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External AI Dependence and Startup Financial Survivability

How Dependence on Externally Owned AI Infrastructure Affects the Financial Survivability of Independent Businesses

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Country Coverage: United States · China · Germany · Japan · India · United Kingdom · France · Brazil · Canada · South Korea

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About This Paper

Shubham Agarwal is the Founder and Chief Executive Officer of triNetra, an independent research organisation focused on the economics of artificial intelligence, digital infrastructure, and entrepreneurial competitiveness across emerging and advanced economies.

The analytical frameworks introduced in this paper, including the External AI Dependence (EAD) framework, the External AI Dependence Index (EADI), the Builder-Dependent Ratio, the AI Dependence Classification, and the Specialized Digital Asset hierarchy, are original contributions proposed by the author and intended for empirical validation and refinement by the research community. All findings are drawn from publicly available institutional sources cited in full. The views expressed are those of the author alone.

Executive Summary

This paper examines a single economic question: how dependence on externally owned AI infrastructure is associated with the financial survivability of independent businesses.

Independent businesses in economies with high or critical External AI Dependence face a structural cost layer absent from conventional startup economics. The tools required to remain competitive are priced in a foreign currency, controlled by foreign commercial entities, and subject to pricing decisions made in jurisdictions those businesses cannot influence. In income-adjusted terms, this layer is material: approximately 12 to 20 percent of average annual formal income in India and Brazil, compared with approximately 1.5 percent in the United States. Both pay the same nominal price.

This paper argues that high AI adoption in a high-EAD environment is not, by itself, a competitive advantage. Without corresponding ownership of specialized assets, it may represent a financial liability operating through five compounding mechanisms: currency-denominated cost asymmetry, price trajectory risk from investor-subsidised pricing, competitive asymmetry between large and small firms, switching costs that accumulate with platform integration, and financial amplification of AI project failures in local-currency terms.

The strategic response proposed is not avoidance of AI. The response is deliberate use of general-purpose infrastructure alongside progressive conversion of rented capability into **Specialized Digital Assets**: proprietary resources that encode unique knowledge, domain expertise, workflows, and accumulated intelligence in forms that compound in value and remain under the business's control regardless of which platform provides the underlying computation.

RESEARCH QUESTION

How does dependence on externally owned AI infrastructure affect the financial survivability of independent businesses operating in AI-intensive sectors?

CORE FINDINGS

	Finding
1	Independent businesses in high-dependence economies pay the same nominal USD price for AI tools as businesses in source economies while absorbing substantially higher income-adjusted costs. This structural asymmetry has no close precedent in prior general-purpose technology adoption cycles.
2	In high-dependence economies, sectors showing the highest AI adoption rates also tend to show the lowest own-AI capability, a configuration associated with heightened structural vulnerability rather than competitive strength.
3	Current AI subscription prices appear to be structurally below the cost of delivery, with the gap funded by investor capital. If that subsidy ends, dependent businesses will absorb price increases as USD-denominated operating costs on local-currency revenues, without a domestic alternative.
4	The most durable path to financial resilience is the progressive conversion of rented AI capability into Specialized Digital Assets: domain-specific knowledge systems, proprietary datasets, industry-specific workflows, and sector-focused products that encode expertise general-purpose platforms cannot replicate.

1. The Problem

An independent business operating in 2026 faces a structural cost condition that earlier generations of entrepreneurs did not encounter: the tools required to remain competitive are concentrated in the ownership of a small number of foreign commercial entities.

1.1 The Structural Shift Since 2022

General-purpose AI tools for research, analysis, writing, code generation, and operational decision support have embedded themselves in the daily functioning of businesses across most sectors. Unlike prior productivity software, the dominant AI infrastructure has concentrated in ownership in ways that create recurring financial dependencies for businesses operating outside source jurisdictions.

