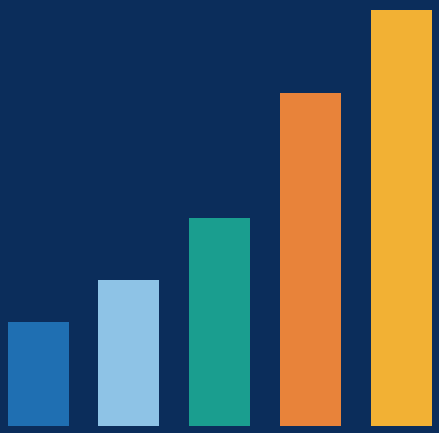
POLICY PAPER · FINANCIAL MARKETS AND GenAI

Depreciating Collateral

Technology risk in AI infrastructure debt and who holds it



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Data as of 7 November 2026.

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Key messages

The financing of AI infrastructure is moving from internal cash flows to debt markets.

Nine large hyperscalers issued USD 122 billion in bonds in 2025, almost half of global technology issuance (OECD, 2026a). Their share of global investment-grade bond issuance has risen from less than 1% to 10% since 2024 (IMF, 2026).

Much of this debt is secured on assets that can lose value much faster than real estate.

Around 60% of data centre investment goes to chips and computing hardware (McKinsey, 2025). New chip generations arrive roughly every year, while the debt that finances them has maturities of 3 to 23 years.

Technology risk can reach credit through five channels.

These are hardware obsolescence, revenue deflation, vendor financing, offtaker concentration and refinancing risk. Early evidence is mixed. H100 rental prices rose by about 44% between December 2025 and October 2026, while token prices fell by about 50% year on year, which points to margin pressure in the middle of the chain.

Credit markets started to reprice the risk in October 2026.

Yields on some neocloud bonds approached 15-16%, and these firms were effectively shut out of the bond market (WSJ, 2026a). Within the same ecosystem, the gap in borrowing costs between debt backed by an investment-grade supplier and unsecured debt ranges from about 4 to 10 percentage points.

Risk is moving from banks to insurers, pension funds and private credit funds.

Private credit to AI-related firms exceeds USD 200 billion and could reach USD 300-600 billion by 2030 (BIS, 2026a). In the euro area, insurers and pension funds would be the most affected sectors in a severe private credit shock.

Financial institutions depend on the same AI providers both as users and as creditors.

This double exposure may call for joint monitoring of third-party risk and credit risk. Leases signed but not yet commenced exceed USD 1.4 trillion at five companies alone, which makes consistent disclosure more important.

Executive summary

This paper examines how the technology cycle of artificial intelligence (AI) may affect the quality of the debt that finances AI infrastructure, and where in the financial system this risk accumulates. The paper does not assess whether AI equity valuations are excessive. Instead, it maps the transmission channels and exposures that are relevant however valuations evolve.

Investment needs are large and increasingly financed with debt

Global data centre capacity is estimated to require USD 6.7 trillion of investment by 2030 (McKinsey, 2025). According to the International Monetary Fund (IMF), around USD 2.9 trillion of investment expected by 2028 will be financed through a mix of cash flows, bank lending, private credit, public debt and securitisation (IMF, 2026). OECD analysis also shows that technology companies are becoming larger issuers in debt markets (OECD, 2026a).

The value of the collateral and the revenues that service the debt depend on technology

A large part of this debt is secured on hardware such as graphics processing units (GPUs) and tensor processing units (TPUs), whose value can fall with each new chip generation, or on long-term contracts with a few large buyers. At the same time, the rapid fall in token prices and the wider use of cheaper open-weight models put pressure on revenues at the end of the chain. Only about 6% of organisations report a material profit gain from AI (McKinsey, 2026).

Credit markets have started to price the risk, and the risk is moving outside banks

In October 2026, borrowing costs for some neoclouds rose sharply and their access to the bond market narrowed. Banks have started to transfer data centre loans to private credit funds, asset managers and insurers (CNBC, 2026a). As a result, risk may accumulate in less transparent institutions with long-term liabilities.

Transparency, data and joint monitoring are the main policy areas

Financial authorities should encourage more consistent disclosure of off-balance-sheet obligations linked to AI, drawing on the G20/OECD Principles of Corporate Governance. Supervisors could consider reviewing valuation assumptions for hardware collateral, measuring indirect exposures held through private credit funds and including AI scenarios in stress tests. The OECD can support this work through its comparative data and the Committee on Financial Markets.

1 The financing of AI investment is shifting from equity to debt

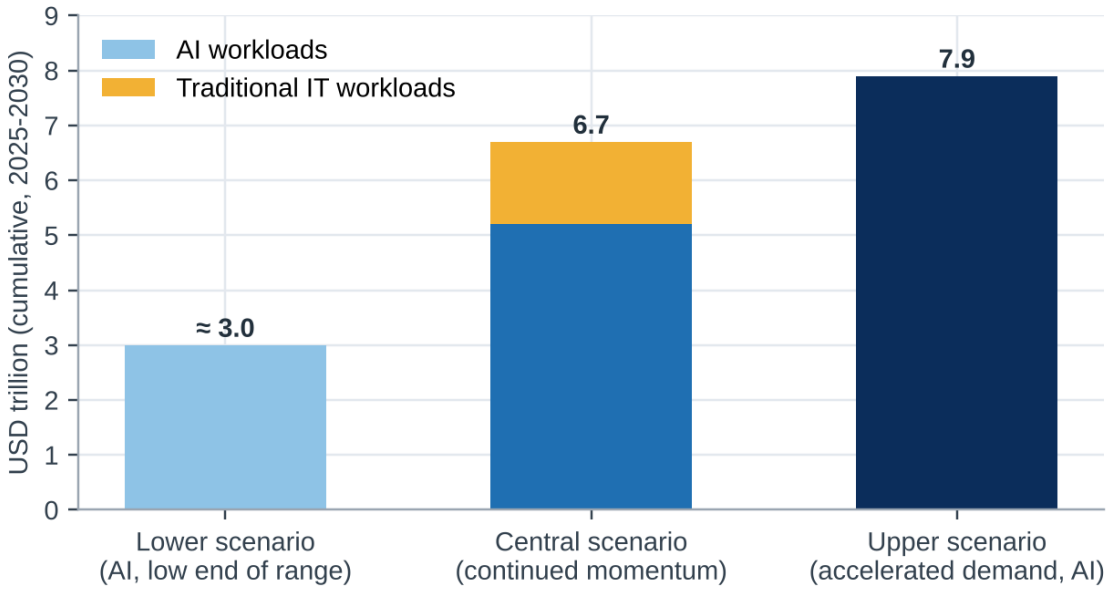
This chapter examines the scale of investment needed for AI infrastructure and the changes in how this investment is financed. It draws on data from the OECD, the IMF and McKinsey, and sets out the scope of the paper.

