

EXECUTIVE EDITION

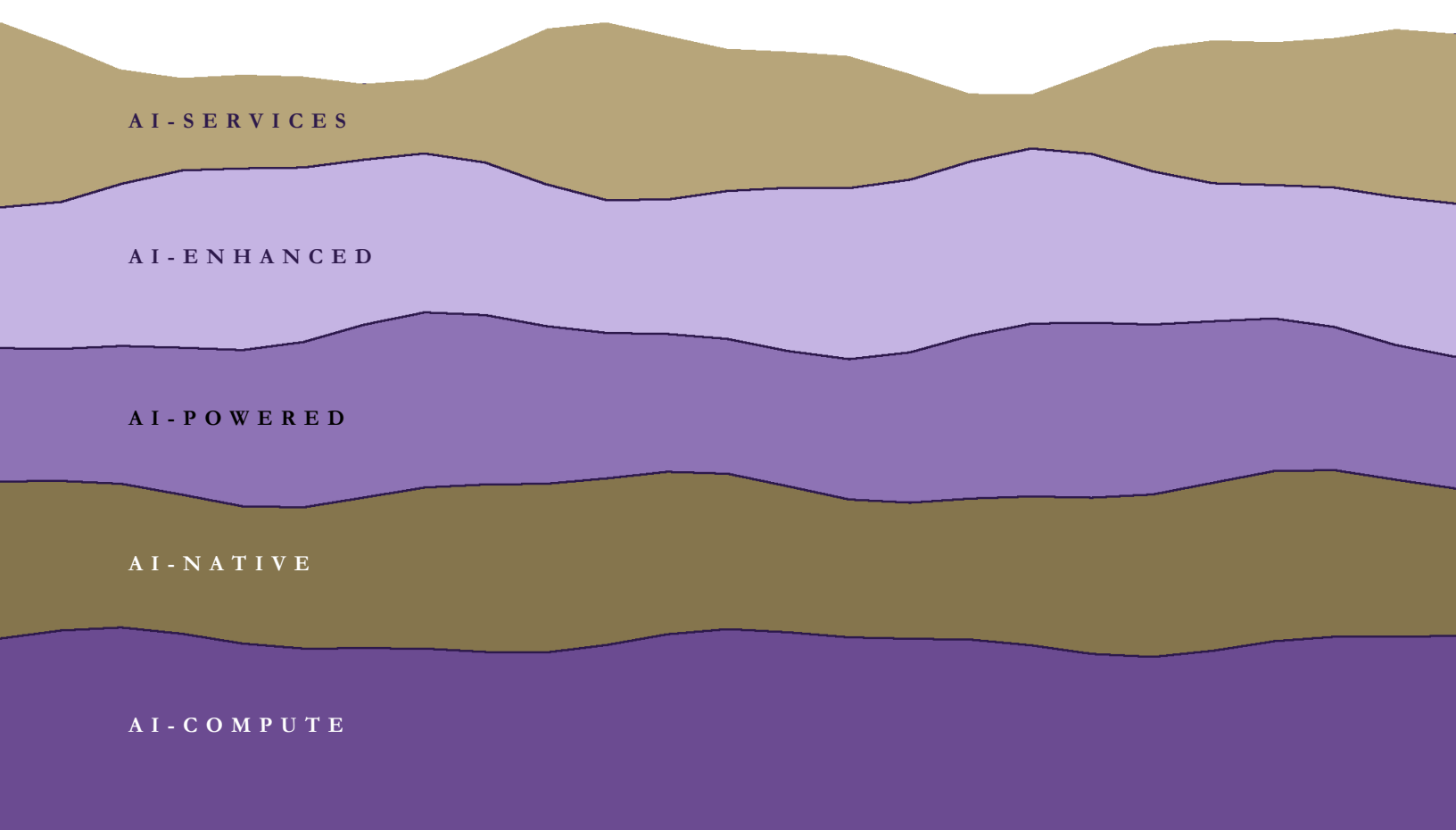
The AI Economy in Five Layers

Where venture capital, federal grants, founders, and jobs have gone so far

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AI-SERVICES

AI-ENHANCED

AI-POWERED

AI-NATIVE

AI-COMPUTE

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How we built this report.

We analyzed 63,686 of the 77,146 companies tagged with PitchBook’s AI/ML label. For each company, a web-grounded large language model (LLM) independently researched and described the product, and a second LLM applied a five-step decision tree procedure to classify the business. This procedure placed 57,074 companies in five AI product layers and the rest in an ‘Other’ category. We then traced venture financing, federal grants, patents, employment, and founder work histories using data from PitchBook, SBIR.gov, PatentsView, and Revelio Labs. We also used more than 1.1 million archived homepages of these companies from the Internet Archive to analyze claims they make regarding AI.

The decision tree procedure begins by identifying human services and computing products purpose-built for AI. It then asks three questions: (1) whether a product still exists without AI, (2) whether the broader product category existed before modern AI, and (3) whether AI materially improves a surviving product. The first is what we call *the collapse test*. We use 2012, the release year of AlexNet, as the boundary between before and after modern AI.

The largest technology companies are not included in these numbers.

PitchBook does not tag Google, Microsoft, Amazon, Apple, Meta, or NVIDIA as AI/ML companies, so we report no figures for them. These companies indirectly appear in our data instead as investors or owners: 1,162 classified companies (1.8%) have one of the six or one of their venture arms as an investor. This broader investor-or-owner relationship is most common in the layers closest to the technology, what we describe as AI-Native and AI-Compute companies.

We also exclude the utility companies that provide energy that powers AI-Compute companies. What follows therefore describes the venture-oriented part of the AI economy, not the whole. This report compares companies across the five AI product layers we define. The employment figures we provide are estimates derived from public professional profiles.

Executive Summary

“AI company” is a broad label that covers five types of businesses. PitchBook’s Artificial Intelligence & Machine Learning (AI/ML) vertical listed 77,146 companies in April 2026, but provides no definition of what constitutes an AI company. Our students asked us what “AI-native” means when so much venture capital (VC) flows to companies using the term. This report therefore addresses two questions: (1) *How should one define an AI company, and* (2) *What does the population of these companies look like?*

We answer the first question by classifying companies by what they sell using a five-step decision tree procedure whose central branch is the collapse test: *if AI is removed from the product, is there still a product to sell?* The procedure places companies in five layers: three product layers emerge from what the collapse test finds (AI-Native, AI-Powered, AI-Enhanced), another from the computing they run on (AI-Compute), and the final layer from the human work around the technology (AI-Services). We set aside the remaining companies (6,612 in total) with no meaningful AI component as ‘Other.’

We found about one company in eight is AI-Native, selling a product in a category that did not exist before modern AI. One in a hundred companies is AI-Compute, and nearly three in four are AI-Powered or AI-Enhanced (see Section 1). The five product layers differ on nearly every measure we examine.

The rest of the report answers the second question.

- **Most venture capital flowed to a single layer, and within that layer, to only a handful of companies.** AI-Native includes about one in eight companies and received just over half of venture capital funding from early 2023 through early 2026. Ten companies garnered 72% of the capital the layer has ever raised, and three — OpenAI, Anthropic, and xAI — hold two-thirds. Federal grants run the other way: AI-Enhanced and AI-Powered companies received 73% of the \$1.5 billion in SBIR/STTR awards matched to the five layers, and grants usually followed private money rather than led it (see Sections 2 and 3).
- **Jobs went where capital did not.** In 2026Q1, 1.8 million people held positions across the five layers — AI-Enhanced accounts for 47% of that employment, and AI-Powered for 22%. AI-Native, which has attracted most recent VC funding, holds 8%. The average AI-Native company employs about 25 people, roughly unchanged since 2023 (see Sections 4 and 9).
- **Founders come from a wide base, and founding an AI company is often a second act.** Google is the most common last employer of AI company founders, but no employer supplies more than a small fraction. Ranked by founding rate, Palantir and DeepMind so far lead the

pack. More than four in ten AI companies founded in 2023 or later have a founder with prior founding experience (see Section 5).

