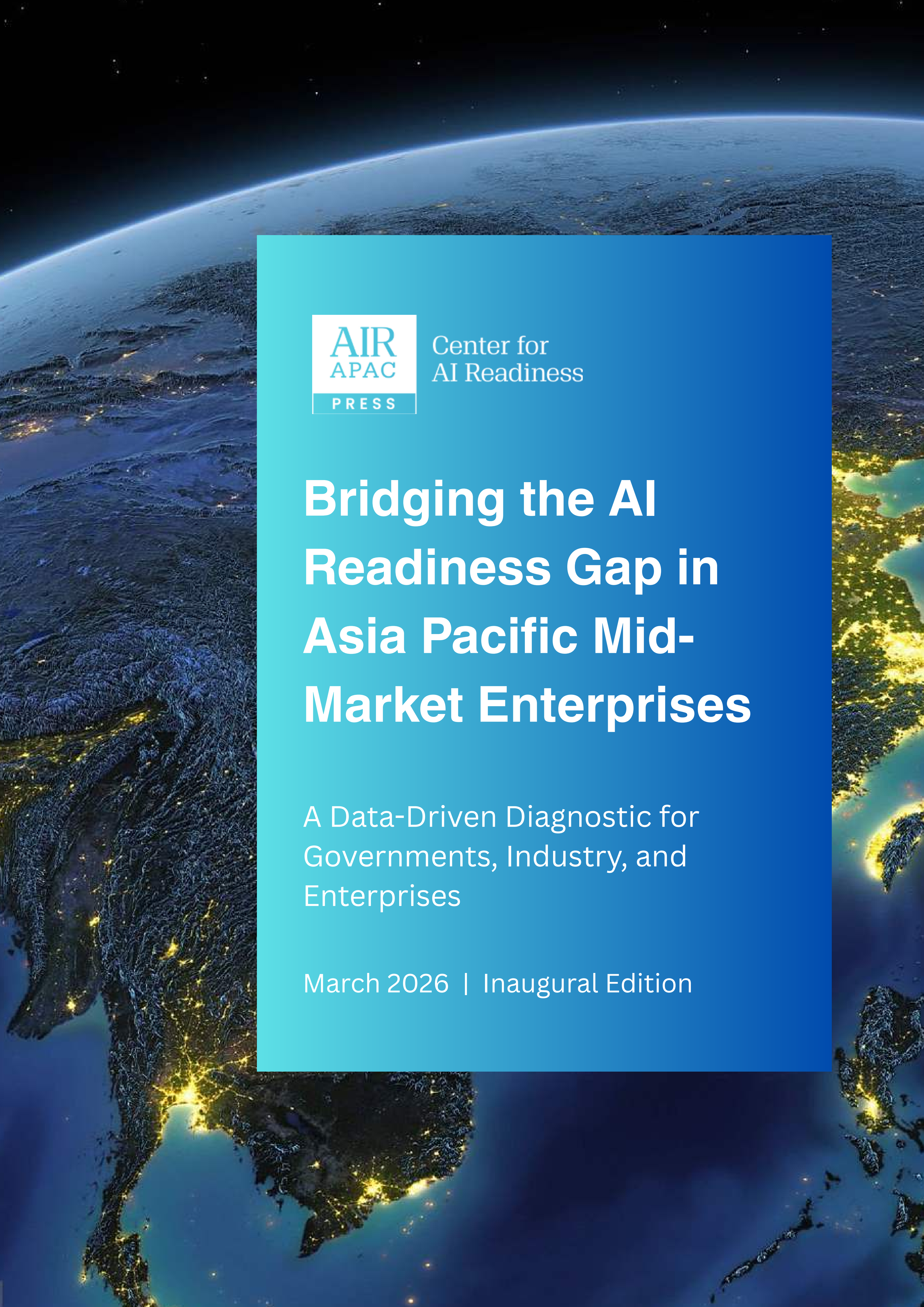

AIR APAC PRESS

Center for AI Readiness

Bridging the AI Readiness Gap in Asia Pacific Mid-Market Enterprises

A Data-Driven Diagnostic for Governments, Industry, and Enterprises

March 2026 | Inaugural Edition

Contents

Executive Summary

The problem. Across Asia Pacific, mid-market companies – the 200–3,000-employee firms that form the backbone of every APAC economy – are struggling to translate AI ambition into execution. Governments are investing billions; large enterprises are deploying at scale. The mid-market is being left behind, not because the technology is unavailable, but because the foundational preconditions for AI adoption remain unbuilt.

What this Index measures. The AIR APAC Mid-Market Readiness Index measures **observable behavioral signals** of digital maturity, talent density, and strategic commitment across 510 mid-market enterprises in five scored markets (Singapore, Australia, Malaysia, Indonesia, Thailand) and six sectors. Every score is derived from public data – cloud platform signals, specialist hiring activity, ERP system detection, and analysed strategic communications – not self-reported surveys. A broader 12-market ecosystem analysis provides regional context.

