REPORT

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AI Washing: Signs, Symptoms, and Suggested Solutions for Investment Stakeholders

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The Increasing Popularity of AI in Investing

The rapid growth of artificial intelligence (AI) technology has led to its widespread adoption across various industries, including finance. Indeed, in the "State of AI in Financial Services: 2025 Trends" report (NVIDIA 2025), 57% of respondents in a survey of 600 global financial services professionals reported that they are using or considering using AI for data analytics. Even more impressive is the 12% jump in the number of survey respondents claiming that they use generative AI, which tries to replicate data (e.g., time series, text) for practical applications (52%, up from 40% in 2023). Further, 37% of survey respondents believe AI has created operational efficiencies, while 32% believe AI has created a competitive advantage for their firms. Drilling down further, 38% of respondents (versus 15% in 2023) stated that they use AI for trading and portfolio optimization, while 32% (versus 13% in 2023) reported using AI for pricing, risk management, and underwriting.

Given this enthusiasm and the perceived benefits of AI to businesses, it is unsurprising that genuine AI usage has been accompanied by a growing risk of AI washing (AIW), in which companies, organizations, and individuals falsely or inaccurately claim to be leveraging AI technologies to enhance their investment processes, including machine learning (ML) and advanced data science capabilities. AIW is likely not widespread at present, given the current state of AI adoption across the investment industry, and because of AIW's inherently subjective nature, it is almost impossible to quantify.

As such, few studies have explored the issue, even though it is a genuine risk that investors should be attuned to. This risk is particularly relevant for asset owners conducting manager due diligence. Therefore, in this report, I identify pertinent questions to raise awareness about AIW and provide guidance to institutions engaged in manager selection and evaluation.

AIW can include using buzzwords and marketing strategies that exaggerate the true capabilities or presence of AI in companies' business activities, leading to client and stakeholder confusion, skepticism, and potential ethical concerns. AIW is starting to become recognized as a serious problem among stakeholders—in particular, customers and regulators. So, this report aims to describe AIW as it occurs in finance, give stakeholders some insight into the signs and symptoms of AIW, and suggest some solutions for stakeholders who are concerned about their ability to detect firms that are being less than genuine in their claims of applying AI and related tools in meaningful ways. Specifically, I will address the following questions:

- What is AIW, and how is it defined in the context of technology and business?
- What are the underlying motivations for companies and organizations to engage in AIW?
- How does AIW impact clients, stakeholders, and the development of AI technologies?
- How can asset owners differentiate between legitimate AI technologies and inflated claims in the market?
- What are the motivations behind AIW?

First, it is important to define "AI." One place to look for a definition is the various pieces of legislation relating to AI. For example, the EU Artificial Intelligence Act[1] (Chapter I, Article 3) defines AI as:

> A machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.

Although useful, this definition is fairly broad and can be refined.

Let me be clear what I *do not* mean by "artificial intelligence." I do not mean what is known as "strong AI," which refers to a replication of generalized human intelligence, presumably including emotions, common sense reasoning, and a strong ability to contextualize (think Commander Data from *Star Trek: The Next Generation*). Rather, when I refer to "AI," I mean what has traditionally been known as "weak AI," a computational and/or statistical tool or system that exhibits an enhanced, extended, or more effective replication of some well-defined aspect of human cognition. This discussion thus encompasses supervised and unsupervised ML, reinforcement learning, natural language processing, and the various forms of so-called generative AI that have become popular in recent years.

[1]EU Artificial Intelligence Act (Regulation [EU] 2024/1689).

The practice of AIW is in almost direct opposition to another popular movement: explainable AI (XAI), which is motivated by the desire to provide the users of AI with the maximum level of transparency and control. XAI is primarily concerned with making naturally opaque algorithms and frameworks, such as many of those found in deep learning, more accessible and understandable. AIW undermines the very premise of XAI, because misleading users of investment products with regard to what degree those products are driven by AI can only make such products harder to understand and use. Thus, minimizing AIW helps make AI applications and methodologies more widely understandable to users and consumers.

The Motivations Behind AIW

Let us begin with an example of what I mean when I refer to a "genuine AI application" in finance, compared with one that makes only superficial use of AI. Consider a portfolio management team that has built an ML model that takes data feeds from a firm's database, trains on the data, learns meaningful patterns, and produces buy and sell trades for specific securities. Assuming this application is supported by measurable investment and business improvements, it would, in my opinion, be a genuine application of AI to finance.

