Man or Machine? Where Artificial Intelligence Adds Value in Asset Management and Where Human Judgement Prevails Asset Allocation and Security Selection by Naive and Professional Investors

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Abstract

This investigation analyzes the comparative advantages of artificial intelligence (AI) relative to human judgment within the asset management process. A distinction is drawn between the naive investor—a private actor relying on autodidactic knowledge—and the professional investor, characterized by a mandate-driven process and institutional accountability. The analysis prioritizes asset allocation decisions, while security selection is evaluated specifically for government and corporate bonds, as well as globally diversified equity holdings, including funds and ETFs. The theoretical framework is grounded in behavioural finance evidence and the empirical record of implemented AI systems.

Human investors, regardless of their professional status, are subject to systematic cognitive biases, including impatience, lack of strategic discipline, and pro-cyclical trading behavior; the resulting return gap in the United States is estimated at approximately 1.2 percentage points annually over a ten-year horizon. Computational systems demonstrate a measurable advantage in data-intensive, repetitive, and rule-based domains—specifically in text analytics, bond ranking, rebalancing, and trade execution. Conversely, AI-managed funds have historically underperformed their benchmark indices over extended periods, and generative

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Statement on the use of AI tools: This work was produced with the occasional use of the AI tool Claude (Anthropic). The text was written by the author. Furthermore, the author produced all core content – including the research question, the objective, the methodology, the data analysis, all calculations, as well as the specialist knowledge and the layout – entirely independently. Claude was used, under supervision, as an auxiliary tool to assist with text condensation, to verify derivations and to cross-check sources. A small number of AI-generated text passages were thoroughly reviewed by the author and only incorporated once the content-related objectives had been met. Finally, the system was used for proofreading (spelling and academic style). The author takes full responsibility for the content of the paper.

language models exhibit a tendency toward factual hallucinations when deployed without rigorous verification.

The study concludes with strategic recommendations for both investor cohorts: AI does not substitute the investor, but rather replaces the investor's suboptimal behavioral habits. The definition of objectives, the assessment of risk capacity, and the assumption of accountability remain fundamentally human domains.

Keywords: Artificial intelligence · Machine learning · Behavioural finance · Asset allocation · Security selection · Robo-advice · Investment advice

JEL codes: C45, D91, G11, G23, G41, G53, O33

Non-Technical Summary

Artificial intelligence has fundamentally shifted the expectations surrounding wealth management. The capacity to process vast quantities of unstructured data—such as annual reports and market signals—in real-time enables capabilities that far exceed human cognitive limits. Consequently, the central inquiry is not whether AI is relevant to asset management, but rather the identification of specific domains where its efficacy surpasses that of human judgment.

This analysis evaluates two investor profiles: the private investor with autodidactic knowledge and the professional manager who administers external capital under a structured process. Research indicates that both types are prone to systematic errors: impatience, strategic inconsistency, and a tendency to enter positions after price peaks and exit after troughs. For fund investors in the United States, this behavioral gap results in an annual return loss of approximately 1.2 percentage points over a ten-year period.

In contrast, machine systems excel in data-rich, rule-governed tasks: robo-advisers optimize allocation via index funds and maintain equilibrium, while learning systems evaluate news and financial statements. Empirical evidence presents a nuanced picture: while AI-driven analysis often outperforms human analysts in precision, many AI-managed funds have failed to beat the market. Furthermore, rigid risk models can lead to suboptimal liquidations during extreme market volatility.

In summary, the machine is superior in the processing, sorting, and execution of complex data sets. The human remains indispensable for goal setting, evaluating personal risk tolerance, navigating unprecedented market scenarios, and assuming fiduciary responsibility. Optimal outcomes are achieved through a synergetic combination. For private investors, this entails the written fixation of strategies, the automation of implementation, and the use of AI as a cognitive tool without blind reliance on raw data. For professionals, it means deploying AI as an analytical partner for data-intensive tasks while retaining final judgment during regime shifts and for non-quantifiable variables.

Contents

1 Introduction

Asset management constitutes a systematic process of information processing, wherein the synthesis of market data, financial statements, and macroeconomic expectations informs the strategic allocation of capital and the selection of specific securities. At this interface, artificial intelligence (AI) is deployed. AI promises to process information with a scale, velocity, and objectivity—free from the influences of fatigue, fear, or greed—that fundamentally exceed human capacities.

This premise is particularly relevant given the established body of behavioural finance research. Over four decades, it has been documented that investors commit systematic errors: excessive trading (Odean 1999; Barber and Odean 2000), the premature realization of gains alongside the protracted holding of losing positions (Shefrin and Statman 1985; Odean 1998), an overarching tendency toward overconfidence (Barber and Odean 2001), and the linear extrapolation of recent trends into the future (Greenwood and Shleifer 2014). The hypothesis that a rational machine could eliminate these psychological vulnerabilities is therefore compelling.[2]

Nevertheless, capital market theory mandates caution. Where information is ubiquitous and computing power is commoditized, identical data and methodologies cannot yield universal outperformance (Grossman and Stiglitz 1980; Sharpe 1991). A ubiquitously available advantage is, by definition, no competitive advantage. The objective of this paper is therefore not to determine whether AI is 'more intelligent' than a human, but to identify the specific stages of the investment process where it delivers demonstrable added value, versus those where human judgment remains superior, and how these dynamics differ for private investors versus professional asset managers.

The investigation proceeds in three stages. First, it examines the mechanisms by which humans reach investment decisions—considering both rational and emotional drivers as well as the influence of financial and social media—and analyzes how this research is condensed into allocations and security selections. A distinction is made between the naive investor (a private actor with self-acquired knowledge) and the professional investor (a manager operating under a mandate and institutional accountability). Second, the analysis describes the technological counterpart: the formation of allocations and security selection via AI, illustrated by existing applications such as digital wealth managers, AI-driven funds, and generative language models. Third, an empirical balance is drawn to evaluate successes and failures and to derive practical implications for both investor types.

The analysis prioritizes allocation decisions, as these account for the majority of portfolio variance (Brinson et al. 1986; Ibbotson and Kaplan 2000). Regarding security selection, the scope is limited to government bonds, corporate bonds, and globally

[2] In this paper the term artificial intelligence serves as an umbrella term for rule-based automation, machine learning and generative language models; Section 4.1 distinguishes the three levels.

diversified equity holdings; individual stocks below a twenty-name diversification threshold are excluded in favor of global equity funds and ETFs. This delimitation aligns with the investment universe relevant to long-term wealth accumulation and avoids the fallacy of deriving general conclusions from idiosyncratic single-stock narratives.

The paper synthesizes several research traditions: behavioural economics (Kahneman and Tversky 1979 to Kahneman 2011), the measurement of the investor return gap (Friesen and Sapp 2007; Morningstar 2025b), the debate on clinical versus statistical prediction (Meehl 1954; Kahneman and Klein 2009), machine learning in finance (Gu et al. 2020; Kelly and Xiu 2023), and empirical research on digital wealth managers (D'Acunto et al. 2019; Reher and Sokolinski 2024).[3]

The contribution of this work lies in the integration of these perspectives and their verification against real-world applications. It is part of a working paper series by the author, which previously analyzed investments in AI (Rupprechter 2026a) and the transparent resolution of allocation questions using Markowitz and Black-Litterman frameworks (Rupprechter 2026b). This paper shifts the focus: not toward investing in AI, but toward investing with AI.

The paper is structured as follows. Section 1 (the present section) serves as the introduction, frames the research question, and surveys the prior literature. Section 2 analyzes the mechanisms of human investment decisions. Section 3 evaluates the systematic weaknesses of human behaviour. Section 4 describes the implementation of AI in allocation and security selection. Section 5 draws an empirical balance of successes and failures. Section 6 addresses limits and risks. Section 7 formulates recommendations for both investor cohorts. Section 8 provides a conclusion and outlook.

2 Mechanisms of Human Investment Decisions

2.1 Differentiation: The Naive and the Professional Investor

The naive investor is defined here as a private actor possessing substantial, albeit autodidactic, knowledge and experience. He manages personal capital without institutional oversight, written mandates, or an investment committee. His time is constrained, his information sources are public, and his decisions are typically autonomous. The term 'naive' thus refers not to a lack of knowledge, but to the absence of a formalized institutional process. In the household finance literature, this profile corresponds to the active, self-directed private investor (Gomes et al. 2021).

In contrast, the professional investor is an asset or fund manager who administers external capital based on a mandate that defines objectives, constraints, and benchmarks.

[3] Bartram et al. (2020) survey the state of machine learning in asset management from a practitioner's perspective; OECD (2021) and IMF (2024) summarise the supervisory view.

His operations are embedded in a process comprising research, investment committees, risk management, and reporting. While his information sources—ranging from data terminals to corporate visits—are broader, he is subject to specific institutional incentives: career concerns (Chevalier and Ellison 1999), performance-dependent fund flows (Berk and Green 2004), and the pressure to align with the market consensus (Scharfstein and Stein 1990).[4] Table 1 contrasts these two investor profiles.

Table 1: Characteristics of the naive and the professional investor

Characteristic	Naive Investor	Professional Investor
Mandate and objective	Personal wealth; objectives often implicit and rarely documented	Third-party wealth; formal mandate with benchmarks, constraints, and reporting obligations
Sources of information	Financial and social media, personal networks, public reports, retail bank advice	Data terminals, sell-side and internal research, corporate contacts, consultants, peers
Decision path	Independent, event-driven, frequently intuitive	Team-based, process-driven, documented; investment committee
Condensation	Heuristics, experience, intuition, occasional use of simple tools	Capital market assumptions, quantitative models, scenarios, risk budgets
Instruments	Equities, funds, ETFs, savings products; bonds primarily via funds	Full instrument universe including individual bonds and derivatives
Time budget	Secondary activity	Full-time professional role with division of labor
Control	Self-regulation; irregular	Continuous: limits, attribution analysis, supervision
Typical incentives	Avoidance of regret, confirmation bias, entertainment	Relative performance, career progression, inflows, proximity to the herd

Source: Author's presentation.

Both cohorts share the fundamental properties of human cognition. Behavioural research demonstrates that neither education nor experience eliminates all cognitive biases. Professional investors exhibit the disposition effect (Frazzini 2006), overconfidence (Puetz and Ruenzi 2011), and herding behaviour (Wermers 1999)[5]. Recent data further confirm that institutional portfolio managers systematically exhibit suboptimal selling decisions relative to their buying decisions (Akepanidtaworn et al. 2023). The distinction between the types therefore lies less in the absence of errors than in the implementation of structural safeguards to mitigate them.