A guardrail. A high readiness score indicates that a company is *well-positioned to adopt AI* – not that it has deployed AI or extracted ROI. "Ready" means the preconditions are in place, not the outcomes.

The central finding is structural: the APAC mid-market is not just lagging in AI adoption; it is systematically invisible to the tools used to measure it. We call this the **APAC Data Desert**. Global business intelligence platforms – built for North American and European enterprises – consistently undercount APAC companies. The Desert manifests in two forms: *coverage gaps* (firms absent from Western platforms, most acute in Indonesia, Thailand, and Malaysia) and *representation gaps* (firms present but mis-measured because their signals travel in non-English channels, most acute in Japan and South Korea). A pipeline that returns no data cannot distinguish between a company with no AI capability and one that is simply invisible. Cross-market scores must be read as a composite of readiness *and* observability.

The human capital constraint. Even adjusted for visibility, the strongest observable constraint is human capital, not infrastructure. Cloud adoption has reached most markets; dedicated AI and data talent has not. No market in the 12-market ecosystem analysis scores above 65 on the AI Talent Pool dimension. Over 70% of scored companies are Low confidence precisely because talent signals – the most discriminating readiness indicator – are too sparse to score with confidence.

Headline Numbers

Metric	Value
Companies scored	510
Markets scored	5 – SG, AU, MY, ID, TH
Sectors covered	6 – Tech/Fintech, Financial Services, Prof. Services, Retail/E-com, Manufacturing, Logistics
Mean TRS (Total Readiness Score)	17.3 / 100
Maximum TRS observed	73.2 / 100 (Secretlab, SG)
Pacesetter tier (top 10%)	51 companies
Developing tier	153 companies (30%)
At Risk tier	306 companies (60%)
High confidence scores	28 companies (5%)
V1 → V2 mean TRS uplift (same 117 firms)	+96% (14.7 → 28.7)

What This Means for Different Audiences

Governments and policy-makers: The mid-market AI gap is a policy problem before it is a market problem. The highest-leverage interventions are national mid-market readiness diagnostics, targeted AI skills funding at the 200–3,000 employee band, and data infrastructure that makes Southeast Asian firms visible to global benchmarking tools.

Enterprise leaders: Use your tier placement as a starting point, not a verdict. Traditionalists should prioritise cloud migration and modern ERP before AI use cases. Strategists have intent but need talent investment. Pragmatists need board-level commitment to translate operational maturity into deployment. Pacesetters have both an opportunity and a responsibility to publish case studies and shape the regional conversation.

Technology vendors and investors: Any market sizing that treats "no data" as "no capability" undercounts the APAC mid-market by 40–60% in Indonesia, Thailand, and Malaysia. Multi-source intelligence is the minimum requirement for accurate coverage in this region.

The full methodology, V1→V2 enrichment comparison, market-level results, sector breakdowns, and company spotlights are in Sections 2–5. This is a first-generation measurement system – structural findings are the load-bearing contribution; specific scores will evolve as coverage and longitudinal data expand.

1. The APAC AI Landscape: The Widening Gap

Asia Pacific is the fastest-growing region for AI adoption globally, with projected compound annual growth rates exceeding 24% through 2035. Investment is surging: 96% of APAC enterprises plan to increase AI spending by an average of 15% in 2026, according to IDC research. Governments across the region have committed substantial national resources – from Singapore's S$1 billion National AI Strategy 2.0 to South Korea's AI Basic Act, Malaysia's National AI Roadmap, and Indonesia's National Strategy for Artificial Intelligence.

Yet beneath these headline figures, a troubling gap persists. Research consistently shows that AI ambition is accelerating faster than enterprise readiness. A 2025 MIT study found that 95% of organisations struggle to generate meaningful return on investment from AI initiatives, largely due to weak data foundations and integration gaps. Boston Consulting Group reports that only around 30% of enterprise workflows across APAC are mature enough to support AI safely at scale. The benefits of national AI investment are flowing disproportionately to large enterprises and well-funded startups, bypassing the mid-market segment that forms the backbone of every APAC economy.

1.1 Why Mid-Market Matters: The Economic Imperative

Mid-market companies – broadly defined as firms with 200 to 3,000 employees – are the engine of economic growth and employment across APAC. In most economies in the region, they account for 40–60% of GDP contribution and represent the largest segment of the formal employment base. They are the primary conduit through which technology adoption reaches the broader economy: when mid-market firms adopt cloud, AI, and digital processes, the effects cascade through their supply chains, partners, and local ecosystems.