In contrast, consider a situation in which a portfolio management team has an investment process driven primarily by qualitative fundamentals but that also uses various large language models (LLMs) to inform some of its investment decision making. Although the team's use of LLMs may be additive to its investment outcomes, *if* the team nevertheless went on to claim that its investment process is "AI driven," that would arguably be an instance of AIW.

One of the motivations behind AIW in investing is related to the challenge in applying AI in portfolio management, trading, and risk management. Although some AI applications in finance are relatively easy to adopt (e.g., the use of chatbots by banks and credit card companies for customer service), others are considerably more difficult, particularly for investment management, for which the relevant data are typically more limited, more volatile, and less uniform than those in other areas of finance. For example, using millions of data points to predict the probability of customer credit card payment defaults, albeit challenging, is considerably less daunting than predicting asset prices with far fewer observations. This is true not only because of the relative paucity of market data relative to other types of financial data but also because the drivers of asset behavior are often more complex than the drivers of other types of financially relevant behavior, such as consumption and debt repayment patterns. The processing of investment data seems even more challenging when compared with the types of data used by, for example, many technology and biotech firms, which primarily use data from the natural world rather than data stemming from human behavior.

This does not mean that applying AI to investment problems is futile. On the contrary, much progress has occurred during the last several years in developing many useful applications in trading, portfolio construction, and risk management, to name just a few areas. Developing useful AI applications, however, is not easy and typically requires a considerable amount of focus, expertise, and resources.

Here, a fundamental tension develops within investment firms that often spurs them to engage in AIW. Investment firms are induced to develop useful AI applications because of commercial reasons. Showing current and potential clients that they are serious about adopting the latest "cutting-edge" technologies and methodologies will presumably increase firms' chances of attracting new business. This quality is especially important in the context of having to compete with a multitude of rival asset managers that are also trying to attract clients and gather assets. Thus, asset managers are reluctant to give potential clients any impression of inferiority from the standpoint of their adoption of technological and quantitative tools.

That said, investment firms may be unwilling or unable to procure the necessary talent and technology to meaningfully enhance their investment processes using AI, because any serious effort to incorporate AI into a firm's systems and processes requires considerable time and resources. Thus, various commercial reasons can induce firms to overestimate the degree to which they are using various types of AI tools, given the challenges inherent in genuinely adopting new technologies and methodologies.

Even if a firm has the means to build out a robust AI-driven investment platform, however, it may still refrain from doing so. Why would this be the case? Remember that, first and foremost, investors—whether asset managers or asset owners—strive to produce the best possible investment performance. In this endeavor, they would understandably want to use the most cutting-edge and potentially useful formal tools in their investment processes. Most professional investors, however, already have well-developed investment processes, which typically precludes them from making immediate and significant modifications to their existing processes and procedures. In the case of asset managers, they may already sell commercially successful products or pursue successful strategies that do not currently use any inputs related to AI or ML. Such asset managers may be reluctant to change a product or strategy that is already achieving positive performance and, by extension, creating positive business outcomes.

Indeed, one of the major reasons that AIW is a risk in the asset management industry, especially in quantitative firms, is that currently, most mature, quantitative firms have a developed and usually fairly intricate investment process in place. If they were to make substantive changes to their existing investment process—in which, for example, they replaced traditional statistical elements with AI-driven components—then they would potentially risk modifying their process in a way that may not produce favorable investment outcomes, especially if the modifications are done too hastily or without the proper vetting and testing.

In this regard, asset managers' fears can be likened to those of players in the game of Jenga. In this game, players take turns removing one block from any level of an existing tower of blocks and placing that block on the topmost level. The risk in removing any block is that the entire structure will collapse. Likewise, asset managers may be concerned that in attempting to advance their investment process with AI, they may end up hurting their investment process more than helping it by removing critical—but nevertheless seemingly outdated—components.

Although the Jenga analogy is useful to a certain extent, remember that as mentioned previously, refining and enhancing a firm's technological and quantitative processes is not as simple as removing and placing blocks. First, it takes considerable resources in terms of technology spending to acquire the software and hardware needed to implement many sophisticated types of AI algorithms. Further, simply allocating resources to acquiring new technology is not enough to imbue a firm's processes with AI capabilities. Indeed, a firm needs the right people to develop program design and to implement and maintain any type of AI platform or system. The process of attracting and hiring the appropriate personnel is generally time consuming and expensive. In short, it takes much effort in terms of both time and resources to build the appropriate team and infrastructure required to implement any substantive AI capabilities at an investment firm.

