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GLOBAL AI GOVERNANCE RESEARCH CENTER

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Toward Measuring AI Infrastructure Investment and Economic Resilience Across Ten Economies:

Financing Architectures, Capital Formation, and Deployment Timing

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Abstract

Countries are expanding AI infrastructure through markedly different combinations of public and private capital, yet cross-country assessment is complicated by inconsistent investment accounting, incomplete national coverage, and the lag between expenditure and usable capacity. This study compares financing architectures across ten economies: the United States, United Kingdom, Canada, Japan, South Korea, Germany, France, Singapore, China, and India. Public AI Infrastructure Investment Share (PAIIS), Private AI Infrastructure Investment Share (PrAIIS), and AI infrastructure investment intensity (AI-IIS) are treated as bounded measurement concepts rather than presently comparable national statistics. The analysis distinguishes source quality, realization status, AI specificity, accounting basis, capital-formation eligibility, and deployment timing. Qualifying AI-specific realized monetary records are available from five economies, but national coverage remains incomplete and several records combine capital and operating expenditure. France provides completed-project funding with unresolved payment timing; Germany and Singapore provide procurement evidence; China provides realized broader-compute CAPEX that is too broad for an AI-only numerator; and India reports mission-wide expenditure without an infrastructure-specific split. The study therefore compares financing architecture, monetary evidence, and deployment timing rather than constructing national investment rankings. Macroeconomic and labor-market indicators are reported only as descriptive context. The findings show that scope, accounting treatment, realization status, deployment timing, and coverage must be aligned before meaningful cross-country investment comparisons or subsequent resilience analysis can be undertaken.

Keywords: AI infrastructure investment; public-private financing; investment measurement; AI compute; capital formation; deployment lag; cross-country comparison; economic resilience

1. Introduction

Artificial intelligence is increasingly a physical-capital system as well as a software technology. Frontier models and AI-enabled services depend on data centers, advanced accelerators, high-capacity networks, reliable electricity, cooling, and the financial arrangements required to build and operate them at scale. These requirements make AI infrastructure a strategic investment problem under conditions of geopolitical, supply-chain, energy, and macroeconomic disruption. Yet countries are not building this capacity through a common model. Some rely primarily on private hyperscale investment, others use direct public procurement or public compute, and others combine subsidies, policy finance, public demand aggregation, and private deployment. The resulting variation raises a question that is more important than whether a country simply invests more: whether different public and private investment structures create different pathways from capital formation to usable AI capacity and, ultimately, to economic resilience.

This paper therefore treats the scale and the structure of AI infrastructure investment as analytically distinct. AI infrastructure investment intensity captures the size of qualifying investment relative to the economy only when the investment flow and GDP denominator are matched to the same period. Public AI Infrastructure Investment Share (PAIIS) and Private AI Infrastructure Investment Share (PrAIIS) identify who bears the capital cost when a defensible financing denominator can be constructed. The conceptual expectation is not that a higher public or private share is mechanically superior. Public capital may absorb risk, coordinate strategic capacity, widen access, or accelerate infrastructure that markets would underprovide, while private capital may contribute speed, operating expertise, commercial discipline, and scaling capacity. The relevant question is how these configurations are converted into operating capability and, subsequently, resilience-relevant economic outcomes.

A direct cross-country test, however, encounters a serious measurement problem. AI infrastructure is disclosed through announcements, multi-year commitments, procurement ceilings, subsidies, financing packages, company capital expenditure, permitting records, tax-incentive programs, and completed facilities. These are not equivalent economic quantities. An announced data-center campus is not realized expenditure; a financing package is not necessarily capital already spent; a government subsidy does not imply that an entire project is publicly financed; and a mixed-use data center cannot automatically be treated as AI-specific. Without explicit measurement boundaries, apparent national comparisons can combine different stages, different accounting bases, and different levels of geographic or AI attribution.

Timing creates a second problem. Infrastructure expenditure can affect capital formation during construction and equipment acquisition, while AI-specific productivity and resilience effects require usable compute capacity to be installed, integrated, and available to firms, researchers, or public agencies. The two stages can occur in different years. South Korea's 2025 government GPU program, for example, records substantial expenditure before broad service activation mainly in March–April 2026 (National Assembly Budget Office [NABO], 2026). This implies that AI infrastructure expenditure in year t is not automatically AI capability exposure in year t. Deployment lag must therefore be treated as part of the mechanism rather than as a minor data limitation.

The study addresses these substantive and measurement problems through a comparison of the United States, United Kingdom, Canada, Japan, South Korea, Germany, France, Singapore, China, and India. All ten economies enter the financing-architecture and descriptive outcome comparison, while the monetary evidence is narrower. Qualifying AI-specific realized records are available from five economies, and those records still differ in national coverage and capital-formation eligibility. National PAIIS and PrAIIS estimates require complete financing denominators, while cross-country AI-IIS requires matched periods, accounting bases, cost composition, and coverage. The monetary comparison therefore includes only records for which realization, AI attribution, location, accounting treatment, and capital-formation eligibility can be stated clearly.