1.1. The scale of investment needs

Projected investment in data centres is far above recent levels of infrastructure spending. In the central scenario of McKinsey, total investment of USD 6.7 trillion is needed by 2030, of which USD 5.2 trillion is for AI workloads (Figure 1.1). Estimates across scenarios range from about USD 3 trillion to USD 8 trillion, which reflects high uncertainty about future AI demand.

The composition of this investment matters for credit risk. Around 60% of AI-related investment, or USD 3.1 trillion, goes to firms that produce chips and computing hardware (McKinsey, 2025). These assets can become obsolete much faster than buildings and energy infrastructure.

Figure 1.1. Data centre investment needs, 2025-2030



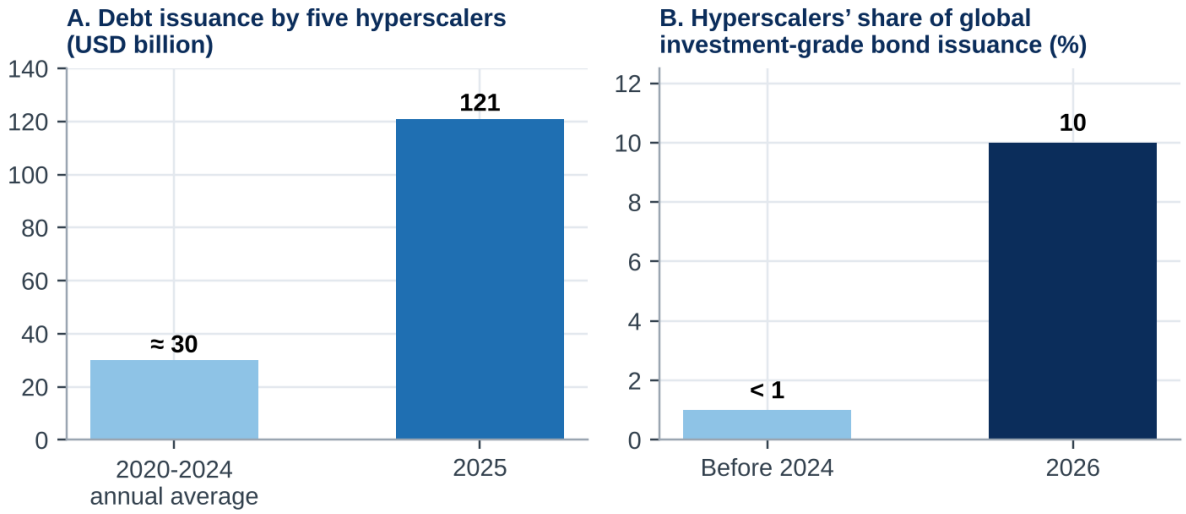
Note: The lower and upper scenarios cover AI workloads only. The value for the lower scenario is the approximate low end of the range reported by McKinsey.
Source: McKinsey (2025), *The cost of compute: A $7 trillion race to scale data centers*.

1.2. A growing weight in debt markets

Hyperscalers increasingly finance their investment with debt. According to the OECD *Global Debt Report 2026*, nine large hyperscalers issued USD 122 billion in bonds in 2025, and their planned capital expenditure for 2026-2030 reaches USD 4.1 trillion (OECD, 2026a). Data from Bank of America show that debt issuance by the five largest hyperscalers in 2025 was about four times the annual average of the previous five years (Figure 1.2, Panel A).

This trend also affects the structure of bond markets. The IMF reports that the share of hyperscalers in global investment-grade bond issuance has risen from less than 1% to 10% since 2024, while their free cash flow has declined (IMF, 2026). The *OECD Economic Outlook* notes that risks could be repriced if expected returns from AI do not materialise, and that forced sales by leveraged non-bank financial institutions could amplify this process (OECD, 2025).

Figure 1.2. Hyperscaler borrowing and weight in bond markets



Note: The 2020-2024 average in Panel A is derived from the statement that 2025 issuance was about four times the average of the previous five years. Panel A covers Amazon, Alphabet, Meta, Microsoft and Oracle.
Source: Panel A: Bank of America, via Fortune (2025). Panel B: IMF (2026), *Global Financial Stability Report*, October 2026.

1.3. Scope and structure of the paper

This paper focuses on how technology risk in AI infrastructure finance may turn into credit risk. Chapter 2 describes the financing chain. Chapter 3 examines five channels through which technology risk can reach credit. Chapter 4 reviews recent pricing in credit markets, Chapter 5 identifies who holds the risk and Chapter 6 discusses transparency and the double exposure of financial institutions. Chapter 7 presents policy considerations.

The paper does not forecast prices or defaults, and it does not assess the solvency of individual firms. Company names are used only as examples of transactions documented in public sources.

2 The financing chain and the nature of the collateral

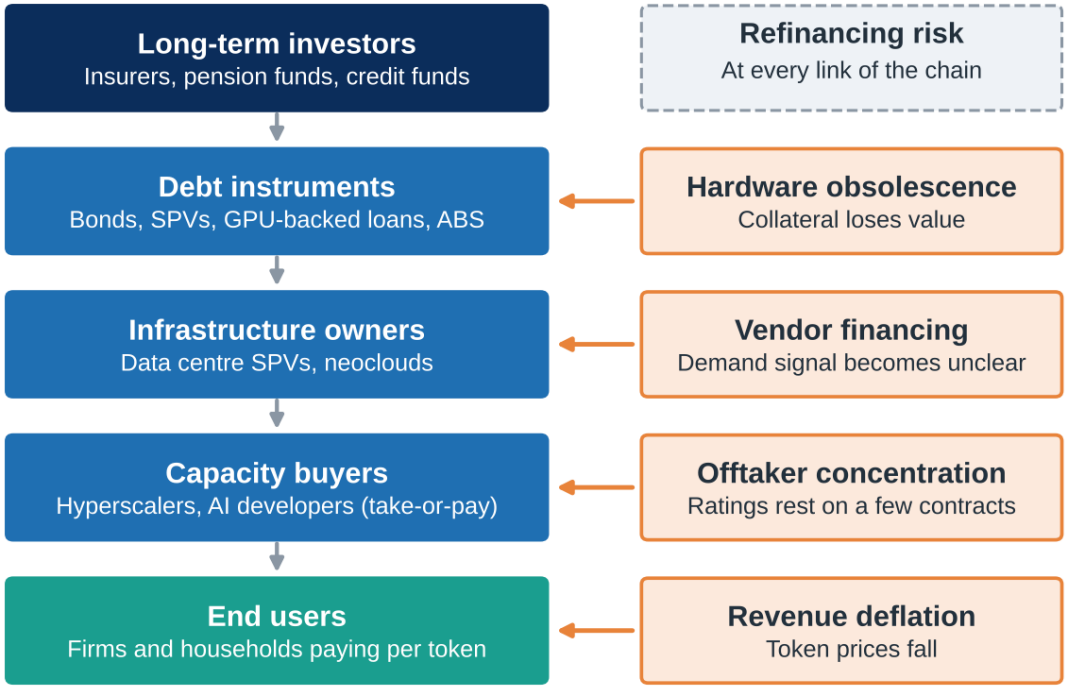
This chapter describes the path that funding for AI infrastructure follows, from long-term investors to end users. It draws on analysis by the Bank for International Settlements (BIS) and on one documented transaction.

