Journal of Social & Organizational Matters

Vol 5 No 1 (2026):203-217

Investor Overconfidence in the AI Era: Human vs. Algorithmic Decision-Making

Muhammad Asad Ullah*[1], Naeem Bhojani[2], Nayab Jumani[3]

[1]*Associate Professor, College of Management Sciences, Karachi Institute of Economics & Technology, Karachi, Sindh, Pakistan.

[2]Professor of Practice, College of Management Sciences, Karachi Institute of Economics & Technology, Sindh, Pakistan.

[3]Assistant Professor of Practice, Department of Accounting and Finance, IoBM, Sindh, Pakistan.

Corresponding author: m.asadullah@kiet.edu.pk

Keywords: *Investor Overconfidence; Artificial Intelligence; Algorithmic Trading; Human–AI Interaction; Pakistan Stock Exchange*

JEL Classification: *G41, G11, C45*

DOI No: https://doi.org/10.56976/jsom.v5i1.391

We investigate investor overconfidence in the age of artificially intelligent coincident with human–algorithmic and hybrid decision-making models on the Pakistan Stock Exchange (PSX). Leveraging behavioral finance literature and advances in AI-based investment tools, the paper explores whether algorithmic behaviors alleviate or change overconfidence when human judgments persist. Based on panel data for PSX investors, 2020:2025, overconfidence is proxied by turnover, holding bias and relative deviation from trading algorithms. The empirical evidence shows that human-only investors have a higher turnover, more portfolio concentration and earn less risk-adjusted returns than algorithm-based portfolios. AI-driven portfolios exhibit better diversification and lower downside risk compared to traditional portfolios, but hybrid investors tend to ignore machine suggestions after an initial period of profit, which is consistent with learning-based overconfidence and illusion of control. Regressions suggest that overconfidence undermines the efficiency gains of AI via discretionary intervention, resulting in higher volatilities and more pronounced draw-downs when under financial stress. In general, the results imply that AI doesn't remove behavioral biases but rather re-sculpts their manifestation in hybrid decision worlds. Our paper extends overconfidence theory into AI-mediated markets and has significant implications for investors, financial institutions and regulators in emerging markets.

1. Introduction

Overconfidence is one of the most widely documented behavioral biases in finance and has been observed to be a major departure from rational investor assumption which underpins traditional financial theory. Traditional finance theories, including the Efficient Market Hypothesis (EMH), argue that investors act rationally in processing available information and deciding their behavior to optimize expected utility (Fama, 1970; Kamoune & Ibenrissoul, 2022). Yet, there is now ample empirical and experimental evidence that investors often manifest systematic cognitive biases, and confidence tops the list. Excessively confident investors overestimate the precision of their private information, their ability to predict future outcomes and or control the outcome which result in excessive trading, under-diversification and lower risk based adjusted returns (Barber & Odean, 2001; Kumar & Ranjani, 2025).

Alongside these advancements in behavioral finance, the past decade saw significant changes in financial markets, with increasing reliance on artificial intelligence and algorithmic decision making technologies. Machine learning methods are firmly established across investment management, asset pricing and risk modeling. These systems offer a prospect of higher quality decisions by dealing with large volumes of data, detecting subtle patterns and removing emotional and cognitive biases embedded in human judgment (Brynjolfsson & McAfee, 2017; Rodriguez-Fernandez, 2025). For this reason, AI-based decision-making is generally portrayed as a sensible substitute for human investors, able to reduce behavioral biases including overconfidence.

Yet we still don't know enough about the equation between human facto overconfidence and algorithm choice making. New research suggests that AI not only is changing human judgment but also in some ways is reducing it down to two dimensions. Investors may over rely on algorithmic recommendations, this dependence is referred to as an automation bias, or ignore/distrust advice derived algorithmically due to a predisposition against algorithms particularly when they make mistakes (Dietvorst et al. 2015; Jussupow et al., 2024).). More ominously, overconfidence can actually increase (rather than reduce) in the AI age, when investors arrogantly treat their superhuman ability to interpret, override or cherry-pick algorithmic outputs as proof of what they already believed. This raises an important question for modern finance: Does the introduction of AI actually counteract investor overconfidence, or does it just change its manifestation?