The paper makes three contributions. First, it develops a comparative framework for describing public-private AI infrastructure financing architectures without assuming that headline investment figures are commensurable. Second, it provides a reproducible approach that separates source quality, realization status, AI scope, accounting treatment, and deployment timing. Third, it places those architectures alongside descriptive macroeconomic and labor-market context while reserving shock-specific resilience testing for future post-operational analysis.

2. Literature Review and Analytical Framework

2.1 AI as a General-Purpose Technology and a Physical Infrastructure System

The literature on general-purpose technologies (GPTs) provides a useful starting point. GPTs are pervasive, improve over time, and generate complementarities with downstream innovation (Bresnahan & Trajtenberg, 1995). AI fits this logic because its economic value depends on complementary investment by firms, workers, and institutions. The Productivity J-Curve further shows that such investment can precede measured productivity gains (Brynjolfsson et al., 2021). AI-infrastructure expenditure should therefore not be interpreted as producing contemporaneous output effects.

The GPT perspective must also be connected to AI's physical intensity. Advanced machine learning requires large compute, networking, cooling, and energy systems, and compute requirements have risen rapidly (Sevilla et al., 2022). The associated electricity and cooling demands make infrastructure location and efficiency economically relevant (Lannelongue et al., 2021; de Vries, 2023). AI infrastructure is therefore not only an intangible complementary asset but also a capital-intensive physical system whose availability can be constrained by hardware, grids, construction, and operating capacity.

Evidence on AI use further illustrates the distinction between capability availability and infrastructure formation. Experimental work shows that generative AI can raise task-level productivity once workers have access to functioning systems (Noy & Zhang, 2023). Such evidence is important for the downstream productivity channel, but it does not imply that upstream infrastructure expenditure generates productivity gains contemporaneously. The analytical bridge between the two literatures is therefore sequential: infrastructure investment creates or expands usable capacity; firms and workers subsequently adopt that capacity; and productivity effects emerge through use and organizational adjustment.

2.2 Public Capital, Private Investment, and Strategic Industrial Policy

AI-infrastructure financing sits at the intersection of public-capital, private-investment, and industrial-policy research. Public infrastructure can raise private output, although estimated effects vary by capital type and empirical design (Bom & Ligthart, 2014), and recent evidence suggests public investment can crowd in complementary private investment over longer horizons (Matvejevs & Tkacevs, 2025). These findings justify treating public and private AI investment as potentially complementary rather than mechanically substitutive.

Institutional form also matters. Public-private arrangements redistribute risks and obligations rather than eliminating them (Engel et al., 2013), while industrial-policy effectiveness depends on design and implementation (Juhasz et al., 2024). The analysis therefore separates the sector bearing capital cost from the infrastructure operator and from enabling policies such as tax incentives or workforce support.

This separation is necessary for PAIIS and PrAIIS because grants, procurement, tax incentives, public loans, private equity, and operating obligations perform different financing functions and should not be pooled automatically.

2.3 Economic Resilience, Innovation, and Digital Infrastructure

Economic-resilience research provides a second foundation. Evolutionary approaches treat resilience as resistance, recovery, adaptation, and possible transformation rather than a simple return to a pre-shock equilibrium (Simmie & Martin, 2010; Martin, 2012; Martin & Sunley, 2015). This multidimensional view supports distinguishing productive from socioeconomic outcomes instead of collapsing them into a single index.

Measurement studies similarly distinguish resistance and recovery across shocks and connect innovation capacity to adaptive resilience (Sensier et al., 2016; Bristow & Healy, 2018). They reinforce the need for shock-specific baselines and trajectories before an indicator can be interpreted as resilience.

Recent empirical work links digital infrastructure to resilience more directly. Studies using Chinese city and firm data find positive associations between digital infrastructure and urban or firm resilience under external shocks (Zhang, Yang, & He, 2023; Guo, 2025). These results motivate the present analysis but do not resolve whether AI-specific physical infrastructure, financing architecture, or deployment timing produces similar effects across countries.

2.4 Deployment Lags, Complementary Investment, and the Research Gap

The distinction between expenditure and productive availability has a long macroeconomic foundation. Time-to-build models allow capital spending to precede entry into the usable capital stock (Kydland & Prescott, 1982), while the Productivity J-Curve places complementary investment before observable gains (Brynjolfsson et al., 2021). For AI infrastructure, the relevant sequence is expenditure, construction and integration, service activation, adoption, and only then broader economic transmission.

Timing is therefore not ordinary missing data: an accurate 2025 expenditure can still be the wrong measure of 2025 AI-capability exposure if the associated capacity enters service in 2026. Expenditure and activation dates are coded separately.

The literature leaves a specific gap: existing work explains complementary investment, public-private financing, resilience, and deployment lags separately, but does not provide a cross-country framework that connects financing structure to verified AI infrastructure formation, operational capacity, and productive versus socioeconomic resilience while preserving evidence boundaries.

2.5 Integrated Framework: Financing, Deployment, and Resilience

The integrated framework treats financing structure as an upstream condition. Public and private actors bear different costs and risks across deployment stages, affecting location, access, and activation speed. The analytical sequence is financing structure, qualifying monetary evidence and capital formation where identifiable, operationalization, AI capacity, productive effects, and socioeconomic transmission. Spending totals and financing shares therefore have limited meaning without evidence on conversion and timing.