2.2 Information Sources and Attentional Steering

Investment decisions are frequently initiated by external triggers. For the naive investor, this is rarely a systematic process but often a reaction to headlines, social media, or acute

[4] The term "professional investor" is used functionally here and is broader than the MiFID II client category of the same name; it denotes anyone who manages other people's wealth professionally under a mandate.
[5] Wermers (1999) measures herding as the co-movement of the trading direction of many funds in the same stock and quarter, adjusted for chance; the measure is highest for small stocks and growth funds.

price movements. Barber and Odean (2008) demonstrate that private investors disproportionately acquire securities that attract high attention—specifically those with extreme daily returns or high trading volumes. Da et al. (2011) confirm this mechanism using internet search queries. Attention thus serves as a filter optimized for salience rather than expected return.

Financial media exert a measurable influence on prices and investor behaviour. Tetlock (2007) shows that a pessimistic tone in the business press depresses prices in the short term; Engelberg and Parsons (2011) document that local coverage causally increases trading volume. Rankings are particularly potent: Kaniel and Parham (2017) show that the mere mention of a fund in a Wall Street Journal ranking leads to substantial inflows without subsequent performance improvement. Media do not merely inform; they direct capital through the steering of attention.[6]

Social media have accelerated this dynamic. Barber et al. (2022) use Robinhood data to show that attention-driven herding episodes lead to negative subsequent returns; Cookson et al. (2023) identify confirmation bias in financial forums. The role of 'finfluencers' is particularly critical: Kakhbod et al. (2023) find that a minority provide valuable guidance, while a majority are 'anti-skilled'—their recommendations are systematically worse than chance, yet they attract followers by confirming existing prejudices.

Personal advice does not guarantee the avoidance of errors. Bhattacharya et al. (2012) show that those who most need unbiased advice are the least likely to seek it; Foerster et al. (2017) document that advised portfolios are often shaped more by the adviser's preferences than the client's risk profile. Linnainmaa et al. (2021) demonstrate that advisers commit the same costly errors in their own portfolios that they recommend to clients. Gennaioli et al. (2015) attribute the enduring success of advice to trust: the adviser acts as a 'money doctor' who removes the investor's psychological barrier to investing.

The professional investor utilizes different sources but remains susceptible to bias. Sell-side research often serves the interests of the provider, and external consultants' recommendations may lack measurable added value (Jenkinson et al. 2016). Hong et al. (2005) show that local networks among fund managers lead to portfolio homogenization. The professional's advantage thus lies not in the purity of information, but in its processing within a controlled, documented process.[7]

[6] The author has himself answered investors' questions for many years in newspaper columns and telephone campaigns; the experience matches the evidence: people ask about whatever is in the headlines.

[7] Sell-side research is research produced by securities firms for their clients; it is financed by trading commissions and underwriting business and is therefore structurally inclined towards buy recommendations.

2.3 Cognitive Architecture: Rationality versus Emotion

The dichotomy between rational and emotional decision-making is theoretically inadequate. Simon (1955) introduced the concept of bounded rationality: individuals do not optimize but seek a satisfactory solution (satisficing) due to constraints on time, information, and computational capacity. Tversky and Kahneman (1974) showed that this process relies on heuristics (availability, representativeness, anchoring) that, while generally efficient, induce systematic errors. Kahneman (2011) differentiated this into System 1 (fast, intuitive, associative) and System 2 (slow, analytical, rule-governed). While the naive investor's decisions are primarily driven by System 1, the institutional process attempts to operationalize System 2.

The reliability of intuitive expertise in asset management is questionable. Kahneman and Klein (2009) demonstrate that intuition is only reliable in environments with high regularity and immediate feedback—not in capital markets, where feedback is delayed and noisy. In such settings, experience often leads to an illusory sense of competence.

Conversely, Gigerenzer and Brighton (2009) argue that simple heuristics can outperform complex optimizations in uncertain environments. DeMiguel et al. (2009) confirm this for portfolio theory: naive equal weighting (1/N) is often superior out-of-sample, as optimization procedures magnify input errors (Michaud 1989). Emotion and heuristics are thus not inherently irrational but are context-dependent.[8]

The professional process mitigates intuitive errors but introduces new ones. Kahneman et al. (2021) describe 'noise' as the phenomenon where experts reach different judgements on identical facts. Furthermore, institutional incentives encourage managers to align with the consensus to avoid the career risk associated with being alone and wrong (Scharfstein and Stein 1990; Chevalier and Ellison 1999).

2.4 From Research to Allocation: The Process of Condensation

Allocation determines the majority of portfolio variance (Brinson et al. 1986; Ibbotson and Kaplan 2000). The derivation of this decision differs fundamentally between investor types.

The naive investor often acts additively. The portfolio is the sum of discrete decisions taken at different times for varying reasons. Benartzi and Thaler (2001) document a tendency toward naive diversification; Goetzmann and Kumar (2008) identify a strong concentration in a few correlated assets. Calvet et al. (2007) quantify the welfare costs of this underdiversification. Allocation thus results from chance, habit, or home bias.

The professional investor employs a multi-stage condensation process. Based on capital market assumptions (returns, volatilities, correlations), a strategic allocation is defined—

[8] Knight (1921) distinguished between risk, which can be expressed in probabilities, and uncertainty, for which this is impossible. Heuristics prove their worth above all under uncertainty; optimisation and machine learning presuppose risk.

using Markowitz optimization (1952) or the Black-Litterman model (1992). To reduce instability, weights are constrained (Jagannathan and Ma 2003), covariances are shrunk (Ledoit and Wolf 2004), or data series are extended (Kritzman et al. 2010). This is followed by tactical adjustments within defined bands. Each stage is documented and ratified by an investment committee.[9]

Figure 1 contrasts these paths: the naive investor's path is short and reactive; the professional's path is circular, beginning with investment policy and proceeding through systematic research to allocation and selection.[10]

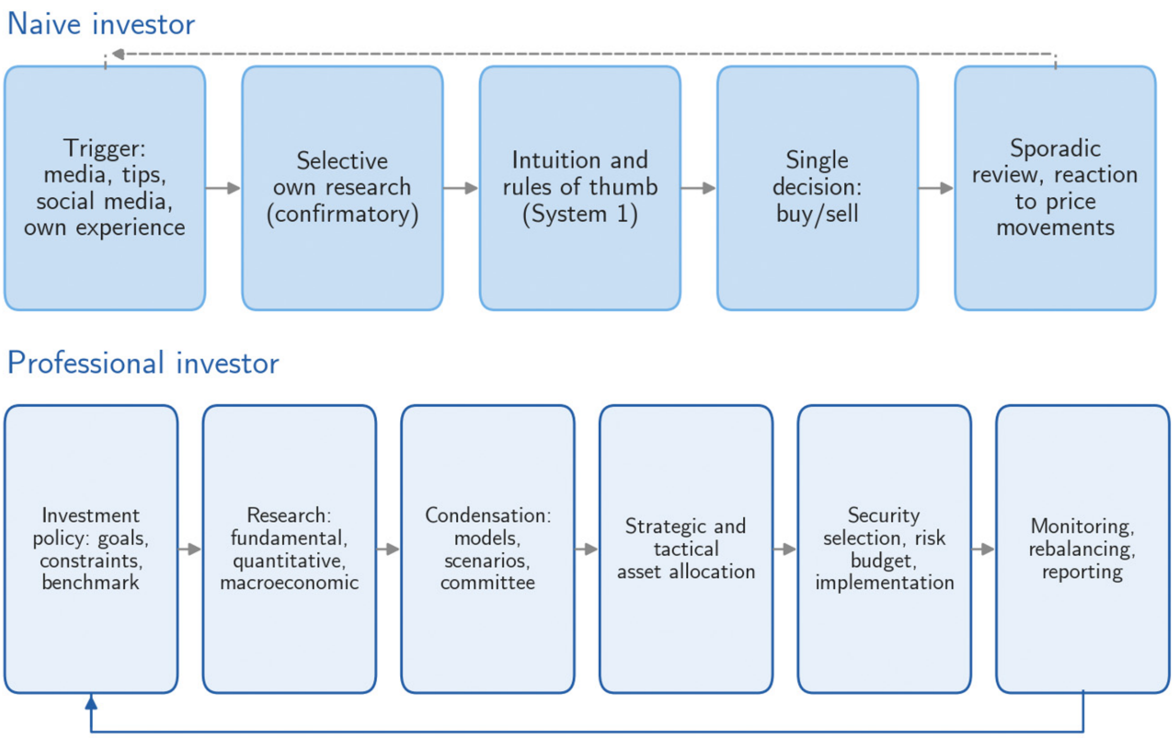

Figure 1: Stylized decision pathway of naive versus professional investors. Source: Own illustration.

2.5 Security Selection: Bonds and Globally Diversified Equity Holdings

Within the allocation, specific securities are selected. For government bonds, the focus is on maturity, issuer, and currency; for corporate bonds, credit quality and sector are added. The naive investor primarily utilizes funds or ETFs for bonds due to minimum denominations and trading costs. In equities, there is a preference for familiar names, where familiarity substitutes for analysis (Barber and Odean 2008; Goetzmann and Kumar 2008).

[9] An example of such a transparent derivation – the emerging-markets weight of a world portfolio according to Markowitz and Black-Litterman – is given in Rupprechter (2026b).

[10] The figure is schematic; in practice the stages overlap, and private investors with high process discipline do follow the lower path.

The professional investor selects methodically. For bonds, yield curve positioning and credit analysis are paramount.[11] In equities, a distinction is made between fundamental analysis (in-depth review of few companies) and quantitative methods (factor-based ranking of thousands of securities) (Grinold and Kahn 2000). Abis (2022) shows that quantitative funds exhibit higher diversification and specialize in selection, whereas discretionary managers switch flexibly between selection and timing.