The United States and China together control approximately 90 percent of the computing capacity required for frontier AI development and own all 50 of the top-ranked foundation models currently tracked (CNAS, 2026). Amazon Web Services, Microsoft Azure, and Google Cloud Platform together hold approximately 63 percent of global cloud infrastructure market share (Synergy Research Group, Q1 2026). For an independent business in a dependent economy, the consequence is specific: every AI-enabled operation generates a recurring USD-denominated cost on a local-currency revenue base, controlled by entities the business cannot influence, and subject to repricing decisions it cannot anticipate.

1.2 Defining External AI Dependence

External AI Dependence (EAD) is defined as the degree to which an independent business's operations rely on foreign-owned AI models, cloud compute, and foundational infrastructure to remain competitive, and the recurring financial liabilities and structural operational constraints that dependence creates.

Three compounding dependency layers are identified, each deepening the structural exposure of those above it.

Layer	What It Provides	Who Controls It (2026)	Nature of Dependence
Foundation Models	Large language models and reasoning systems on which downstream applications depend	OpenAI, Anthropic, Google, Meta (United States); Baidu, Alibaba, DeepSeek (China)	Pricing risk; capability trajectory set externally; switching costs from embedded workflows; policy decisions in a foreign jurisdiction
Cloud Compute	Data centres where models serve outputs and business data is processed	AWS (approx. 28%), Azure (approx. 21%), GCP (approx. 14%), representing approximately 63% of global market (Synergy, Q1 2026)	US CLOUD Act jurisdictional exposure; data transfer switching costs; pricing power; service deprecation risk without domestic alternative
AI Chips	Specialised processors that train and serve AI models at scale	Nvidia (United States chip design); TSMC (Taiwan manufacturing)	No commercially available alternative at comparable performance; long procurement lead times; supply chain geopolitical risk

Table 1-1. The Three-Layer AI Dependency Stack. Source: CNAS Sovereign AI Index (2026); Synergy Research Group Q1 2026.

1.3 The External AI Dependence Index

To make EAD measurable and comparable across economies, this paper proposes the External AI Dependence Index (EADI) Version 1.0. Scores range from 0 (complete dependence) to 100 (complete sovereignty). Five components are used: domestic cloud market share (25 percent), domestic foundation model availability (25 percent), sovereign compute capacity (20 percent), own-AI capability in high-risk sectors (20 percent), and AI talent retention rate (10 percent).

EADI Version 1.0 is a first-generation research instrument intended for empirical validation. Component weights are judgement-based at this stage and should be tested through expert elicitation or principal component analysis in subsequent versions. Country rankings are robust to reasonable variations in individual component weights, but absolute scores are indicative rather than precise.

Country	EADI Score	Confidence Range	EAD Level	Independent Business Implication
United States	92	88 to 95	None (Source)	No foreign jurisdiction risk at any infrastructure layer
China	64	58 to 70	Low	Domestic stack extensive; CNY-denominated costs; intentional decoupling underway
South Korea	45	39 to 51	Moderate	Partial domestic model alternatives; Samsung and SK Hynix hardware leverage
France	32	26 to 38	High	Mistral AI provides partial domestic foundation model; EUR pricing removes currency risk
Germany	28	22 to 34	High	Industrial AI capability via SAP; EU AI Act compliance adds cost; compute US-dependent
Japan	24	18 to 30	High	Robotics AI domain strength; JPY depreciation has raised effective USD AI costs approximately 30% since 2022
Canada	19	13 to 25	Critical	Research-strong; AI talent and commercial value flow primarily to US platforms
United Kingdom	17	11 to 23	Critical	Third-largest AI market globally (approximately USD 92 billion) operating on entirely foreign infrastructure
India	12	7 to 17	Critical	Near-total USD dependency; IT services sector faces structural automation risk from the same platforms it pays to use
Brazil	7	3 to 11	Critical	No domestic AI infrastructure at commercial scale; highest income-adjusted AI cost burden in this study

Table 1-2. EADI Version 1.0 Scores: Ten Economies (July 2026). Source: Author's derivation. All scores Category B (Derived). Scores are directional indicators, not precise cardinal measures.