2.6 Public-Private Financing Architecture

The financing component distinguishes direct procurement, grants, and public-capital contributions from corporate capital, private debt, and private equity. Tax incentives, guarantees, workforce support, and enabling infrastructure are tracked separately unless an actual asset-linked public outlay is documented. This permits architecture comparison even without national public/private shares: Japan combines subsidies with corporate capital; South Korea combines public acquisition with private operation; and the United States relies primarily on private hyperscale capital with decentralized public enabling measures.

2.7 Productive and Socioeconomic Resilience

Economic resilience is treated conceptually as multidimensional. Productive resilience concerns resistance, recovery, and adaptation in output and productivity under disruption, whereas socioeconomic resilience concerns employment and distributional conditions. Because the present cross-sectional outcome layer lacks a common shock, pre-shock baseline, and recovery path, GDP growth and volatility, employment-to-population, and youth-unemployment indicators are used as descriptive economic context rather than as direct resilience measures (International Monetary Fund [IMF], 2026; OECD, 2026a, 2026b; World Bank, 2026a, 2026b). This distinction follows the resilience literature's emphasis on resistance, recovery, adaptation, and longer-run transformation (Martin, 2012; Martin & Sunley, 2015; Sensier et al., 2016).

The standardized outcome composites are not national resilience indices. They only make recent macroeconomic and labor-market divergence visible. Whether productive effects precede socioeconomic effects remains a conceptual expectation for later longitudinal testing, not a causal finding of this study.

2.8 Research Questions and Conceptual Expectations

RQ1. How do public-private AI infrastructure financing architectures differ across the ten selected economies, and what roles do public capital, private capital, and enabling policy play in capacity formation?

RQ2. To what extent can AI-IIS, PAIIS, and PrAIIS be measured comparably when investment periods, accounting status, national denominators, and financing disclosure remain incomplete?

RQ3. What descriptive macroeconomic and labor-market positions characterized the ten selected economies during 2023–2025, without attributing those positions to AI infrastructure investment?

RQ4. How do deployment lags and capability activation condition the interpretation of contemporaneous relationships between AI infrastructure expenditure and descriptive economic outcomes?

Investment scale alone is unlikely to characterize AI infrastructure strategy because financing architecture shapes how capital is mobilized and converted into usable capacity.

Public-private arrangements may combine public risk absorption and coordination with private deployment and operating capability, but their economic significance depends on successful and timely operationalization rather than financing shares alone.

Productive effects may also emerge before broader socioeconomic effects if infrastructure and AI capabilities diffuse through production and organizational systems before appearing in employment, wages, and distribution. These expectations guide interpretation rather than serving as hypotheses tested with the present cross-section.

3. Methods

3.1 Research Design and Country Coverage

This study uses a comparative cross-country design with three analytical components: a ten-country comparison of public-private AI infrastructure financing architectures; project- or program-level financing measures when the relevant denominators and periods can be identified; and record-level monetary evidence that distinguishes realized expenditure from contracts, budgets, commitments, and announcements. This structure permits institutional comparison without converting incomplete disclosure into artificial national scores or capital-formation estimates.

The analysis covers the United States, United Kingdom, Canada, Japan, South Korea, Germany, France, Singapore, China, and India. The cases were selected to span distinct financing architectures, major geographic regions, and different state-market configurations while allowing each monetary observation to be verified at the 19 August 2026 data freeze. Inclusion required at least one official or first-party source documenting an AI-infrastructure project, program, financing mechanism, or operating arrangement. Monetary observations additionally required a project- or program-specific amount with identifiable accounting status and scope. Source, scope, timing, accounting, inclusion, and deduplication information were recorded for each observation.

Case selection followed two criteria: institutional distinctiveness and documentary traceability. Each case added a substantively different financing or operating configuration, such as private-led hyperscale deployment, publicly funded national compute, catalytic contribution programs, subsidy-leveraged private capacity, state-coordinated operator investment, or mission-based shared compute. Each case also required at least one traceable source with a defined project or program object, date, scope, and accounting status. Country inclusion did not require a fully realized AI-specific monetary amount because that threshold would bias the institutional comparison toward jurisdictions with unusually transparent accounts. Quantitative comparisons were therefore restricted to observations that met the stricter monetary requirements described below.

3.2 Classification of Investment Evidence

The evidence assessment separates source quality, realization status, AI specificity, and accounting basis. Sources range from audited public accounts and annual reports to official project documentation and, where unavoidable, secondary mirrors. Monetary amounts are distinguished according to whether they represent actual expenditure, outturn, payment, accepted CAPEX, or final execution; completed or operational project funding with unresolved payment timing; executed contracts or procurement awards; budgets, revised estimates, or commitments; or announcements and plans. Scope is assessed separately as AI-specific, mission-wide, broader-compute, mixed-use AI/HPC, or unknown. Accounting treatment further distinguishes cash outturn, payment-basis CAPEX, acceptance-basis CAPEX, company-reported actual investment, incurred project cost, program execution, completed-project funding, procurement awards, revised estimates, and mission-wide expenditure. A realized amount can therefore still be excluded from an AI-infrastructure numerator when its scope is too broad.