- **New entrants targeted problems closest to AI technology.** One AI company was founded after 2022 for every three that existed before — more than four times the rate outside AI. Across 25 problem areas that AI companies were built around before the release of ChatGPT, the ones that attracted the most entrants concerned AI builders. By contrast, healthcare treatment, industrial safety, and agriculture saw the lowest entry ratios (see Section 6).
- **So far, AI companies are not more likely to fail than non-AI companies.** The software and services layers attract Series A funding within 24 months at similar rates (12% to 14%) but separate only on later outcomes. Even AI-Native companies, arguably the riskiest software layer, go out of business less often than venture-backed companies outside AI (see Section 7). AI-Compute companies are the outlier, standing apart on every measure.
- **Words outran products.** After ChatGPT’s introduction, positioning as an AI company rose across every layer, including for companies whose products do not depend on AI. Among 19,104 companies that could have pivoted their product to depend on AI, positioning claims outnumbered actual product pivots 19 to one in 2025H2 (see Section 8).
- **New companies increasingly sell products that depend on AI, and shutdowns and acquisitions have risen.** AI-Native and AI-Powered companies made up 43% of the 2022 founding cohort and 59% of the 2025 cohort, while shutdowns and acquisitions more than doubled between 2023 and 2025. New founding fell from its 2023 peak (see Section 9).

What to do with the report.

In Section 10, we translate these findings into six decisions for investors and managers. In sum: (1) benchmark by product layer, not by the broad AI category label, (2) parse out the largest VC fundraisers before using any aggregate AI-funding figure, (3) treat grants as a supplement, not core capital, (4) hire employees and find co-founders from companies that have been producing them, (5) expect more rivals in layers that depend on AI and consolidation happening now, and (6) treat a claim that positions a company as AI as marketing until the product has been tested. If you take one thing from the report, it is this: judge an AI company by its product layer, not by its label or its claims.

What counts as an “AI company”?

We begin by analyzing what constitutes an AI company. OpenAI and Canva both carry the AI/ML tag. So do Anthropic and Snowflake, CoreWeave and Turing, Scale AI and ByteDance. Each of these companies is in PitchBook’s Artificial Intelligence & Machine Learning vertical, the list many professionals use to define the AI company category. In our classification, these eight companies span five product layers, and they diverge on every measure we provide in this report.

We note one boundary condition at the outset. The 77,146 tagged companies in PitchBook are a thin, venture-oriented or venture-backed slice of the startup economy rather than a census of AI adoption. For context, the United States alone has 6.2 million employer businesses (as of 2022).¹

Why five layers, and why these five? We did not cluster the companies and name the clusters afterward. Instead, we used a five-step decision tree procedure that first asks whether the customer buys human work or computing purpose-built for AI. For the remaining companies, the decision tree procedure applies the collapse test: *if AI is removed, is there still a product to sell?* A product that collapses is AI-Native when its commercial category did not exist before modern AI (e.g., OpenAI) and AI-Powered when the category already existed (e.g., Cursor). We use 2012, the release year of AlexNet, as the practical boundary to distinguish before and after modern AI.

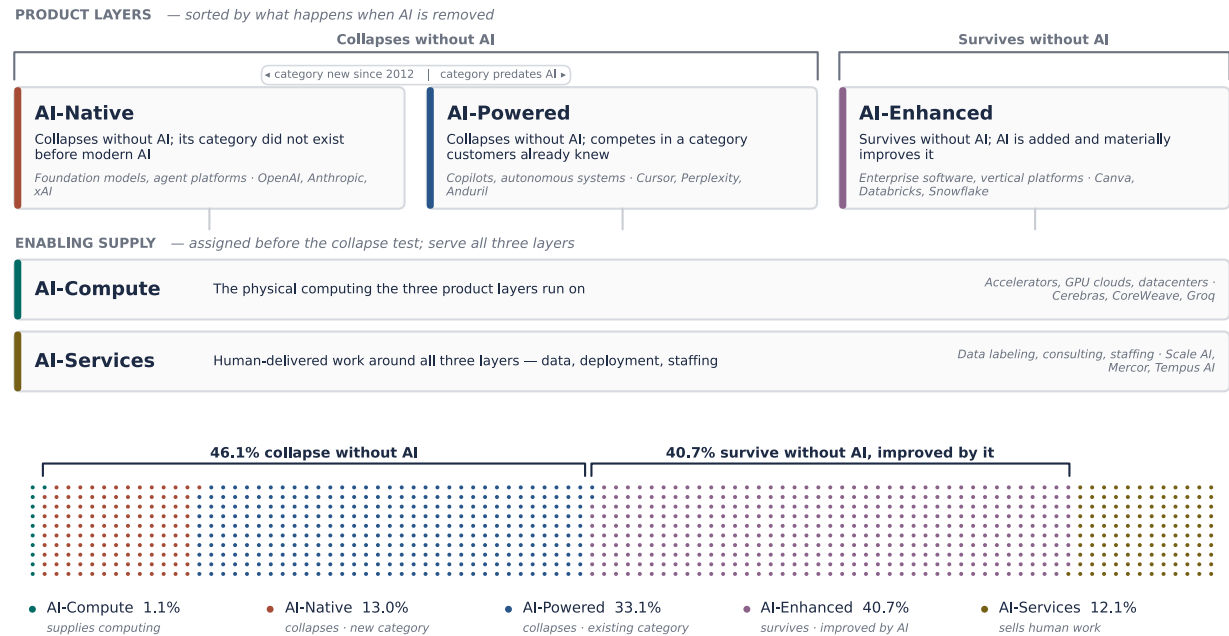
A company that sells a product that survives but is materially improved by AI represents the AI-Enhanced category (e.g., Canva); one that is not materially improved is classified as Other.

Hence, our five layers capture the five ways a product with a meaningful AI connection relates to AI. Each company is assigned to one layer by its primary product offering. The Technical Note at the end of the report describes the procedure we employed, and in Section 8 we explain why we classify the companies by the product they sell rather than by what they describe about themselves.

Exhibit 1 arranges the five in the order they relate to one another; whenever a later exhibit lists the layers, it uses this order.

EXHIBIT 1

Three product layers, two supply layers, and how 57,074 companies are distributed



Companies are assigned by their primary offering. Each dot represents about 57 of the 57,074 companies in the five layers. The 6,612 in Other are excluded from the grid.

¹ U.S. Census Bureau, 2022 Economic Census, First Look estimates: 6.2 million employer firms in the United States.

<https://www.census.gov/library/stories/2024/06/economic-census-annual-business-survey-results.html>

In **Exhibit 2**, we compare the layers. The Forbes 2026 AI 50 spans all five layers, though most companies on the list are AI-Native or AI-Powered.² We use this exhibit to anchor the rest of the report, since most figures that follow are reported by layer.

The five-step decision tree procedure employed is summarized in product-description and diagnostic columns. For example, AI-Enhanced companies represent companies that sell products that are AI-enhanced. For our purposes, AI-Powered, another layer, is a test, not a marketing claim: remove AI and no product is left, and much of the company’s AI-powered language or claim would not meet that test.

The “companies” column highlights the counts of the companies in each layer and helps one understand the shape of the population in terms of count and percentages. AI-Powered and AI-Enhanced together account for nearly three quarters of the companies in the five layers.

Products born on AI (AI-Native) and the computing they run on (AI-Compute) are a small minority of the population. AI-Native companies represent about one company in eight; AI-Compute is one in a hundred. Under the column “highest-valued examples,” we provide names that readers will recognize.

EXHIBIT 2

The five layers, what separates them, and who is in each

Layer	Companies	What the company sells	Remove the AI: is a product left?	Category existed before 2012?	Highest-valued examples
AI-Compute	620 1.1%	Physical computing capital built for AI — chips and accelerators, GPU clouds, AI datacenters	Not reached	Not reached	Cerebras, CoreWeave, Groq
AI-Native	7,422 13.0%	AI technology itself, in a commercial category that did not exist before modern AI	No	No	OpenAI, Anthropic, xAI
AI-Powered	18,882 33.1%	A product that collapses without AI, competing in a category that predates AI	No	Yes	Cursor, Perplexity, Anduril
AI-Enhanced	23,247 40.7%	A product that exists without AI, with AI added as a marketed feature that improves it	Yes, degraded	Not reached	Databricks, Canva, Snowflake
AI-Services	6,903 12.1%	Human work — consulting, data annotation, staffing — however AI-related the work	Not reached	Not reached	Scale AI, Mercor, Tempus AI
<i>Other</i>	6,612 —	No meaningful AI component in the product	Yes, unchanged	Not reached	Figma, Polymarket, Grafana Labs

Percentages use the 57,074 companies in the five layers; Other is separate. “Not reached” means the decision tree assigned the company before that question was needed. Examples are among the companies with the highest latest recorded post-money valuations as of April 2026.