The selection of global equity funds and ETFs follows distinct criteria: costs, replication method, fund size, and tax treatment. Here, the evidence is unambiguous: after costs, the majority of actively managed funds fail to beat their index (Jensen 1968; Carhart 1997; Fama and French 2010). SPIVA data confirm that over twenty years, approximately 93% of US large-cap funds trailed the S&P 500 (S&P Dow Jones Indices 2026). Fund selection is therefore primarily a decision on costs and discipline, not forecasting ability.[12]

2.6 The Temporal Dimension of the Portfolio

Allocation is a long-term commitment. While the professional investor utilizes rules (bands, rebalancing) to maintain the target, the naive investor's portfolio typically drifts with market movements, with interventions driven by emotion rather than plan.

The costs of this behavior are quantifiable. The investor return gap—the difference between fund returns and actual investor returns—results from suboptimal timing. Friesen and Sapp (2007) estimate this gap for US equity funds at 1.6 percentage points p.a. Morningstar (2025b) calculates a gap of 1.2 percentage points annually through 2024. DALBAR (2025) reports that in 2024, investors forfeited over 8 percentage points of return due to poor timing.[13]

Figure 2 shows that the gap is largest for sector funds, which invite pro-cyclical behavior. The gap correlates positively with flow volatility (Morningstar 2025b). This result is central: the return lost to behavior is comparable to the cost of active management and could be recovered through pure process discipline—without requiring forecasting skill.

[11] Rating migration denotes the movement of an issuer between credit quality grades; forecasting it is an essential part of the return on corporate bonds.

[12] The threshold of twenty names is a lower bound of meaningful diversification, not a recommendation: idiosyncratic risk falls steeply and then flatly with the number of names, and global index funds diversify across more than a thousand of them.

[13] DALBAR and Morningstar use different methods; the order of magnitude of the gap, however, is stable across decades and data providers: between one and two percentage points a year.

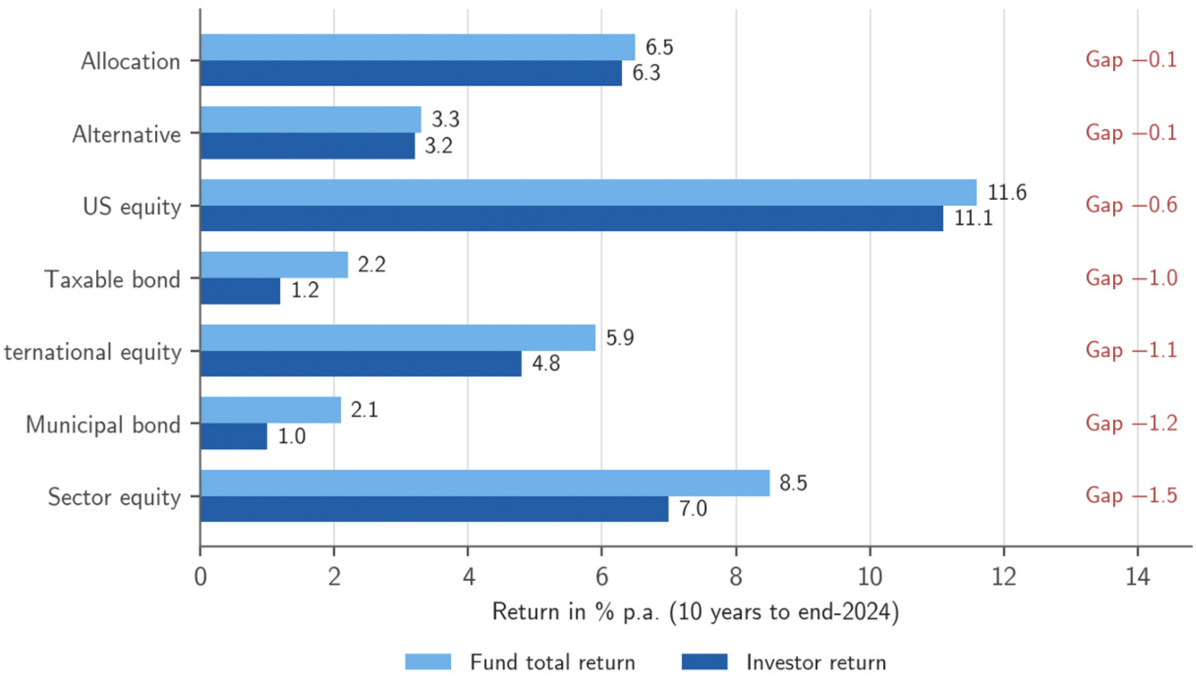

Figure 2: Investor returns compared to total fund returns by category in the United States over the ten-year period ending December 31, 2024. Source: Morningstar (2025b); own presentation.

3 Systematic Weaknesses of Human Investment Behaviour

3.1 Impatience and Lack of Strategic Discipline

The most significant weakness is a lack of temporal discipline. Odean (1999) demonstrates that private investors exhibit excessive trading volume that cannot be explained by liquidity needs or rebalancing, with purchased securities subsequently underperforming those sold. Barber and Odean (2000) quantify this: the most active households earned significantly lower net returns than the market. Bogle (2012) notes a general decline in holding periods over time.

This is driven by myopic loss aversion (Benartzi and Thaler 1995): frequent portfolio reviews cause losses to be weighted disproportionately (Kahneman and Tversky 1979). This results in a shortened effective investment horizon, regardless of the stated objective.[14]

Professional investors are similarly affected. Goyal and Wahal (2008) show that managers are often hired after short-term outperformance and fired after weak periods, with terminated managers often subsequently outperforming their replacements. Strategy shifts occur not due to fundamental failure, but due to temporary performance volatility.

[14] Benartzi and Thaler (1995) estimate that the observed equity risk premium is consistent with an evaluation interval of about one year; whoever evaluates daily demands a higher premium and holds fewer equities.

3.2 Pro-cyclical Behavior: Buying High and Selling Low

A second weakness is the systematic lag in expectation formation. Investors extrapolate recent trends into the future (Greenwood and Shleifer 2014). Malmendier and Nagel (2011) show that macroeconomic experiences (e.g., depressions) permanently shape risk tolerance. De Bondt and Thaler (1985) identified the tendency to overreact, leading to a scenario where past losers become future winners.

Fund flows reflect these expectations: capital enters when returns are high and exits when prices have already fallen (Frazzini and Lamont 2008). Figure 3 illustrates this. In 2024, investors reduced equity exposure immediately before the largest rally (DALBAR 2025).

Professional investors are not immune, though the cycle is slower. Mandate shifts described by Goyal and Wahal (2008) represent institutional pro-cyclicality. Brunnermeier and Nagel (2004) and Greenwood and Nagel (2009) show that inexperienced managers overweighted technology stocks at the peak of the bubble.[15]

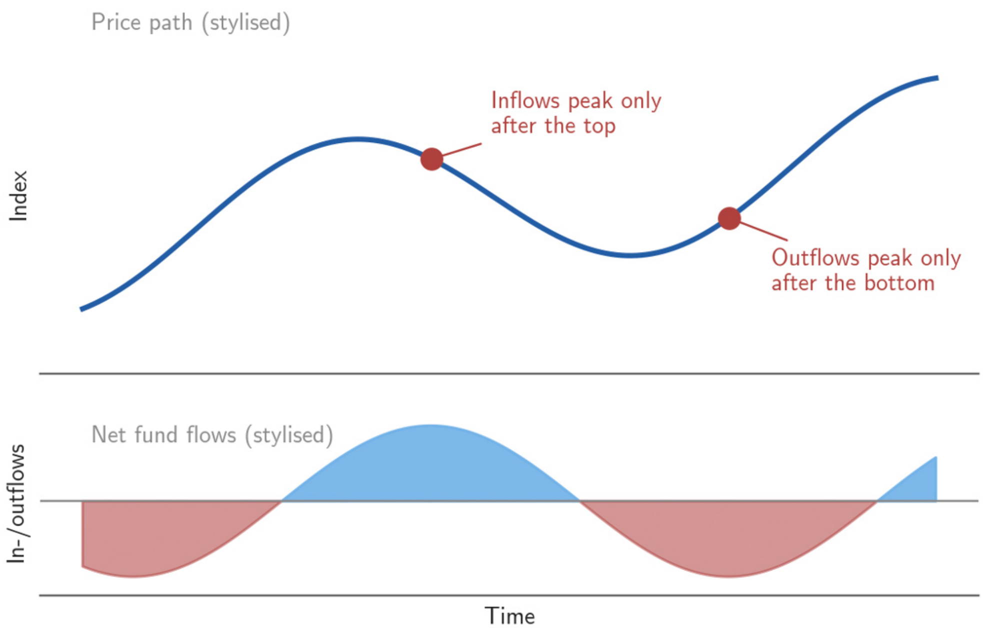

Figure 3: Buying high and selling low: a schematic diagram illustrating the relationship between price paths and fund flows. Source: Author's own illustration (schematic, not based on empirical scaling).

3.3 Thematic Trends and Herding

Susceptibility to fashion is a pervasive weakness. Cooper et al. (2001) demonstrate that mere name changes to include trending terms (e.g., '.com') led to short-term gains. Cooper et al. (2005) show that funds adapting their names to current styles attract inflows without

[15] The author has witnessed every crisis live since 1985, from the crash of 1987 to the AI euphoria; the most important lesson is not to foresee the next crisis but to hold an allocation that one need not abandon in it.

strategic change. Thematic funds are typically launched at the peak of popularity and subsequently deliver subpar results. The behavior gap is largest for sector funds (Morningstar 2025b) (Figure 2).[16]

Herding among professionals is often a rational response to institutional incentives. Scharfstein and Stein (1990) show that the reputational risk of being alone and wrong outweighs the benefit of being alone and right. Lakonishok et al. (1992) and Wermers (1999) document this empirically. Cremers and Petajisto (2009) identify 'closet indexing' as a risk-mitigation strategy. Social media have accelerated these cycles (Barber et al. 2022). Welch (2022) notes that while aggregate portfolios may track the market, the individual distribution remains volatile.

3.4 Overconfidence, the Disposition Effect, and Loss Aversion

The tendency to realize gains prematurely while holding losses too long (the disposition effect) is widespread. Shefrin and Statman (1985) and Odean (1998) document that private investors realize gains significantly more often than losses, driven by the asymmetric value function of Kahneman and Tversky (1979). Overconfidence leads to excessive trading and reduced returns, particularly among male investors (Barber and Odean 2001).