A record was treated as realized AI-specific monetary evidence when three conditions were met. First, the amount had to represent realized expenditure, outturn, accepted or paid CAPEX, or a government-verified incurred or final program cost rather than a plan or contract-only figure. Second, the spending had to be attributable to qualifying AI infrastructure. Third, it had to be assigned to the country in which the physical infrastructure was located. This three-part screen prevented global corporate CAPEX or mixed-use data-center announcements from being treated as national AI investment. Meeting these conditions established realization and scope, but did not imply that the full amount represented capital formation.

Capital-formation eligibility was assessed separately as CAPEX-only, mixed CAPEX/OPEX, or unknown. Realized monetary evidence is not automatically realized capital investment. SoftBank's selected acceptance-basis record and the Chinese operator records were explicitly reported as CAPEX, whereas the Korean GPU-program execution included hardware, integration, and multi-year operating-cost support. The Canadian contribution records covered procurement and operation, and the Wisconsin project-expenditure records did not provide a complete CAPEX/OPEX decomposition. Mixed and unknown records therefore remained useful evidence of realized spending but were not interpreted as capital-investment floors. A capital-only AI-IIS would require CAPEX-only records or a documented decomposition that removes operating and other non-capital expenditure.

$$\boldsymbol{AI-IIS_{i,t} = \frac{I_{AI,i,t}}{GDP_{i,t}} \times 100} \quad (1)$$

AI-IIS is valid only when numerator and denominator periods match and when the numerator represents a sufficiently complete, consistently scoped, and capital-eligible investment flow. An annual observation would use annual qualifying AI-infrastructure capital formation divided by nominal GDP for the same year; a multi-year measure would require cumulative qualifying capital formation divided by cumulative nominal GDP over the same period. The present realized monetary records span different fiscal/calendar periods, national coverage is incomplete, and several observations are mixed CAPEX/OPEX or unknown in cost composition. Cross-country AI-IIS ranking is therefore deferred until those conditions can be harmonized.

3.3 Public-Private Financing Classification

Public and private financing are classified by the institutional sector that ultimately bears the capital cost. Direct government grants, procurement, and public-capital contributions are coded as public financing; company capital, market debt, and private-equity financing are coded as private. Where public and private amounts are known for a common project denominator, the following project-level shares may be reported:

$$\boldsymbol{PAIIS_{i} = \frac{I_{public,AI,i}}{I_{total,AI,i}} \times 100} \quad (2)$$

$$\boldsymbol{PrAIIS_{i} = \frac{I_{private,AI,i}}{I_{total,AI,i}} \times 100} \quad (3)$$

Where part of the capital stack is unresolved, the residual is retained as unclassified rather than assigned mechanically. PAIIS and PrAIIS are reported only for a bounded financing pool with a defensible total-investment denominator. Project- or program-level financing shares remain at that level when national coverage is incomplete. A separate numerical complementarity index is omitted because a balanced financing share alone cannot establish economic complementarity, crowding-in, or higher conversion efficiency.

3.4 Outcome Profiles and Resilience Interpretation

Macroeconomic and labor-market outcomes were drawn from official or harmonized sources. Real GDP growth used the April 2026 World Economic Outlook values for 2023–2025; the 2025 observations were WEO estimates or preliminary vintage values where applicable rather than uniformly final national-account outturns. Employment-to-population ratios and youth unemployment used 2025 World Bank indicators based on modeled ILO estimates (International Monetary Fund [IMF], 2026; World Bank, 2026a, 2026b). The analysis retained the underlying observations, series identifiers, vintages, retrieval metadata, and calculation inputs for reproducibility. India's GDP observations follow the WEO fiscal-year convention, whereas the other cases are predominantly calendar-year observations; this limits direct interpretation of the three-year growth-volatility statistic.

For descriptive comparison, the analysis constructed sample-standardized macroeconomic and socioeconomic outcome composites. Each composite was the unweighted arithmetic mean of two sample-standardized z-scores. The macroeconomic composite averaged the z-score of mean 2023–2025 GDP growth and the sign-reversed z-score of three-year growth volatility; the socioeconomic composite averaged the z-score of the 2025 employment-to-population ratio and the sign-reversed z-score of youth unemployment. These composites summarize recent economic context rather than shock resistance, recovery, or causal resilience.

The descriptive outcome calculations used the API-reported precision of the World Bank labor-market observations rather than manually rounded transcriptions. The GDP-volatility component is the population standard deviation of only three annual growth observations from 2023 to 2025, so it is a compact description of recent variation rather than a stable estimate of macroeconomic volatility. The standardized coordinates are sample-relative and change with the country set. A direct resilience test would require shock-specific measures of resistance, recovery, adaptation, and distributional adjustment.

3.5 Temporal Alignment and Operational Availability

The final methodological step separates realized monetary flows from operational AI capacity. Capital formation may occur during construction and equipment acquisition, while mixed program spending can also include integration and operation. Productivity and broader resilience effects require infrastructure to be installed, integrated, and available for use. The analysis therefore distinguishes whether capacity was operational within the 2023–2025 outcome window. Records with verified spending but post-2025 service activation are retained for financing and timing analysis but are not treated as contemporaneous measures of usable AI capacity.

