



AI in Systematic Investing: Continuity and Transformation

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- Modern AI extends a longstanding progression toward increasingly flexible analytical methods in systematic investing, but it represents an important break from the past in that it is altering the analytical architecture underlying the investment process.
- Agentic AI also accelerates a longstanding shift of analytical responsibilities from humans to systems. That changes, but does not diminish, the role of human judgment and expertise in the investment process.
- Because active investing is competitive, better investment performance will depend not simply on access to AI capabilities, but on how a manager's organizational foundations compare with those of its peers. Four characteristics for asset owners to evaluate are a manager's people, tools, data, and culture.

Modern AI is expanding the capabilities available to systematic investors, allowing them not only to automate existing processes but to broaden the scope for research and innovation. This evolution raises two questions: how is AI changing the investment process, and what are the implications for investment outcomes?

This paper examines these questions from the perspective of an institutional asset owner, focusing on developments reasonably within view over the next few years rather than speculative technological end-states.

We address the first in two parts: how AI is rearchitecting the analytical underpinnings of the investment process, and how it is shifting the division of responsibilities between people and systems.

Modern AI changes the technology available, but not the underlying investment problem, either the sources of opportunity or the analytical logic for exploiting them.

The implications for investment outcomes are harder to assess. The assumption that greater productivity and more research firepower will necessarily translate into better active performance is simplistic, because applying AI does not create new underlying mispricings to harvest and active investing is inherently competitive. So in the final section, we highlight four organizational

characteristics—people, tools, data, and culture—that can help investors judge which managers are best positioned to turn these new technologies into durable investment advantage.

The Investment Process

Systematic investing has always involved a competitive effort to identify mispricings and capture them efficiently. Modern AI changes the technology available for that search, but not the underlying investment problem, either the sources of opportunity or the analytical logic for exploiting them. Markets still reflect the behavior of diverse participants whose biases, incentives, and risk

preferences influence stock prices, while managers still seek a forecasting edge through increasingly sophisticated models and rich data.

But modern AI is transforming the investment process by changing the analytical architecture that underlies it and shifting the roles played by people and systems.

REARCHITECTURE

In the decade before generative AI captured public attention, machine learning (ML) had already materially expanded systematic investing's analytical toolkit. It helped managers capture nonlinear and conditional predictive relationships and detect structure in complex data.¹ Yet managers still developed and implemented

¹ See Acadian, [Machine Learning in Quant Investing](#): Revolution or Evolution, March 2019.

the algorithms largely within their own organizations, typically inserting them into existing workflows as more sophisticated replacements for traditional analytical components.

Viewed functionally, modern AI still sits on a longer continuum of increasingly flexible statistical and ML methods.² What distinguishes the transition to modern AI, for the purposes of this discussion, is that it is changing how the analytical components of the investment process are organized and sourced.

The core revolution in AI during the early 2020s was one of scale: as models grew enormously large, they became markedly more capable across a broad range of tasks.³ That scale came with new requirements. These huge models—called foundation models—depended on massive training datasets, specialized computing infrastructure, and increasingly sophisticated technologies for training and deployment. (See the sidebar on p. 4 for an intuitive way to understand foundation models.)

Those requirements pushed important parts of the analytical stack outside the investment organization,

As systems take on more of the analytical work, higher-level human decisions become more consequential because they govern downstream activity of greater scope and scale, much of which may not be transparent.

increasing managers' reliance on an emerging industrial ecosystem of specialized AI model developers, chipmakers, cloud providers, and other technology suppliers.

Exhibit 1 depicts the resulting structure. Three features warrant special mention.

First, there are new elements, which we have emphasized with bright blue borders. Foundation models add broad, general-purpose capabilities that can be applied across research, coding, information processing, and other investment tasks. AI agents build on those models to carry out sequences of tasks with a degree of discretion, for example, proposing, testing, rejecting, and refining candidate analyses. Orchestration, i.e., the coordination of models, tools, data, and workflows, is not itself new, but it has become more important as managers integrate externally sourced foundation models and proprietary agents with the more traditional analytical components that remain part of the investment process.

Second, there has been a shift in the boundary between what is externally sourced (gray) and internally developed (blue). Some analytical elements, notably foundation models and much of the infrastructure supporting them, now sit on the sourced side of the stack, while proprietary investment research, models, knowledge bases, agents, and workflows remain manager-specific.

Third, the sources of investment edge have shifted upward in the stack. As foundation models and supporting infrastructure have become broadly available, managers need to devote less effort to building general-purpose analytical machinery themselves. They can and must focus more of their work on developing proprietary investing resources, including models, workflows, and knowledge bases, built on top of the externally sourced technologies.

SHIFTING RESPONSIBILITIES: ABSTRACTION

Modern AI is not just changing the structure of the analytical stack in systematic investing; it is also accelerating a longstanding trend toward “abstraction,” i.e., the transfer of responsibility from people to systems.