Yet mid-market enterprises are systematically underserved by existing AI readiness frameworks, which tend to be designed for Fortune 500 companies or venture-backed startups – not for a 500-person manufacturer in Greater Kuala Lumpur or a financial services firm in Singapore with 300 employees. This gap has policy consequences: when governments design AI capability programmes based on readiness data that excludes or under-represents the mid-market, the resulting interventions miss their most important target segment.

The AIR APAC Mid-Market Readiness Index exists to close this intelligence gap. It provides governments, industry associations, development agencies, and enterprise leaders with a rigorous, evidence-based benchmark of where mid-market AI readiness actually stands – and where intervention can have the greatest impact.

1.2 The Regulatory and Policy Landscape

Governments across APAC are not waiting for the market to self-organise. The regulatory and policy landscape is evolving rapidly, creating both frameworks for responsible AI deployment and incentive structures to accelerate adoption:

- **Singapore:** The Monetary Authority (MAS) issued comprehensive AI Risk Management Guidelines in November 2025. The National AI Strategy 2.0 targets S$1 billion in investment, complemented by the AI Verify framework for testing and the FEAT principles for fairness, ethics, accountability, and transparency.

- **South Korea:** The AI Basic Act took effect in January 2026, establishing mandatory risk assessments for AI in critical sectors and a national competence framework.
- **Malaysia:** The 13th Malaysia Plan explicitly targets digitalisation and AI capability as a national priority through 2031. The National AI Roadmap (NAIR) outlines sector-specific adoption goals.
- **Indonesia:** The National Strategy for Artificial Intelligence (Stranas KA) 2020–2045 sets a framework for AI adoption, with the Ministry of Communication and Informatics (Kominfo) driving digital literacy and infrastructure programmes.
- **Thailand:** The National AI Strategy and Ethics Guidelines, coupled with the Digital Economy Promotion Agency (depa) incentives, target mid-market digital transformation.

For mid-market enterprises, these regulatory developments create both urgency and opportunity. But there is a critical disconnect: most national AI strategies lack granular data on where mid-market readiness actually stands. Without baseline measurement, governments cannot target interventions effectively, track programme impact, or allocate resources where the readiness gap is widest. This Index is designed to provide that baseline.

> **For policy-makers:** Without baseline measurement of mid-market AI readiness, governments cannot target interventions effectively, track programme impact, or allocate resources where the gap is widest.

2. Methodology: Behavioral Signals, Not Surveys

Operational definition. In this Index, "AI readiness" is defined operationally as *the presence of observable preconditions for AI adoption* – digital infrastructure, accessible talent, and articulated strategic intent. It is not a measure of deployed AI systems, realised ROI, or internal capability depth. A company with a strong TRS has the foundational preconditions for AI adoption; it has not necessarily adopted AI successfully, and a low TRS does not prove absence of AI capability, it indicates absence of the *observable signals* of readiness.

Scope definition. The Index evaluates mid-market enterprises using a three-criteria definition: **(1) headcount of 200–3,000 employees**; **(2) annual revenue between approximately US$50M and US$500M** where revenue data is available; and **(3) not classified as enterprise-scale by funding or valuation** – companies with confirmed valuations above US$1 billion, last-round funding above US$200M, or status as a regional subsidiary of a global conglomerate are excluded as enterprise-tier outliers regardless of headcount. Headcount alone is necessary but not sufficient: a company in the 200–3,000 band may still exhibit enterprise-like revenue, funding, or operational characteristics that distort comparability. The data quality screening in Section 8.3 applies 14 exclusion categories (including revenue and funding filters) to enforce this definition; the Klook case study in Section 5.6 illustrates why all three criteria are needed.

The Center for AI Readiness built this Index on a foundational principle: measure what companies do, not what they say. Traditional AI readiness assessments rely on self-reported survey data – responses subject to social desirability bias, strategic misrepresentation, and the simple problem that many mid-market executives do not yet have the vocabulary to accurately describe their AI capabilities. For governments and policy-makers who need to make resource allocation decisions based on readiness data, survey-based approaches carry unacceptable methodological risk.

The Index instead uses behavioral signal analysis: algorithmic scoring based on observable signals drawn from public and semi-public data sources. This approach is not objectively "more accurate" than surveys; it trades self-report bias for a different set of tradeoffs (visibility, platform, and language bias), but it is more observable and more reproducible. Readers should treat the Index as a measure of *observable indicators* of AI readiness – digital footprint, talent signals, and articulated strategic intent – not as a direct measure of internal AI capability or realised business impact. Every proxy signal must pass four validation criteria: Observable, Relevant, Discriminating, and Defensible.