Compounding the situation for some firms is the reality that inevitably, some competitor firms will be able to move faster in terms of their ability to modify their processes with genuine ML and AI capabilities. It is this fear and risk of falling behind that often induce firms to engage in AIW. Appearing inferior in terms of developing what are considered cutting-edge, novel, and potentially "game-changing" technologies and methodologies is often perceived as a cardinal sin, especially for quantitatively oriented investment firms.[2]

Thus, given the high stakes, it is important that potential clients possess an adequate methodology to determine whether a firm's claims of AI-driven processes and products are genuine, fabricated, or exaggerated to a greater or lesser extent. Not only will such a methodology reveal the trustworthiness of a potential asset manager, it will also allow clients to determine whether a given strategy or product delivers something that is actually novel and potentially adds value to their current portfolios—or whether it is simply commoditized, bereft of new or useful features.

[2]For some managers, especially those with a more qualitative or discretionary process, the opposite fear may exist: that appearing to be overly reliant on AI will undermine investor confidence in the manager's ability to add independent or unique value to the investment process.

Uncovering Potential AIW

Given the technical nature of AI, uncovering AIW is often a painstaking endeavor that typically requires a fair amount of domain knowledge and patience. This situation is compounded by the fact that investment firms will likely be reluctant to reveal the details of their proprietary investment processes and will often use the "secret sauce" defense to shield them from revealing too much detail about what tools they are using, including AI tools. A thorough "interrogation" of any investment team or firm claiming to use AI in meaningful ways, however, is necessary in order to determine whether it is making genuine claims or is using AI in only a superficial way while keeping the core of its presumably more rudimentary investment process intact.

Before asking any direct questions of asset managers regarding their specific uses of AI, however, investors have a much easier way to determine the veracity of a firm's AI claims: Simply investigate or inquire about the personnel supposedly working on AI projects, especially the leadership of the department or division responsible for AI applications. For example, if a firm's head of data science or AI is simply an individual who has worked at that firm for a long time but has scant experience and education in AI, that is a good indication that the asset manager's claims of applying AI in any material way are probably exaggerated.

The leadership responsible for technical areas of any firm needs to be able to evaluate what that firm or department produces. If the leadership of a data science or AI department is simply somebody with institutional knowledge of the firm but no technical knowledge of AI, then it is unlikely that the firm is producing anything novel, rigorous, or substantive in that arena. This point extends beyond simply having technical knowledge. A firm may have "quants," but they may be insufficiently versed in AI. If those individuals received their education in other fields, such as mathematics or physics, what evidence can the firm provide that its quants are competent in AI?

In contrast, in the technology sector, it is very rare that the leadership of a given department, including those dealing with AI, is *not* someone with a great deal of expertise in the field. At the very least, these leaders tend to have extensive experience and/or education relevant for contributing to and leading their respective departmental effort. This situation is the natural outcome from the fact that tech firms are producing and selling technology—they cannot give the illusion of applying any type of innovation when they are in fact not doing so. Such an illusion would result in inferior products and eventually hurt the company's bottom line, as customers discover more genuine and perhaps higher-quality alternatives.

Investment firms, however, primarily deliver investment services—namely, asset management services—so if an investment firm is confident that it can deliver investment performance without any substantive AI/ML modifications to its approach, it may feel more comfortable using its current process. The link between technological innovation and product performance is less direct than it is for tech or biotech firms. Thus, merely paying lip service to the application of these novel technologies may seem more efficient in some cases. That is no excuse, however, for exaggerated claims and unfounded marketing. Financial products are just as much products as computers and pharmaceuticals are, and truth in advertising should be provided regardless of product type.

The case of fundamental managers, who do not use quantitative tools to drive the majority of their investment decisions, creates a different situation. AI and ML have become very trendy and topical items that many asset owners and clients would like to discuss and claim to be using. For a fundamentally driven process, however, it can be challenging to substantively incorporate AI in ways that will stay faithful to the investment process and leave most of the decision making in the hands of human portfolio managers. This dilemma may thus tempt fundamental managers to exaggerate the ways in which they are using AI and related technologies.