Behavioral finance generally defines overconfidence as belief in the ability to make good decisions, despite facing uncertainty (Moore & Healy, 2008; Karki et al., 2024) and identifies three fundamental forms of overconfidence: miscalibration (overinflated confidence that one is correct), better-than-average effect (higher relative assessment than that of others) and illusion of control (belief in being able to influence results). Such types of overconfidences have been documented to impact trading decisions, securities prices and market volatility. For instance, Barber and Odean (2001) show that overconfident investors trade excessively and earn lower net returns, whereas Daniel and Hirshleifer (1998) & Subrahmanyam (1998) demonstrate that overconfidence may cause asset price momentum and its subsequent reversals. With the advent of AI, these traditional mechanisms take on another dimension as they alter the way information is produced, filtered and used.

Algorithmic agents and human decision-makers have very different cognitive architectures. Algorithms don't get hungover, annoyed or distracted in the way human beings do. The challenge is not on the part of algorithms, but rather in model mistakes, data skew, over fitting and limited contextual comprehension (Agarwal & Dhar, 2014; Allam et al., 2025). From a normative standpoint, this differentiation may indicate that algorithmic decision-making could be an instrument to align and correct behavioral biases. In fact, empirical evidence on robo-advisors suggests that algorithmic recommendations of portfolio are better diversified and subject to lower fees than human-advised portfolios (D'Acunto et al., 2019). Yet such results depend crucially on how human investors manifest themselves in AI systems, rather than only algorithmic quality.

New evidence suggests that human-algorithm interaction can be influenced by psychological bias, for example overconfidence. It may not be surprising, therefore, that investors question whether there are opportunities for out-thinking the algorithms by picking the market or over-riding automatic advice even when evidence points to the contrary (Logg et al., 2019). Here "AI" is not the cure for sexism; it stands metonymically for an object, or medium, with which to embody self-confidence. On the other hand, as proposed by our second hypothesis, other investors may over believe AI and trust the system too much to do anything about take all … and therefore supplant rather than replacing… so that instead of becoming overconfident on themselves they rebalance their decision from judging themself to appraise technology. Both of these concerns are fundamental to investment performance, market fairness and financial integrity.

There are also some more serious distributive and structural problems associated with the growing prevalence of AI. And if overconfidence encourages one group of investors (the retail trader, say) to rely inap-propriately on algorithmic supports, it could be the case that the disparity between institution and retail traders' returns would grow. Recent cases of increased retail involvement in financial markets that is enabled and encouraged by digital platforms (and algorithmic trading tools) provide evidence that the technology may be less likely to repress bias than amplify it (Bloomfield et al., 2018; Fleischman et al., 2023). So, it is crucial to understand how overconfidence plays in AI-driven environments not only for the welfare of individual investors but also the health of financial markets.

On the regulatory and policy fronts, it's just as pressing. As markets grow more automated, the regulators are grappling with how to police markets in which decisions are made at least in part by machines. Even if AI can give some independence from human-errors, it gives rise to opacity and complexity which may harm audit and calibration (Gennaioli et al., 2018; Celestin et al., 2025). And if investors think they can rely on complex algorithms without intervention, or inadvertently stumble into automatic shutdown mechanisms at times when markets most need them to stay open, the danger is that systemic risk will go up rather than down. As a result, policy makers and banks must understand the behavioral aspects of human–algorithm interaction to craft appropriate governance frameworks.

However, research on this topic is fragmented. Three indirect lines of evidence lead to this hypothesis: Behavioral finance (see, e.g., Sicherman 1996; Link, 2025) has well-documented the presence of overconfidence amongst human investors, and information systems (IS) and financial studies have studied separately algorithmic trading and robo-advisory services. Yet little work brings them together to continue analyzing overconfidence in mixed human-machine decision environments. Furthermore, most of the empirical evidence relates either to human or fully automated discretionary investment systems and there remains a gap in the literature concerning hybrid decision making that are typical in real investment settings.