² Forbes, “AI 50 2026,” published April 16, 2026, <https://www.forbes.com/lists/ai50/>. Company matching and product-layer assignments are the authors’ analysis.

How different are the five layers?

In Exhibit 3, we compare the five product layers and use this scorecard as the key reference. Each block addresses a different question, and the blocks follow the report’s sequence: companies, funding, and jobs; founder characteristics; founder entry; venture outcomes; and AI positioning.

For instance, the “Layers’ Footprint” block highlights how companies, funding, and jobs are distributed across the five layers. The ‘Founder Characteristics’ and the ‘Venture Outcomes’ blocks show the share of observations in each layer that meet the condition described in the column titled ‘Measure.’ The ‘Founder Entry’ and ‘AI Positioning’ blocks report changes within each layer. VC funding and grants, as we describe them, span different time periods, so we compare how funding is distributed across the layers, not their size. The final column, ‘Venture-backed, excluding AI,’ provides a context for comparing venture outcomes of AI companies with the rest of the venture capital-oriented or -backed companies in general.

EXHIBIT 3

How the five layers differ

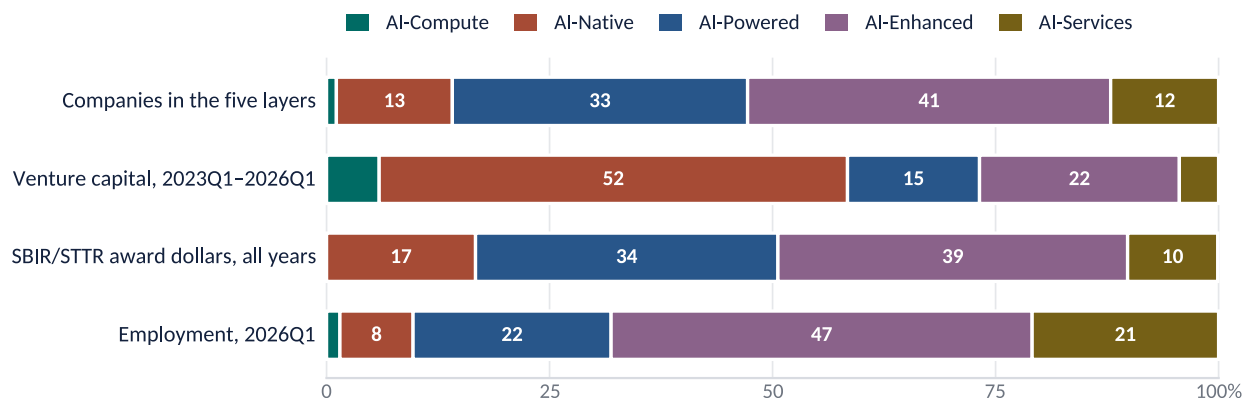
Measure	AI- Compute	AI- Native	AI- Powered	AI- Enhanced	AI- Services	Venture- backed, excluding AI
THE LAYERS’ FOOTPRINT — COMPANIES, FUNDING AND JOBS						
Share of the companies in the five layers (%)	1.1	13.0	33.1	40.7	12.1	—
Share of VC funding, 2023Q1–2026Q1 (%)	5.9	52.5	14.8	22.4	4.4	—
Share of SBIR/STTR award dollars, all award years (%)	0.0	16.7	33.9	39.2	10.1	—
Share of employment, 2026Q1 (%)	1.5	8.2	22.2	47.2	20.9	—
FOUNDER CHARACTERISTICS — RATES WITHIN EACH LAYER						
Founder-company observations: prior founder title, companies founded 2023+ (%)	44.6	47.2	42.4	42.1	41.5	—
Founder-company observations: prior AI-company work, companies founded 2023+ (%)	45.8	42.8	37.9	32.2	33.1	—
FOUNDER ENTRY — CHANGE IN MEAN ANNUAL ENTRIES						
Change in mean annual entries, 2023–2025 vs 2020–2022 (%)	45.7	64.8	31.4	-29.0	-18.9	—
VENTURE OUTCOMES — RATES WITHIN EACH LAYER						
Seed to Series A within 24 months of a first seed round (%)	31.6	12.2	12.3	13.7	12.0	11.0
Out of business within 30 months of first financing (%)	0.6	4.1	2.6	2.1	3.5	4.9
\$100M+ valuation within 36 months of first financing (%)	18.2	4.2	2.8	3.8	2.2	3.6
Holds at least one U.S. patent filing (%)	27.1	9.6	10.3	9.3	3.6	—
AI POSITIONING — CHANGE AMONG INCUMBENTS						
Incumbents (founded 2021 or earlier) adding AI positioning, 2022Q4–2026Q1 (percentage points)	21.9	14.6	15.3	11.6	8.1	—

Each footprint row totals 100% across the five layers, apart from rounding; the remaining rows report rates or changes within a layer. Venture capital covers 2023Q1–2026Q1, while federal grants cover all award years for 950 matched companies founded since 2012. Founder characteristics use recorded work histories for founders of companies started in 2023 or later. The final column gives the same venture outcomes for venture-backed companies outside the AI population; dashes mean no comparison is available. Recent founding years are still filling in across every layer, so the 2023–2025 entry counts are conservative, while the layer ratios remain comparable.

No single layer leads every measure. AI-Compute companies lead the financing funnel and patents. AI-Native companies have garnered the largest share of VC funding. AI-Native and AI-Services companies have the highest recorded ‘out-of-business’ rate. However, their out-of-business figures are still lower than the larger population of VC-backed ventures excluding AI companies. Interestingly, apart from AI-Compute, AI-Native and AI-Enhanced companies have the highest rates of reaching \$100 million within 36 months of first financing. The AI-Enhanced layer holds the most companies and the most jobs. AI-Services sells the human work around AI and holds about one fifth of employment but less than 5% of recent VC funding.

EXHIBIT 3A

AI-Native holds 13% of companies, 52% of recent venture capital and 8% of jobs



Each bar shows how one total is divided among the five layers; percentages may differ from 100 because of rounding. Venture capital covers 2023Q1–2026Q1; grants cover all award years for 950 matched companies founded since 2012; employment counts distinct people in current positions in 2026Q1. Shares below 7% are not labeled.

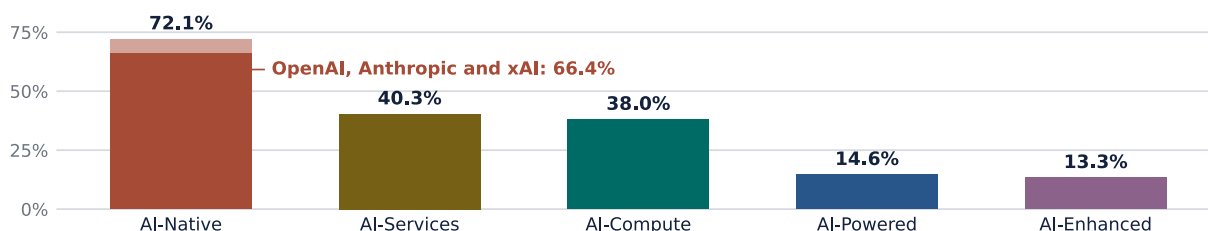
Who funds each layer?

Here we describe the funding patterns in our population of AI companies. From 2023Q1 through 2026Q1, AI-Native companies received 52.5% of the VC funding allocated across the five layers. Across the full population, including Other, OpenAI, Anthropic, and xAI alone received 37% of reported VC funding over the same period. The aggregate therefore reflects both a product layer and a few companies inside it.

Ten AI-Native companies account for nearly three quarters of the venture capital raised in that layer. OpenAI, Anthropic and xAI alone account for about two thirds. Concentration is much lower in the other layers, especially AI-Powered and AI-Enhanced.