2.1. A chain with five links

The financing of AI infrastructure can be described as a chain with five links (Figure 2.1). Long-term investors provide funds to data centre owners through instruments such as bonds, special purpose vehicles (SPVs) and credit funds. These assets are leased to hyperscalers and AI developers that buy capacity under long-term contracts. The whole chain ultimately depends on what end users pay for AI services.

The BIS finds that off-balance-sheet structures strengthen the links between hyperscalers and non-bank investors such as private credit vehicles and insurers (BIS, 2026b). The BIS also notes that the terms of these arrangements are often poorly disclosed, and that the same asset may be pledged as collateral more than once.

Figure 2.1. The AI infrastructure financing chain and points where risk enters



Funds flow down the chain; repayment flows back up from what end users pay.

Note: Orange boxes show where technology risk enters the chain. Refinancing risk can arise at every link.
Source: Author's analysis, based on BIS (2026a, 2026b).

Box 2.1. Key concepts

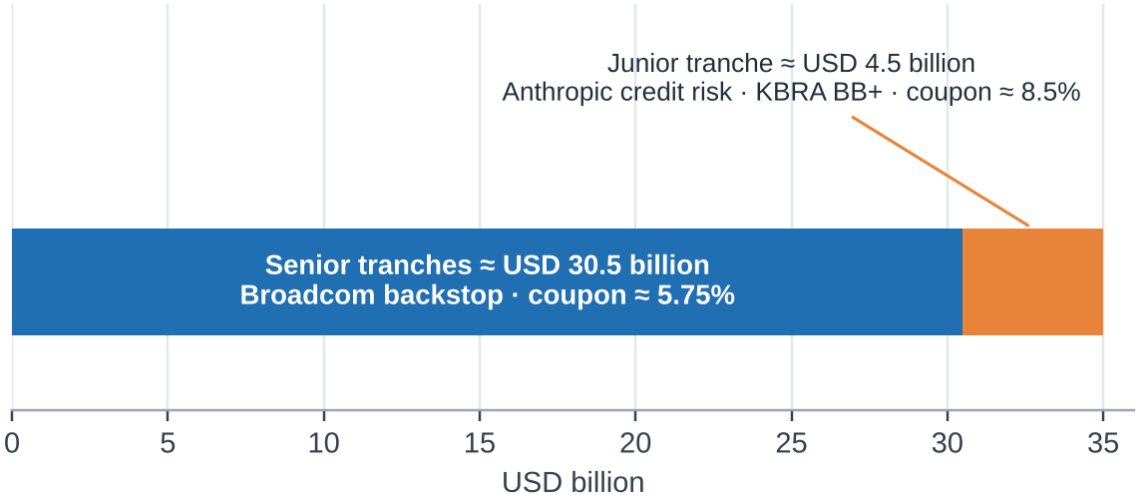
- **Special purpose vehicle (SPV):** a separate company set up to finance a single project. The debt sits on the balance sheet of the SPV, and the company that uses the project is usually only a tenant.
- **Take-or-pay contract:** a contract under which the buyer commits to pay whether or not it uses the capacity. Such contracts shift attention from the credit quality of the borrower to that of the buyer.
- **GPU-backed loan:** a loan secured on graphics processing units (GPUs) and related lease income.
- **Private credit:** lending to companies by investment funds rather than banks. Disclosure requirements are more limited than in public bond markets.
- **Neocloud:** a specialised cloud provider that rents out computing capacity, mostly on GPUs bought with borrowed money.

2.2. An example transaction: TPU lease financing

A transaction of about USD 35 billion closed in June 2026 shows several links of the chain in one structure (Figure 2.2). Private credit arranged by Apollo and Blackstone finances the purchase of Google-designed TPUs that are leased to Anthropic. Two senior tranches are backstopped by Broadcom, which co-develops the chips with Google, and carry a coupon of about 5.75%. A junior tranche of about USD 4.5 billion carries the credit risk of the tenant and was sold at about 8.5% (The Paypers, 2026).

The structure illustrates two points. First, the rating often depends on the credit quality of the guarantor or buyer rather than on the value of the collateral. KBRA rated the junior tranche BB+, based on limited information selected by the company (FT, 2026). Second, Broadcom's liability under the backstop is calculated as 85% of amounts outstanding minus the sale value of the hardware (Implicator, 2026a). The market value of the collateral therefore determines directly how losses would be shared.

Figure 2.2. Tranche structure of the TPU lease financing



Note: Amounts are approximate. Broadcom has also agreed to lend Anthropic up to USD 42 billion in convertible notes restricted to TPU lease payments; the Anthropic prospectus discloses this as a potential conflict of interest.
Source: The Paypers (2026); FT (2026), via Dealroom; Implicator (2026a).

3 Channels through which technology risk reaches credit

This chapter identifies five channels through which the features of AI technology may affect the quality of infrastructure debt. For each channel, it presents current evidence and the credit variables that could be measured.