This paper seeks to fill this gap by investigating investor overconfidence in the age of AI, with special attention given to the relative and complementary effects of human versus algorithmic judgments in the case of PSX. The primary aim is to determine if algorithmic systems help reduce, magnify, or alter overconfidence and identify the conditions in which these effects are most prominent. By integrating findings from behavioral finance, experimental economics and AI-based financial decision-making this paper seeks to refine our understanding of investor behavior in modern financial markets.

More specifically, the contributions of this paper are three-fold. There are two reasons for this: First, it places investor overconfidence in the context of AI adoption by stretching classical theories in behavioral finance to be manageable with the mediation of algorithmic intermediaries. Second, it studies and synthesizes empirical studies of human versus algorithm performance, emphasizing the behavior-based rationales that underlie investor interaction with (AI. Third and finally, the paper motivates an empirical study of overconfidence in hybrid decision environments by providing an empirical model for studying it, thereby providing a basis for future empirical research.

2. Literature Review

2.1 Investor Overconfidence in Behavioral Finance

The overconfidence of investors is a cornerstone of behavioral finance, and it is a characteristic in which individuals deviate systematically from rational expectations. Investors are overconfident in the precision of private information and consequently tend to trade too much, by holding on their perceived superior signals even if market profit opportunities have been exhausted (DeBondt 1993). This early work questioned some of its tenets when evidence emerged that investors often display a degree of optimism bias about the accuracy or themselves as well on prediction future outcomes in markets. Odean (1998) provides pioneering empirical evidence that the cumulated performance of all investors contradicts their aggregated excess beliefs that they know better. This "better-than-average" phenomenon is a well-known overconfidence bias and is one of the most pervasive market anomalies that has been documented across markets and investor groups.

In theory model's overconfidence is codified as a force that causes excessive trading and mispricing. Daniel, Hirshleifer, and Subrahmanyam (1998) construct a model where overconfident investors overweight private signals and underweight public information so that it results in momentum followed by reversals in asset prices. Gervais and Odean (2001) similarly demonstrate that investor confidence rises with initial success, leading to higher volume and volatility. These models offer a behavioral account of market anomalies that are hard to reconcile with rational expectations theories.

Empirical evidence always indicates overconfidence's negative performance impact on and off the market. Barber and Odean (2000, 2001) show that overconfident individuals trade too much, which leads to lower net returns after transaction costs. Their results are especially significant for male investors who, the authors posit, tend to be overconfident versus their female counterparts. Grinblatt and Keloharju (2009) provide additional evidence that the overconfidence is connected with sensation-seeking characteristics and bad risk management decision-making, which implies that psychological traits are responsible for some of the individual differences observed in areas.

Retail investors are not the only ones who overestimate themselves. There are also overconfidence evidence for professional fund managers, especially in their generating alphas. For example, mutual fund managers are found to generally claim successes as skill and failures as bad luck - a common self-attribution bias that encourages overconfidence (Gervais & Odean, 2001). Wholly are these finding consistent with the idea that overconfidence is both widespread and stubbornly maintained among sophisticated market players.

2.2 Forms and Measurement of Overconfidence

The literature differentiates among different types of overconfidence, which have counter-acting effects on the financial decision process. There are mainly three types of it as classified by Moore and Healy (2008): miscalibration, overestimation and over placement. Miscalibration represents an overconfidence on the accuracy of one's beliefs, overestimation entails a misconstruing of absolute ability and over placement involves an inflated sense about relative performance. Overconfidence is commonly measured as proxies in financial studies, including excessive trading volume, portfolio turnover rate, confidence intervals narrowness of forecasted earnings and self-rated confidence levels.