EXHIBIT 4

Ten companies hold 72% of AI-Native's venture capital; three hold two-thirds



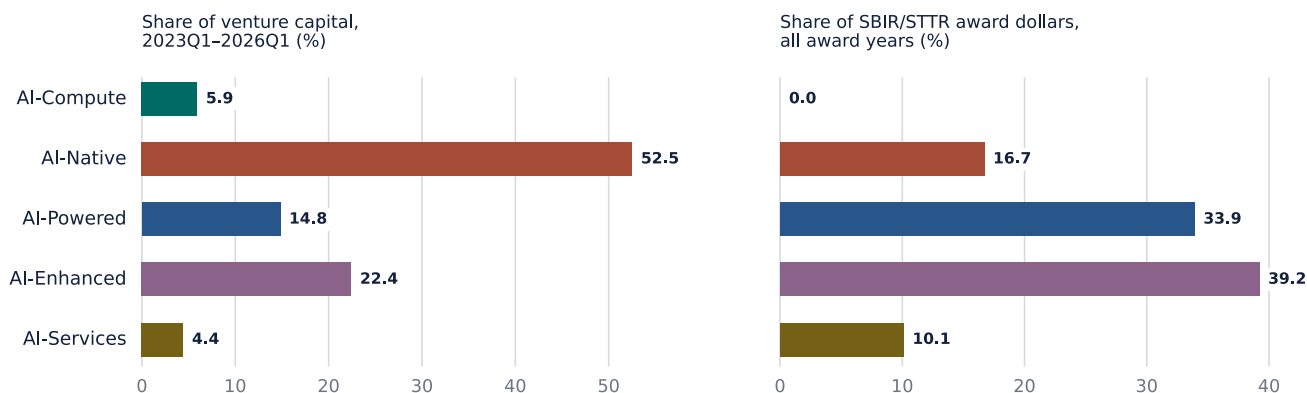
Each bar shows the share of reported venture capital across all recorded years through 2026Q1 raised by the ten largest fundraisers in that layer.

Although a high degree of skew is normal in VC funding, this magnitude is relatively new. For comparison, among VC-backed companies excluding the AI population, the 10 largest fundraisers hold 3.5% of VC funds raised, and the top 1% of companies hold 36%. Within AI-Native, the same two figures are 72% and 81%. The result is a funding boom concentrated in one layer and, within that layer, in a few companies. **Exhibit 5** below highlights the share of VC funding companies in each layer received. The bulk of the funding went to AI-Native companies.

Federal grants offer a second view of funding over a different period. SBIR and STTR make non-dilutive awards to small companies to develop their technology. Across all award years in the matched data, \$1.5 billion went to 950 companies founded since 2012 in the five product layers excluding the 'Other' category. AI-Enhanced and AI-Powered together received nearly three quarters of the matched federal grant dollars. AI-Native and AI-Services received much smaller shares.

EXHIBIT 5

Recent venture capital concentrates in AI-Native; grants favor AI-Enhanced and AI-Powered



Each panel totals 100% across the five layers, apart from rounding. Venture capital covers 2023Q1–2026Q1; SBIR/STTR grants cover all award years for 950 matched companies founded since 2012. The periods and dollar totals differ; the bars show each layer's share of each funding source.

Interestingly, we found that grants usually *followed* private capital rather than led it. Among the 788 grant holders with a recorded first financing date, 488, or 62%, raised private money before their first federal grant; the first financing came one year earlier.

Who works in AI companies?

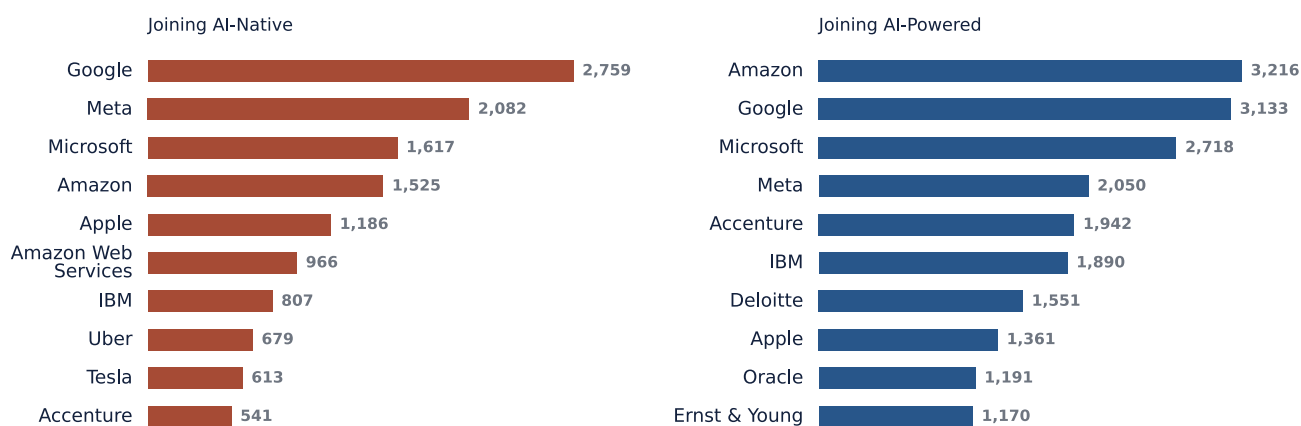
We found employment data for nearly 50,000 companies in the five layers, with about 1.8 million people holding current positions in early 2026.

AI-Enhanced held nearly half those jobs and AI-Powered about a fifth, while AI-Native, which received most recent venture capital, held fewer than one in ten.

Where workers came from. Google, Meta, Microsoft, and Amazon are AI-Natives' largest sources of employees (see **Exhibit 6**). The AI-Powered category adds Accenture, IBM, Deloitte, and Ernst & Young, mixing professional-services pipelines with technical ones.

EXHIBIT 6

Workers join AI-Native from the large technology companies; AI-Powered adds consulting



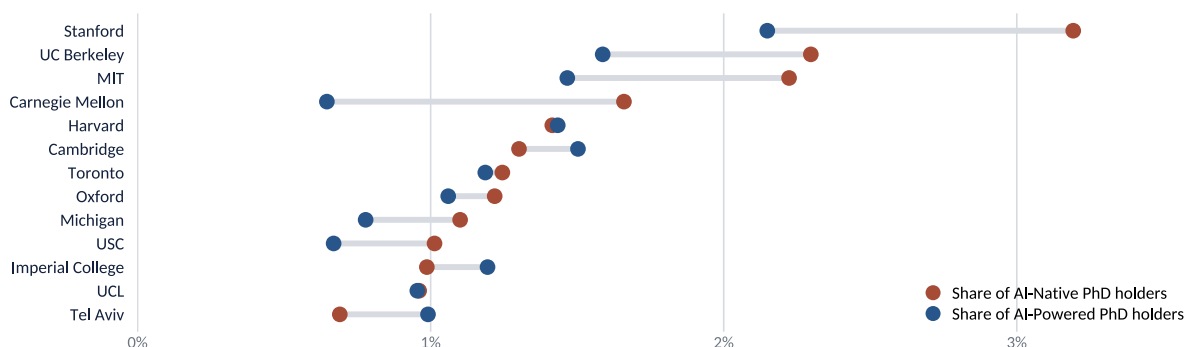
Bars count distinct people by the employer where they worked immediately before first joining an AI-Native or AI-Powered company, using Revelio Labs professional profiles.

Interestingly, doctoral talent is distributed differently from current employment. Across the matched-worker population observed over all the years, recorded PhD-holder shares are 8.7% in AI-Compute, 6.4% in AI-Native, and 2.7% in AI-Enhanced.

In both AI-Native and AI-Powered, fewer than one in five recorded PhD holders came from the ten largest source institutions.

EXHIBIT 7

Ten institutions supply 16.7% of AI-Native doctorates and 13.5% of AI-Powered doctorates



Each dot shows the share of recorded PhD holders in that layer whose doctorate is from the institution shown. The 13 schools combine the ten leading institutions for each layer.

Who starts AI companies?