Table 3.1. Five channels through which technology risk reaches credit

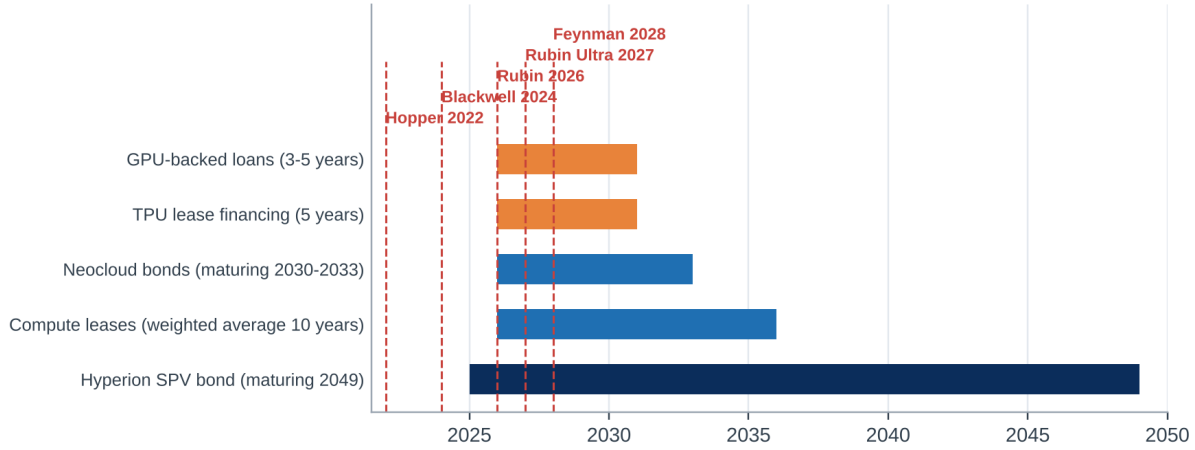
Channel	Mechanism	Variable to measure
Hardware obsolescence	New chip generations reduce the value of hardware used as collateral.	Loan maturity compared with economic life; loan-to-value ratio
Revenue deflation	Falling token prices and cheaper models reduce the revenues that service the debt.	Token price indices; debt service coverage ratio
Vendor financing	Chip suppliers finance or guarantee their own buyers, which makes the signal of end demand less clear.	Share of contracts with supplier financing or guarantees
Offtaker concentration	Ratings rest on contracts with a few large buyers.	Share of debt serviced by the five largest buyers
Refinancing	Borrowers must keep raising new debt; stress can start before collateral loses value if markets close.	Maturity profile; annual refinancing needs

Source: Author's analysis.

3.1. Hardware obsolescence

Debt maturities span several chip generations (Figure 3.1). Nvidia plans to release a new data centre chip about every year. By contrast, GPU-backed loans usually have maturities of three to five years, and some data centre SPV bonds run until 2049. One market analysis finds that the main risk in this type of financing has shifted from obtaining GPUs to managing their rapid obsolescence (ENKI, 2026).

Figure 3.1. Debt maturities and chip generations



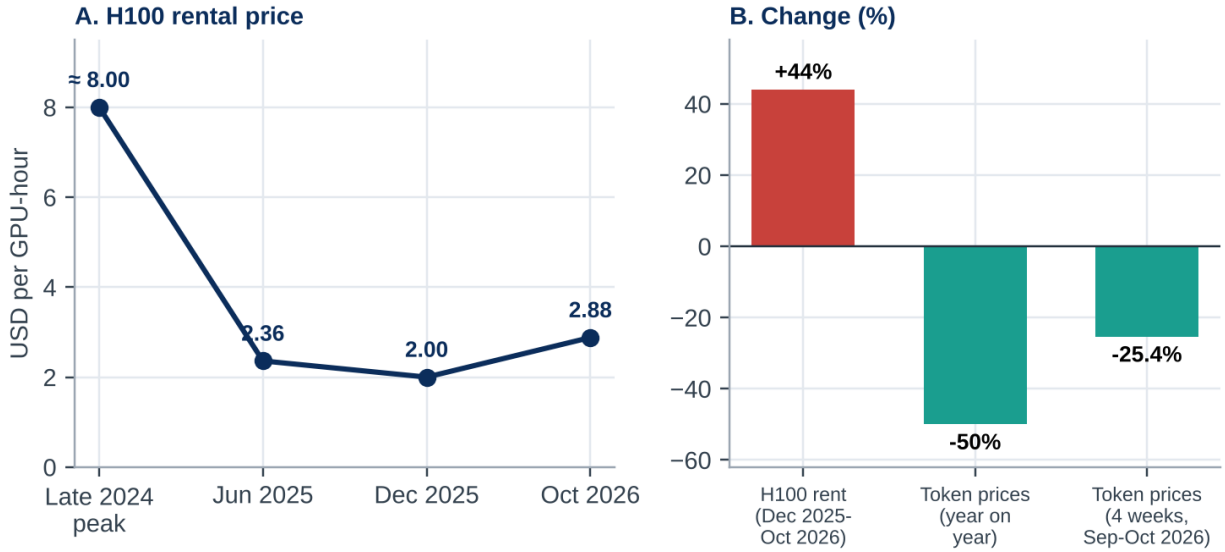
Note: Dashed lines show the release years of Nvidia data centre chip generations. Bars show the maturity ranges of documented transactions.
Source: Nvidia (2025); Steffen (2026); Anthropic (2026); Crypto Briefing (2026).

3.2. Revenue deflation and margin pressure

Rental prices and token prices are moving in opposite directions (Figure 3.2). The rental price of H100 GPUs fell sharply from its peak in late 2024 to mid-2025, but rose by about 44% between December 2025 and October 2026. Over the same period, token prices fell by about 50% year on year (FourWeekMBA, 2026a). This suggests that the value of the collateral has not collapsed, but that margins are narrowing for firms that rent hardware and sell tokens.

Price data have limited reliability. Different GPU price indices can show values up to eight times apart for the same chip (Implicator, 2026b), which makes it harder to verify the assumptions used to value collateral. Plans by CME and ICE to launch futures contracts on computing capacity could provide a more transparent price reference over time.