2.1 The Multi-Source Intelligence Pipeline

A critical evolution from V1 to V2 of the Index was the recognition that no single data source provides adequate coverage for APAC mid-market companies. The V2 pipeline implements a multi-source intelligence architecture:

- **Apollo.io:** People data, job postings, company metadata. Strong for LinkedIn-heavy markets (SG, AU), weak for Southeast Asia.
- **Wappalyzer:** Technology detection via HTTP headers. Captures frontend technologies but misses backend systems (ERP, data platforms) behind firewalls.

- **Serper Web Search:** Structured Google search with localised queries. Entity disambiguation via domain/country appending. Localised hiring keywords for non-English markets (Indonesian, Thai, Malay).
- **Jina Reader:** Anti-bot scraping fallback for company pages that block direct HTTP requests.
- **Claude Structured Extraction:** LLM-powered extraction via tool_use function calling, enforcing strict JSON schemas. Extracts headcount, cloud platforms, ERP systems, AI roles, and seniority from unstructured search results.
- **OpenAI GPT-4o Scoring:** Calibrated LLM scoring for strategic narrative (Signal F) and digital commitment evidence (Signal G) with function-call-enforced integer output.

The pipeline runs both Apollo and web enrichment, taking the maximum score from each source. This eliminates the "fallback only when empty" anti-pattern.

What the pipeline cannot see. All sources above are web-based, externally observable, and HR- or marketing-driven. *The pipeline detects the presence of systems and talent, not the depth or intensity of their use.* Internal data pipelines, ML infrastructure, model-deployment volume, and the actual usage intensity of detected platforms remain outside the signal set. A company that has fully deployed AI internally but does not hire visibly, publish press releases, or expose tooling via HTTP headers will appear as signal-poor in this methodology. This is a structural limitation of any observable-signal approach, not a flaw correctable by more scraping.

2.2 Three-Layer Scoring Architecture

Layer	Weight	What It Measures	Data Sources
Digital Footprint	25%	Cloud infrastructure, ERP systems, technology stack maturity	Wappalyzer, Serper, job postings
Talent Capacity	45%	AI/data talent density, digital generalists, active hiring signals	Apollo, LinkedIn, Serper (localised)
Strategic Intent	30%	Public narrative, digital commitment evidence	Company websites, Google search, press releases

The weighting is **hypothesis-driven, not empirically derived**. It reflects an analytical judgment that talent signals are the most reliable and discriminating data currently available for APAC mid-market companies, while technology signals from web scraping tools produce significant false positives and false negatives in this segment. The weights will be recalibrated as longitudinal data emerges and as behavioural outcomes (ROI, deployment volume, workflow integration) become observable at scale; until then they should be read as a deliberate prior, not a settled fact.

2.3 Seven Behavioral Signals

Signal	Name	Weight	Description
A	Cloud Nativity	25% × 50%	Primary cloud (AWS/ Azure/GCP) detection via Wappalyzer, Serper, and job postings
B	Modern ERP	25% × 50%	Cloud ERP (100), Modern SaaS (60), Legacy on-prem (40), None (0)
C	AI Talent Density	45% × 45–55%	Weighted role count / headcount, calibrated by sector benchmarks
D	Digital Generalist	45% × 0–20%	IT/digital staff density; activates ONLY when AI density < 1%
E	Hiring Activity	45% × 35–45%	Highest seniority of AI/ data/digital job postings (C-level=100, none=0)
F	Strategic Narrative	30% × 55%	LLM-scored press releases and company communications (1–10 × 10)
G	Digital Commitment	30% × 45%	LLM-scored Google search evidence of AI/ digital investment (1–10 × 10)