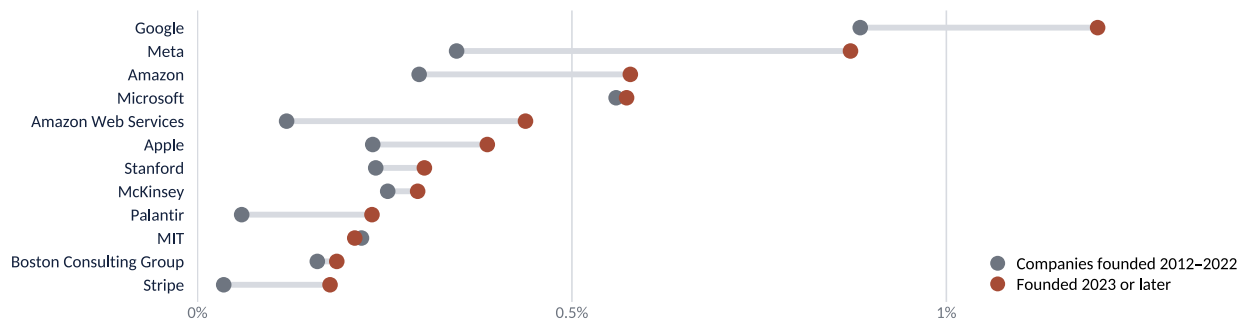
PitchBook names a founder for more than 50,000 classified companies. We traced the last employer of more than 80,000 founders.

Where they came from. Contrary to folklore that founders come from well-known large technology companies, we found that no employer supplies more than a small fraction. Google leads both cohorts, with Meta, Amazon, and Microsoft behind it. However, the percentage of founders leaving these companies is relatively small (see **Exhibit 8** below).

Ranking employers by rate rather than by count changes the order: Palantir produced 34.6 AI founders per 10,000 distinct people ever recorded working there and DeepMind 31.9, while Google and Amazon produced the largest absolute numbers and sit far lower per head.

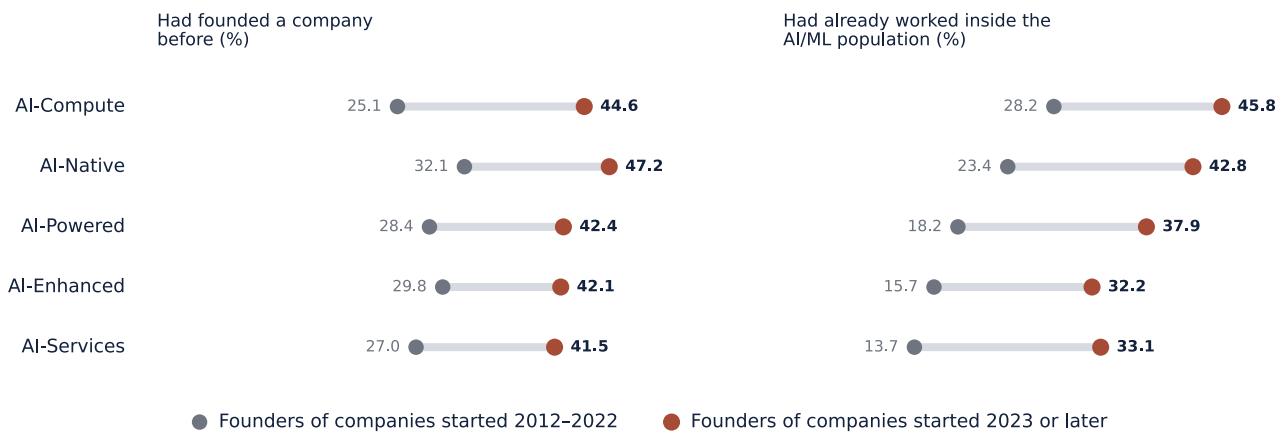
Founders of newer AI companies are more likely to have founded a company before and to have worked in AI. Prior founding experience is common across all five layers, while prior AI work is most common in AI-Compute and AI-Native.

EXHIBIT 8
Google is the most common last employer of AI founders; Meta gained the most after 2022



Each dot shows an employer’s share of founders with a traced last employer in that cohort. We count a founder once for each company they founded.

EXHIBIT 9
Prior founding converged across the layers after 2022; prior AI employment did not



Each line links companies founded in 2012–2022 to those founded in 2023 or later. We count a founder once for each company they founded. “Had founded a company before” means a founder title at another employer; prior AI work means employment at a company in PitchBook’s AI/ML population. Public profiles can miss prior founder roles.

We note two limitations that apply. First, public professional profiles skew toward the United States and technical careers.

Second, we exclude founders with no recorded prior position rather than counting them as having none.

Where did founders enter fastest, and where did they lag?

In this section, we analyze each company by the problem it addresses rather than the technology it sells: who the customers are and what pain the product aims to address. We used an LLM to read company descriptions after all the AI and solution vocabulary was stripped out. Entering a problem area means founding a company to work on it.³

The analysis grouped companies into 25 problem areas, including healthcare treatment, industrial monitoring and safety, and agriculture.

Across the 25 problem areas, roughly one company was founded after 2022 for every three founded earlier. Areas above this overall rate attracted more entrants relative to their existing company base; areas below it attracted fewer.

The area serving AI builders had nearly as many companies founded after 2022 as before, almost three times the overall

rate. Software development followed. Healthcare treatment, industrial monitoring and safety, and agriculture had the least entry relative to their existing companies.

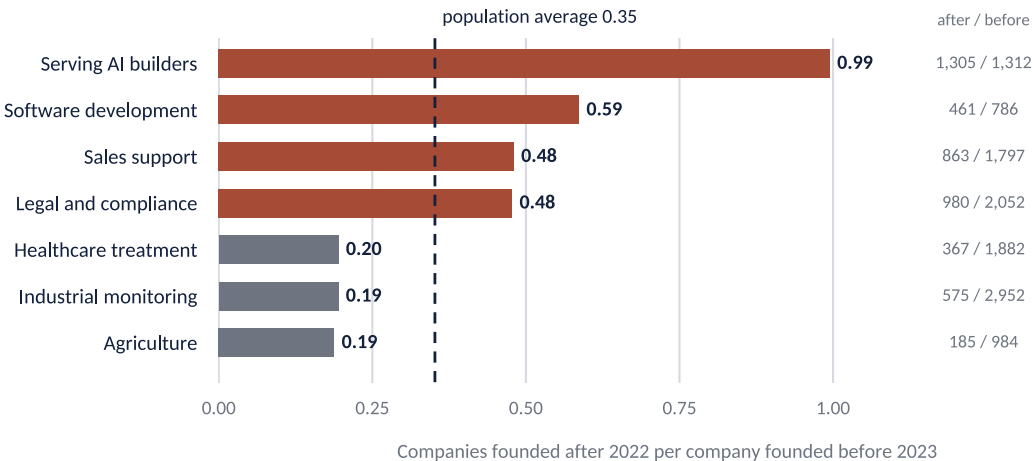
These AI companies were founded during a period when Americans filed more than five million new business applications each year from 2021 through 2024, peaking at 5.5 million in 2023.⁴

Among VC-backed companies, the ratio of post-2022 entrants to earlier companies was more than four times as high inside the AI/ML tag as outside it. Across the full venture universe, about one new company was founded for every ten that existed earlier.

Even the AI problem areas with the least entry had about three times the non-AI ratio. Healthcare and agriculture still drew new companies, but far fewer per incumbent than other areas.

EXHIBIT 10

Entry was highest for products serving AI builders, lowest for health and agriculture



Bars show the number of companies founded after 2022 per company founded before 2023 in each problem area. The chart shows the four highest and three lowest ratios among 25 areas. Copper bars exceed the overall AI/ML ratio of 0.35; grey bars fall below it. Counts at right give the after-2022 and before-2023 totals.

³ This analysis is exploratory because the grouping is a descriptive partition, not a fixed taxonomy. The Technical Note reports the model, clustering settings, label review, and stability check we employed.

