg, Minson, and Moore (2019) found that individuals were more likely to prefer algorithmic to human advice when they believed that the algorithm was derived from objective data rather than subjective opinion.

These impressions directly affect investor return beliefs. A distrusted algorithm will lead to an investor anticipating negative outcomes, diminishing confidence, and greater risk aversion. Implications of algorithmic capability or competence, on the other hand, can overstate anticipated returns and result in riskier investment (Benartzi & Thaler, 1995; Barberis & Thaler, 2003). Trust in the decision source therefore affects not just the investment process but the outcome expected by investors.

In addition, the presentation of algorithms is significant. Framed as complements to human knowledge and not replacements algorithms have a greater chance of being accepted. This framing effect can explain investor-type variation: institutional investors, who are more at ease with algorithmic platforms, can have higher appreciation and take-up rates, while retail investors are more susceptible to perception-based resistance.

It is important to understand the impact of algorithm perceptions on investor attitudes in order to design tools that enable soundly informed, confident, and evidence-based investment decisions.

5. Implications for financial markets and decision-making

In the context of decision-making in financial markets, algorithm aversion and appreciation among retail and institutional investors reveal different patterns. Previous studies have shown higher levels of retail aversion among retail compared to institutional investors (Tan et al., 2024; Briere et al., 2023). This has been demonstrated to be driven by factors including limited financial literacy and behavioral biases (Briere et al., 2023; Sivaramakrishnan et al., 2017).

Behavioral biases in this group of investors are shown in the fact that even when presented with evidence of algorithm superiority, retail investors may still prefer human advisors due to a perceived need for empathy or the human touch (Mahmud et al., 2022).

On the other hand, institutional investors demonstrate a higher appreciation for algorithms. This has been linked to the ability of these investors to process complex information, respond quickly to major events, and make timely, informed decisions (Ben-Rephael et al., 2015). However, it is also important to note that even among professionals, skepticism can arise, particularly in the face of black-box models lacking interpretability (Rane et al., 2024).

The varying levels of algorithm trust across investor classes can influence market dynamics (Mahmud et al., 2022). Because institutional investors adopt algorithmic trading more readily than retail investors, there is a gap in the trading behavior and performance of both (Tan et al., 2024). Algorithm appreciation among institutional investors may allow for more disciplined decision-making (Mahmud et al., 2024).

For instance, the use of algorithm-based robo-advisors helps reduce the degree of emotional interference in the decisions made by an investor. This helps ensure that their portfolios are always aligned with the company's long-term investment goals (Mahmud et al., 2024; Maheshwari & Samantaray, 2025). Moreover, institutional investors also benefit from the ability of algorithms to handle vast amounts of data and execute tasks faster with fewer errors (Maheshwari & Samantaray, 2025). Ultimately, these advantages make them more efficient (Maheshwari & Samantaray, 2025).

On the other hand, widespread algorithm aversion among retail investors may negatively affect the decision-making process of the retailer (Silber et al., 2025). This could lead to biases in behavior and judgment. The result of this includes overtrading, panic selling, or herding.

For instance, a risk-averse retail investor may ignore a robo-advisor's suggestion to rebalance into equities during a market dip, fearing further losses despite possible long-term gains. Unfortunately, this is detrimental to the retail investor (Silber et al., 2025).

Despite the existing divide, the rise of robo-advisors reflects growing algorithm appreciation (Onabowale, 2025). This evolution, shaped by the dynamics of algorithm aversion and appreciation, is poised to redefine advisor roles and robo-advisory scalability (Onabowale, 2025). Currently, the surge in robo-advisory adoption is pushing traditional financial advisors toward adopting a hybrid style (Eapen & Sakthivel, 2025). This approach combines both algorithmic recommendations with human guidance. Since algorithm aversion is driven by investors' desire for control and emotional connection, this balance is necessary for the future of robo-advisory (Eapen & Sakthivel, 2025).

6. Practical applications and recommendations

The advent of robo-advisors and growing algorithm appreciation necessitate practical strategies to address algorithm aversion. Recent research findings have identified several strategies which could be employed in this regard.

Comparing the impact of different kinds of influence exerted on an algorithm on the participants' aversion to its use, Gubaydullina et al. (2022) observed that participants were more likely to have reduced aversion to algorithm use for tasks if they were given the opportunity to alter the output from that algorithm. Interestingly, this could not be said when participants were allowed to alter the algorithm's input.

This, however, contrasts with a previous study where participants' influence on algorithm input significantly reduced their degree of aversion to algorithm use (Burton, Stein & Jensen, 2020). The authors attributed this difference in results to the relatively smaller influence participants could exert on the algorithm's input.

The positive impact of user autonomy in mitigating algorithm aversion may be explained by the fact that it gives the user a sense of control over the decision mankind process. This itself is crucial for user acceptance of whatever recommendation the algorithm eventually offers (Dietvorst et al., 2016).

Another strategy involves building trust gradually through performance transparency. Research has shown that users tend to build more trust in algorithms if they deliver accurate results over time. Interestingly, this finding remains true even when those users initially displayed skepticism about their use (Logg et al., 2019). In line with these findings, platforms could consider onboarding users with simpler, low-stakes tasks to demonstrate algorithmic reliability before they are exposed to more complex decisions. Additionally, users should be allowed some degree of autonomy over either the input or output of their algorithms.

Meanwhile, it is worth noting that investor perceptions of algorithm systems are built on effective communication. When algorithms are presented as "cold," "opaque," or "data-driven" without explanation, they are less likely to be trusted by investors (Mahmud et al., 2022). This underscores the need for transparency in designing an algorithm.

It is therefore important that algorithms should not be treated as black boxes. Instead, algorithms could be designed with simple, user-friendly explanations of how the algorithm works, including its logic flow and decision boundaries.

For instance, robo-advisory interfaces could benefit from incorporating visual summaries of risk models or portfolio simulations to help users understand how their personalized recommendations are actually generated (Onabowale, 2025). Indeed, even brief tooltips or FAQs explaining the model's rationale could help enhance perceived competence and fairness.

Furthermore, emphasis should be placed on helping users understand that algorithmic tools are decision aids and not necessarily decision replacers (Hassan et al., 2024). This places them as collaborators rather than controllers and respects the investor's autonomy, which would help reduce emotional resistance to automation (Hassan et al., 2024). Hybrid systems that combine algorithmic suggestions with optional human feedback are particularly effective in this regard.

7. Conclusion

As algorithm technology becomes increasingly integrated into financial decision-making, it is essential to understand how investors feel about them.

As such, this review has compared two contrasting but not entirely dissimilar behavioral responses: algorithm aversion and algorithm appreciation. These responses are typical examples of how emotion and cognition influence investor behavior.

While the former is a product of fear and distrust, the latter is built on objectivity, transparency, and prior success. These responses are typical examples of the emotional and cognitive intricacies of investor behavior.

Investors' acceptance or rejection of algorithmic forecasts also affects their level of confidence, appetite for risk, and in the long-term, investment strategies. This perception not only results from personal bias but also has an influence on market behavior.

This review also explored the fact that the gap between institutional and retail investors in the acceptance and use of algorithmic technologies can continually affect performance differentials and further widen trust gaps.

The challenge, therefore, is not only to develop algorithm systems that are technically accurate but also to create systems that encourage transparency and user control.

Going forward, it is the challenge of research to examine

- The dynamic nature of such perceptions
- How different types of investors interact with algorithmic systems
- How human-machine hybrid systems can optimally enhance both trust and performance

As the financial sector becomes increasingly data-driven, closing the gap between algorithmic perception and user trust will be at the forefront of developing a more rational and resilient investment sphere.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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