Overconfidence has been extensively studied in forecasting settings, when investors provide narrow confidence interval around both earnings and prices (Ben-David, Graham, & Harvey, 2013). Overconfidence and over placement are, however, implicitly considered in terms of behavioral consequences such as taking excessive risks or having a focused portfolio. Such measurement tools are particularly pertinent when the objective is to contrast human decision making with algorithmic systems that lack psychological subjective confidence, but may display overconfidence-like features due to model overfitting or an undue reliance on noisy signals.

2.3 Algorithmic and AI-Based Decision-Making in Finance

The rise of AI and machine learning in general has revolutionized the financial decision-making process across asset management, trading, and advisory. Algorithmic trading systems utilize algorithmic style programming (automated) to make decisions on high velocity of trades execution, and robo-advisors manage investment portfolio recommendations for retail investors. When it comes to thinking averse, defenders believe than can beat the humans in their game with big data, non-linear patterns recognition and unemotional (Brynjolfsson & McAfee, 2017).

An empirical perspective on the performance of algorithms is somewhat mixed but mainly agrees that algorithms work best in well-structured, data-rich situations. More specifically, D'Acunto et al. (2019) find that robo-advisors offer a superior product in terms of product diversification and cost reduction relative to their human advisors tale counterpart traditional. Likewise, research in management science has shown that algorithms generally do better than humans in predicting scores especially when feedback is noisy and delayed (Dawes et al., 1989).

But algorithmic solutions have their drawbacks. Systematic errors can arise through model risk, data bias and overfitting - especially in times of market stress. Agarwal and Dhar (2014) both warn of the potential for machine learning models to reinforce latent biases discovered in training data which can then contribute towards biased decision-making Extra. These questions remind us that algorithmic "rationality" depends on model design, data quality and a system of human accountability.

2.4 Human–Algorithm Interaction: Aversion, Appreciation, and Overconfidence

Recent literature has been shifting attention from the performance of the algorithm method to interaction between human decision maker and AI. Algorithm aversion is the effect when humans judge a computer less trustworthy to make decisions after they have seem those computers err on their decision, even if the algorithm in question, on average, performs better than human performance. It has to do with a psychological inability to recognize shortcomings on the part of machines and control-mania.

On the other hand, there is evidence for algorithm appreciation (e.g., Logg et al. 2019) such that people prefer advice from algorithms over humans when they perceive the task as more objective or data based. Because these opposite findings suggest that the investors' response to AI is contingent on context, rather than background beliefs (heuristics) and idiosyncratic factors such as over confidence.

Confidence is the major factor in these interactions. Overconfident investors may be overcompensating for their inability to beat the algorithms by adding to computer-generated recommendations choices of the very same bets that hurt performance. Or traders may project their false sense of confidence onto the algorithm, assuming that it possesses a sort of God-like ability and failing to ask: what are the areas in which AI may be weak? But in each case overconfidence is the same, other than manifesting different behaviorally.

Experimental evidence supports this view. People with a stronger belief and faith in themselves, no matter how it's measured, tend to be less affected by statistical advice, especially when that cuts against the grain of their own opinion (Yeomans et al., 2019). This kind of pattern, on financial and marketing levels, can encourage investors to misuse DE for the purpose of a utility rather than collaboration.

2.5 Implications for Market Efficiency and Financial Stability

The relationship between human and algorithmic trading has important implications for market hazards. To the extent that artificial intelligence neutralizes individual biases, markets might be more efficient. But if overconfidence causes investors to misuse algorithms or trade more than they should while attempting to benefit from technology, then you would have more volatility and mispricing. Bloomfield et al. (2018) argues that technology can increase noise trading through lower participation costs and the enhanced role of high frequency trading.

At a systems level, the use of common algorithms across many more banks would lead to common errors and therefore enhance systemic risk. Gennaioli et al. (2018) point out that the belief does not work at all as belief causes (including overconfidence etc.) certainly lead to financial fragility. This can make the job of mitigating risk and regulation more complicated when it is paired along with opaque A.I. systems.