Professional investors are similarly affected. Frazzini (2006) identifies a delayed response to new information; Puetz and Ruenzi (2011) show that positive results induce riskier, suboptimal trading. Chevalier and Ellison (1997) document pro-cyclical risk adjustments at year-end. Akepanidtaworn et al. (2023) demonstrate that institutional managers make excellent buying decisions but suboptimal selling decisions, relying on flawed heuristics.[17] Table 2 summarizes these anomalies.

[16] Rupprechter (2026a) treats investing in AI companies as a megatrend; the present paper emphasises that "investing in AI" and "investing with AI" are two different questions – and that the first is subject to the fashion cycles described here.

[17] Akepanidtaworn et al. (2023) estimate that the sales of the managers studied cost around 0.8 percentage points of return a year relative to a random selling rule – alongside purchases that beat the market.

Table 2: Behavioural anomalies in asset management: description and empirical evidence

Anomaly	Description	Evidence (Naiv)	Evidence (Professional
Excessive trading / Impatience	Turnover beyond necessity; purchased securities underperform those sold	Odean (1999); Barber and Odean (2000); Barber et al. (2009)	Puetz and Ruenzi (2011); Goyal and Wahal (2008)
Extrapolation / Lateness	Expectations follow the recent past; pro-cyclical flows	Greenwood and Shleifer (2014); Frazzini and Lamont (2008); DALBAR (2025)	Goyal and Wahal (2008); Jenkinson et al. (2016); Greenwood and Nagel (2009)
Fashionable themes / Herding	Purchasing based on popularity; name/theme trends	Cooper et al. (2001, 2005); Barber et al. (2022); Kakhbod et al. (2023)	Scharfstein and Stein (1990); Lakonishok et al. (1992); Wermers (1999); Brunnermeier and Nagel (2004)
Disposition effect	Premature sale of winners; prolonged holding of losers	Shefrin and Statman (1985); Odean (1998)	Frazzini (2006); Akepanidtaworn et al. (2023)
Overconfidence	Overestimation of own information and skill	Barber and Odean (2001)	Puetz and Ruenzi (2011)
Loss aversion / Framing	Asymmetric weighting of losses; risk-taking after losses	Kahneman and Tversky (1979); Benartzi and Thaler (1995)	Coval and Shumway (2005); Chevalier and Ellison (1997)
Underdiversificatio n / Home bias	Concentrated portfolios; preference for familiar assets	Goetzmann and Kumar (2008); Calvet et al. (2007); Benartzi and Thaler (2001)	Hong et al. (2005)
Incentive-driven distortion	Risk adjustment for reporting; window dressing; index hugging	–	Chevalier and Ellison (1997); Lakonishok et al. (1991); Cremers and Petajisto (2009)

Source: Author's presentation based on cited studies.

3.5 Comparative Analysis: Professional vs. Naive Investors

Despite shared cognitive biases, the professional investor is systemically superior in key dimensions. He achieves higher diversification (Goetzmann and Kumar 2008; Calvet et al. 2007), has access to complex asset classes, and operates within a regulated process with mandatory rebalancing. This mitigates the extreme effects of the behavior gap.

However, there is no significant advantage in alpha generation (market outperformance). Jensen (1968), Carhart (1997), and Fama and French (2010) find negligible evidence of persistent skill. SPIVA data confirm that most professionals underperform indices over long horizons. Berk and Green (2004) explain this through the effect of asset growth on alpha. The professional's edge lies in process quality—the avoidance of errors—rather than predictive inspiration.

This distinction is critical: to surpass the professional, a machine must deliver a superior process, not merely better forecasts. Table 3 contrasts these dimensions.[18]

[18] The comparison holds on average. Individual private investors with process discipline beat many professionals, and individual professionals commit every error of the naive investor – only with other people's money.

Table 3: Dimensions of the professional investor's advantage over the naive investor

Dimension	**Professional's Advantage**	**Reasoning**	**Evidence**
Diversification (names, regions, assets)	Large	Mandate and process enforce diversification; naive portfolios are concentrated	Goetzmann and Kumar (2008); Calvet et al. (2007)
Access to bonds and instruments	Large	Denomination and costs make diversification feasible only institutionally	Author's presentation
Cost awareness and bargaining power	Large	Costs are a reliable predictor of net return	Sharpe (1991); Carhart (1997)
Discipline (rebalancing, rules)	Large	Avoids drift and lateness; reduces the behavior gap	Morningstar (2025b); Friesen and Sapp (2007)
Third-party control	Medium	Investment committees and risk management; but subject to noise and herding	Kahneman et al. (2021); Scharfstein and Stein (1990)
Selling discipline	Small	Professionals also rely on heuristics for selling	Akepanidtaworn et al. (2023); Frazzini (2006)
Market timing and forecasting	Small to none	Mandate awards and thematic trends often follow the past	Goyal and Wahal (2008); Greenwood and Nagel (2009)
Outperforming the market (net of costs)	None (on average)	Arithmetic of active management; diseconomies of scale	Sharpe (1991); Fama and French (2010); Berk and Green (2004); S&P Dow Jones Indices (2026)

Source: Author's presentation.

3.6 Optimization of Human Decision-Making

The reduction of cognitive errors is achieved by shifting decisions from an emotional state to a structured process. Central to this is the written investment strategy (objectives, horizon, allocation, bands). This transforms the decision into a comparison against a defined norm.[19]

Precommitment is also effective. Thaler and Benartzi (2004) show that future commitments are more easily accepted than immediate ones. Automated savings plans and rebalancing reduce friction and error. Reducing review frequency prevents panic induced by myopic loss aversion.

Methodological tools from other disciplines further enhance quality: checklists (Gawande 2009), premortems (Klein 2007), the use of base rates (Tetlock and Gardner 2015), and decision journals. For committees, 'decision hygiene'—obtaining independent judgments before discussion—is recommended (Kahneman et al. 2021).

The value of these measures is quantifiable. Kinniry et al. (2019) estimate the contribution of behavioral coaching at approximately 1.5 percentage points p.a.; Blanchett and Kaplan (2013) quantify the gain from allocation and tax discipline at roughly 1.6

[19] The goal should be formulated in amounts and dates ("amount X in year Y for purpose Z"), not in returns; return targets invite comparison with neighbours and headlines.

percentage points. Institutional improvements include separated buy/sell rules (Akepanidtaworn et al. 2023) and anonymized polling. Table 4 summarizes these measures.[20]

Table 4: Measures to improve human investment decisions

Measure	Effect	Target Group	Evidence
Written investment strategy (goals, horizon, bands)	Transforms decision into a deviation check; protects against lateness and trends	Naive (Professional: standard)	Author's presentation
Precommitment (savings plans, auto-rebalancing)	Reduces turnover; extends effective investment horizon	Both	Thaler and Benartzi (2004); Benartzi and Thaler (1995)
Four-eyes principle for unscheduled interventions	Delays emotional decisions; ensures accountability	Both	Kahneman et al. (2021)
Checklists and premortems	Reduces expert errors	Both	Gawande (2009); Klein (2007)
Decision journal and hit-rate tracking	Makes patterns visible; calibrates confidence	Both	Tetlock and Gardner (2015)
Separate selling rules	Closes the gap between buying and selling quality	Professional	Akepanidtaworn et al. (2023)
Behavioral coaching by advisers	Approximately 1.5 percentage points per annum	Naive	Kinniry et al. (2019); Blanchett and Kaplan (2013)

Source: Author's presentation.

4 The Implementation of Artificial Intelligence in Allocation and Security Selection

4.1 Taxonomy of Automation Levels

A differentiation between three levels of automation is essential. The first level is rule-based automation: systems execute predefined rules (e.g., target allocation with bands) without learning. Digital wealth managers and index replication fall into this category. The second level is machine learning (ML): algorithms autonomously derive rules from data by estimating relationships between predictors and target variables (Mullainathan and Spiess 2017). Gu et al. (2020) show that neural networks and decision trees improve out-of-sample predictability over linear models. The third level is generative AI: large language models (LLMs) that analyze and synthesize text and draw inferences from financial statements (Kim et al. 2024).[21]

[20] The estimate of Kinniry et al. (2019) is an average over time and investors; in calm years the value of coaching is zero, in crisis years a multiple of the average.

[21] Dedicated language models have been trained for finance, such as BloombergGPT (Wu et al. 2023); in practice, however, general models supplemented with proprietary data dominate.

These levels differ in their promises and risks: rule-based systems offer discipline but are limited by the correctness of the rule.[22] ML systems offer predictive power but are susceptible to overfitting (Bailey et al. 2014; Harvey et al. 2016) and structural breaks. Generative AI offers synthesis and understanding but is prone to hallucinations. Table 5 and Figure 4 illustrate these distinctions.

Table 5: Three levels of automation in asset management

Level	Function	Typical Applications	Strengths and Primary Risks
Rule-based automation	Executes human-defined rules; does not learn	Robo-advisers, savings plans, index replication, rebalancing, order execution	Discipline, cost, scalability; risk: incorrect or rigid rules
Machine learning	Estimates relationships from data; derives rules autonomously	Return prediction, factor weighting, credit risk, sentiment, anomaly detection	Capacity for non-linear patterns in large datasets; risk: overfitting, structural breaks, crowding
Generative AI (LLMs)	Processes and produces language; draws inferences from text and numbers	Report and earnings call summaries, chat-based advice, financial statement analysis	Breadth, speed, accessibility; risk: hallucinations, prior training knowledge, liability

Source: Author's presentation; see Bartram et al. (2020) and Kelly and Xiu (2023) for further delimitation.