Deployment lags were treated conservatively. When a service activation date was known, the lag was measured from the expenditure or build period to the first broadly available service date. When a project remained under construction or the exact operating date was unknown, the lag was treated as right-censored rather than assigned an arbitrary number of months. This approach keeps valid expenditure observations separate from same-year measures of usable compute capacity.

The empirical sequence runs from public-private financing structure to qualifying investment, capital formation, operationalization, AI capability, productive effects, and socioeconomic transmission. Each transition may involve a distinct lag, and expenditure and service availability are recorded separately. The outcome composites are used only to describe the economic context in which these architectures are developing.

4. Results

4.1 Public-Private Financing Architectures across Ten Economies

The ten-country evidence showed that public-private AI infrastructure investment did not follow a single institutional model. Japan used public subsidies and policy finance to leverage privately owned GPU-cloud capacity (Ministry of Economy, Trade and Industry, Japan, 2024); South Korea's 2025 GPU program combined government funding with private CSP hosting and operating responsibilities, although the hardware-versus-integration-and-operating-cost split remained incompletely disclosed (NABO, 2026); and the United States relied primarily on private hyperscale capital with decentralized public incentives. The United Kingdom combined private build-out with publicly funded compute and reported AIRR actual outturn, while Canada combined catalytic public support with private/host delivery and reported actual federal spending for dedicated AI computing capacity (UK Research and Innovation, 2025; Public Services and Procurement Canada, 2025).

The remaining cases broadened the institutional range but were supported by different types of monetary evidence. Germany's JUPITER project had an executed EUR273 million procurement contract that bundled acquisition, delivery, installation, and maintenance and was therefore treated as procurement evidence rather than cash outturn (EuroHPC Joint Undertaking, 2023). Official CNRS documentation reported a EUR40 million France 2030 grant for the Jean Zay extension, while GENCI later documented delivery and operationalization; payment timing remained unresolved (CNRS, 2024; GENCI, 2024). Singapore's ASPIRE 2B system was operational, but its exact S$137.85034055 million award was supported by a GeBIZ mirror rather than a direct payment or outturn record; NSCC independently verified operationalization (NSCC Singapore, 2026; RecordOwl, 2026). China Mobile and China Telecom disclosed realized corporate CAPEX for computility or computing infrastructure, but the broader-compute scope prevented its use as an AI-only national numerator (China Mobile Limited, 2025; China Telecom Corporation Limited, 2026). This company-level evidence also sat within a wider state-coordinated computing-power interconnection agenda (Ministry of Industry and Information Technology of China, 2025). India reported mission-wide expenditure, but the source did not isolate the compute or infrastructure share (Parliament of India, 2026). The ten-country comparison therefore captured distinct financing and operating arrangements without treating differently scoped monetary amounts as comparable national AI-investment totals.

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Table 1. Public-Private AI Infrastructure Financing Architectures across Ten Economies

Economy	Public role	Private / operating role	Evidence status	Share status	Financing architecture
United States	Tax incentives, permitting, grid support	Hyperscaler capital and operation	Realized project expenditure + broader commitments	No national PAIIS	Private-led hyperscale + public enabling
United Kingdom	Public compute and strategic capacity	Private data-center build-out	AIRR actual outturn + overlapping procurement award	No national PAIIS	Private build-out + public compute
Canada	Federal dedicated-AI-compute support	Private/host delivery	Actual public-program spending	Program monetary evidence only	Catalytic public capital + private/host delivery
Japan	Subsidies and policy finance	Corporate CAPEX, debt, equity, operation	Actual / acceptance-basis company records	Project/program only	Subsidy-leveraged private capacity
South Korea	Government GPU-program funding	CSP hosting and operation	Final program execution	Program only; capex/opex split unresolved	Public program + private hosting
Germany	Public/EU HPC procurement and siting support	Supplier delivery under JUPITER procurement	Executed procurement contract	No national PAIIS	Public/EU HPC procurement + supplier delivery
France	France 2030 project funding	Eviden supplier delivery	Completed-project funding; payment timing unresolved	No national PAIIS	Public-funded compute extension + supplier delivery
Singapore	Public HPC procurement and support	HPE supplier delivery / support	Procurement award + operational verification	No national PAIIS	Public procurement + private supplier delivery
China	National compute-network coordination	Commercial operators and SOE CAPEX	Realized broader-compute CAPEX; AI scope incomplete	No national PAIIS	State-coordinated multi-operator hybrid
India	Mission funding, subsidy, demand aggregation	Empaneled compute providers	Mission-wide actual expenditure + infrastructure revised estimate	No national PAIIS	Public demand aggregation + private providers

Sources: Author's compilation based on the sources cited in the text and reference list.
Notes: The classifications describe observed financing and operating arrangements and are not national PAIIS or PrAIIS estimates.