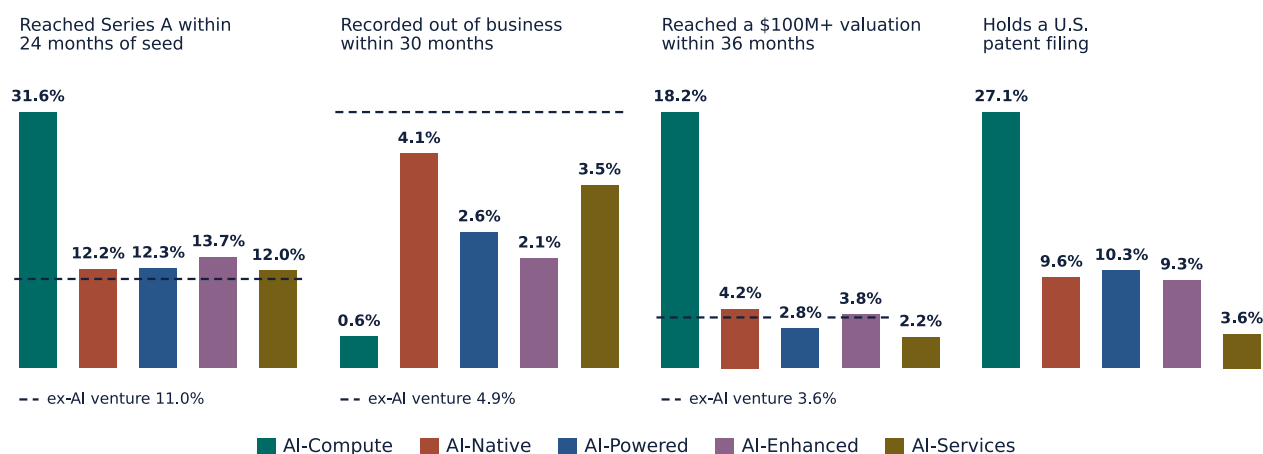
⁴ U.S. Census Bureau, Business Formation Statistics: 5.4 million business applications in 2021, 5.1 million in 2022, 5.5 million in 2023 and 5.2 million in 2024. <https://www.census.gov/econ/bfs/>

How do the layers perform?

We compare the five layers on four measures drawn from our data. The four software-related and services layers graduate from Seed to Series A at similar rates, then separate on recorded out-of-business status, outsized valuation, and patents. AI-Compute stands apart on all four outcomes in **Exhibit 11**.

EXHIBIT 11

AI-Compute is the outlier; the other four layers diverge only on later outcomes



The first three panels include only companies with enough follow-up to observe the full 24-, 30-, or 36-month period shown above each panel. The patent panel includes every company in each layer. Dashed lines show rates over the same periods for venture-backed companies outside the AI population.

A note on reading these findings. Familiar claims about startup outcomes use lifetime windows and loose definitions. Every rate we offer is measured over a fixed horizon in one dataset, and each is a floor. We suggest that readers compare the panels against one another and against the benchmark we provide.

Graduation. Here we capture the share of seed-funded companies that then go on to raise a Series A within 24 months. To us, this represents a test for a venture's early success. The four layers (excluding AI-Compute) sit within two points of one another, at 12% to 14%, while AI-Compute reaches 32%. The benchmark figure outside AI companies, measured the same way, is about 11.0%.

Out of business. This measure is the share of financed companies that were recorded out of business within 30 months of first financing. AI-Natives were recorded out of business most often, at 4.1%, and AI-Compute least often, at 0.6%. PitchBook records status changes with a lag, so each rate is a floor. The benchmark figure outside AI is 4.9%: even AI-Native, which perhaps is the riskiest software layer within the AI firm population, is recorded out of business less often than the venture world at large.

Valuation. This measure highlights the percentage of companies that reach a \$100 million post-money valuation within 36 months of first financing. Since valuations are disclosed for only a minority of deals in our population, these figures represent lower bounds. Against the 3.6% benchmark outside AI, AI-Native companies edge ahead, and AI-Compute quintuples it.

Patents. This represents the share of companies holding at least one U.S. patent filing. Not surprisingly, patenting is highest in AI-Compute companies, the hardware layer, at 27%; the rest of the software-based layers cluster near 10%. It is important to note that patents (as an asset class) miss inventions held as trade secrets, proprietary training data and open-source work, so a flat rate across the software layers is not evidence of equal invention or innovation.

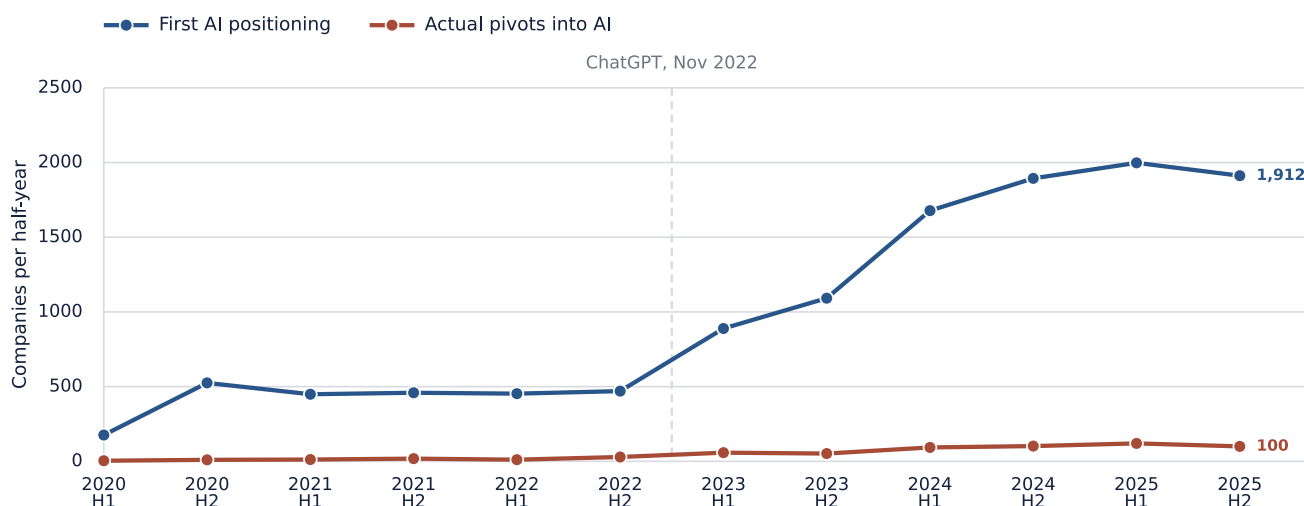
Can you trust what companies say about AI?

In Section 1, we classified companies by what they sell rather than by what they say. Here we explain why that choice matters. To undertake this analysis, we tracked the claims companies make on their homepages and the products they sell.

AI positioning language rose in the quarter ChatGPT launched (November 2022), across every layer, including those whose products *don't depend on AI*. It had changed little in the preceding year. In the following year, AI positioning rose about two percentage points in AI-Services and nine in AI-Native. By early 2026, nearly one in four AI-Enhanced companies positioned themselves as AI, up from fewer than one in ten at the launch.

EXHIBIT 12

Companies positioned themselves as AI far more often than they actually pivoted into AI



Both lines count events per half-year among the 19,104 companies examined for a possible product pivot. A first AI-positioning event is the earliest usable archived homepage with AI language in its title or heading. An actual pivot means the founding product did not depend on AI and a later flagship product would not exist without it.

Among companies examined for a possible pivot, first AI-positioning events rose sharply after 2022 and eased slightly in late 2025. Actual product pivots followed the same broad timing but remained far less common. A positioning event records a public claim; a pivot records a change in the product sold.

More than two in five companies with archived webpages have at some point described themselves as AI companies. The homepage label also misses companies whose products depend on AI: on their latest accessible homepages, only about half of AI-Native companies describe themselves as AI.

Among companies examined for a possible pivot, positioning claims outnumbered actual product pivots 19 to one in 2025H2. Even the real pivots were modest. Among the pivoting companies we could classify by problem area, nearly nine in ten stayed in the same area while changing how they addressed the problem.

How a company presents itself on its homepage tells us about its positioning. The layer it belongs to is determined by what it sells, as researched from the product itself.

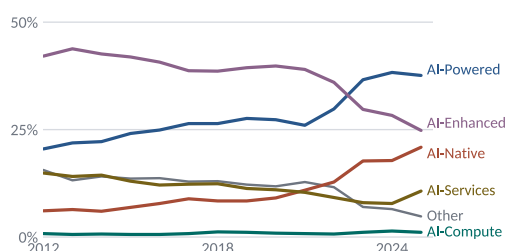
Where is this all headed?

AI-Native's venture funding reached \$286 billion in the year ending 2026Q1. Here, we track changes in who enters the sector, what they work on, where the jobs are, and how many companies are recorded as out of business or acquired.