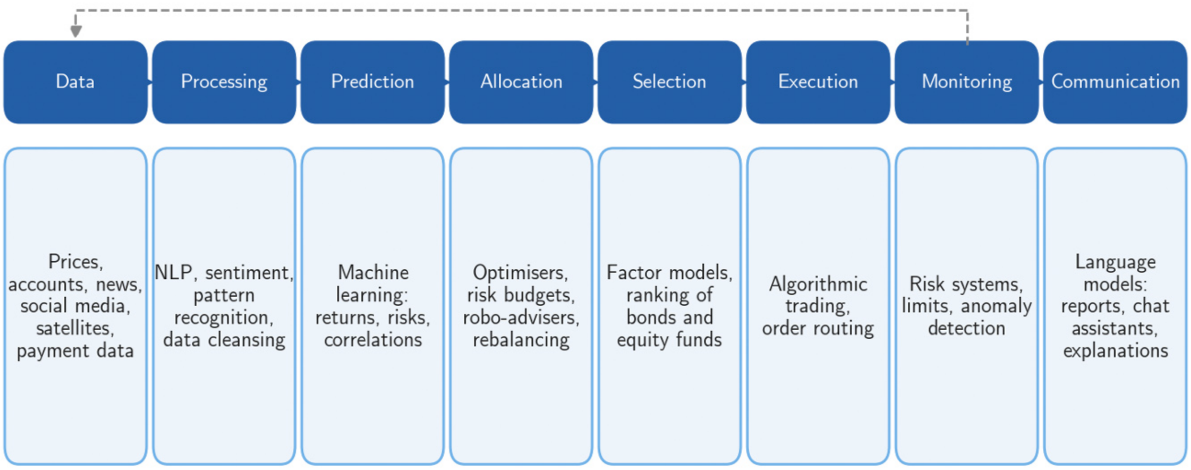

Figure 4: Deployment of artificial intelligence across the asset management value chain. Source: Authors' own creation.

4.2 Data Analysis and Sentiment Measurement

A primary advantage of AI is the processing of unstructured text. Systems analyze millions of documents—news, reports, earnings calls—at a scale exceeding human capacity. The

[22] Rule-based systems are frequently marketed as "AI"; for the assessment the only thing that matters is whether a system learns from data or merely executes predefined rules.

evolution ranges from simple word counting (Tetlock 2007) and specialized financial dictionaries (Loughran and McDonald 2011) to autonomous feature identification (Ke et al. 2019). Lopez-Lira and Tang (2023) show that LLMs can predict short-term price reactions. Jiang et al. (2023) demonstrate that neural networks can extract return patterns from price charts that surpass classical momentum signals.[23]

AI also leverages alternative data (satellite imagery, credit card data), which increases informational efficiency (Zhu 2019). Professional investors use these sentiment indicators in real-time; for private investors, these sources are often inaccessible or risk-prone without processing.[24]

Two systemic constraints exist: first, the ubiquity of signals leads to rapid arbitrage, eroding the advantage. Second, LLMs suffer from a look-ahead bias: they may 'predict' events already present in their training data (Glasserman and Lin 2023; Lopez-Lira et al. 2025). Furthermore, predictive gains often concentrate in illiquid securities and diminish after trading costs (Avramov et al. 2023).[25]

4.3 Machine-Driven Allocation: From Optimizers to Robo-Advisers

Machine-driven allocation is based on the mathematical formulation of portfolio selection (Markowitz 1952). Modern approaches stabilize input data: Black and Litterman (1992) combine equilibrium returns with subjective views; Ledoit and Wolf (2004) employ robust covariance estimation; López de Prado (2016) uses hierarchical allocation. Chen et al. (2024) utilize deep neural networks to estimate risk premia. The machine computes with precision, but remains dependent on the quality of the estimates.[26]

For the private investor, this manifests as the robo-adviser. These systems use a standardized process (questionnaire -> risk class -> index portfolio) with automated rebalancing. This is primarily rule-based automation; Morningstar (2025a) notes that generative AI is generally avoided in recommendation generation due to hallucination and privacy risks. The value lies in cost reduction and process discipline. Providers like Vanguard and Betterment offer efficient solutions, although some high cash allocations are criticized as hidden costs. Table 6 provides examples.

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[23] Jiang et al. (2023) train a convolutional network on images of price charts; the method originates in image recognition and carries over to financial time series without modification.

[24] Providers include RavenPack for news sentiment and Bloomberg for terminal data; the costs are in the range of professional data subscriptions.

[25] The prior-knowledge problem affects backtests only. In live operation a model does not know the future – but neither can it predict it better than the backtest suggests.

[26] López de Prado (2016) calls his method Hierarchical Risk Parity; it dispenses with the inversion of the covariance matrix, which is the main cause of the instability of classical optimisers.

Table 6: Digital wealth managers and allocation tools: empirical examples

Provider (Country)	**Since**	**Method**	**Costs and Particulars**
Vanguard Digital Advisor (USA)	2020	Rule-based: questionnaire-derived allocation, in-house index funds, automatic rebalancing	Approx. 0.20% p.a. incl. fund costs; rated "High" overall by Morningstar (2025a)
Betterment (USA)	2010	Rule-based: ETF portfolios by risk class, tax-loss harvesting	0.25% p.a. advisory fee
Wealthfront (USA)	2011	Rule-based: ETF portfolios, tax-loss harvesting, direct indexing	0.25% p.a. advisory fee
Schwab Intelligent Portfolios (USA)	2015	Rule-based: ETF portfolios with fixed cash allocation	No advisory fee; avg. 13% cash share as hidden cost (Morningstar 2025a)
Fidelity Go (USA)	2016	Rule-based: portfolios of in-house funds	Free up to USD 25,000, then 0.35% p.a.
Scalable Capital (DE)	2016	Until 2024: dynamic risk limitation via VaR; now world portfolio strategies	VaR strategy lost 8.2% (2017–2024) vs. MSCI World +77% (FinanceFWD 2024)
Quirion, Ginmon, Growney, Whitebox, etc. (DE)	2013–16	Rule-based: ETF world portfolios by risk class, incl. factor/sustainability variants	22 providers tested since 2015 (Brokervergleich.de 2026)
Online portfolio calculators/optimizers	Var.	Markowitz optimization, Black-Litterman, Monte Carlo simulations	No narrow-sense AI; results dependent on input quality (Michaud 1989)
General language models (ChatGPT, etc.)	2022	Allocation proposals via dialogue; no portfolio access, no liability	Reasonable but home-biased proposals; insensitive to investment horizon (Fieberg et al. 2023)

Source: Author's presentation based on provider information, Morningstar (2025a), FinanceFWD (2024), and Brokervergleich.de (2026).

Empirically, robo-advisers benefit investors with suboptimal prior behavior. D'Acunto et al. (2019) show increased diversification and reduced disposition effects. Rossi and Utkus (2020) document improved risk-adjusted outcomes through risk reduction. Reher and Sokolinski (2024) highlight the democratization of professional wealth management. D'Acunto and Rossi (2023) conclude that robo-advice aligns households more closely with portfolio theory.[27]

The limits of rule-based systems were evident in the Scalable Capital case: a dynamic risk model sold equities during the 2020 Covid crash and missed the recovery, resulting in significant underperformance relative to the MSCI World (FinanceFWD 2024). The machine executed the rule precisely, but the rule was suboptimal for the crisis.[28]

The real-money test by Brokervergleich.de (2026) shows that while robo-advisers often beat simple mixes, they trail an optimally weighted world portfolio over the long term. Discipline is not a substitute for a fundamentally sound equity share.[29]

[27] D'Acunto et al. (2019) studied the robo-adviser of a large Indian broker; Rossi and Utkus (2020) used data from a large US provider offering hybrid advice.

[28] The case is instructive because the model did not fail but worked: it reduced measured risk. The error lay in the rule, which equated risk with volatility, not in its execution.

[29] The real-money test has invested real money with the providers since May 2015; the benchmarks are a 50/50 portfolio of global equities and global bonds and a broadly diversified world portfolio (Brokervergleich.de 2026).

Figure 5 displays the results of the real-money test conducted by Brokervergleich.de since 2015, which pits 22 German robo-advisors against two benchmarks using real capital. For the twelve-month period ending July 2026, nearly all providers outperformed the 50/50 mix of global equities and bonds, though none managed to beat the world portfolio. Looking at the eight-year horizon, the average robo-advisor delivered a cumulative return of 41 percent, lagging significantly behind both benchmarks, which yielded 79 and 66 percent, respectively (Brokervergleich.de 2026).

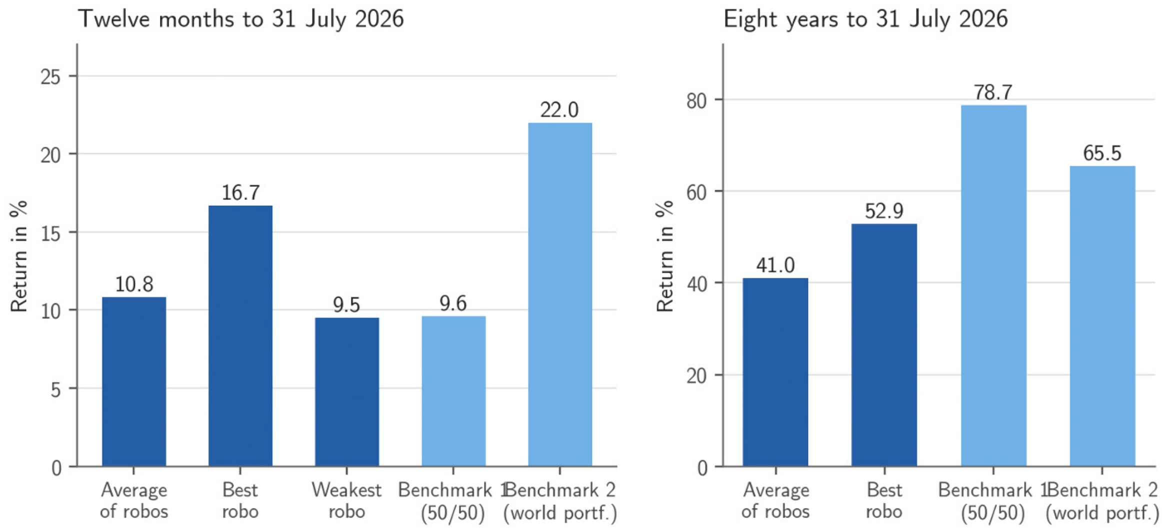

Figure 5: Real-money test Robo-advisers: average, best and weakest results versus two benchmarks, as of 31 July 2026. Source: Brokervergleich.de (2026); Authors' own creation.

4.4 Machine-Driven Security Selection: Bonds and Equities

The learning machine is most effective when the universe is vast and data are rich. For bonds, neural networks improve risk premia prediction (Bianchi et al. 2021) and enable the systematic ranking of thousands of individual securities (Kelly et al. 2023), which is an essential infrastructure for institutional investors.[30]

Equity evidence is more heterogeneous. Gu et al. (2020) and Leippold et al. (2022) show that neural networks outperform linear models in return prediction. Avramov et al. (2023) note that these gains are often limited to illiquid stocks.[31] Cao et al. (2024) find that AI models beat human analysts in 54.5% of cases, while humans remain superior in assessing intangible assets and special situations. Kim et al. (2024) demonstrate a 60% hit rate for earnings direction using LLMs.[32]

[30] Several tens of thousands of corporate bonds are outstanding worldwide; most trade rarely, which is why liquidity must be considered as a separate dimension in every ranking.