2. The Economic Mechanism

Five financial mechanisms connect external AI dependence to reduced startup survivability. Each is independently material; together they compound in ways that do not appear in conventional startup economics frameworks.

2.1 The Recurring Cost Layer

A lean but operationally competitive AI tool stack for an independent knowledge-economy business in 2026 costs approximately USD 94 per month at retail pricing. Three structural characteristics make this figure significant: it is entirely USD-denominated regardless of where the founder operates; it is controlled by a small number of US-domiciled companies; and available evidence suggests it is currently priced below the full cost of service delivery.

Category	Representative Tool	USD/Month	Function	Pre-AI Labour Equivalent (USD/Month)
AI assistant and LLM	ChatGPT Plus or Claude Pro	20.00	Research, drafting, analysis, code generation	500 to 2,000
AI research and synthesis	Perplexity Pro	17.00	Real-time research and factual synthesis	100 to 500
Cloud productivity	Google Workspace Business Starter	7.20	Documents, email, storage, calendar	50 to 200
CRM and pipeline	HubSpot Starter	20.00	Contact management, revenue pipeline	200 to 500
Accounting	Xero Starter	15.00	Invoicing, expense tracking, tax preparation	200 to 600
Design and content	Canva Pro	15.00	Visual assets, presentations, content production	500 to 2,000
Total, lean competitive stack		94.20	Annual: USD 1,131	1,550 to 5,800

Table 2-1. Competitive AI Tool Stack for an Independent Business (July 2026). Source: Official provider pricing pages, verified July 5, 2026. All components are USD-denominated and invoiced by US-domiciled companies regardless of customer location.

2.2 Mechanism 1: Currency-Denominated Cost Asymmetry

The same USD 1,131 annual cost represents materially different financial burdens across economies when expressed as a percentage of average formal-sector annual income.

Country	EAD Level	Annual AI Stack	USD Income Equiv.	AI Cost % of Income	Currency Risk
United States	None	USD 1,131	USD 75,000	Approx. 1.5%	None (domestic USD)

Country	EAD Level	Annual AI Stack	USD Income Equiv.	AI Cost % of Income	Currency Risk
China	Low	Approx. USD 400 (CNY)	Approx. USD 13,800	Approx. 0.5 to 0.8%	None (domestic CNY)
Germany	High	USD 1,131 (EUR)	Approx. USD 48,000	Approx. 1.8%	Minimal (EUR)
France	High	USD 800 to 1,131	Approx. USD 45,000	Approx. 1.7%	Minimal (EUR)
South Korea	Moderate	USD 1,131 (USD on KRW)	Approx. USD 29,000	Approx. 2.8%	Moderate (KRW/USD)
United Kingdom	Critical	USD 1,131 (USD on GBP)	Approx. USD 40,000	Approx. 2.7%	Moderate (GBP/USD)
Japan	High	USD 1,131 (USD on JPY)	Approx. USD 24,600	Approx. 4.4%	High (JPY approximately -30% since 2022)
India	Critical	USD 1,131 (USD on INR)	Approx. USD 8,900	Approx. 12 to 15%	High (INR/USD)
Brazil	Critical	USD 1,131 (USD on BRL)	Approx. USD 6,500	Approx. 15 to 20%	Very high (BRL/USD: 20 to 40% annually)

Table 2-2. Annual AI Stack Cost as Percentage of Average Annual Income. Source: OECD Average Annual Wages database (2024); IMF IFS exchange rates (June 2026).

> **An independent founder in Brazil pays approximately 15 to 20 percent of average annual formal income for the AI tool stack required to remain competitive. The equivalent cost for a United States founder is approximately 1.5 percent. Both pay the same nominal price.**

2.3 Mechanism 2: Price Trajectory Risk

Current AI subscription prices appear to be structurally below the full cost of service delivery. Analysis by SemiAnalysis (2026) suggests that heavy users of the USD 20 per month ChatGPT Plus plan consume compute services with a market value of approximately USD 70 to 100 per month, with the gap funded by investor capital. OpenAI raised USD 40 billion in early 2025 at a USD 300 billion valuation. Should investor-funded subsidisation transition to profit-seeking pricing, dependent businesses would absorb price increases as USD-denominated operating costs on local-currency revenues without a domestic fallback.