Figure 3.2. GPU rental prices and token prices

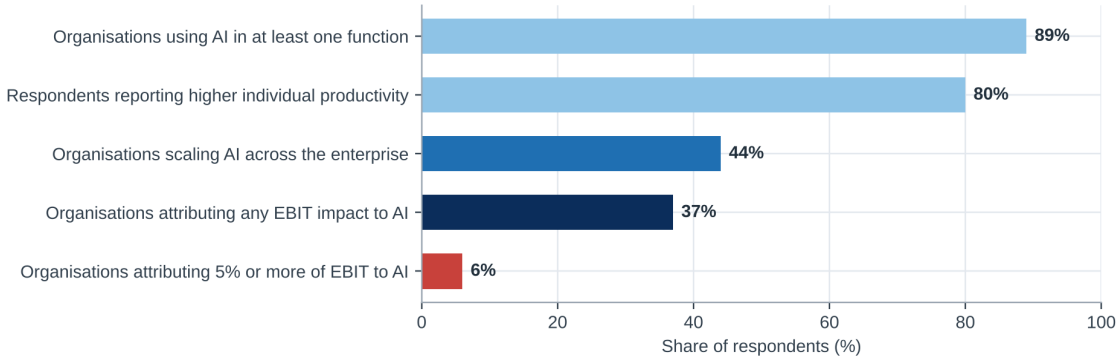


Note: The series in Panel A are compiled from different sources: the late 2024 peak is based on market listings, and other values on Silicon Data H100 indices. Changes in Panel B cover different periods.
Source: Introl (2025); Silicon Data; YipitData and Ramp AI Index, via FourWeekMBA (2026a).

3.3. Slow returns for enterprise users

Revenues at the end of the chain depend on the returns that enterprise users obtain from AI. In a McKinsey survey of 1 719 executives, 89% of organisations use AI, but only 37% attribute any impact on earnings before interest and taxes (EBIT) to it (Figure 3.3). The share of organisations attributing at least 5% of EBIT to AI stood at 6%, unchanged since 2025 (McKinsey, 2026). Users that cannot show a return may reduce spending or move to cheaper models.

Figure 3.3. AI use and profit impact



Note: The survey was conducted in May and June 2026 among 1 719 executives. Data are self-reported.
Source: McKinsey (2026), *The state of AI in 2026: On the road to ROI*.

3.4. Vendor financing

Chip suppliers increasingly finance or guarantee the firms that buy their products. According to summaries of IMF analysis, hyperscalers have channelled about USD 300 billion in equity and USD 650 billion in debt into weaker AI firms (IMF, 2026). Supplier-linked financing platforms are estimated at about USD 500 billion (Steffen, 2026). Such arrangements may make it harder to assess how much demand comes from independent customers.

3.5. Offtaker concentration and refinancing

Investment-grade ratings often rest on contracts with a few large buyers. For example, a USD 8.5 billion CoreWeave facility received an A3 rating on the strength of a hyperscaler contract, and Meta's Hyperion SPV carries USD 27 billion of A+ rated debt outside Meta's balance sheet (Steffen, 2026). A change in the credit quality of one buyer could therefore affect many debt instruments at the same time. In addition, most of these firms need to keep borrowing for years, so a loss of market access could cause stress before collateral loses value.

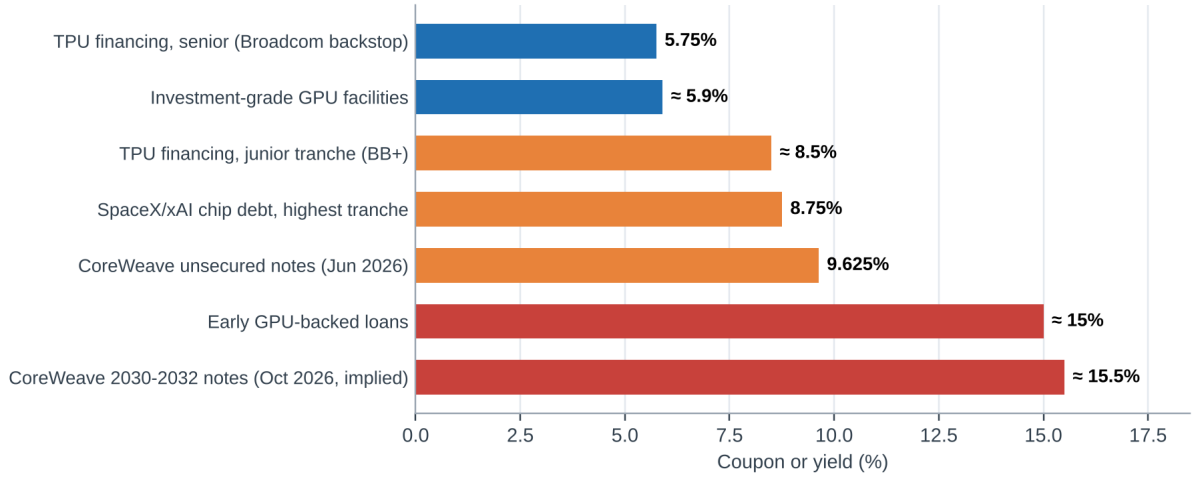
4 Credit markets have started to reprice the risk

This chapter examines the divergence in borrowing costs across the AI ecosystem and market developments in October and November 2026. It combines analysis by the IMF and the BIS with recent market data.

4.1. Borrowing costs are diverging

Borrowing costs within the same ecosystem differ widely depending on who stands behind the debt (Figure 4.1). Debt backed by an investment-grade supplier is priced at about 5.75%, while junior tranches stand at 8.5-8.75%. The cost of unsecured neocloud debt rose from 9.625% in June 2026 to an implied 15-16% in October 2026 (Crypto Briefing, 2026).

Figure 4.1. Borrowing costs across the AI ecosystem



Note: Values refer to different dates and instruments and should be read as indications of scale rather than direct comparisons. Blue: investment-grade guarantee or rating; orange: speculative grade; red: high stress.
Source: The Paypers (2026); Steffen (2026); Semafor (2026); TIKR (2026); Crypto Briefing (2026).