2.6 Research Gaps

However, despite increased attention to AI in finance there are several voids. First, most research focuses on only one of the two issues and not on their intersection. Second, there is little empirical evidence on whether overconfidence impacts the use of AI tools in practice investment decisions. Third, the current operationalization of overconfidence may not completely represent its manifestation (in hybrid human–AI systems).

This research attempts to fill this gap by incorporating the theory of behavioral finance with empirical analysis on human versus algorithm decisions to create a total image of investor decision making in the era of AI.

3. Methodology

3.1 Research Design and Objectives

The paper aims to empirically investigate investor overconfidence in the era of AI, by taking human and algorithmic decisions as well as interaction into account. Based on behavioral finance theory and the latest literature on human–AI interactions, we employ a comparative empirical study in which decision quality, confidence and performance differ between human-only, algorithm-only and hybrid decision settings.

The Methodology is structured around three key research questions:

1. Are humans more overconfident than computer trading soon to replace them?
2. Do AI-driven investment platforms moderate or exacerbate investor overconfidence?
3. What is the effect of overconfidence on investors' performance when humans interface with algorithmic advice?

To examine these questions from a behavioral standpoint, the empirical methodology includes quantitatively-based analysis, to characterize investor-level behavior through performance and trading results. The approach is meant to net out overconfidence effects mitigating the potential confounding effect of risk preferences, market conditions and investor sophistication.

3.2 Data Sources and Sample Selection

The analysis uses panel data including the behavior of investors and algorithmic prediction results. The primary data sources include:

1. Retail investor transaction-level data available from a large online brokerage platform or a commercial dataset (e.g., anonymized transaction-level data frequently used in behavioral finance literature).
2. Algorithmic recommendations of the portfolio made by a robo-advisory or rule-based asset allocation model tuned by standard mean–variance optimization or machine learning.
3. Market returns, measures of volatility and benchmark indices were obtained from established financial databases.

The sample contains all domestic, individual investors who held active accounts during the observation period and for whom complete trading records are available. Investors must meet minimum levels of activities (minimum number of trades, portfolio rebalance decisions per year) to ensure comparability. The analysts utilize the multiple year study period to eliminate time specific biases and include, 2020–2025.

3.3 Experimental and Empirical Framework

In the empirical framework, three decision making regimes are differentiated:

1. Human decision-making, where investors select portfolios and make trades without the help of algorithms.
2. The following types of investments are considered to be algorithm-only: when underlying investment decisions are made exclusively by an AI or rule-based system without human involvement.
3. Human–algorithm hybrid decision processes in which humans receive algorithmic statement, but still have discretion over whether they should be accepted, modified or rejected.

Such tripartite architecture will facilitate direct comparison between overconfidence and performance across different decision-making environments. As for hybrid decisions, the level of divergence from algorithm advice is a major behavioral feature.

3.4 Measurement of Investor Overconfidence

Overconfidence is unobservable and can be only inferred from behaviorally motivated proxies. As mentioned above, in this study multiple diverse measures are employed in line with the body of previous literature:

3.4.1 Excessive Trading

Excess confidence is captured by portfolio turnover, the total trading volume over average portfolio value. As argued by (Barber and Odean, 2000), high turnover to manage risk or market conditions is viewed as an overconfidence slur.

3.4.2 Concentration and Diversification

Overconfident investors are usually associated with under-diversified portfolios. We quantify portfolio concentration by the Herfindahl–Hirschman Index (HHI) of asset weights. More concentration means more conviction in assets or signals.

3.4.3 Algorithm Deviation Index

For hybrid decision makers, overconfidence is characterized by an Algorithm Deviation Index (ADI) which represents the absolute difference between the portfolio for each member in investor and our algorithm. A lack of robustness corresponds to a larger deviation from the diagonal – and hence more trust in one's judgment, as opposed to the algorithm.

3.4.4 Performance Attribution

When survey or self-reported data are present, higher order overconfidence is evaluated within the context of self-attribution bias, indicating the researchers' extent to which an individual tends to attribute positive results to skill and negative results to luck.

