AUGUST 2026

Find value in the AI stack

As AI's investment opportunity broadens, finding value is becoming more important and more difficult. Our framework helps investors navigate the AI ecosystem layer by layer, testing where the investment case still holds, where bottlenecks are emerging and where pricing power and profits may concentrate.

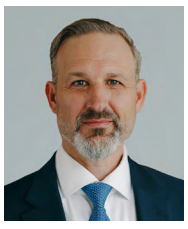
Investing in artificial intelligence (AI) can feel daunting. The ecosystem is broad, spanning vast data centres through to the applications used by businesses and governments. So how can investors capture existing and emerging opportunities and seek to maximise returns while managing risk?

Rather than viewing AI as a single investment theme, we assess each stage of the value chain separately. This helps identify where the investment case remains correct, where risks are emerging, and where economic returns are shifting.

While many AI investment analyses focus on how the technology is built, our approach focuses on where the investment case remains strongest, where value can be created, and which parts of the ecosystem are strongly positioned to outperform and those that may be constrained by bottlenecks.

Key takeaways

- Our framework applies testable questions to AI's "five-layer cake" – applications, models, infrastructure, chips and energy – to assess if and where the investment case remains intact.
- This approach helps determine where, and how much, capital to allocate across overall AI exposure and specific layers of the ecosystem.
- Our analysis shows that leading indicators, including adoption trends, infrastructure build-out and semiconductor demand, can help to reveal shifts before they show up in earnings.
- As AI adoption broadens, leadership may rotate across the value chain, with energy availability and grid capacity becoming potential critical constraints.



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Testing the AI investment thesis

Our investment framework assesses the AI investment opportunity through a series of testable questions spanning the entire value chain. It has three distinguishing features.

First, it is diagnostic rather than predictive. The framework's objective is to evaluate the health of the AI investment thesis through a sequence of falsifiable questions. We use data from multiple perspectives to distinguish meaningful AI developments from hype.

Second, it focuses on leading rather than lagging indicators. A diverse range of operational metrics, such as the speed of AI adoption by companies or the breadth of employee usage, can point to where the market is heading before quarterly earnings confirm the trend.

Third, it acknowledges that economic profit pools shift over time. AI adoption defines the size of the opportunity, while bottlenecks and competitive advantages determine who benefits. For example, if high-bandwidth memory becomes a limitation, companies in the sector may be able to raise prices, supporting stronger earnings and, potentially, higher share prices.

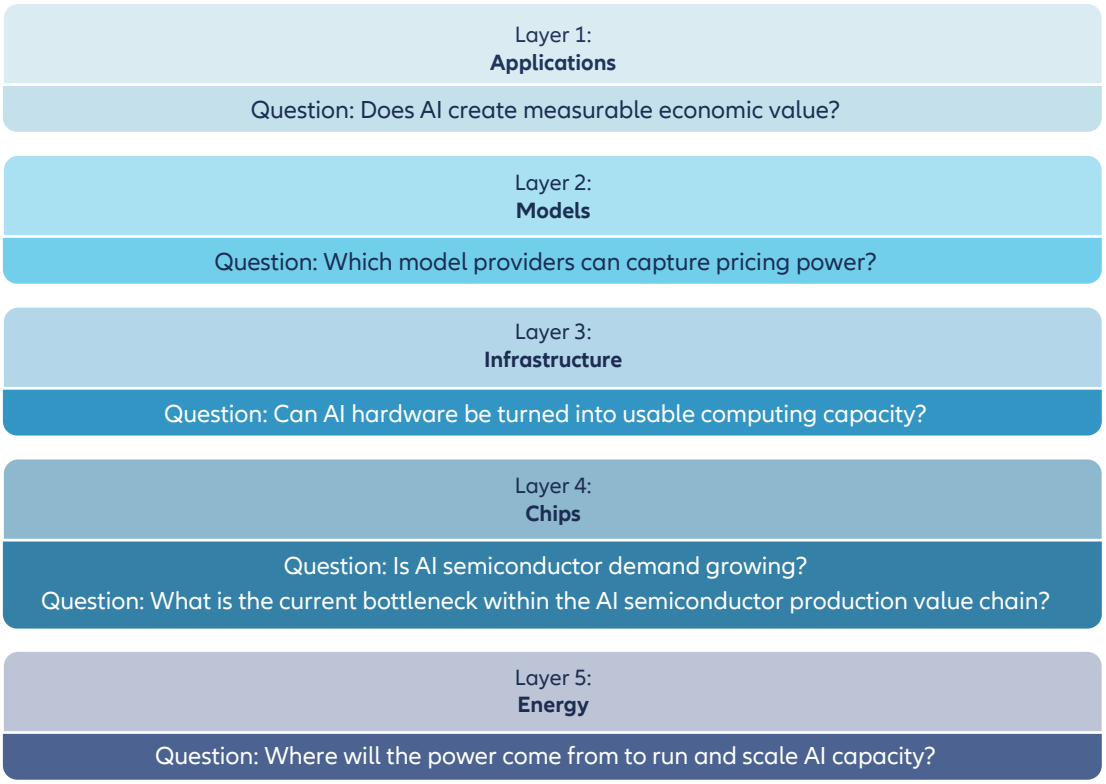
Nvidia coined the term "five-layer cake" to describe the AI ecosystem as a comprehensive, full-stack industrial infrastructure with the following sequential layers:

1. **Applications** – the AI products and services that solve problems for users.
2. **Model** – the systems trained to understand language, images, video, biology and more.
3. **Infrastructure** – the data centres, networking equipment, cooling systems, power connections and physical facilities needed to operate AI at scale.
4. **Chips** – the graphics processing units (GPU) and central processing units (CPU), memory chips and advanced semiconductor components that make AI possible.
5. **Energy** – the power needed to run data centres.

We use this structure to link each layer to a testable investment question, supported by objective indicators. Rather than forecasting quarterly earnings or trying to identify the next short-term winner, we assess whether the structural AI investment thesis remains intact and where economic rents – excess profits earned from controlling scarce digital assets – are emerging as the industry evolves.

We apply that lens across the AI ecosystem (see Exhibit 1).

Exhibit 1: Our AI Investment diagnostic framework



Layer 1: Applications – proving AI's value

Question: Does AI create measurable economic value?

This question underpins the AI investment thesis. For AI spending to remain structural rather than cyclical, the technology must deliver measurable economic benefits. For businesses, that means higher productivity, stronger revenue growth or lower costs. Without measurable economic value, AI spending risks becoming discretionary. Investors should therefore monitor companies' productivity improvements and their returns on AI investment.

If AI is creating value, the next test is whether adoption broadens beyond pilot programmes. The real impact comes when companies deploy AI at scale and pay for it consistently.

Key factors to watch

Public dashboards and publications from leading technology companies and AI model providers can indicate adoption levels, drawing on proprietary usage data and surveys.

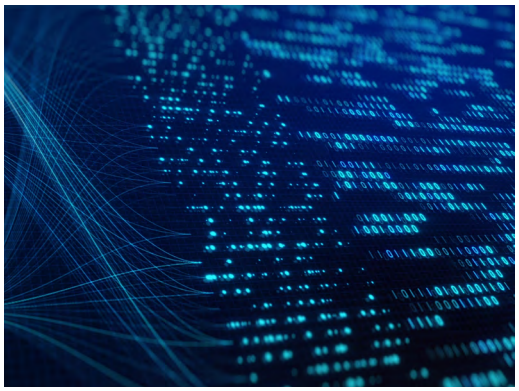
Studies and data from the National Bureau of Economic Research or US Bureau of Labor Statistics and consultancies can shed light on labour productivity, while university research can track AI capability relative to human performance, providing evidence of potential productivity gains, the range of viable use cases, and the willingness of firms to spend on AI agents.

AI's adoption across companies can be tracked through real-time job postings data and enterprise AI spending surveys, which are published regularly by industry participants and research providers.

Layer 2: Models – gauging pricing power

Question: Which model providers can capture pricing power?

Profitability of AI models is one of the ecosystem's biggest uncertainties. Competition among leading model providers, the rise of more efficient lower-cost and open-source/open-weight architectures and the shifting cost of training models all raise important questions about pricing power and market structure. In some jurisdictions, such as China, economic profitability may come second to strategic goals, including technological sovereignty and market share. This creates a risk of "AI price dumping", where state-backed or strategically driven players accept structurally lower margins, weakening the pricing power of global competitors.