Box 4.1. A pricing gap between equity and credit markets

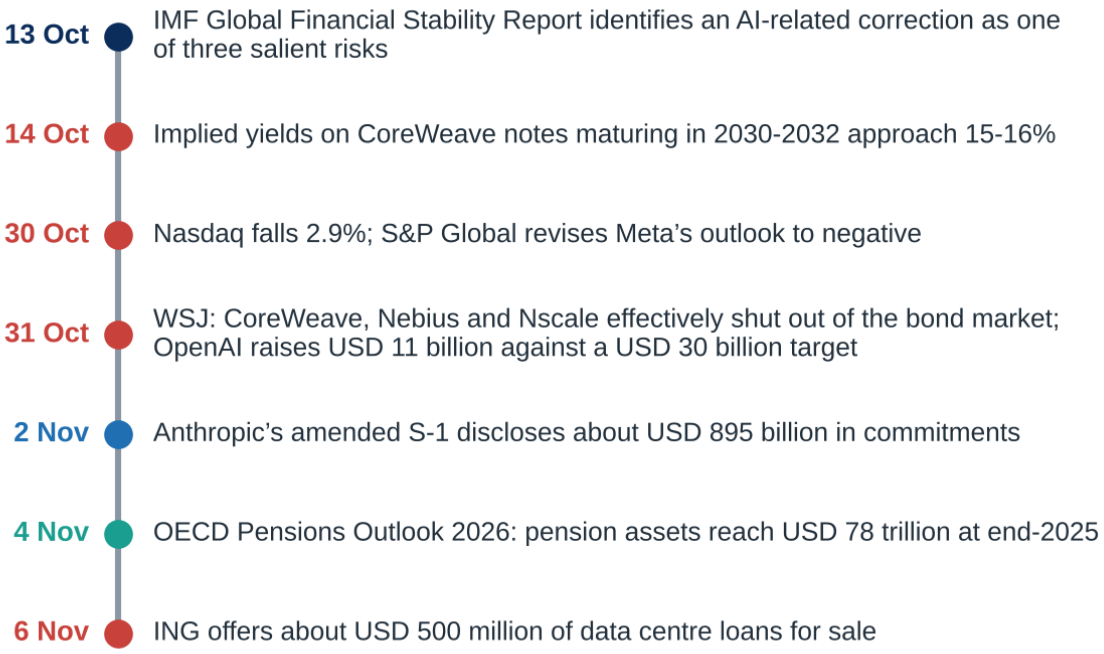
In early 2026, the BIS found that equity markets expected very strong earnings from AI, while private credit markets did not charge AI loans a clearly higher risk premium than other corporate loans (BIS, 2026a). Developments in October 2026 suggest that this gap has started to close for neoclouds. By contrast, some hyperscalers were still able to issue new bonds in the same period (Reuters, 2026). This indicates that markets are not treating the AI ecosystem as a single risk, but are differentiating by the strength of the borrower.

4.2. Developments in October and November 2026

Events since mid-October 2026 show the risk moving from equity to credit markets (Figure 4.2). The IMF identified an AI-related market correction as one of three salient risks to global financial stability (IMF, 2026). At the end of October, CoreWeave, Nebius and Nscale were effectively shut out of the bond market, and their shares fell by at least 30% during the month (WSJ, 2026a; CNBC, 2026b). In private funding markets, OpenAI raised about USD 11 billion against a target of USD 30 billion (WSJ, 2026b).

In the first week of November, ING offered about USD 500 million of data centre loans for sale. This illustrates a tendency for banks to transfer this risk to private credit funds, asset managers and insurers (CNBC, 2026a). Expectations that some US states may tighten permitting for data centre construction could also affect the financing of new projects (CNBC, 2026b).

Figure 4.2. Developments in October and November 2026



Source: IMF (2026); Crypto Briefing (2026); Reuters, via Investing.com; WSJ (2026a, 2026b); Anthropic (2026); OECD (2026d); CNBC (2026a).

5 Who holds the risk

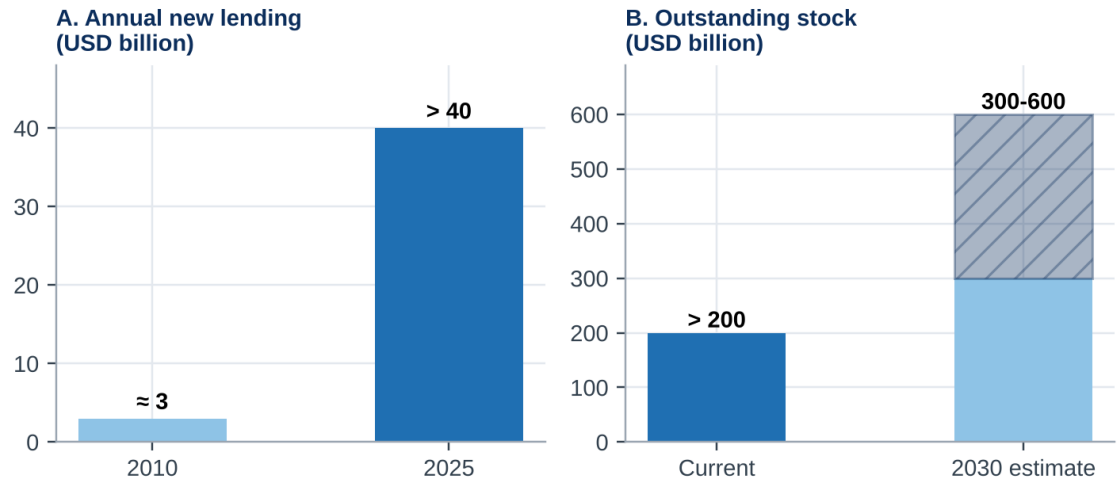
This chapter examines which institutions in the financial system hold AI infrastructure debt. It draws on data from the BIS, the European Insurance and Occupational Pensions Authority (EIOPA), the European Central Bank (ECB) and the OECD, and sets out the limits of current data.

5.1. A rapidly growing role for private credit

Private credit has become a main source of funding for AI infrastructure. According to the BIS, annual lending by private credit funds to AI-related firms rose from about USD 3 billion in 2010 to more than USD 40 billion in 2025 (Figure 5.1). The outstanding stock exceeds USD 200 billion, and the share of AI-related loans in private credit has risen from less than 1% to about 8%. This stock could reach USD 300-600 billion by 2030 (BIS, 2026a).

The direct role of banks has remained relatively limited, in part because capital rules may assign higher risk weights to fast-depreciating hardware collateral. However, indirect bank exposure is rising. The IMF reports that loans from US banks to non-bank financial institutions increased by 18% in 2026, and their exposures to private equity and private credit firms by 30% (IMF, 2026).