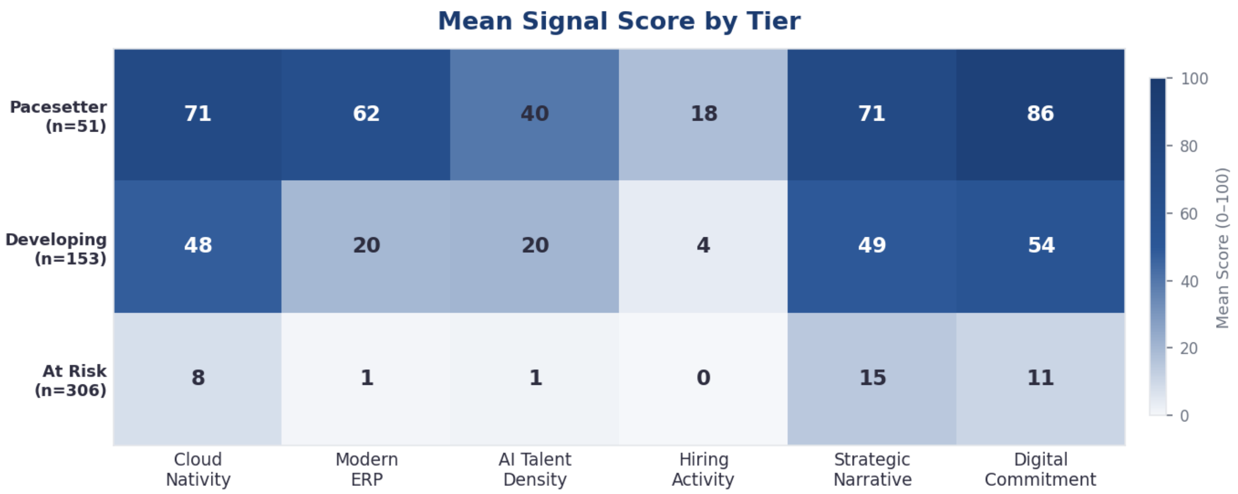

Figure 8: Mean score per behavioral signal, broken down by tier. Pacesetters score markedly higher on Cloud, ERP, Narrative, and Digital Commitment; AI Talent Density and Hiring Activity are the sharpest discriminators between Developing and At Risk.

Signal overlap within the Talent layer. Signals C (AI Talent Density) and E (Hiring Activity) both sit inside the 45% Talent layer and are partially correlated – hiring activity is in many cases a proxy for talent growth. This introduces a known overlap that can amplify scores for markets with strong visible hiring churn (Singapore, India, Australia) relative to markets where AI talent is internalised and turns over less (Japan, Korea). The two signals remain separate because they capture different time horizons (stock vs. flow), but readers should note the overlap when interpreting cross-market talent comparisons.

Important caveat on Signals F and G: these signals measure *external articulation* of strategic intent, not internal execution. A company with sophisticated AI marketing and polished press coverage will score higher than a quieter operator with comparable (or stronger) internal AI capability. LLM scoring is run at temperature=0 with function-call-enforced output and calibration examples to manage variance, but these controls reduce, not eliminate, the risk of rewarding PR fluency. The cross-layer confidence check (Section 2.5) is the primary defence against narrative-only scores dominating the Index: a high Strategy score without corroborating tech or talent evidence is forced to Low confidence and excluded from the Pacesetter tier.

2.4 Total Readiness Score (TRS)

TRS = (Digital Footprint × 0.25) + (Talent × 0.45) + (Strategy × 0.30)

Output range: 0–100. All layer scores are computed on a 0–100 scale before weighting. The theoretical minimum is 3.0.

2.5 Data Confidence Score

Every company receives a Data Confidence Score based on nine binary checks across the three scoring layers, plus a critical cross-layer validation:

1. Cloud platform detected
2. ERP or business system detected
3. AI/data talent count > 0
4. IT/digital staff count > 0
5. Job postings found
6. Company news/press content scraped
7. Company about page content scraped
8. Google search returned relevant results
9. CEO/Founder LinkedIn identified

Cross-layer check (critical): A company with 8 confidence points but zero tech signals AND zero talent signals is forced to Low confidence. This prevents "ghost companies" – entities with rich web content but no measurable operational footprint – from inflating the Index.

An edge case users should know about. Confidence scoring validates signal *presence*, not signal *quality*. A company that clears the Medium threshold by registering weak or generic signals across multiple layers (a cloud platform detected but not central to operations; a generic IT hire; a PR-heavy strategy page) will be classified Medium confidence even though the underlying evidence is thin. The

Medium band should be read as "enough signals present to place in a tier," not as "evidence of robust readiness." Company-level decisions that depend on the *magnitude* of TRS, not just its tier, should be taken from High-band scores only.

Tier	Signal Points	Signal Coverage	Cross-layer Check	Interpretation Guidance
High	≥ 7 of 9	≥ 78%	Cross-layer signals confirmed	Scores reportable at company level; robust for benchmarking
Medium	4–6 of 9	44–78%	Cross-layer signals confirmed	Scores usable for tier assignment; interpret specific numbers with caution
Low	< 4 of 9	< 44%	Cross-layer check fails	Scores retained for visibility but excluded from Pacesetter tier; treat as directional only

2.6 Digital Visibility Score (DVS)

The Index introduces a companion metric: the Digital Visibility Score (DVS). This is a diagnostic that measures how discoverable a company's digital footprint is across public data sources.

DVS is calculated from the 9 base confidence signals plus up to 5 web enrichment signals (search results found, headcount discoverable, tech stack visible, AI talent visible, ERP visible), normalised to 0–100. The gap between DVS and TRS across markets is itself diagnostic. Markets with high average DVS but low TRS (e.g., Singapore) have companies that are visible but not yet ready. Markets with low DVS (e.g., Indonesia, Thailand) face a more fundamental challenge: their companies cannot even be measured by existing tools.