Follow the money: the structure of AI spending

Exactly how money is spent on AI by companies matters as much as the total amount. It can reveal where productivity gains are likely to emerge and how they are distributed across the workforce.

One emerging pattern is tiered access: model capability and token budgets vary by employee role rather than being rolled out uniformly. Some employees receive access to more powerful and more expensive models, along with higher usage limits.

For investors, this differentiation is important because AI's economic value will depend increasingly on whether the employees best placed to benefit from the technology can generate outsized productivity gains.

Therefore, the key question is which frontier models – those models at the cutting edge of capability – have the most durable advantage. Alternatively, a part of the market may become commoditised, where providers are differentiated mainly by price.

Key factors to watch

Relative market share among AI model providers, measured by usage and revenue; how much market share correlates with objective measures of model quality; changes in input and output pricing across models, including price-performance ratios; and the balance of computing power used for training versus inference – the phase where trained models apply their knowledge in real time.

Layer 3: Infrastructure – building usable AI capacity

Question: Can AI hardware be turned into usable computing capacity?

Demand for AI applications creates economic value only when purchased hardware is converted into usable computing capacity for training and running AI models. Achieving the transition requires sustained investment in data centres and supporting infrastructure.

Key factors to watch

Cumulative spending by hyperscalers (the cloud providers building the AI infrastructure) and data centre development activity across planning, construction and operational phases. Investors should also monitor equipment order backlogs and lead times (for example, for advanced cooling systems), as well as real estate metrics such as lease rates and vacancy rates.

Layer 4: Chips – tracking semiconductor demand

Question: Is AI semiconductor demand growing?

Every increase in both training and inference activity ultimately requires additional GPUs, CPUs, memory, and semiconductor packaging. This layer tracks the scale of semiconductor demand, rather than how profits are distributed across the industry.

Key factors to watch

Market-based measures of AI compute demand, AI accelerator shipments, shifts in demand for high-quality versus cheaper chips, GPU rental prices over time, and chip replacement cycles. Model efficiency is also worth tracking, as it shows how much computing power, energy and resources models need to deliver results. For example, if newer large language models need less compute or less memory because of better software the result may be lower demand for chips.

Within this layer, the framework poses an additional question:

What is the current bottleneck within the AI semiconductor production value chain? (see Exhibit 2)

Overall semiconductor demand and semiconductor profit distribution are not the same. Pricing power and industry profits tend to concentrate where physical capacity is most constrained. During the current AI investment cycle, the primary constraints have moved along the hardware stack, from initial GPU scarcity to high bandwidth memory (HBM) today. Given the limited availability of high-frequency data, investors can use expert interviews and other industry intelligence to assess where constraints are emerging.

Exhibit 2: AI accelerator production flow, the step-by-step pipeline used to create AI hardware
For illustrative purposes only

*The physical manufacturing process of building digital circuits.

Lagging or infrequently published indicators can also be valuable, including the pricing and volume terms of long-term supply agreements across the semiconductor value chain. Investors should also scrutinise the physical composition of leading AI systems, including their GPU, CPU and memory requirements.

Layer 5: Energy – powering AI growth

Question: Where will the power come from to run and scale AI capacity?

AI is power hungry. Global power demand from data centres needed to run AI is expected to double by 2030 (from 2025 levels), according to the International Energy Agency.

As AI roll-out widens, energy can become a binding constraint. Grid capacity and electricity costs play a growing role in determining how quickly new AI capacity is deployed and how efficiently existing data centres can operate.

Key factors to watch

Grid connection requests and queue lengths, order backlogs/lead times for onsite power generation equipment, and trends in energy prices.

Our framework: pinpointing AI value

AI presents vast opportunities, but the pace of development and deployment can make it tricky for investors to keep up and identify value.

Our approach tests whether the investment case holds across the AI ecosystem, highlighting where value creation is most likely to translate into pricing power and outsized profits. It also informs capital allocation by guiding both overall AI exposure and positioning within specific ecosystem layers.

As the AI opportunity set broadens, our framework can help identify where success is most likely to take shape.

MACS-P-22018190

ADM-W5825570