Agents can increasingly exercise discretion over the analytical process itself, rather than simply executing specified tasks. They can help to define, sequence, and refine the tasks required to pursue an objective.

Greater abstraction does not eliminate the need for human involvement, however; far from it. As systems take on more of the analytical work, higher-level human decisions become more

consequential because they govern downstream activity of greater scope and scale, much of which may not be transparent. Moreover, specifying objectives, setting constraints, and establishing validation standards all require deep contextual knowledge and experiential judgment. And even with well-designed *ex ante* guardrails, *ex post* human judgment is required to assess whether AI-generated analysis is sound.

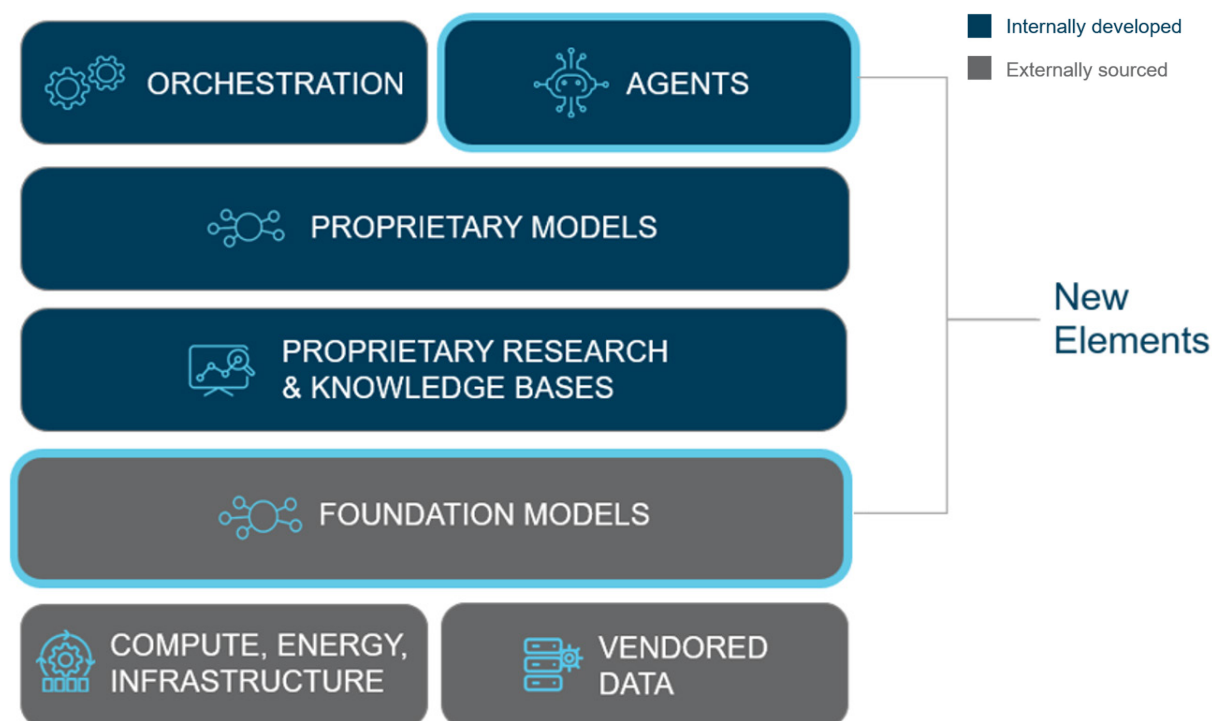
Table 1 illustrates the longer arc of abstraction in the investment process using the evolution of value-signal design as an example. Across the first three levels, systems assume progressively greater responsibility for decisions within a researcher-defined problem. At the fourth, the character of abstraction changes: an agentic research process takes some discretion over the research path itself.

While abstraction may be easiest to envision in the context of forecasting, similar progressions apply to other parts of the investment process, including data ingestion, portfolio construction, implementation, risk management, and trading.

² See Hastie, Tibshirani, and Friedman, *The Elements of Statistical Learning*, 2nd ed. (2009), for a unified treatment of traditional statistical and machine-learning methods across increasing levels of model flexibility.

³ See Acadian, [Generative AI in Systematic Investing: The Sizzle and the Steak](#), April 2024 and Kaplan et al., *Scaling Laws for Neural Language Models*, OpenAI Working Paper, Jan 23, 2020.

Exhibit 1: The Investment Process in a Modern AI Environment



Source: Acadian.

Table 1: Progressive Abstraction—A Value-Signal Example

LEVEL OF ABSTRACTION	SYSTEM'S ROLE	DESIGNER'S ROLE
1. Specify Valuation Metric	Ranks companies using a specific valuation ratio (e.g., B/P or E/P).	Chooses the valuation metric and supplies the data.
2. General Valuation Measure	Adjusts valuation metrics for potential pollutants, such as intangibles or risk exposures	Specifies the adjustments to be made.
3. Generalized Signal Design	Incorporates nonlinear prediction using machine learning.	Defines the candidate features, modeling objectives, constraints, and validation tests.
4. Generalized Research Process	Proposes, tests, and refines candidate value signals.	Defines the research protocol, permissible data, and validation criteria.