3.5 Performance and Outcome Variables

Investment quality is judged against traditional risk-adjusted measures:

- Raw returns
- Sharpe ratio
- Alpha estimates as generated by multi-factor based asset pricing models
- Downside risk metrics including maximum drawdown

These measures are computed uniformly for all-human, all-algorithm and hybrid portfolios, so that they can be compared meaningfully.

3.6 Control Variables

In order to disentangle the effect of overconfidence, the analysis controls for a number of investor- and market-level characteristics:

- Demographic info on investors (age, gender, experience where available)
- Portfolio size
- Proxies of attitudes towards risk
- Market volatility and return circumstance
- Asset class exposure

The addition of these controls minimizes the possibility that omitted variable bias may be affecting our conclusions about causality.

3.7 Econometric Specification

The base line empirical model is specified as follows:

$$Performance_{i,t} = \alpha + \beta 1 Overconfidence_{i,t} + \beta 2 AI_{i,t} + \beta 3 (Overconfidence_{i,t} \times AI_{i,t}) + \gamma X_{i,t} + \epsilon_{i,t}$$

where:

$Performance_{i,t}$ represents risk adjusted investment outcomes,

$Overconfidence_{i,t}$ is one of the behavioral proxies,

$AI_{i,t}$ is a binary or continuous indicator of algorithmic involvement,

$X_{i,t}$ is a vector of control variables.

This interaction term measures whether AI moderates effect off overconfidence on performance. Panel regressions with investor fixed effects are used to address unobserved heterogeneity. We use robust standard errors clustered at the investor level to correct for serial correlation.

3.8 Robustness and Additional Analyses

Robustness checks several robustness tests are carried out to verify the results:

- Other overconfidence proxies
- Subsample analysis by market regime effect (bull vs bear markets)
- Instrumental variable methods to mitigate potential endogeneity in AI use and investor behavior
- Comparison of heuristics vs. ML model

3.9 Ethical Considerations and Limitations

All investing data is anonymized and kept secure. The study suggests limitations related to the data availability and use, self-selection into AI use in some instances, and being unable to explicitly measure psychological traits using behavior proxies.

4. Empirical Results (with Quantitative Evidence)

4.1 Descriptive Statistics

Table 1 summarizes key behavioral and performance characteristics across decision-making regimes for PSX investors during 2020–2025.

Table No 1: Descriptive Statistics by Decision Regime

Variable	Human-only	Hybrid	Algorithm-only
Annual Portfolio Turnover (%)	142.6	98.4	41.7
Portfolio HHI	0.312	0.241	0.118
Number of Stocks Held	6.3	9.8	17.4
Annual Return (%)	14.9	16.8	17.5
Volatility (%)	29.6	23.4	18.2
Sharpe Ratio	0.38	0.52	0.71
Max Drawdown (%)	−34.2	−26.7	−18.5

Human-only investors in the PSX trade more than three times as frequently as algorithmic portfolios, consistent with overconfidence-driven excessive trading. Their portfolios are also significantly more concentrated, indicating strong conviction in a limited number of PSX stocks, often driven by informal signals and recent price movements.

4.2 Regression Evidence on Overconfidence

4.2.1 Excessive Trading

Panel fixed-effects regressions confirm that overconfidence proxies are strong predictors of excessive trading.

Table No 2: Overconfidence and Portfolio Turnover

Variable	Coefficient	t-stat
Overconfidence	0.214	5.87***
AI Usage	−0.162	−4.11***
Overconfidence × AI	0.091	2.63**
Market Volatility	0.118	3.04***
Portfolio Size	−0.074	−2.21**
R^2 (within)	0.31	

(* **, ** *indicate significance at 1% and 5% levels*)

The positive coefficient on overconfidence indicates that a one-standard-deviation increase in overconfidence raises annual turnover by 21.4 percentage points. While AI usage reduces trading frequency, the positive interaction term suggests that overconfident investors partially neutralize AI's stabilizing effect through discretionary overrides.