[31] The Sharpe ratio relates excess return to volatility; Gu et al. (2020) report values for their best long-short portfolio roughly double those of classical factor portfolios.

[32] Kim et al. (2024) anonymised the statements and removed company names and years so that the model could not retrieve the answer from its training knowledge.

Real-world products like the AI Powered Equity ETF (AIEQ)[33] and Social Sentiment ETF (BUZZ)[34] illustrate the difficulty of translating signals into returns; both have trailed the S&P 500 long-term (Amplify ETFs 2026; VanEck 2026).[35] Success is primarily found in closed systems (Medallion) or houses with deep quantitative expertise (Bridgewater, Two Sigma).[36] Retail AI funds have generally failed to deliver promised alpha (Stiftung Warentest 2025). The application of these results in commercial products is detailed in Table 7.

[33] The S&P 500 return over the AIEQ period results from the price index (2,559 points on 17 October 2017, 7,499 points on 30 June 2026, corresponding to 13.2 % p.a.) plus a dividend yield of around 1.5 % p.a.

[34] Assets and fees according to provider information (Amplify ETFs 2026; VanEck 2026); returns are net of fees on the basis of net asset value.

[35] The figures in Table 7 rest on provider data and the sources cited; total returns of the comparison indices are given where the providers report them.

[36] Two Sigma and Man Group have used machine learning for more than a decade; their results are not published by method and are therefore not used as evidence here.

Table 7: AI-based funds and strategies: empirical examples and performance

Fund or Strategy (Country)	**Since**	**Method**	**Record (as of)**
AI Powered Equity ETF, AIEQ (USA)	2017	IBM Watson: NLP on news, social media, analyst reports, financial statements; ~160 holdings	10.0% p.a. vs. ~14.7% S&P 500 (30 Jun 2026); 0.75% fee
VanEck Social Sentiment ETF, BUZZ (USA)	2021	AI analysis of social media and news; 75 stocks with most positive sentiment	7.4% p.a. vs. 14.9% S&P 500 (31 Aug 2026); 0.76% fee
Qraft AI-Enhanced U.S. Large Cap, QRFT (USA)	2019	ML weights factors based on macro and valuation conditions	Roughly level with S&P 500 since inception
BTD Capital Fund, DIP (USA)	2022	AI system purchases oversold stocks in anticipation of a rebound	2023 to 20 Nov: -4.8% vs. +18.9% S&P 500; 1.25% fee
Intelligent Livermore ETF, LIVR (USA)	2024	Committee of LLMs selects 60–90 global large caps in the style of renowned investors	Record too short; 0.69% fee
ACATIS AI Global Equities (DE)	2017	Neural networks on financial statements and earnings calls; regions/sectors per MSCI World Equal Weighted	Trailed MSCI World in Stiftung Warentest (2025) comparison
Pictet Quest AI-Driven, Vontobel AI Powered, WWK KI Alpha (CH/DE)	Var.	Machine-based stock selection in global equity universes	11 of 32 AI funds disappeared since 2024 (Stiftung Warentest 2025)
Tungsten TRYCON AI Global Markets (DE/LU)	2013	AI trading system on futures in >60 markets; risk budget up to 10%, remainder bonds	Approx. 3.7% p.a. since 2019; volatility <5% (31 Oct 2024)
Bridgewater AIA Labs (USA)	2023	Ensemble of ML and LLMs; humans train the rule-setting system	2025: +11% vs. +34% Pure Alpha; 11.3% p.a. since inception
Renaissance Medallion (USA)	1988	Statistical pattern recognition, short holding periods; closed to outsiders	~66% gross and 39% net p.a. 1988–2018 (Zuckerman 2019)
Eurekahedge AI Hedge Fund Index	2009	Index of hedge funds utilizing AI and ML approaches	9.8% p.a. Dec 2009–Jul 2024 vs. 13.7% S&P 500 (IG 2024)
Sentient Investment Management (USA)	2016	Evolutionary algorithms breed trading strategies on historical data	+4 % in 2017, losses in 2018, liquidation September 2018 (Bloomberg 2018)

Source: Author's presentation based on provider information and cited sources.[37]

[37] Assets and fees according to provider information (Amplify ETFs 2026; VanEck 2026); returns are net of fees on the basis of net asset value.

4.5 Algorithmic Trading and Signal Providers

Algorithmic execution is the industry standard, reducing trading costs and market impact (Kirilenko and Lo 2013), though it introduces systemic risks, as seen in the 2010 Flash Crash and the 2012 Knight Capital event (Kirilenko et al. 2017).[38]

AI signal providers for private investors (e.g., Tickeron, Stoic AI) are viewed critically. They often suffer from backtest overfitting and encourage frequent trading, which erodes returns (Barber and Odean 2000). Moreover, leveraged products in these systems carry a significant risk of total capital loss.[39]

4.6 Interactive Advice and Generative AI

LLMs have transformed access to financial knowledge, enabling the efficient analysis of complex documents and the explanation of concepts at an individual's level. Niszczota and Abbas (2023) show high competence in standardized tests. Fieberg et al. (2023) find that LLM-proposed portfolios can compete with professional ones on a risk-adjusted basis, though they often exhibit home bias.

Institutions deploy LLMs primarily as internal analytical tools (Morgan Stanley, J.P. Morgan, BlackRock). Externally, they are used for initial guidance and knowledge transfer (e.g., 'Susi' by WhoFinance).[40] Regulatory bodies (ESMA 2024, EU 2024) emphasize that responsibility for recommendations remains with the provider. The machine handles preparation; the human handles the decision and responsibility.[41]

4.7 Synthesis of AI Applications

Table 8 systematizes these applications.[42] AI enables capabilities previously reserved for large institutions: global text analysis, systematic bond ranking, measurable sentiment, low-cost discipline, broad personalization, and on-demand education.[43] Furthermore, it optimizes analyst workflows by automating routine tasks (Cao et al. 2024).

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[38] Kirilenko et al. (2017) show that high-frequency traders did not trigger the flash crash but amplified its dynamics by passing positions among themselves in rapid succession.

[39] The trading platform Robinhood and the broker eToro have offered their own AI assistants since 2025 and 2026 respectively; they, too, provide explanations and pointers, not verified forecasts.

[40] The applications named are described according to company statements; independent measurements of their effects are not yet available.

[41] On the limits of language models with numbers see Section 5.2: in a test with questions on annual reports, a leading model answered four out of five questions wrongly or not at all even with document access (Islam et al. 2023).

[42] The overview makes no claim to completeness; the number of providers grows monthly, and many products disappear just as quickly (Stiftung Warentest 2025).

[43] The enumeration follows the order of the value chain in Figure 4; it names possibilities, not evidence – the record follows in Section 5.

Table 8: Overview of AI applications in asset management

Field of Application	Function	Real Examples	User	Evidence of Added Value
Text and Sentiment Analysis	Condensing news, reports, and social media into signals	RavenPack, Bloomberg sentiment, BloombergGPT; BUZZ, AIEQ	Prof.	Documented short-term (Tetlock 2007; Lopez-Lira and Tang 2023); products often trail the market
Pattern Recognition in Prices	Comparing historical patterns with current situations	Tickeron, Trade Ideas; CNN models (Jiang et al. 2023)	Both	Documented academically; unverified in retail products
ML-based Return Prediction	Non-linear factor models for equities and bonds	Quantitative houses (Two Sigma, Man AHL, Bridgewater AIA); QRFT	Prof.	Documented (Gu et al. 2020; Bianchi et al. 2021; Kelly et al. 2023); diminished after costs
Risk Profiling and Allocation	Questionnaire-based risk classification and automatic rebalancing	Vanguard Digital Advisor, Betterment, Wealthfront, Quirion, Scalable Capital	Naive	Documented for previously poorly diversified investors (D'Acunto et al. 2019; Rossi and Utkus 2020)
Bond Selection	Ranking large universes by expected return, credit quality, and liquidity	Internal systems of large bond houses	Prof.	Documented (Kelly et al. 2023); effectively mandatory for large universes
Equity and Fund Selection	Factor ranking, financial statement analysis, analyst substitution	AIEQ, ACATIS AI, LIVR; robo-analysts	Both	Mixed: studies positive (Kim et al. 2024; Cao et al. 2024), funds often trail the market
Trading Signals and Robots	Buy/sell signals, automated trading	Tickeron, Stoic AI	Naive	Not documented; encourages turnover; risk of total loss with leverage
Algorithmic Execution	Slicing orders, seeking liquidity, reducing market impact	Execution algorithms of brokers and banks	Prof.	Documented; industry standard (Kirilenko and Lo 2013)
Risk Monitoring	Limits, anomalies, stress tests, fraud detection	Aladdin, in-house systems	Prof.	Documented in operation; model risk during structural breaks
Explanation and Research Assistants	Summarizing reports, explaining terms, answering questions	ChatGPT, Gemini, Claude; Morgan Stanley, J.P. Morgan (internal)	Both	Productivity documented (Sheng et al. 2025); hallucination risk (Islam et al. 2023)
Chat-based Initial Advice	Basic knowledge, needs assessment, hand-over to adviser	WhoFinance "Susi", broker assistants	Naive	Useful as an access tool; no recommendation without liability (ESMA 2024)
Reporting and Compliance	Client reports, minutes, suitability documentation	Internal systems	Prof.	Efficiency documented (Mercer 2026: 69% of houses)

Source: Author's presentation.

Beyond this inventory, artificial intelligence introduces capabilities that were previously nonexistent or limited to the largest firms:

(1) Unlimited Reading Capacity: The continuous analysis of all annual reports, bond prospectuses, and earnings calls across a global universe is now possible, moving beyond the limited capacity of human analysts.

(2) Manageable Bond Universes: Systematic daily ranking of thousands of corporate bonds by expected return, credit risk, and liquidity makes professional security selection feasible in this asset class.

(3) Quantifiable Sentiment: Market mood, once an intuitive "feel," can now be converted into a time series that can be tested, calibrated, and integrated into risk budgets.