Source: Acadian.



Foundation Models: A Surprisingly Simple Way to Understand Them

Any analytical model can be understood by answering three questions:

What are its inputs and outputs?

For a foundation AI model, the inputs may be text, images, audio, or other forms of information, and the outputs may take similarly varied forms. In the case of a large language model, both inputs and outputs are primarily text; multimodal foundation models can operate across several types of data.

What are the functional elements that relate the two?

How a foundation model transforms inputs into outputs depends on its parameters and their arrangement. The parameters determine how input information is filtered, transformed, and combined. The architecture determines how those parameters are organized and how they interact to successively alter the input information. Traditional statistical models and modern foundation models can be viewed as occupying opposite poles on a spectrum of complexity. At the simpler end, traditional models like linear regression have few parameters, and the relationships among them are completely specified or tightly constrained in advance. At the other pole, foundation models may have billions or hundreds of billions of parameters arranged within enormously complex architectures, allowing far more flexible functional relationships to emerge.

How are the functional elements determined?

Like a traditional statistical model, the parameters of a foundation model are estimated from data. Their broad architecture is specified in advance, while training determines the enormous number of parameters through repeated exposure to data and adjustment against specified objectives.

The scale and flexibility of their parameters are what make foundation models so broadly capable and their training so demanding, requiring enormous datasets, specialized computing infrastructure, and sophisticated methodologies.

Investment Outcomes

It is easier to trace AI's broad impact on how analytical work is being done in systematic investing than it is to assess which managers will deliver better active performance through their use of AI. That evaluation must look beyond AI technologies themselves to organizational characteristics that will be crucial to determining which managers succeed: people, tools, data, and culture. Exhibit 2 poses pragmatic questions that asset owners can use to evaluate managers and highlights key practices and capabilities that strong answers should reveal.

Conclusion

Many discussions about AI get lost in projections about distant future states, where we simply cannot know what the technology or its implications will ultimately look like. Focusing instead on the here and now, the transition to modern AI in systematic investing is marked by a combination of transformative change and continuity. The analytical architecture underlying the investment process is being reshaped, but the underlying investment problem remains the same.

For asset owners, a practical challenge is to assess whether a manager's use of AI is likely to result in better investment outcomes. Doing that requires examining more than the AI technologies a manager chooses. Whether those technologies produce better active performance also depends on how the manager's people, tools, data, and culture compare with those of its competitors.

Exhibit 2: Four Lenses for Evaluating a Manager's Use of AI

PEOPLE

What expertise and judgment does AI require?

AI expertise

Understanding foundation-model capabilities and limitations has become a distinct competency that managers should possess.

Analytical oversight

Scrutinize AI outputs and behavior for plausible-but-wrong analyses, unintended methods or data, and look-ahead bias in historical applications.

Investment and methodological knowledge

Retain deep expertise in the investment logic, statistical methods, institutional knowledge, and data issues underlying delegated work; higher-level responsibility cannot come with lower-level ignorance.

TOOLS

How do you deploy and govern AI tools?

Set boundaries for autonomy

Give AI greater freedom in engineering and other well-specified contexts; tightly select, scope, and constrain AI investment-modeling work.

Source intelligently

Match external models and infrastructure to the task rather than defaulting to maximum capability. Factor in all costs—compute, data, integration, and operations.

Manage complexity

Implement common standards for data, business logic, and implementation to integrate proprietary and sourced components coherently. Establish clear decision rights and lifecycle controls for AI tools and processes.

DATA

How do you optimize data for AI?

Build an industrial-grade data process

Standardize mappings and business logic so results can be reproduced, errors diagnosed, and AI systems operate on consistent inputs. Track data provenance, lineage, and transformations from source through research and production.

Leverage institutional knowledge

Systematically preserve research results, code, documentation, data histories, validation results, and lessons from what worked, what failed, and why. Carefully curate knowledge bases so AI draws on what is relevant and reliable.

Govern access

Use defined access points for AI systems and tightly control what they can read, modify, or expose. Prevent proprietary information from being exposed to external AI systems.

CULTURE

How do you innovate without chaos?

Experiment with deliberation

Give AI greater freedom in engineering and provide latitude to test new capabilities while tolerating well-motivated failures. Be selective about what is retained, institutionalized, and scaled.

Preserve investment discipline

Keep the investment what and why grounded in human judgment to avoid a deluge of AI-generated “investment slop.” Sound investment principles and institutional knowledge become more important as automated exploration expands.

Maintain healthy skepticism

Raise the evidentiary bar as experimentation becomes easier. Complex methods should earn their place by demonstrating value beyond simpler, more transparent alternatives.

Source: Acadian.

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