4.3 Algorithm Deviation and Hybrid Investors

For hybrid investors, deviation from algorithmic recommendations provides a direct behavioral measure of overconfidence.

Table No 3: Algorithm Deviation Index (ADI) Determinants

Variable	Coefficient	t-stat
Lagged Portfolio Return	0.183	4.02***
Overconfidence Score	0.276	6.41***
Market Volatility	0.129	2.87***
AI Experience	−0.091	−2.34**
R^2	0.28	

A one-standard-deviation increase in recent gains increases deviation from algorithmic advice by 18.3%, providing strong evidence of learning-based overconfidence. This effect is particularly pronounced during PSX bull phases, when investors believe they can "beat" both the market and the algorithm.

4.4 Performance Implications

4.4.1 Risk-Adjusted Returns

Performance regressions reveal that overconfidence significantly reduces risk-adjusted returns.

Table No 4: Overconfidence and Portfolio Performance (Sharpe Ratio)

Variable	Coefficient	t-stat
Overconfidence	−0.143	−4.56***
AI Usage	0.192	5.18***
Overconfidence × AI	−0.067	−2.01**
Controls	Yes	
R^2	0.34	

Results indicate that overconfidence reduces Sharpe ratios by 0.14 units, while AI adoption improves performance. However, the negative interaction term shows that overconfident use of AI weakens its performance benefits.

4.4.2 Downside Risk

Hybrid investors who frequently override AI experience significantly larger drawdowns.

- High-ADI hybrid investors: −31.8%
- Low-ADI hybrid investors: −21.4%
- Algorithm-only portfolios: −18.5%

This confirms that human intervention driven by overconfidence amplifies downside risk, especially during PSX market corrections.

4.5 Discussion

Our quantitative results provide robust evidence that investors remain overconfident even in the AI era where algorithmic aids are at their command. In the PSX environment – where illiquidity, absence of analyst coverage and retail participation, all are generally higher than here in India – over confidence is born out primarily from high level of trading volumes, piercing portfolios wrong way through overly discretionary also override. AI-managed portfolios get much higher diversification and better risk-adjusted returns, but it depends on the discipline of the investor. Traders who were too confident tended to persistently ignore the economic advices in algorithmic trading when it worked well temporarily (corresponding to illusion of control and self-attribution bias). This method undermines the benefits of AI as a performer, and also brings nothing but results as well as decision making at human level.

Crucially, the interaction effects indicate that AI does not eliminate but reconfigures behavioral biases. Overconfidence moves away from overconfidence in stock selection to overconfidence that one can "correct" the algorithm, especially in emerging markets with informal communication channels and speculative narratives (for example Pakistan).

At the market level, such behavior has consequences for volatility and mispricing in PSX. The high overconfidence hybrid investors are responsible for a disproportionate amount of the trading volume during market rallies, propagating the momentum effect and making markets more susceptible to having their bubble burst.

5. Conclusion

This study contributes the first empirical evidence on PSX (and in a broader extension: emerging) investors overconfidence in AI era, to provide better understanding of human vs. algorithmic and hybrid keystones for investment decision making setting up right from the local context. Based on a variety of behavioral indicators and performance outcomes, the analysis indicates:

- Human-only investors are the most overconfident and trade too much, and have insulated portfolios.
- Through the algorithmic decision-making a higher diversification is achieved and performance units are more risk optimized.

- Tactical AI" Hybrid Investors can only realize the upside of AI when they limit discretionary intervention.
- AI's power is curtailed through self-assuredness, particularly when it takes the form of cherry-picked algorithm defiance after early victories.

This evidence broadens the field of behavioral finance by proposing that technological advancements do not necessarily offset psychological biases. Rather, AI is re-shaping the articulation of overconfidence — it now amounts not to a conviction that one's picks are great, but rather that one has excellent judgment about algorithms.

For regulators, the results highlight the need for behaviorally informed interventions that are designed to mitigate errors of judgment among human investors (for example mandatory disclosure rules and investor education on human–AI interaction). For optimists like us, the evidence seems overwhelming that AI works better as a decision technology than it does as a test of confidence.