(4) Low-Cost Discipline: Automated rebalancing, savings plan execution, and tax-loss harvesting are now available to small portfolios at a fraction of the cost of personalized wealth management.

(5) Personalization at Scale: Portfolios can be continuously tailored to the specific goals, tax situations, and constraints of every individual client—a service previously reserved for private banking.

(6) On-Demand Education: Investors have access to an infinitely patient explainer for technical terms and product relationships, representing a significant advancement for the naive investor.

(7) Behavioral Mirroring: Systems that record transactions alongside their triggers and reasoning can confront investors with their own patterns—such as lateness or theme-chasing—before they become costly.

(8) Scenario-Based Analysis: Stress tests across thousands of market paths, formerly the domain of high-performance computing centers, can now be integrated into advisory meetings.

(9) Analyst-Support Automation: The automation of data collection, model updating, and documentation allows human analysts to focus on areas where they are superior, such as intangible assets, special situations, and management quality (Cao et al. 2024).

(10) Real-Time Supervision: Suitability checks and anomaly detection can be monitored continuously rather than through sampling, benefiting both the client and the institution.

These capabilities are real and, in some cases, already routine. Whether they add value for the investor, however, depends not on the capability of the machine, but on the empirical record of its application. The following section evaluates this balance.

5 Empirical Balance: Successes and Failures of AI

5.1 Documented Added Value

Evidence for machine added value is concentrated in four areas. First: the prediction of risk premia in large cross-sections. Gu et al. (2020), Bianchi et al. (2021), and Kelly et al. (2023) demonstrate that neural networks increase the out-of-sample predictive power of returns.

Second: the analysis of corporate information. Kim et al. (2024), Cao et al. (2024), and Coleman et al. (2022) show that machines outperform the average analyst in processing financial data. Sheng et al. (2025) document a risk-adjusted excess return for hedge funds that strategically integrate generative AI.[44]

Third: rule-based allocation discipline. D'Acunto et al. (2019) and Rossi and Utkus (2020) show that robo-advisers reduce behavioral errors. The near-elimination of the investor return gap in allocation funds (Morningstar 2025b) underscores this effect.

Fourth: systematic implementation at scale. Harvey et al. (2017) show that systematic approaches yield lower dispersion of outcomes. The exceptional performance of Medallion (Zuckerman 2019) demonstrates the potential of high-frequency statistical pattern recognition under strict capacity constraints.[45]

5.2 Documented Failures

AI failures illustrate its fundamental limits. Figure 6 shows the underperformance of prominent AI strategies (AIEQ, BUZZ) relative to the S&P 500. The erosion of advantages through the ubiquity of the same technology reduces alpha sources (Tint / IG 2024).

Individual cases reveal specific patterns: the liquidation of Sentient Investment Management (Bloomberg 2018) highlights the risk of overfitting in backtests. The Tyndaris supercomputer case (Bloomberg 2019) illustrates the dangers of unverified algorithmic execution.[46]

[44] Sheng et al. (2025) measure AI reliance indirectly through the explanatory power of ChatGPT signals for the funds' position changes; the adoption rate rose from 21 % at the end of 2022 to around 60 % in 2024.

[45] Bridgewater's AI strategy AIA returned around 11 % in 2025 and 8.1 % in the first half of 2026 – exactly as much as the flagship strategy Pure Alpha in the same half-year (Institutional Investor 2026); in 2025 Pure Alpha had still been far ahead with 34 %.

[46] The investor had contributed USD 250 million of his own capital, to be leveraged to 2.5 billion with credit; the daily loss arose at a stop-loss threshold of 1.4 per cent (Bloomberg 2019).

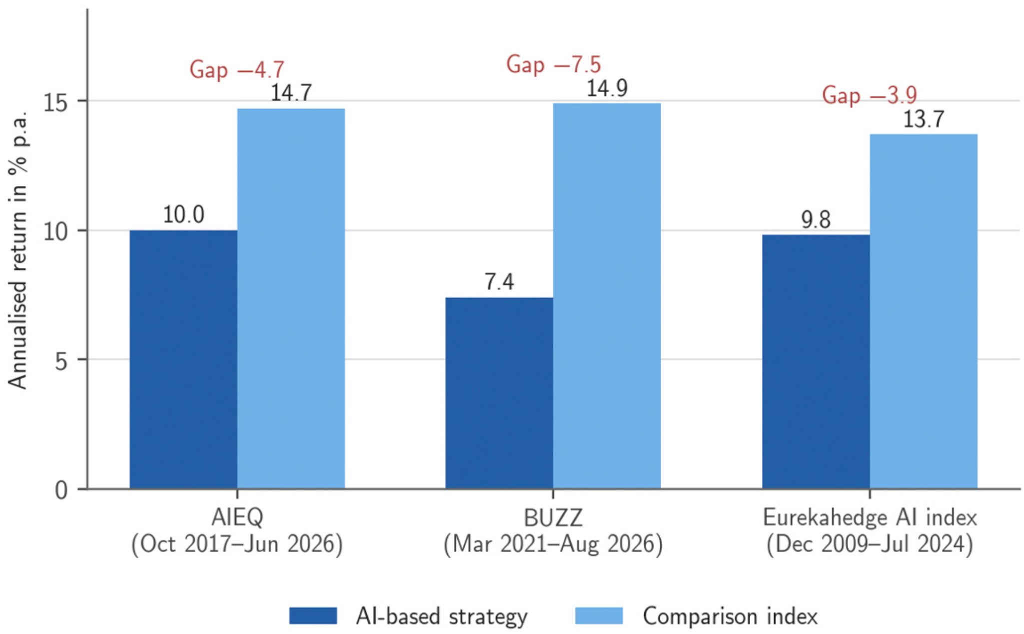

Figure 6: Performance comparison of AI-based strategies against their benchmark indices, measured by annualized return since inception or index launch. Sources: Amplify ETFs (2026), VanEck (2026), IG (2024), and the Federal Reserve Bank of St. Louis (2026); author's calculations and presentation.

The Scalable Capital case (FinanceFWD 2024) and Stiftung Warentest (2025) results show that neither rigid risk models nor commercial AI funds guarantee value. The Knight Capital event reminds us that speed without supervision is a systemic risk.[47]

Language model hallucinations represent a distinct category of error. Islam et al. (2023) document high error rates in factual questions regarding annual reports. Anekdotical successes of short-term chatbot portfolios often lack statistical significance.[48]

5.3 Synthesis: Comparative Advantages of Man and Machine

The analysis of successes and failures reveals a pattern consistent with the work of Meehl (1954) and Grove et al. (2000): mechanical rules surpass clinical experts in environments with stable structures and sufficient data. In asset management, this applies to ranking, text analysis, and rebalancing.[49]

The human is superior when these conditions are absent. Abis (2022) shows that discretionary funds perform better during recessions; Cao et al. (2024) identify a human advantage in intangible assets and special situations. This aligns with the distinction between risk (measurable) and uncertainty (non-measurable) (Knight 1921; Taleb 2007).

[47] Knight Capital survived the loss only thanks to an emergency financing and was absorbed in the merger with Getco in 2013; the cause was an obsolete piece of code that had not been replaced on one of eight servers.

[48] A language model without tool access does not calculate, it formulates. Current models therefore call computational tools and databases; the duty to verify the result remains with the user.

[49] Dawes et al. (1989) also show that even crude linear models with equal weights beat experts – a result reminiscent of DeMiguel et al. (2009) and the 1/N rule.

Figure 7 synthesizes this pattern. The optimal configuration is a synergetic collaboration: the AI provides hypotheses and the human validates them, or the human defines the objective and the AI implements it. Agrawal et al. (2018) provide an economic rationale: as AI lowers the cost of prediction, the relative value of judgment increases.

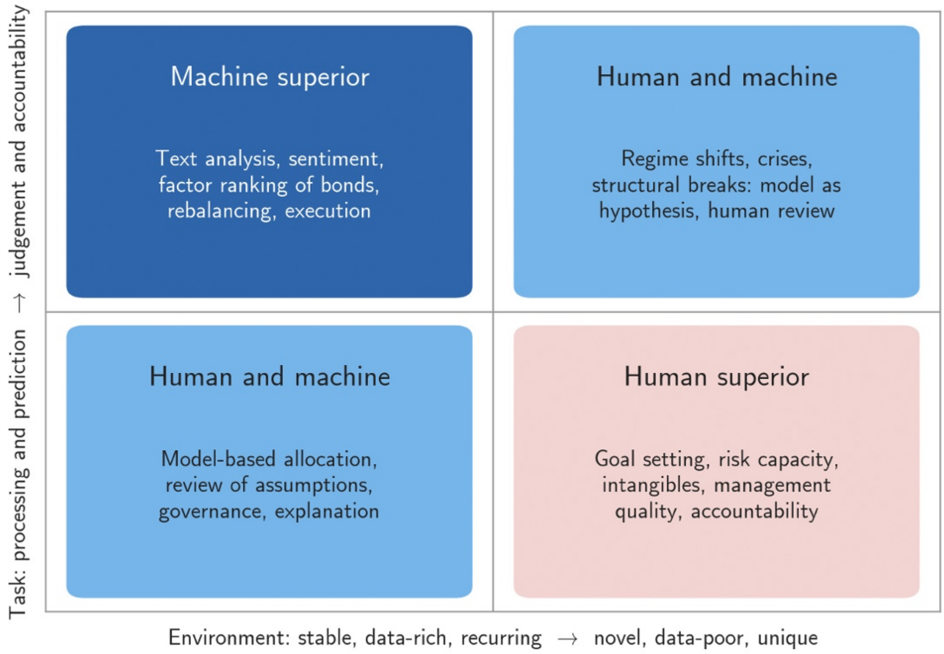

Figure 7: Which one decide better? Comparative advantages of man and machine by environment and task. Source: Own presentation.

6 Limits and Risks of Artificial Intelligence in Investing

The implementation of AI systems is subject to fundamental limits. First is the epistemological limitation: learning systems rely on historical data and can only identify existing patterns. Entirely novel events—'Black Swans' (Taleb 2007)—cannot be predicted. While humans share this ignorance, they possess the ability to question the validity of models during a regime shift (Knight 1921; Kahneman and Klein 2009). Models that excel in stable phases often fail precisely when volatility increases (Abis 2022).[50]

Second is the tendency toward hallucination in generative models. LLMs may present outdated or invented facts with high linguistic confidence; Islam et al. (2023) demonstrate that figures from standard chatbots must be verified. Furthermore, the look-ahead bias (Glasserman and Lin 2023) can distort backtest results.