(1) Who enters. New companies being founded are moving closer to the technology. As shown in **Exhibit 13**, AI-Native and AI-Powered took a growing share of each founding cohort, and gained momentum after ChatGPT's introduction. These two layers accounted for 43% of the 2022 cohort and 59% of the 2025 cohort.

EXHIBIT 13

AI-Native and AI-Powered take a growing share of new companies

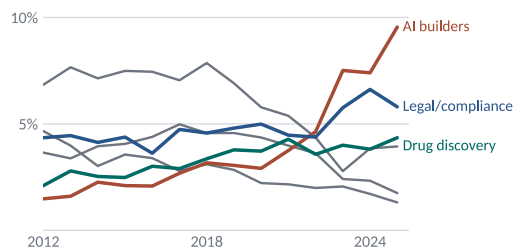


Lines are each layer's share of the classified companies founded that year, by what they sold at founding; the grey line is Other.

(2) What they work on. Companies serving AI builders rose from 1.5% of the 2012 cohort to 9.6% of the 2025 cohort, the largest increase among 25 problem areas (see **Exhibit 14**). Legal and compliance work and drug discovery ventures also gained share, while industrial monitoring, retail and healthcare treatment lost it.

EXHIBIT 14

Entrants shifted toward serving AI builders

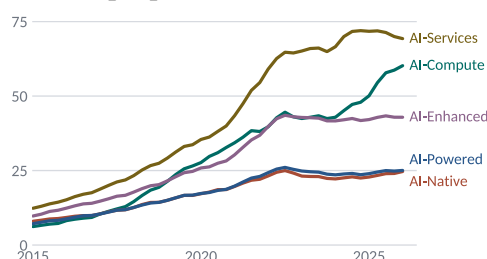


Each line shows a problem area's share of companies founded that year. The grey lines show industrial monitoring, retail, and healthcare treatment.

(3) Where the jobs are. The average AI-Native company remains relatively small: it employed about 25 people in 2026Q1, roughly unchanged since 2023. In contrast, as shown in **Exhibit 15**, the averages grew to 60 people in AI-Compute and 69 in AI-Services. Outside AI-Compute, hiring has settled below their respective 2022 peak levels.

EXHIBIT 15

The average AI-Native company stays near 25 people

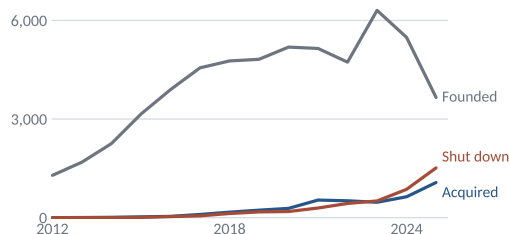


Average recorded employees per company active in the quarter, from Revelio professional profiles.

(4) Recorded shutdowns and acquisitions. PitchBook records 1,514 classified companies as newly "out of business" in 2025 and 1,069 as "acquired," figures that are more than twice the 2023 count in each case (see **Exhibit 16**). Also, new venture foundings have fallen significantly from their 2023 peak. AI-Services has the highest rate of exits and AI-Compute the lowest.

EXHIBIT 16

Shutdowns and acquisitions more than doubled since 2023



Shutdowns and acquisitions are counted in the year PitchBook lists for each company's current status. Recent founding totals may rise as PitchBook adds companies.

What should investors and managers do differently?

What we found is that a benchmark, a deal, a partnership, or a hiring plan built on the AI/ML label mixes five businesses. Each card below turns one set of findings into a decision; the evidence sits in the section named.

1. The four software and services layers have similar Seed to Series A rates, with differences in later outcomes

Every software layer reaches Series A within 24 months at about the same rate; the differences appear in the tails. AI-Native is recorded out of business about twice as often as AI-Enhanced and is only slightly more likely to reach \$100 million; AI-Compute stands apart on every measure (Section 7). Hence, one should benchmark cohorts by layer, not by one AI success rate.

2. Three companies took a third of recent AI venture capital

OpenAI, Anthropic and xAI received more than a third of recent AI venture capital. Within AI-Native, ten companies account for nearly three quarters of the layer's venture capital; the ten largest ventures outside AI account for less than 5% (Section 3). Hence, it is critical to highlight the layer and its largest fundraisers before using any aggregate AI-funding figures as a benchmark.

3. Federal grants follow private money and favor the applied layers

SBIR and STTR dollars run opposite to VC funding. Among grant recipients with a financing record, 62% raised private money *before* their first grant (Section 3). It is helpful to treat federal grants as a supplement to financing already under way, not as first money.

4. Hire and partner where the people are

AI-Powered and AI-Enhanced ventures provide about seven in ten of the 1.8 million jobs in the five layers; AI-Native, with about half of recent venture capital, holds fewer than one in ten and averages about 25 employees (Sections 4 and 9). No employer supplies more than a small share of founders. More than 40% of recent founders have founded a company before (Section 5). These findings suggest that one should recruit and partner from that wide base, and expect a second-time founder across the table.

5. Entry crowded the problems nearest the technology; the shakeout has begun

One company was founded after 2022 for every three that existed before, four times the rate outside AI founding. Products serving AI builders drew nearly three times that entry; healthcare, industrial safety and agriculture the least (Section 6). In Section 9, we document shutdowns and acquisitions, which have more than doubled recently. This suggests the beginning of consolidation based on the growing number of exits we documented.

6. An AI claim is a positioning signal; a pivot is a product change

Positioning claims outnumbered *actual* pivots 19-to-1 in 2025H2 (Section 8). Hence, it is important to weight a claim by the vendor's layer and test the product, not rely on the language and claims they use. Nine in ten actual pivots stayed in the same problem area, so it is useful to verify that the product and the customer problem changed before treating a company as a new entrant into that space.

What we now tell our students

The students' question that started this report has a short answer and a long one. The short answer is that "AI company" is not a single kind of company: the label the industry uses covers five distinct businesses. They are related yet share little in common — not their capital, not their customers, not their odds of success. The long answer is the 12 pages behind you.

So, when a student — or an investor, a partner, or a regulator — asks what kind of AI company they are looking at, we start with what it sells. If that does not settle the question, we ask: if AI is removed, is there still a product to sell? Depending on the answer, we look at whether the product category existed before modern AI or whether AI improves what remains. Together, those answers tell us which of the five businesses, if any, the company belongs to. The next time we hear a claim about "AI companies," we can ask whether it describes the business in front of us.

Technical note

Population. The starting population is PitchBook's Artificial Intelligence & Machine Learning vertical, which held 77,146 companies as of April 2026.

Product research. We ran Google Gemini 2.5 Flash in batch mode with public web search enabled on May 20, 2026, giving it each company's name and PitchBook-listed website. We asked for a factual account of the product, customer, use case, and revenue model, without restricting searches to the company website. The classifier received the resulting description, not Gemini's category suggestion.

Product classification. We ran Qwen3.5-397B-A17B locally in Q5_K_XL quantization at temperature 0 and gave it only the researched description. It answered five yes-or-no questions in order: whether revenue comes from human labor; whether the company sells computing purpose-built for AI; whether the product collapses without AI; whether its commercial category predates modern AI, using 2012 as the practical boundary; and whether AI materially improves a product that survives. Code mapped those answers deterministically to five layers or Other. The base cascade finished July 10, 2026, and an August v2.1 pass applied the purpose-built-compute question to an expanded candidate set. We applied no numeric quality-score cutoff; inclusion required a valid six-category output. To judge category age, we use the product category a buyer would name as a budget line. Companies near the 2012 boundary could reasonably fall in either AI-Native or AI-Powered.

Sample flow and selection. The 77,146 tagged companies form three mutually exclusive groups: 2,113 have no listed website; 9,376 have a website but no founding year or a year before 2012; and 65,657 entered product research. Research produced a valid category for 63,686 companies, no valid category for 1,970, and a parse error for 1. Among companies with websites, the retained 65,657 and excluded 9,376 differ sharply in founding year by design (standardized mean difference 2.16). The corresponding differences are -0.17 for log capital, -0.18 for any recorded financing, 0.01 for U.S. headquarters, -0.06 for recorded out of business, and -0.04 for unicorn status. These diagnostics describe selection; we do not extrapolate layer shares to excluded companies.