Figure 5.1. Private credit to AI-related firms



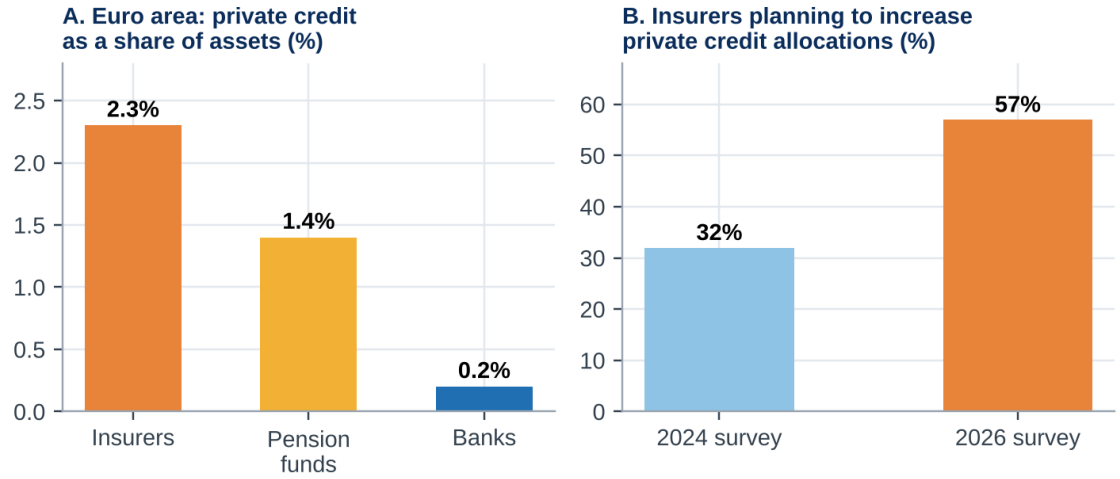
Note: The 2030 value in Panel B is an estimated range.
Source: BIS (2026a), *Financing the AI boom: from cash flows to debt*, BIS Bulletin No. 120.

5.2. Insurers and pension funds

Long-term investors such as insurers and pension funds are among the final holders of a large part of this debt. Private credit investments of EU insurers reached EUR 514 billion at the end of 2024, or 5.1% of their assets, while occupational pension funds held EUR 128 billion, or 4.4% (EIOPA, 2025). In the euro area, private credit accounts for 2.3% of assets for insurers, 1.4% for pension funds and 0.2% for banks (Figure 5.2, Panel A). An ECB stress exercise finds that insurers and pension funds would be the most affected sectors in a severe private credit shock (ECB, 2026).

Interest from these institutions continues to grow. In a 2026 survey, 57% of insurers plan to increase private credit allocations over the next 12 to 24 months, compared with 32% in 2024 (Mercer, 2026). OECD data show that pension assets reached USD 78 trillion at the end of 2025, or 106% of the combined GDP of OECD countries (OECD, 2026d). At this scale, even a small portfolio share can represent a large amount.

Figure 5.2. Insurers, pension funds and banks



Source: Panel A: ECB, via Beinsure (2026). Panel B: Mercer (2026), *Global Insurance Investments Survey*.

Box 5.1. A data gap

Current statistics measure private credit exposure in general, but do not show how much of it is linked to AI infrastructure. Insurers and pension funds often invest in these loans through funds, so identifying the AI-related share requires look-through data. The comparative data sets used in the OECD *Global Insurance Market Trends* and *Pensions Outlook* could provide a starting point for closing this gap (OECD, 2026d, 2026e).

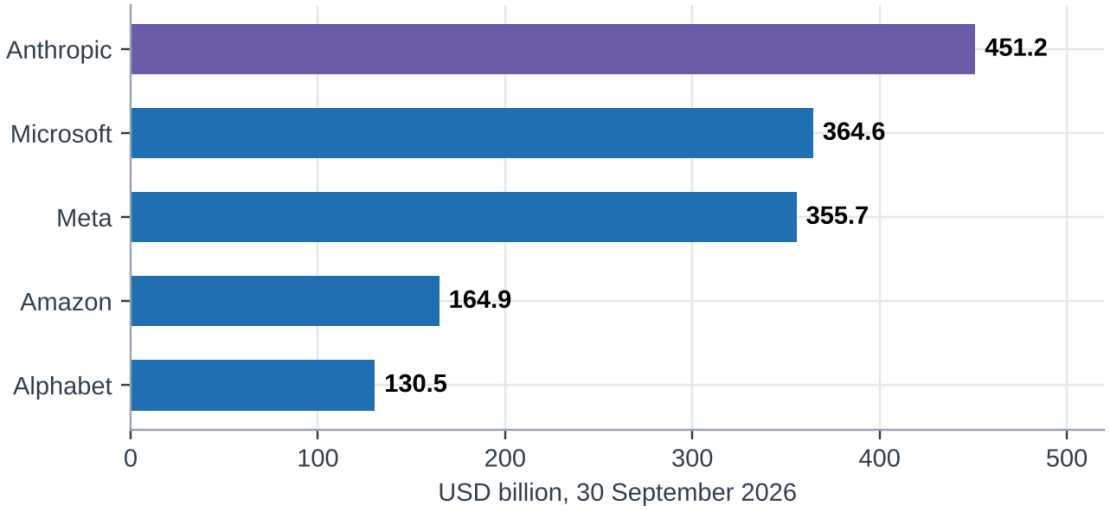
6 Transparency and the double exposure of financial institutions

This chapter examines the extent to which obligations linked to AI are disclosed, and how financial institutions are connected to the same AI providers in two different ways.

6.1. Off-balance-sheet obligations

Leases signed but not yet commenced appear in the notes rather than on the balance sheet, and the amounts are very large. At 30 September 2026, these obligations exceeded USD 1.4 trillion in total at five companies alone (Figure 6.1). Companies disclose the start dates, terms and cancellation conditions of these obligations in different ways, which makes it harder for investors to compare total leverage.

Figure 6.1. Leases signed but not yet commenced



Note: Each company measures this item under its own accounting policies; the value for Anthropic is an estimated undiscounted obligation.
Source: Company filings with the US Securities and Exchange Commission (Form S-1/A and Form 10-Q), compiled by FourWeekMBA (2026b).

Box 6.1. An example of disclosure: an IPO prospectus

The prospectus that Anthropic amended on 2 November 2026 is one of the first documents to set out in detail the obligations and resources of an AI developer. The main obligations table lists about USD 320 billion. Including leases not yet commenced and contracts signed later, total commitments reach about USD 895 billion. The same document reports liquidity of USD 146.6 billion and third-quarter revenue of about USD 17 billion, up about 47% on the previous quarter (Anthropic, 2026).