4.2 Realized Monetary Evidence and Bounded Quantitative Evidence

The analysis identified qualifying AI-specific realized monetary records from the United States, United Kingdom, Canada, Japan, and South Korea. Because national coverage and capital-formation eligibility differed across records, the values were treated as project- or program-level monetary evidence rather than national investment totals. SoftBank reported JPY213.3 billion of cumulative FY23–FY25 AI computing and data-center CAPEX on an acceptance basis, while its JPY198.7 billion payment-basis figure represented the same investment and was not added; SAKURA internet Inc. separately reported JPY52.1 billion of actual generative-AI infrastructure investment (SoftBank Corp., 2026; SAKURA internet Inc., 2026). Wisconsin records reported US$262.5 million of Microsoft expenditure in 2024 and US$215.3 million of Meta/Degas expenditure in 2025; Epic Hosting's US$97.8 million was excluded for insufficient AI attribution (Wisconsin Legislative Fiscal Bureau, 2026). UKRI reported GBP64 million and GBP131 million of AIRR outturn in FY2023–24 and FY2024–25, while Canada's Public Accounts reported C$2.309193 million and C$22.004327 million of dedicated-AI-compute spending in the same fiscal years (UK Research and Innovation, 2025; Public Services and Procurement Canada, 2025). Korea's final CSP execution totaled KRW1,417.484 billion but retained a mixed hardware, integration, and operating-cost basis (NABO, 2026).

The other cases were retained with clearly differentiated evidence status. France's EUR40 million Jean Zay H100 funding documented a completed project but did not disclose payment timing. Germany's EUR273 million JUPITER amount and Singapore's ASPIRE 2B amount were procurement awards rather than realized expenditure. China's RMB57.2 billion two-operator amount was derived from realized company CAPEX but covered broader computing infrastructure rather than AI alone. India reported INR518.87 crore of mission-wide expenditure through 13 March 2026, while the INR286.67 crore capital-assets figure was a revised estimate rather than actual spending (Government of India, Ministry of Finance, 2026; Parliament of India, 2026). These distinctions preserved the ten-country institutional comparison without constructing false cross-country investment totals.

Table 2. Verified Realized and Excluded Monetary Evidence Records

Country / Entity	Period	Amount	Accounting status	Treatment in analysis	Key caveat
Japan: SoftBank	FY23–FY25	213.3 JPY billion	CAPEX, acceptance basis	Recorded as realized company monetary evidence.	The JPY198.7 billion payment-basis figure refers to the same investment and is therefore not additive.
Japan: SAKURA internet Inc.	Jan 2024–FY3/2026	52.1 JPY billion	Company-reported actual investment	Recorded as separate company-level actual investment evidence.	Public subsidy support is documented, but the paid public/private split is not separately disclosed.
United States: Microsoft WI	2024	262.5 USD million	WEDC-reported expenditure	Included as project-level actual expenditure	Later Microsoft spend is truncated because WEDC reporting stopped after threshold achievement.
United States: Meta/Degas WI	2025	215.3 USD million	WEDC-reported expenditure	Included as project-level actual expenditure	Project remained pre-operational in the outcome window; expected online in 2027.

Table 2. Verified Realized and Excluded Monetary Evidence Records (Cont.)

Country / Entity	Period	Amount	Accounting status	Treatment in analysis	Key caveat
United States: Epic Hosting WI	Through 2025	97.8 USD million	WEDC-reported expenditure	Excluded from the AI-specific monetary total because AI attribution was insufficient.	AI-specific attribution is insufficient despite verified expenditure.
South Korea: CSP total	2025	1,417.484 KRW billion	Final CSP program execution	Recorded as realized program expenditure.	The total includes unresolved hardware, integration, and operating-cost components and is not treated as pure CAPEX.
United Kingdom: AIRR	FY2023/24 and FY2024/25	195.0 GBP million	Actual public-program outturn	Recorded as realized public-program expenditure; national coverage remains incomplete.	GBP64 million + GBP131 million; GBP175.875 million Isambard-AI procurement overlaps and is not additive.
Canada: PAICE	FY2023/24 and FY2024/25	24.31352 CAD million	Actual spending / authorities used	Recorded as realized public-program expenditure; national coverage remains incomplete.	Federal program actual only; private/host match and national denominator remain incomplete.

Sources: Author's compilation based on SoftBank Corp. (2026), SAKURA internet Inc. (2026), Wisconsin Legislative Fiscal Bureau (2026), NABO (2026), UK Research and Innovation (2025), and Public Services and Procurement Canada (2025).
Notes: Amounts retain their original reported units and accounting status. The records are project- or program-level observations rather than comparable national totals, and overlapping contracts were not added to reported outturns.

Table 2 illustrates both the feasibility and the limits of using realized monetary records in cross-country analysis. Accounting treatment varied across acceptance-basis CAPEX, company-reported actual investment, government-verified project expenditure, public-program outturn, authorities-used spending, and mixed program execution. These amounts were therefore not treated as a homogeneous cash-flow measure. The five-country set provided well-documented realized monetary evidence under incomplete national coverage, while only records with clearly identified capital expenditure supported a capital-only interpretation.

4.3 Investment and Operational Capacity Are Temporally Distinct

The timing rule further narrowed contemporaneous interpretation. Figure 1 presents cases with sufficiently documented service timing. Japanese company evidence included GPU and data-center service launches during 2024–2026; Microsoft Wisconsin expenditure preceded expected first-campus completion in early 2026; Meta's Beaver Dam project was expected online in 2027; and Korea's 2025 program entered broad service mainly in March–April 2026 (Wisconsin Legislative Fiscal Bureau, 2026; NABO, 2026). Expenditure and usable-capacity dates were therefore recorded separately.