2.4 Mechanism 3: Competitive Asymmetry

Large enterprises negotiate AI platform contracts at prices substantially below retail, while independent founders pay USD 20 to 25 per month with no negotiating leverage. The OECD (2025) documents that firms with 250 or more employees adopt AI at approximately 1.5 to 2 times the rate of firms with fewer than 50 employees across G7 economies. A large firm that adopts AI faster, pays less per seat, and maintains a dedicated team to manage the documented 80 percent or higher AI project failure rate (RAND, 2024) accumulates a compounding competitive advantage that an independent business operating in the same market cannot match.

2.5 Mechanism 4: Platform Switching Costs

An independent business that integrates its operations, client workflows, and institutional processes with a specific AI platform accumulates switching costs that increase with time. In a foreign platform environment, the absence of a credible domestic exit option removes all negotiating leverage. A business that cannot credibly migrate is structurally exposed to the platform provider's pricing and policy decisions, independent of its own market position.

2.6 Mechanism 5: AI Project Failure Cost Amplification

RAND Corporation (2024) finds that more than 80 percent of enterprise AI projects fail to deliver intended business value. MIT Project NANDA (2025) documents that 95 percent of generative AI pilots achieve no measurable return to the income statement. For independent businesses in high-dependence economies, each failed AI project generates sunk costs denominated in USD on local-currency revenues, without a domestic alternative. A three-month failed implementation for a founder in India represents approximately 3 to 4 percent of average annual formal-sector income in direct subscription costs alone.

2.7 The Compounding Effect

> **High AI adoption in a high-EAD environment is not, by itself, a competitive advantage. Without corresponding ownership of specialized assets, it may represent a financial liability with five compounding mechanisms that do not appear in conventional startup economics models.**

3. Evidence

3.1 AI Dependence Classification for Sectors

Level	Definition	Survivability Implication	Representative Sectors
Critical	AI is embedded in primary service delivery. Removal of AI access is associated with inability to operate at a commercially viable standard.	All five mechanisms operate at full intensity. Financial survivability is most directly affected.	IT services delivery (AI-augmented), legal research, healthcare diagnostics, financial risk modelling
High	AI is the primary competitive differentiator. The business could operate without AI but at a quality level insufficient to maintain competitive positioning.	Mechanisms 1, 2, and 3 operate at high intensity. Platform switching cost compounds with time.	Management consulting, creative agencies, accounting practices, education technology, marketing services
Moderate	AI enhances specific operational functions without being central to product delivery.	Mechanism 1 is present but proportionally smaller. Mechanisms 2 through 5 operate at lower intensity.	Retail operations, logistics coordination, local professional services
Minimal	AI is used for peripheral tasks or not used. Core operations function independently.	Minimal direct financial exposure through EAD mechanisms.	Physical trades, construction, agriculture, personal care services

Table 3-1. AI Dependence Classification for Sectors (Proposed Framework). Source: Agarwal, S. triNetra Research, 2026.

3.2 Financial Survivability Pressure Matrix

The interaction between AI Dependence Classification and EAD Level determines the compound financial survivability pressure on an independent business.

Dependence Level	None (EADI 92)	Low (EADI 64)	Moderate (EADI 45)	High (EADI 24 to 32)	Critical (EADI 7 to 19)
Critical	Low	Low to moderate	Moderate	High	Severe: all five mechanisms operate simultaneously
High	Minimal	Low	Moderate	Moderate to high	High
Moderate	Negligible	Negligible	Low	Low to moderate	Moderate
Minimal	None	None	None	None	Minimal

Table 3-2. Financial Survivability Pressure Matrix. Source: Proposed framework. Category B (Derived).