[50] The tariff shock of April 2025 and the escalation in the Middle East in June 2025 are recent examples of events that had no precedent in the training data of most models.

Third is the absence of common sense and contextual understanding. A machine processes numbers and text but lacks insight into intangible values, management quality, or emotional client needs. Cao et al. (2024) identify this as a domain of human superiority.[51]

Fourth is overfitting. Testing excessive rules on a single dataset often leads to 'pseudo-mathematics' (Bailey et al. 2014; Harvey et al. 2016). A strict protocol separating test and validation data is essential (Arnott et al. 2019; López de Prado 2018).[52]

Systemically, the proliferation of similar models may induce synchronized market behavior. The IMF (2024), FSB (2024), and BIS (2024) warn of increased volatility and herding risks during stress periods. The Eurekahedge index (IG 2024) illustrates the erosion of alpha through the crowding of signals.[53]

Finally, practical hurdles persist: data quality, regulatory requirements (ESMA 2024), and costs. AI-managed products for retail investors are often significantly more expensive than passive alternatives. Moreover, the question of liability for algorithmic errors remains a legal risk (Tyndaris case).

7 Recommendations for the Beneficial Integration of AI

7.1 Recommendations for the Naive Investor

For the private investor, a clear division of labor is recommended: the machine should substitute suboptimal human behaviors—specifically in discipline, diversification, and execution—while goal setting and accountability remain human domains.

The foundation is a written investment strategy defining objectives, horizon, and strategic allocation. Implementation should be maximally automated: a low-cost world portfolio of diversified ETFs, funded via savings plans and rebalanced by fixed rules. For those lacking discipline, low-cost robo-advisers are an effective solution, as they reduce systemic errors (D'Acunto et al. 2019; Rossi and Utkus 2020). In selecting a provider, costs and an appropriate equity share should be prioritized; dynamic risk models that sell during crashes are viewed critically (FinanceFWD 2024).[54]

Generative AI should be deployed as a cognitive tool (explainer), not an oracle. It is suited for analyzing reports and clarifying technical terms, but not for querying ratios or returns without verification (Islam et al. 2023). Retail investors should avoid AI trading robots and leveraged products due to the risk of overfitting and total capital loss. AI-

[51] The point about management quality applies to equities; for government and corporate bonds the share of machine-readable quantities is higher, which is why the machine is comparatively stronger there.

[52] Harvey et al. (2016) count more than 300 return factors published in academic journals and demand a t-statistic of at least three instead of the usual two for new factors.

[53] The IMF (2024) also points to the dependence on a few providers of computing power, data and models, whose failure would hit many market participants simultaneously.

[54] A world portfolio consisting of one global equity ETF and one global bond ETF costs less than 0.2 per cent a year today; any added value of a provider must be measured against that yardstick.

managed funds are, given their cost and record, viewed as experimental rather than core investments (Stiftung Warentest 2025).[55]

7.2 Recommendations for the Professional Investor

For asset and fund managers, the synergetic combination of 'man and machine' is the most effective configuration (Cao et al. 2024). The machine is deployed in data-intensive, rule-based tasks: text and sentiment analysis, ranking of bonds and equity universes, estimation of risk premia, and reporting. The human retains decision-making authority over investment policy, the assessment of special situations, and fiduciary responsibility. Mercer (2026) confirms that the industry is increasingly adopting this analytical partnership.[56]

Concrete implementation rules include: first, every model must be treated as a hypothesis, economically motivated and validated out-of-sample (Arnott et al. 2019; López de Prado 2018). Second, decision processes should be decoupled: independent judgments from human and machine should be obtained before synthesis to minimize complementary error sources (Kahneman et al. 2021). Third, every model requires a defined failure rule to prevent systemic missteering.

Fourth, the professional must monitor signal crowding. A competitive advantage arises from proprietary data and the integration of AI into a proprietary process.[57] Fifth, generative AI should be used for research preparation and documentation, subject to human review and source attribution (ESMA 2024). Sixth, the machine should be used to enhance the manager's own discipline, for instance, through the automated logging of decisions.

Table 9 summarizes these recommendations.[58]

[55] A useful exercise is to ask the language model to criticise one's own investment strategy and to name the three most common mistakes investors make with it; the answers are usually more accurate than its price forecasts.
[56] The survey was conducted in February 2026 among 131 asset managers worldwide; 69 % report measurable efficiency gains, but only 8 % measurably better investment returns (Mercer 2026).
[57] The concentration of AI gains among large houses (Sheng et al. 2025) suggests that smaller asset managers benefit more from purchased tools for research and documentation than from proprietary forecasting models.
[58] The division follows the evidence of Sections 4 and 5; it is intended as a starting point for in-house specification, not as a norm.

Table 9: Recommendations for the professional investor: integration of AI in the investment process

Process Stage	Role of the Machine	Role of the Human	Evidence
Investment policy, mandate	Computing scenarios, checking constraints	Setting and owning goals, benchmarks, and risk budgets	Agrawal et al. (2018)
Research, data analysis	Condensing text and sentiment; analyzing financial statements	Framing questions, source criticism, intangibles, management quality	Kim et al. (2024); Cao et al. (2024)
Strategic allocation	Covariances, risk premia, robust optimization, hierarchical allocation	Reviewing assumptions, recognizing regime shifts, setting bands	López de Prado (2016); Abis (2022)
Bond selection	Ranking the universe by expected return, credit quality, and liquidity	Issuer judgement in special situations; portfolio construction	Kelly et al. (2023); Bianchi et al. (2021)
Equity and fund selection	Factor ranking, pre-selection, anomaly detection	In-depth analysis of selected names; rule-based selling discipline	Gu et al. (2020); Akepanidtaworn et al. (2023)
Implementation and trading	Algorithmic execution, rebalancing	Managing exceptions and liquidity events	Kirilenko and Lo (2013)
Model risk and governance	Documenting trials, monitoring model quality	Establishing backtesting protocols, switch-off rules, and liability	Arnott et al. (2019); ESMA (2024)
Communication and compliance	Preparing reports, minutes, and suitability documentation	Reviewing, signing, and conducting client meetings	Mercer (2026); Sheng et al. (2025)

Source: Author's presentation.[59]

7.3 Domains for Full Automation

Certain tasks warrant full delegation to the machine, as human intervention in these areas is demonstrably detrimental. These include: the allocation and rebalancing of core wealth for behaviorally prone private investors (Morningstar 2025b), index replication and algorithmic order execution (Kirilenko and Lo 2013), the systematic ranking of corporate bonds (Kelly et al. 2023), and large-scale text processing (Sheng et al. 2025).[60] In contrast, equity selection and tactical allocation remain domains where fully automated solutions have not consistently outperformed benchmarks after costs.[61]

7.4 The Transformation of Investment Advice

AI does not render investment advice obsolete but transforms its nature. Technical tasks such as calculation, explanation, and documentation are automated. The value of the adviser shifts toward trust-building, behavioral guidance during crises (Kinniry et al. 2019),

[59] The division follows the evidence of Sections 4 and 5; it is intended as a starting point for in-house specification, not as a norm.

[60] For government bonds the universe is smaller, but the yield curve data are rich; Bianchi et al. (2021) show that it is precisely the breadth of macroeconomic data that underpins the advantage of neural networks.

[61] Harvey et al. (2017) examine hedge fund data for the years 1996 to 2014; after adjustment for factor risks, systematic macro funds are ahead, while there is no difference for equity strategies.

and individualized goal definition.[62] The 'Turing trap' (Brynjolfsson 2022)—where technology merely imitates human behavior—is replaced by a complementary model in which the adviser utilizes the machine as an analytical partner.

The future resides in hybrid models combining efficient machine-driven basics with human empathy and accountability. Advice that consisted merely of calculating and explaining will become obsolete.

8 Conclusion and Outlook

This investigation has analyzed the comparative advantages of artificial intelligence relative to human judgment in asset management. The findings are consistent across naive and professional investors: humans are susceptible to systematic errors—including impatience, pro-cyclical timing, and flawed selling discipline. This behavioral gap results in a measurable return diminution of approximately one to two percentage points per annum.

The professional investor's advantage over the naive investor is derived not from superior forecasting, but from a superior process structure (diversification, cost control, rebalancing). The machine adds value precisely where these human weaknesses manifest and where the task is simultaneously data-intensive, repetitive, and rule-based: in text and sentiment analysis, the ranking of large universes, allocation discipline, and trade execution. In these domains, the machine is not merely equal, but superior.

Conversely, AI fails in environments characterized by high uncertainty, regime shifts, or the evaluation of intangible assets. The record of commercial AI funds and the documented failures of algorithmic systems underscore these boundaries.

For the naive investor, the implication is a shift toward written strategies, automated implementation (e.g., via low-cost robo-advisers), and the use of LLMs as cognitive tools, while avoiding unverified signal providers.[63] For the professional, the strategy involves integrating AI as an analytical partner while retaining human judgment for complex contexts and treating every model as a documented hypothesis.

AI does not replace the investor, but rather substitutes the investor's suboptimal habits. Goal definition and accountability remain fundamentally human domains.

The outlook is one of hybrid architecture. Investment advice is being restructured: technical analysis and documentation migrate to the machine, while empathy, judgment, and responsibility remain with the human. While the machine will continue to evolve, permanent excess returns will remain elusive, as any ubiquitous advantage is rapidly eroded

[62] Dietvorst et al. (2018) also show the way out of algorithm aversion: those allowed to adjust the algorithm slightly trust it considerably more – an argument for hybrid models in which the human keeps the last word.
[63] The recommendations rest on the evidence cited and do not replace an individual suitability assessment within the meaning of MiFID II.

in capital markets.[64] Open questions remain regarding the distribution of generative AI gains, the systemic risks of synchronized models, and the psychological resilience of investors when the machine errs visibly.[65] Behavioural economics suggests that the final answer resides once again with the human.

[64] The crowding of known signals is no argument against using AI, but against the expectation of earning systematic excess returns with it; its benefit lies in cost, discipline and breadth, not in alpha.

[65] On the three open questions see the research agendas in Kelly and Xiu (2023) and D'Acunto and Rossi (2023).

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