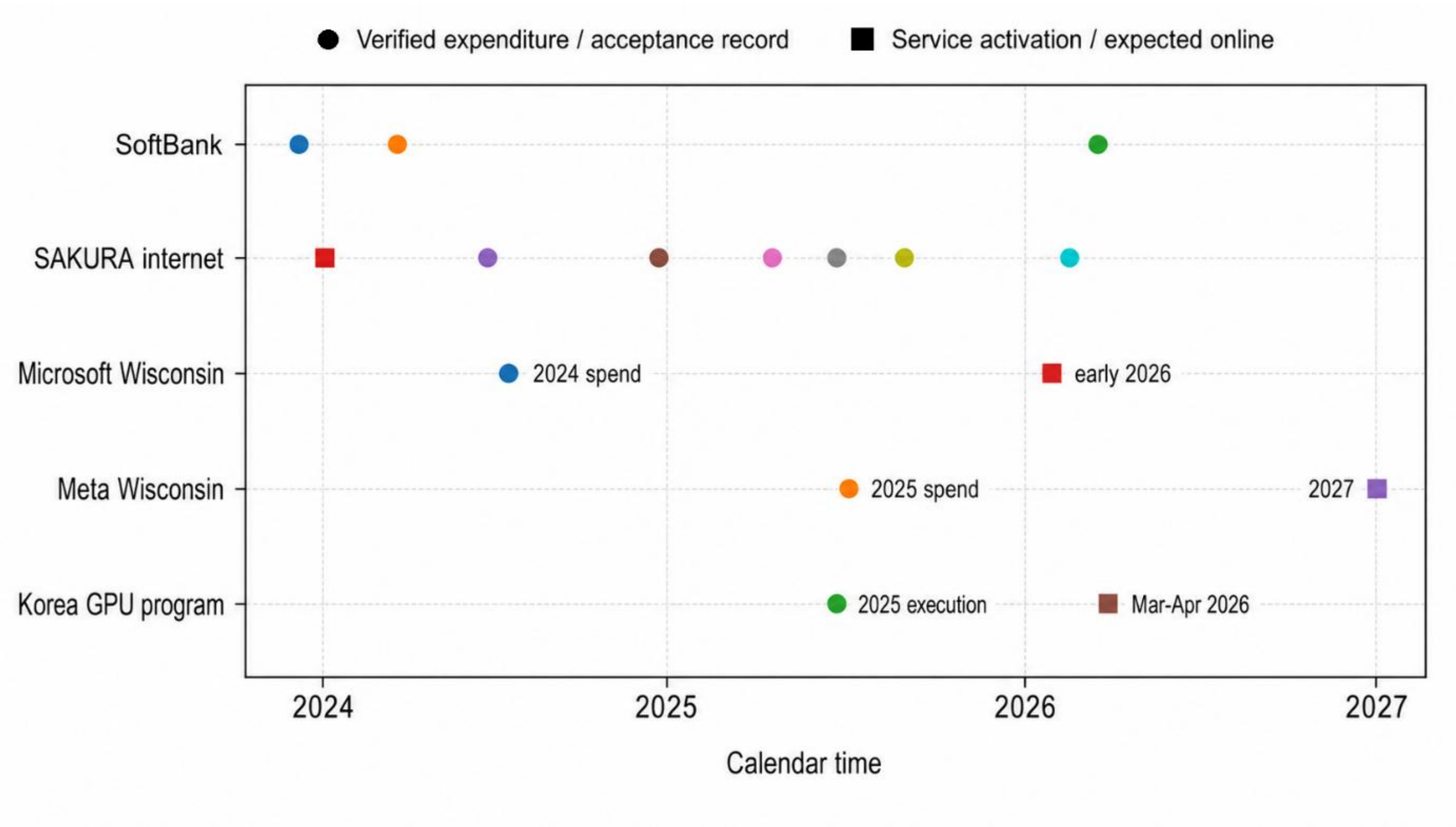

Figure 1. Event-based Timing of Verified Monetary Evidence and Service Activation.

Source: Author's compilation from SoftBank Corp. (2026), SAKURA internet Inc. (2026), Wisconsin Legislative Fiscal Bureau (2026), Meta (2025), and NABO (2026).

Note: Circles indicate reported expenditure or acceptance events, while squares indicate service activation or expected online timing. Colors are used only to distinguish labeled entities visually.

As **Fig. 1** showed, valid monetary records could not be interpreted automatically as same-period usable AI capacity. The evidence supported analysis of financing architecture, capital formation, accounting status, and deployment lag, but not a same-window estimate of AI capacity's effect on economic resilience.

4.4 Financing Architectures and Descriptive Outcome Positions

The ten-economy descriptive outcome layer showed substantial variation. China and India had stronger sample-relative macroeconomic than socioeconomic positions, whereas Japan, South Korea, Germany, and Singapore had stronger socioeconomic than macroeconomic positions. The United States was modestly above the sample mean on both measures, Canada was positive only on the macroeconomic composite, and the United Kingdom and France were below the sample mean on both. The three-year GDP-volatility measure and India's fiscal-year convention were taken into account when interpreting these positions. The results are descriptive and are not interpreted as resilience rankings.