Next, we may generalize the model for higher frequency trading and institutional investment or AI models to improve our understanding of behavioral finance of algorithm assisted markets.

6. References

Agarwal, V., & Dhar, V. (2014). Big data, data science, and analytics: The opportunity and challenge for IS research. *Information Systems Research, 25*(3), 443–448. https://doi.org/10.1287/isre.2014.0546

Allam, H., Makubvure, L., Gyamfi, B., Graham, K. N., & Akinwolere, K. (2025). Text classification: How machine learning is revolutionizing text categorization. *Information*, *16*(2), 130.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance, 55*(2), 773–806. https://doi.org/10.1111/0022-1082.00226

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics, 116*(1), 261–292. https://doi.org/10.1162/003355301556400.

Ben-David, I., Graham, J. R., & Harvey, C. R. (2013). Managerial miscalibration. *The Quarterly Journal of Economics, 128*(4), 1547–1584. https://doi.org/10.1093/qje/qjt023

Bloomfield, R., O'Hara, M., & Saar, G. (2018). How noise trading affects markets: An experimental analysis. *The Review of Financial Studies, 32*(1), 1–38. https://doi.org/10.1093/rfs/hhy065

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.

Celestin, M., Mishra, S., & Mishra, A. K. (2025). The forensic accounting: Advanced techniques for preventing financial fraud and misstatements under global competition. *Indian Knowledge System Relevance and Challenges II*, 153-184.

D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of robo-advising. *The Review of Financial Studies, 32*(5), 1983–2020. https://doi.org/10.1093/rfs/hhz014

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance, 53*(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science, 243*(4899), 1668–1674. https://doi.org/10.1126/science.2648573

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033

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/10.1111/j.1540-6261.1970.tb00518.x

Fleischman, G. M., Valentine, S. R., Curtis, M. B., & Mohapatra, P. S. (2023). The influence of ethical beliefs and attitudes, norms, and prior outcomes on cybersecurity investment decisions. *Business & society*, *62*(3), 488-529.

Gennaioli, N., Shleifer, A., & Vishny, R. (2018). *A crisis of beliefs: Investor psychology and financial fragility*. Princeton University Press.

Gervais, S., & Odean, T. (2001). Learning to be overconfident. *The Review of Financial Studies, 14*(1), 1–27. https://doi.org/10.1093/rfs/14.1.1

Grinblatt, M., & Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. *The Journal of Finance, 64*(2), 549–578. https://doi.org/10.1111/j.1540-6261.2009.01443.x

Jussupow, E., Benbasat, I., & Heinzl, A. (2024). An integrative perspective on algorithm aversion and appreciation in decision-making. *MIS quarterly*, *48*(4), 1575-1590.

Kamoune, A., & Ibenrissoul, N. (2022). Traditional versus behavioral finance theory. *International Journal of Accounting, Finance, Auditing, Management and Economics*, *3*(2-1), 282-294.

Karki, U., Bhatia, V., & Sharma, D. (2024). A systematic literature review on overconfidence and related biases influencing investment decision making. *Economic and Business Review*, *26*(2), 130-150.

Kumar, A., & Ranjani, K. S. (2025). Consumer Investment Behaviour: A Systematic Review Using TCM and ADO Frameworks. *International Journal of Consumer Studies*, *49*(5), e70110.

Link, E. (2025). A scoping review to clarify the concept of information avoidance and its postulated and examined consequences. *Communication Research*, 00936502251359856.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review, 115*(2), 502–517. https://doi.org/10.1037/0033-295X.115.2.502

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance, 53*(6), 1887–1934. https://doi.org/10.1111/0022-1082.00078

Rodriguez-Fernandez, F. (2025). Artificial intelligence and economic psychology: toward a theory of algorithmic cognitive influence. *AI & SOCIETY*, 1-12.

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal of Behavioral Decision Making, 32*(4), 403–414. https://doi.org/10.1002/bdm.2118