The primary challenges in applying many AI tools are their often-daunting data requirements, necessary for properly training algorithms, and the opacity of some algorithms that makes their output difficult to explain relative to more-traditional statistical models. In many applications, however, especially in the predictive realm, ML and AI seem to be a step ahead in terms of their potential investment utility compared with more traditional statistical tools. This is because many ML algorithms were designed with prediction (the primary focus of active management) explicitly in mind.

With that said, forecasting in financial markets is different from forecasting in a laboratory setting in natural science applications. Investors cannot conduct closed experiments, and the number of relevant variables is typically higher and harder to discover in investment applications. Investment forecasting models are also disadvantaged compared with their natural science counterparts in terms of data availability.

This does not mean, however, that AI and ML are useless. Their ability to detect nonlinear behavior and interaction effects in data and their often unique modes of problem solving bring many potentially useful dimensions to investors' analytical toolkits. In addition, I am not advocating that investors *must* use AI tools to produce useful financial products. Rather, I am advocating that if such tools are used, investors must be truthful about *how* they are being used, and if they are not being used, investors must refrain from undermining those who *are* using AI successfully.

Q&A

This section lists some questions that can provide stakeholders with the level of depth of insight needed when inquiring about an asset manager's purported use of AI. Some of the questions appear to demand some level of technical familiarity with AI and ML, which speaks to the fact that asset owners themselves must develop some minimal competence in AI methodologies.

Indeed, any asset manager or asset owner must be able to provide sufficient detail regarding why and how they implemented a piece of AI technology in their process, what specific frameworks they used, and what results or improvements they observed. Being able to do so is in line with the ethical principles of transparency and duty to clients, as set out in the CFA Institute Code of Ethics and Standards of Professional Conduct.

Of course, not all of these questions will apply in every context. Nevertheless, they should provide insight into the types of questions required to gain an insightful view of an investor's application of AI.

The most pertinent questions for asset owners and prospective clients are as follows:

- Can you specify what type of algorithm or combination of algorithms you are using and how it enhances the forecasting of asset returns?
- How does your AI-driven model outperform simpler models? Can you provide a quantitative comparison of relevant performance metrics?
- What data sources are you using to train your model(s), and how do these sources integrate with the rest of your process, if at all? Are you using alternative data, such as satellite imagery or sentiment analysis of earnings calls?
- What preprocessing and feature selection techniques are used to prepare the raw data for input into your model(s)? Do you use fundamental features, such as earnings surprise, price momentum, or other signals and indicators? How do you preprocess the data before feeding the data into your model(s)? Do you standardize or normalize the input features, and what techniques do you use to handle missing data, outliers, and limited datasets?
- How do you maximize model interpretability? Is it through model choice or postimplementation communications? If the latter, can you give some concrete examples?
- Can you provide an example of a recent investment decision that was influenced by the model's output? How was the rationale for that decision explained to the investment team?
- Can you provide out-of-sample backtest results or cross-validation results using your model? Have you tested the model's efficacy on bootstrapped or otherwise synthetic data? How does the model perform relative to simpler models, traditional benchmarks, and equal-weighted portfolios?
- How do you validate the robustness of the models you develop? What precautions do you take to guard against overfitting? For example, how do

you tune hyperparameters in your models? How do you monitor "model drift," and what mechanisms are in place to retrain the models and/or adapt to shifts in the market landscape?

- What governance structures are in place to ensure the responsible use of AI firmwide? Do you have an internal AI audit process, and how often are the models reviewed for compliance with generally accepted standards and protocols?
- If you use outsourcing for some or all of your AI technology needs, what processes are in place to ensure the quality and robustness of the services and products used in your investment process?

Conclusion

Firms selling financial products should conform to the same standards of transparency that stakeholders demand from other types of products. This idea applies to the use of AI technology as well. Unfortunately, because of AI's headline-grabbing popularity, some investment firms may rush to exaggerate their success in applying AI technologies to their investment processes. This phenomenon, known as AI washing, has increasingly become the subject of heightened scrutiny from the investment community, including regulators.

It is therefore important for stakeholders to understand the motivations and telltale signs of AIW. Accordingly, this report reviewed the broad points relating to AIW, including the motivations behind the phenomenon and a suggested approach to uncovering the extent to which an investment manager may be engaging in it, including a template questionnaire to guide the development of more case-specific questions. By understanding and learning to detect AIW, stakeholders can help minimize and eventually eliminate this phenomenon, resulting in better investment outcomes.

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