No Pearson, Spearman, or other cross-country correlation coefficient was estimated because the set of comparable realized monetary observations was small, national coverage differed sharply, reporting periods and accounting bases were not harmonized, and contemporaneous capability exposure was insufficient.

Broader commitment and procurement evidence was used only to classify financing architecture and evidence status; announced or committed amounts were not mixed with realized records in a regression or ranking.

5. Discussion

5.1 Public-Private Structure and the Pathway to Resilience

The ten-country comparison supported a structural rather than volume-only interpretation of AI-infrastructure strategy. Systems differed in who supplied capital, owned or hosted assets, absorbed risk, coordinated infrastructure, and operated capacity. These differences shaped the route from financial commitment to usable capacity, but no public-private mix was treated as intrinsically optimal. Any later resilience effect would also depend on access, complementary skills, energy and network reliability, and the shock examined.

5.2 Measurement Approach and Comparability

The comparison required source quality, realization status, scope, accounting basis, and capital-formation eligibility to be assessed separately before period matching and denominator checks. This prevented contracts, budgets, mission expenditure, broader-compute CAPEX, and mixed CAPEX/OPEX flows from being combined into a common national total. The same principle applies to PAIIS and PrAIIS. Project- or program-level shares can be reported when the denominator is known, but they should not be interpreted as national financing shares or as evidence of complementarity without information on crowding-in, risk sharing, deployment, access, and conversion efficiency.

5.3 Outcome Divergence and Requirements for a Resilience Test

The descriptive outcome data showed that macroeconomic and labor-market positions could diverge across countries, but they did not measure resilience. A valid resilience design would require a common disruption, a pre-shock baseline or counterfactual, and post-shock resistance and recovery measures aligned with operational AI-capacity exposure.

This was particularly important because several verified 2024–2025 expenditures preceded broad service activation. A next-stage design should therefore pair post-operational exposure with shock-specific resistance and recovery metrics in a panel or quasi-experimental framework.

5.4 Policy Implications

For policy makers, AI-infrastructure strategy should be evaluated through qualifying monetary scale, the allocation of cost and risk, conversion speed, access and strategic purpose, and outcomes after an identifiable disruption. Announced investment with long deployment delays or narrow access cannot be assumed to improve resilience, and neither a high public nor a high private share proves effective coordination. Financing architecture becomes informative when linked to what the arrangement actually does to risk, timing, access, and operating capability; subsidies, procurement, or incentives matter only insofar as those mechanisms are demonstrated in financing and deployment evidence.

5.5 Limitations

Several limitations were fundamental. Harmonized national accounts of AI-infrastructure investment do not exist, so the available monetary evidence consists primarily of project- and program-level records rather than national totals. Records from the United States, United Kingdom, Canada, Japan, and South Korea documented realized AI-specific spending, but national coverage remained incomplete, accounting bases differed, and capital-formation eligibility ranged from CAPEX-only to mixed or unknown. These observations are therefore useful for comparing evidence and financing arrangements, but not for constructing a single cross-country investment-rate statistic.

The remaining cases also differed in the status and scope of their monetary evidence. France provided completed-project funding with unresolved payment timing; Germany and Singapore provided procurement-award evidence; China's company records documented realized CAPEX for broader computing infrastructure; and India reported mission-wide actual expenditure together with a capital-assets revised estimate. The outcome composites provide sample-standardized context, and the 2023–2025 window preceded full operation of several major programs. Future work should use post-operational panels, matched investment periods, explicit coverage denominators, and resistance and recovery metrics around identifiable disruptions.

6. Conclusion

The study identified substantial variation in how the ten economies financed and organized AI infrastructure. The cases ranged from private-led hyperscale investment with public enabling measures to publicly funded national compute, catalytic contribution programs, subsidy-supported private deployment, public procurement with private operation, and state-coordinated systems. These differences show why ownership, risk bearing, procurement, operation, and access are more informative than headline investment totals alone.

The measurement exercise also showed that AI-IIS, PAIIS, and PrAIIS cannot yet be constructed as comparable national statistics from the available records. Period matching, denominator completeness, scope, realization status, accounting basis, and capital-formation eligibility all affect comparability. Realized AI-specific monetary observations from the United States, United Kingdom, Canada, Japan, and South Korea therefore remained analytically separate from completed-project funding, procurement awards, broader-compute CAPEX, and mission-wide expenditure observed in the other cases. Cross-country investment intensity or financing shares should not be calculated until these dimensions can be aligned.

The descriptive economic indicators and project-timing evidence further showed why expenditure, operational capacity, and resilience outcomes must be separated. Several projects entered service after the period in which spending was recorded, while some program expenditures combined acquisition, integration, and operation. The present evidence therefore does not support a simple claim that greater AI-infrastructure spending, or a higher public or private share, produces greater resilience. Instead, the study provides a measurement framework for later testing with post-operational, period-matched data and identifiable economic shocks.

Working Paper

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