The quantitative link. Across the 510-company V2 universe, TRS and DVS are strongly correlated (Pearson r = 0.86). This is the analytical backbone of the Data Desert thesis: observed readiness is, in substantial part, a function of observability. At the market level the pattern is consistent – Australia (mean TRS 27.0, mean DVS 32.1) and Singapore (19.1 / 24.2) pair high readiness with high visibility, while Thailand (10.0 / 10.4) and Malaysia (11.3 / 15.1) pair low readiness with low visibility. The gap between a company's TRS and its DVS is a diagnostic signal: companies with TRS ≫ DVS are readiness-strong but poorly surfaced by the pipeline; companies with DVS ≫ TRS are well-surfaced but have thin underlying readiness. Policy and commercial users should consider both numbers, not TRS in isolation.

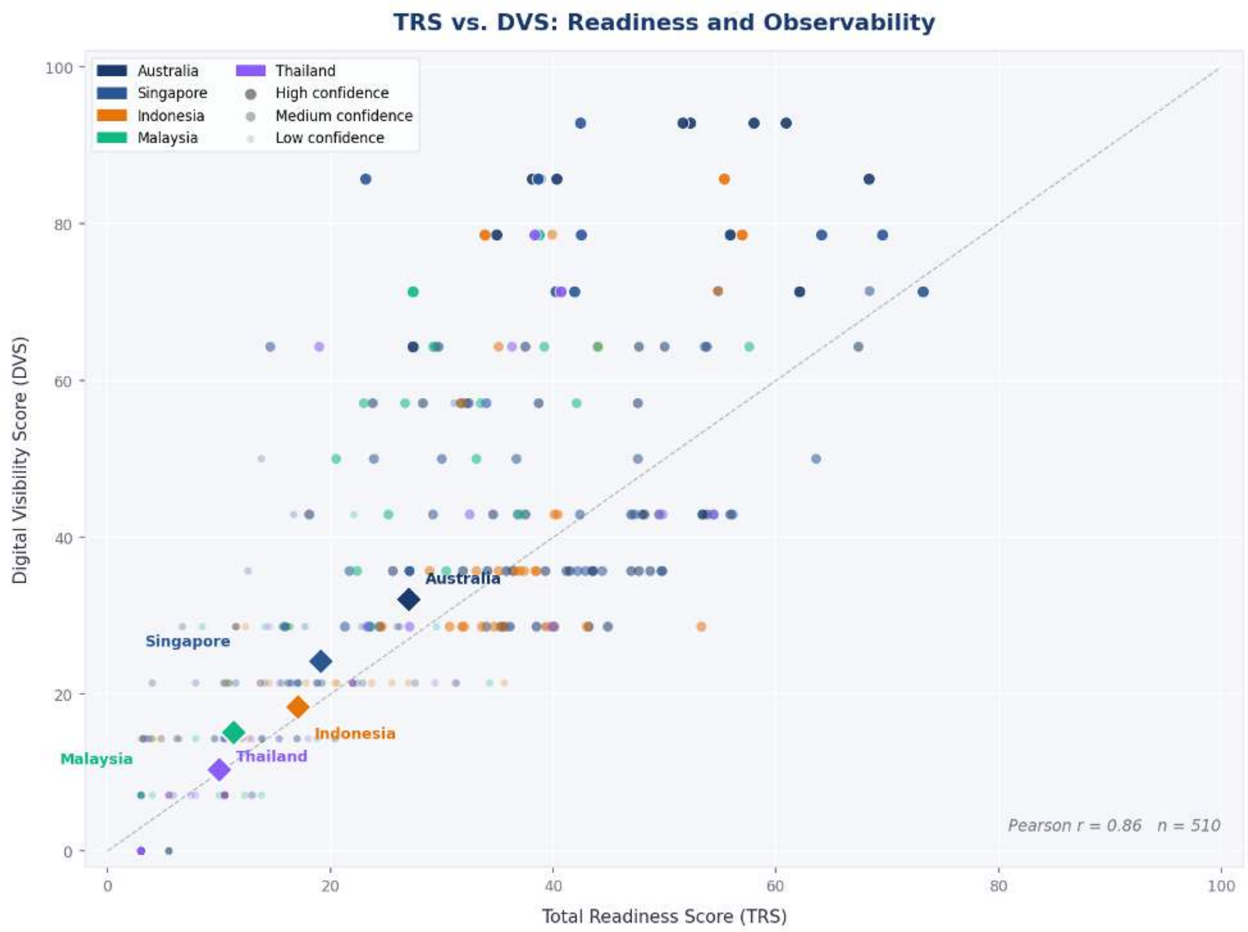

Figure 7: TRS vs. DVS scatter for all 510 companies. Diamond markers show market centroids. Dashed line = y=x (perfect observability). Opacity indicates confidence tier.