Human validation. A stratified validation study is under way in which research assistants answer the same five questions from the same descriptions. Coders answer questions rather than choose categories, and the code derives the human and model categories in the same order. This edition reports the model classifications; model-human and human-human agreement will be reported when coding is complete.

Category coverage. The classified population contains 620 AI-Compute companies, 7,422 AI-Native, 18,882 AI-Powered, 23,247 AI-Enhanced, 6,903 AI-Services, and 6,612 reported as Other.

Venture capital. Venture capital covers PitchBook Seed, Early Stage VC, and Later Stage VC rounds with reported capital. Allocation shares in the scorecard exclude Other and are normalized over the five layers. Exhibit 4 reports concentration within each layer. The venture panel in Exhibit 5 covers 2023Q1 through 2026Q1.

Federal grants. We link SBIR and STTR awards from SBIR.gov to PitchBook companies by website domain or a unique normalized company name, excluding the shared-name tier. Section 3 covers all award years in the August 2026 matched file for 950 companies

founded in 2012 or later across the five product layers; Other is excluded from the recipient count, dollar total, and normalized shares. Companies headquartered outside the United States have no awards by construction. Exhibit 5 presents separate descriptive distributions because the grant panel covers all award years while the venture panel begins in 2023Q1. The first-financing comparison uses PitchBook's recorded FirstFinancingDate and annual award dates, so timing is measured in years.

Founders. PitchBook names at least one founder for 52,543 classified companies. Revelio Labs provides work histories for founders of 44,102 of them, covering 82,162 unique people. Exhibit 8 contains 84,391 founder-company observations because a person appears once for each classified company they founded and can therefore appear in more than one layer or cohort. For each observation, we use the employer of the position that began most recently before the founding year. Spawning rates divide founder counts by all distinct people ever recorded at that employer. This denominator is a stock across all years, not a headcount, so the rate is relative rather than an annual hazard. For the cohort product-mix comparison, we restore each judged pivot to its founding-product layer and divide by all classified companies recorded as founded in that year: $n=1,502$ in 2012 and $n=3,836$ in 2025. Exhibit 8 uses 62,934 founder-company observations for companies founded in 2012–2022 and 21,457 for companies founded in 2023 or later. Stealth placeholders, incubators, and accelerator programs are excluded as prior employers.

Patents. Patenting links companies to U.S. patent documents from PatentsView, both granted patents and published applications, counting each invention once. Filings are complete through June 25, 2024. The scorecard reports the share of companies in each layer with at least one accepted linked filing.

Ownership. The cap-table measure counts PitchBook investor relations naming the six large public technology companies or their equity investment arms, including GV, CapitalG, Gradient Ventures, M12, the Amazon funds, and NVentures. Accelerator and startup programs such as Google Accelerator, Microsoft for Startups and NVIDIA Inception are excluded. Majority-owned means PitchBook records the holding as majority.

Homepage archive. We assembled 1,141,418 archived homepage versions from the Internet Archive, with a usable archive for 60,661 classified companies. We count a company as positioning when the lowercased page title, Open Graph title, or one of the first five H1 headings matches one of 14 case-insensitive patterns: AI; artificial intelligence; machine learning; deep learning; LLM, LLMs, or large language model; GPT with an optional hyphen and one digit; generative; agent, agents, or agentic; chatbot or chat bot; computer vision; NLP or natural language; neural; foundation model; and copilot or co-pilot. We apply no stemming or translation. We exclude duplicate www copies, captures with no readable content, pre-founding pages, parked domains, and error pages. Restricting matches to identity fields removes body boilerplate, but we do not apply a separate semantic false-positive classifier. Exhibit 12 assigns each candidate company to its first qualifying capture. Removing the language later does not erase that onset, and archive gaps mean the observed onset can follow the underlying wording change. Among companies founded in 2021 or earlier, the share of Other companies using AI positioning on their homepages rose 3.6 percentage points from 2022Q4 to 2026Q1.

Pivot coding. Two detectors screened the classified companies for candidate product changes, and we judged 19,104 candidates from founding-era product descriptions, researched company histories, and dated archived homepages. We used the 2,000 no-signal companies to audit detector misses; they are not candidates and do not enter either line in Exhibit 12. A pivot means the founding product did not rely on AI and a later flagship product would not exist without it. The reconciled master combines three successive coding rounds, with later review overriding earlier judgments for the same company. Exhibit 12 accepts exact single months and month ranges, places a range in its midpoint quarter, and includes only pivots whose intervals span at most two calendar quarters inclusively. We excluded 4 year-only or mixed-format intervals rather than imputing them to January. Of the 609 pivots in the chart window, 149 use a single recorded month, and 460 use a range midpoint. Of 1,217 actual-pivot companies whose two products were assigned by the problem-cluster procedure, 1,090 remained in the same cluster and 127 changed clusters. The judgments are machine-generated; human validation is pending.

Problem clusters. For 63,653 of the 63,686 classified companies, a language model produced a usable, structured problem statement that described the customer, the activity the product supports, and the problem it solves. We excluded the 33 companies without one and omitted AI and solution vocabulary from the statements. Qwen3-Embedding-8B converted them to normalized 4,096-dimensional vectors. MiniBatchKMeans formed 8,000 micro-clusters with a batch size of 4,096, three starts, and seed 42. We then used 50-component PCA and Ward linkage to form 25 groups, and TF-IDF unigrams and bigrams to label them. The groups range from 1,169 to 4,483 companies. For a blinded content audit, three independently prompted model coders each read 30 statements from companies founded by 2021 in every group, without seeing the labels or entry results. Their ratings on six domain dimensions produced a composite Krippendorff alpha of 0.966, which assesses prompt robustness rather than human validity. A partial build of 48,276 companies and the final build agree imperfectly on their shared companies (adjusted Rand index 0.35), but assigning companies to pre-2022 centroids preserves the same four highest- and three lowest-entry groups shown in Exhibit 10. Section 6 therefore treats the groups as a descriptive partition rather than a fixed taxonomy. The entry ratio divides companies founded after 2022 by those founded before 2023.

Employment. Employment uses Revelio Labs records covering roughly 6.2 million positions, excluding companies headquartered in China, South Korea, Japan, Russia, Taiwan and Hong Kong, where professional-profile coverage is thin.

Employment shares count 1,800,527 distinct people in current positions across 49,569 companies in the five layers; including Other gives 1,959,966 people across 54,998 companies.

Doctorates. Doctoral measures use the Revelio 202605 vintage and distinct people ever observed with any position at a sample company through the last complete quarter, 2026Q1, rather than current workers. The matched-worker denominators are 46,291 in AI-Compute, 359,552 in AI-Native, 973,834 in AI-Powered, 2,102,409 in AI-Enhanced, and 960,415 in AI-Services. A recorded PhD requires an education row whose degree equals Doctor. Where a person has more than one doctorate, we select the latest end date and then the school name for one institution. People without a recorded doctorate remain in the denominator, including those without an education record, so the percentages are recorded-doctorate shares rather than verified degree prevalence.

Venture benchmarks. We compute benchmark rates from the same April 2026 export, using the same deal types and complete-window rules as the AI figures. The primary benchmark covers the venture-backed universe excluding the 77,146 tagged companies. Five-layer seed cohorts run from January 2012 through April 9, 2024; first-financing cohorts run from January 2012 through October 9, 2023, for recorded out-of-business companies, and through April 8, 2023, for \$100 million valuation. We exclude 8 seed dates and 18 first-financing dates that precede the company's recorded founding year. The pre-2012 seed anomalies are a 2003 date for a company founded in 2023 and a 2011 date for a company founded in 2012; the first-financing anomalies are a 2009 date for a company founded in 2019 and a 2011 date for a company founded in 2013. Status is observed through April 9, 2026, and benchmark cohorts use the same cutoff dates. Entry-ratio benchmarks apply the same founding-year rules to the same populations. Patents carry no venture-wide benchmark because the PatentsView linkage covers only the AI universe.

Disclosure and acknowledgments. We drafted and revised this report with Anthropic's Claude, working from our own analyses, outlines, and successive edits. Every figure is built from project data and statistics files; we checked every claim against those files, and we alone are responsible for the contents. We thank the colleagues who commented on earlier drafts.

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