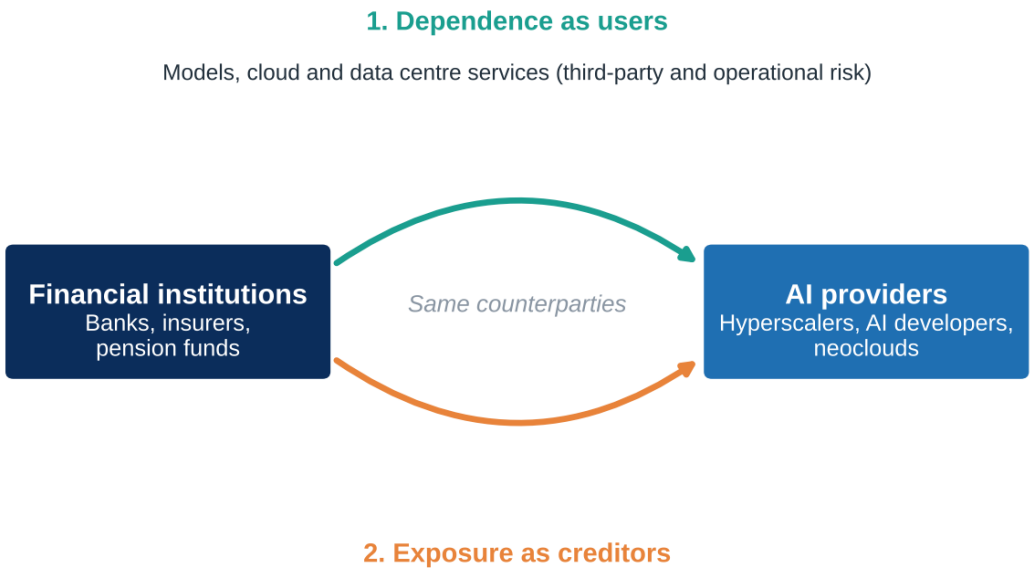
The example shows that more detailed disclosure makes the full size of obligations more visible. Comparable disclosure of the same items by other AI developers and infrastructure firms could help investors and supervisors in their assessments. This box does not assess the solvency of the company.

6.2. The double exposure of financial institutions

Financial institutions are connected to the same small group of AI providers in two ways (Figure 6.2). First, they use the models and cloud services of these firms. The OECD notes that supervisors see dependence on third-party AI providers that are outside the supervisory perimeter as a significant challenge (OECD, 2026b). Second, they hold the bonds, loans and securitised debt of the same firms, directly or through funds.

These two exposures are usually monitored by different units and under different frameworks. In early 2026, the ECB started to review both bank lending to the AI sector and banks' use of GenAI, which shows that the two dimensions can be considered together (Bloomberg, 2026). Financial distress at one provider could lead at the same time to service disruption and to credit losses.

Figure 6.2. The double exposure of financial institutions



Source: Author's analysis, based on OECD (2026b) and ECB practice.

7 Policy considerations

This chapter presents policy options for the risk channels identified in previous chapters. Considerations are expressed more firmly where they draw on existing OECD standards, and as options for discussion elsewhere.

Taken together, the five risk channels and five policy tools show that disclosure and stress testing have the widest coverage (Figure 7.1). The considerations below are intended for discussion in the OECD Committee on Financial Markets.

Figure 7.1. Risk channels and policy tools

	Disclosure	Collateral valuation	Look-through data	Stress testing	Third-party oversight
Hardware obsolescence	Supporting	Core tool	Supporting	Core tool	
Vendor financing	Core tool	Supporting	Supporting	Supporting	Supporting
Offtaker concentration	Core tool		Core tool	Core tool	Core tool
Revenue deflation	Supporting	Supporting		Core tool	
Refinancing	Supporting		Core tool	Core tool	Supporting

Note: "Core tool" shows tools that can address a channel directly; "supporting" shows tools that contribute indirectly.
Source: Author's analysis.

Strengthen disclosure of off-balance-sheet obligations linked to AI

Leases not yet commenced, take-or-pay commitments and SPV obligations are disclosed in different ways across companies. In line with the principles on disclosure of material information in the G20/OECD Principles of Corporate Governance, financial authorities should encourage comparable disclosure of these obligations (OECD, 2023b).

Review valuation assumptions for hardware collateral

Loan maturities span several chip generations, and price indices differ widely. Supervisors could consider comparing the economic life assumptions that lenders and institutional investors use for GPU and TPU collateral with observed chip cycles.

Improve look-through data

The AI-related exposure that insurers and pension funds hold through private credit funds cannot be measured today. Supervisors and statistical agencies could consider identifying this exposure within existing reporting frameworks. The OECD could support this work through its comparative insurance and pension data.

Include AI scenarios in stress tests

The *OECD Economic Outlook* has called for stress tests that model a sharp correction in AI valuations (OECD, 2026c). Financial authorities could consider extending AI scenarios beyond equity price falls to credit channels such as hardware depreciation, falling token prices and refinancing difficulties.

Monitor user and creditor exposures together

The same AI providers act both as critical third-party suppliers and as borrowers. Within their mandates, supervisors may wish to assess third-party risk oversight and credit risk monitoring together for the same counterparties.

Monitor access by retail investors

Some semi-liquid funds open to retail investors buy data centre loans. Market supervisors may wish to review whether existing rules on liquidity mismatch and risk disclosure are adequate for these products.

Limitations and further work

This paper relies mainly on public reports, company filings and press coverage. Some figures were obtained through secondary sources, and this is indicated in the relevant figure notes. Further work could extend the inventory of documented transactions, classify each transaction by the five channels and prepare simple sensitivity scenarios for representative transactions.

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Annex A. Research design

This annex summarises the research design of the study.

Table A.1. Components of the research design

Component	Description
Research question	How does the technology cycle of AI affect the quality of the debt that finances AI infrastructure, and where in the financial system does this risk accumulate?
Type of research	Descriptive and exploratory policy analysis; a mixed-methods design that does not forecast.
Unit of analysis	Documented AI infrastructure financing transactions and the types of institutions that are party to them.
Data sources	Reports of international organisations (OECD, IMF, BIS, EIOPA, ECB); company filings with the US Securities and Exchange Commission; rating agency publications; industry surveys; financial press.
Method	1) Document analysis; 2) transaction inventory and content coding by the five channels; 3) simple sensitivity scenarios for representative transactions; 4) mapping of exposures by type of institution.
Validity and reliability	Verification of each figure against a primary source; comparison of several sources (triangulation); clear identification of secondary sources.
Limitations	Limited transparency of private credit data; self-reported surveys; differences between GPU price indices; rapidly changing market conditions.
Ethics	Only publicly available data are used; no assessment of the solvency of individual firms is made; the use of an AI tool is disclosed in Annex B.

Annex B. Note on preparation

Claude, an AI assistant developed by Anthropic, was used for the literature search, drafting and preparation of the figures in this study. Anthropic is an AI developer and a buyer of computing capacity within the ecosystem examined in this paper. Examples involving the company are therefore based only on public filings and independent news sources, and are presented using the same criteria as for other companies. Responsibility for the figures and interpretations lies with the author.