3.3 The Builder-Dependent Ratio

Raw AI company counts are frequently used as indicators of ecosystem health. Within the scope of this study, that measure may be misleading for dependent economies: a large AI company count in a high-EAD economy may indicate a large population of founders paying USD-denominated costs to build applications on foreign-owned infrastructure, potentially amplifying structural dependence rather than reducing it.

India's approximately 8,178 AI companies, the second-largest national count in this study, operate at near-total USD dependency. A large AI company count in a dependent economy appears to be evidence of scaled consumption rather than scaled capability.

4. The Strategic Response: Specialized Digital Assets

General-purpose AI provides capability. Specialized Digital Assets capture value. This distinction is the economic foundation of the strategic response proposed in this paper.

4.1 Infrastructure Versus Assets

General-purpose AI tools function as infrastructure. They provide productive capability that is broadly available at retail pricing, not differentiated by user, and whose trajectory is determined by its providers. Resource-based theory (Wernerfelt, 1984; Barney, 1991) identifies that durable competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable. General-purpose AI infrastructure fails the rarity and inimitability tests by construction: it is broadly available, priced identically for all users, and its capability is determined by the platform rather than by any individual user's choices.

Specialization is where economic value is captured. The law firm that owns a proprietary case outcome database captures more durable value than one using the same general-purpose legal research tool as all competitors. General-purpose infrastructure enables; specialization compounds.

4.2 Definition

> **Specialized Digital Assets are proprietary digital resources created through the application of general-purpose AI to a specific business, industry, customer base, workflow, dataset, or knowledge domain. Their value arises from specialization, ownership, and cumulative learning, not from the underlying AI infrastructure itself.**

The definition has three constitutive elements. The asset is **proprietary**: it is created and owned by a specific business, not licensed from an external provider. The asset is **specialized**: it encodes knowledge, relationships, or expertise specific to a domain, sector, or customer base. The asset's value is **cumulative**: it improves with use, accumulates institutional knowledge, and generates increasing returns over time, consistent with learning-by-doing dynamics (Arrow, 1962).

4.3 Five Levels of Specialization

Level	Asset Type	Domain Encoding	Defensibility	Compounding Mechanism
1	Reusable Workflows	Low to moderate	Portable across platforms; reduces time cost per engagement	Each documented process reduces future time cost; workflow library grows with every engagement
2	Structured Proprietary Knowledge	Moderate	Cannot be replicated by a competitor using the same AI tools without equivalent domain experience	Knowledge base deepens with every engagement; client-specific intelligence increases in value
3	Industry-Specific Datasets	High	Proprietary by construction; cannot be replicated without equivalent operational history	Dataset value grows with every added example; provides the primary input for Level 4

Le vel	Asset Type	Domain Encoding	Defensibility	Compounding Mechanism
4	Business-Specific AI Systems	Very high	Owned by the business; not subject to external repricing; capability is firm-specific and cumulative	Each fine-tuning cycle improves performance; the system becomes increasingly differentiated
5	Specialized Domain Products	Maximum	Creates the business's own platform position; generates network effects from user data	User adoption improves the underlying model; the product becomes the sector's preferred domain intelligence resource

Table 4-1. Specialized Digital Asset Hierarchy (Proposed Framework). Source: Agarwal, S. triNetra Research, 2026.

4.4 Open-Weight Models and the Ownership Transition

Open-weight models, including Meta's Llama series, Mistral's models, Alibaba's Qwen, and DeepSeek, can be downloaded, operated, and fine-tuned on proprietary datasets without ongoing payment to any foreign commercial entity. Available benchmarks suggest the performance gap between open-weight and frontier proprietary models has narrowed from approximately 8 percent to approximately 1.7 percent on selected assessments in a single year (Stanford HAI, 2025). Fine-tuning a capable open-weight model on domain-specific data using managed services costs approximately USD 100 to 5,000 (Hugging Face, Replicate; July 2026 pricing). The bottleneck for reaching Level 4 is consistently the proprietary dataset, not the model. A business that begins systematically accumulating Level 3 assets today is building the primary input for Level 4 specialization regardless of which specific AI tools are dominant at the time of transition.