TRS and DVS are correlated, not interchangeable. A fair reading of $r = 0.86$ is that these two metrics share substantial variance; an unfair reading is that TRS is "just a visibility index with extra steps." The two constructs measure different things: DVS measures *discoverability* – how findable a company is across public data sources – while TRS measures *the presence of readiness signals once discovered*. A company with high DVS but low TRS has been discovered and measured but lacks the underlying readiness signals; a company with high TRS but medium DVS has been discovered adequately and demonstrably carries readiness signals within that data. The correlation is strong because the pipeline cannot evaluate what it cannot see – this is a feature of the underlying epistemology, not a collapse of the constructs.

3. The Readiness Quadrant Framework

The Index places every evaluated company into a two-dimensional quadrant matrix based on two composite axes:

X-Axis – Operational Maturity: The average of Digital Footprint and Talent scores.

Y-Axis – Strategic Momentum: The Strategy Score.

3.1 Cohort-Relative Tier Assignment

The Index uses percentile-based tiers calibrated to the evaluated cohort, not fixed absolute thresholds. A company scoring 65 in this APAC mid-market cohort IS a pacesetter relative to its peers – even if it would score differently in a Fortune 500 cohort.

Tier	Percentile Band (V2 applied)	Observed %	Interpretation
Pacesetter	Top 10% (P90+)	10% (51 cos)	Leading within this cohort; potential case study
Developing	P60–P90	30% (153 cos)	Above-median; meaningful progress, targeted gaps remain
At Risk	Below P60 (merged with Critical in V2)	60% (306 cos)	Below median; significant gaps, needs intervention
Critical	*(collapsed into At Risk for V2 – see note)*	0%	Restored in future editions once floor cluster eases

Quality floor: Companies with Low confidence are excluded from Pacesetter tier regardless of TRS percentile.

Why At Risk = 60%, not 35% (tier compression in V2). The V1 framework defined four tiers – Pacesetter (top 10%), Developing (P60–P90, 30%), At Risk (P25–P60, 35%), and Critical (bottom 25%). In the V2 dataset, a substantial share of companies cluster at or near the TRS floor (3.0) due to the Data Desert effect, producing a long tail of statistically indistinguishable scores at the low end. A percentile cut between At Risk and Critical in this distribution would draw a boundary through a mass of tied or near-tied scores – false precision. For V2 the two lower bands are therefore merged into a single At Risk tier (~60%, everything below P60). The separate Critical tier will be restored in future editions as enrichment reduces the floor cluster and the lower distribution becomes differentiable.

3.2 Quadrant Labels

Quadrant	Profile	Recommended Action (Enterprise & Policy)
Pacesetter	High operational maturity + high strategic momentum	Case studies; advisory boards; contribute to national AI strategy consultations; mentor ecosystem
Strategist	Low operational maturity + high strategic momentum	Highest-value for intervention; capability assessment, talent strategy, skills programme eligibility
Pragmatist	High operational maturity + low strategic momentum	Executive engagement; peer benchmarking; regulatory preparedness; board-level AI governance
Traditionalist	Low on both dimensions	Foundation-building; digital infrastructure grants; long-term upskilling; revisit in 12–18 months

Figure 1: AIR APAC Readiness Quadrant – 510 companies across 5 markets

4. APAC Ecosystem Context: Twelve-Market Regional Landscape

Important framing note: this section describes the APAC regional environment in which the scored companies operate. It is separate from the company-level Index. The Index itself scores 510 mid-market enterprises across five markets only. The 12-market ecosystem profile below is a country-level landscape assessment used for context and interpretation.

Each of the twelve ecosystem markets is assessed across six dimensions using structured web search and LLM-powered evidence scoring, with full citation trails.

What this ranking is not. The ecosystem ranking is *not a definitive league table of national AI capability*. It is a ranking of observable ecosystem signals, filtered through the biases described below. Countries with deep but internalised AI capability (Japan, South Korea) will rank below their actual capability; countries with strong English-language visibility but shallower execution will rank above theirs. The ranking is useful for spotting coverage and representation gaps, not for adjudicating which economy is "winning" AI.

> **Methodology note – visibility bias:** Ecosystem scores reflect observable, predominantly English-language signals: hiring activity, policy announcements, startup visibility, and public research output. Markets with non-English-dominant ecosystems (Korea, Japan) or heavy chaebol/keiretsu concentration of AI talent are systematically under-detected by this methodology and their scores should be read as understated. **No manual numeric correction is applied in v2.1** – applying an ad-hoc adjustment only to selected markets would introduce post-hoc correction risk. A formal per-capita density overlay applied consistently across all 12 markets is planned for the H2 2026 refresh. Readers should treat individual country ranks within ±5 points as statistically indistinguishable and should not over-interpret ecosystem scores for Korea, Japan, and other North Asian markets.