5. Implications

The principal economic challenge is not the existence of external AI infrastructure. The challenge is remaining permanently dependent on it while building nothing of proprietary and specialized value.

5.1 For Independent Founders

Assess total AI dependence before expanding it. Evaluate total USD-denominated AI cost as a percentage of current revenue, the degree to which existing AI usage produces proprietary data and workflow IP versus consuming platform capability, and the switching costs already accumulated through platform integration.

Begin Level 1 and Level 2 asset development immediately. Structured workflow documentation and systematic knowledge organisation require no capital and no technical infrastructure. A founder who treats every AI-assisted engagement as an opportunity to document a reusable process is accumulating Level 1 and Level 2 assets at zero additional cost.

Identify the knowledge that is genuinely proprietary. The direction of specialization should be determined by the knowledge, relationships, and expertise that are genuinely proprietary to the business, not by which AI tools are currently popular.

Treat proprietary data as a primary strategic asset. Domain-specific, labelled, structured data is the primary input that external platforms cannot purchase, replicate, or substitute. Data accumulation is the highest-value activity available to an AI-intensive independent business before any technical infrastructure is required.

5.2 For Investors

The EAD framework introduces a structural risk variable absent from conventional startup due diligence. Risk is most acute in three profiles: startups in critical AI-dependence sectors in economies with EADI scores below 20; startups whose technical position consists exclusively of prompt engineering or workflow design on external AI platforms; and startups in economies with high USD/local-currency volatility where AI operating costs represent a material revenue percentage.

The Builder-Dependent Ratio provides a useful first-order signal: a startup building on open-weight infrastructure fine-tuned on proprietary domain data has more durable competitive positioning than one building exclusively on foreign proprietary platforms.

5.3 For Policymakers

Incentivise Specialized Digital Asset creation, not only AI adoption. Current AI policy incentives in most dependent economies subsidise AI adoption, which primarily benefits foreign platform revenue. Tax incentives or grant programmes for businesses that develop Level 3 and Level 4 specialized assets would redirect incentives toward domestic knowledge accumulation and enduring economic value creation.

Fund domain-specific fine-tuning programmes for small and medium enterprises. Fine-tuning a capable open-weight model costs approximately USD 100 to 5,000. Government programmes providing technical assistance and domestic compute access for SMEs at this cost would reduce foreign platform dependency at substantially lower cost than sovereign foundation model development.

Conclusion

Modern economies have historically accumulated wealth through the ownership of productive assets. In the industrial era, that meant land, machinery, and physical infrastructure. In the knowledge economy, it has increasingly meant brands, patents, networks, and proprietary information systems. Specialized Digital Assets offer an increasingly accessible path for independent businesses to create enduring enterprise value using tools that are now widely available.

The evidence assembled in this paper indicates that high AI adoption, in the absence of corresponding Specialized Digital Asset development, is associated with a specific and compounding financial risk. Independent businesses in high-dependence economies absorb substantially higher income-adjusted AI operating costs, face price trajectory uncertainty without domestic alternatives, compete against large firms with structural cost and adoption advantages, accumulate switching costs that remove negotiating leverage, and bear amplified financial consequences when AI projects fail.

The income-adjusted cost asymmetry is the most immediately visible dimension. The same AI tool stack costs approximately 1.5 percent of average annual income for a United States founder and approximately 15 to 20 percent for a Brazilian founder. This is not a consequence of different pricing; it is a structural consequence of where productive AI infrastructure is owned.

General-purpose AI capability is commoditising. The performance gap between frontier proprietary models and open-weight alternatives has narrowed substantially, and this convergence is likely to continue. As general-purpose AI capability becomes available at lower marginal cost, competitive advantage will shift toward businesses that have encoded specific knowledge, relationships, and expertise into owned domain assets.

> **Use general-purpose AI as productive infrastructure. Build and own the Specialized Digital Assets that encode what is uniquely yours.**

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