Known scope gap: Taiwan is not included in this edition's ecosystem profile despite its material AI relevance (TSMC, semiconductor-linked AI supply chain, Foxconn industrial automation). Its inclusion is planned for the H2 2026 refresh alongside native-language signal collection for North Asian markets.

4.1 Ecosystem Ranking

Rank	Country	Score	Strongest Dimension	Weakest Dimension	Interpretation flag
1	Singapore	78.3	Infra (85)	Talent (65)	
2	India	71.7	Infra (75)	Talent (65)	
3	South Korea	68.8	Infra (78)	Talent (45)	understated (visibility bias)
4	Australia	66.7	Infra (75)	Talent (55)	
5	Malaysia	64.5	Digital Econ (75)	Talent (55)	
6	Japan	63.5	Infra (72)	Talent (45)	understated (visibility bias)
7	Thailand	61.7	Infra (72)	Talent (45)	
8	Vietnam	61.2	Digital Econ (72)	Talent (45)	
9	Hong Kong	60.0	Infra (75)	Talent (45)	
10	New Zealand	60.0	Infra (75)	Talent (35)	
11	Indonesia	55.5	Digital Econ (75)	Talent (45)	
12	Philippines	53.3	Infra (65)	Talent (35)	

Markets flagged "understated" are subject to representation-gap bias (non-English ecosystems, chaebol/keiretsu concentration). Scores are shown as produced by the pipeline; no numeric correction has been applied.

4.2 Market Narratives

Singapore: The Regional Benchmark

Singapore leads APAC with an ecosystem score of 78.3, driven by world-class digital infrastructure (85), a thriving startup ecosystem (85), and the region's most mature AI policy framework. The MAS AI Risk Management Guidelines and the National AI Strategy 2.0 create a regulatory environment that simultaneously enables innovation and manages risk. Singapore's challenge is talent: at 65, its AI talent pool score reflects the reality that mid-market firms compete against DBS, GIC, Temasek, and global tech giants for a limited specialist pool.

India and South Korea: Visibility vs. Execution

India ranks second in the ecosystem table (71.7); South Korea ranks third (68.8). To downstream users, this ordering may appear counterintuitive given South Korea's highly advanced manufacturing, robotics, and corporate AI research stack (Samsung AI Research, Naver's HyperCLOVA, Kakao Brain, LG AI Research). The divergence is real, but it is a divergence of *observability*, not of underlying capability. This is a deliberate boundary of the methodology.

Methodology Context: The Visibility vs. Execution Divergence (India & South Korea). The ecosystem pipeline measures publicly observable signals, which are heavily influenced by platform and language dynamics. India's score is driven by massive talent visibility – an English-first digital footprint, widespread LinkedIn adoption, and high volumes of public job postings in IT and outsourced services. South Korea is subject to a different form of the Data Desert, a *representation gap*. Deep enterprise AI capability embedded within chaebol structures, a Korean-language internet ecosystem, and lower reliance on Western HR platforms all result in fewer detectable signals for global data pipelines. On a per-capita basis Korea has roughly four times India's AI talent density (~57,000 professionals in a 51M population vs. ~416,000 in 1.4B), but this density does not surface through the observable channels the pipeline monitors. We considered a density-adjusted numeric recalibration in v2.1 and deliberately did not apply it – ad-hoc correction of only selected markets would introduce post-hoc bias of its own. The scores above are the pipeline's raw output; Korea and Japan should be read as understated by commentary, not by number. **The symmetry also holds in the other direction:** markets with high observability – most notably India – may appear stronger in the Index than their underlying execution depth would suggest. An English-first digital footprint and heavy LinkedIn/job-board visibility amplifies observable talent signals; when a large share of that visible talent is employed in services and outsourcing rather than in-house enterprise AI deployment, the ecosystem score will over-represent capability-to-deploy. Readers should apply the visibility correction in both directions. A formal per-capita density overlay applied consistently across all 12 markets is planned for the H2 2026 refresh.

Indonesia, Thailand, and the Data Desert

Indonesia (55.5) and Thailand (61.7) occupy a critical position in the APAC landscape. Both countries have growing digital economies and active policy frameworks, but their mid-market companies are nearly invisible to Western data platforms. In our V1 pipeline, Indonesia was 100% Low confidence and Thailand was 95% – not because these companies lack AI capability, but because the tools used to measure them were not designed for these markets.

This finding has significant implications for technology vendors, advisory firms, and investors operating in Southeast Asia. Any market sizing, competitive analysis, or investment thesis that relies solely on Apollo, LinkedIn, or BuiltWith will systematically undercount the Indonesian and Thai mid-market. The multi-source pipeline developed for this Index demonstrates that these companies can be measured – but it requires localised search queries, non-English keyword sets, and alternative data sources.

4.3 Cross-Market Dimension Analysis

Country	Digital Infrastructure	AI Policy & Governance	AI Talent Pool	Startup & Innovation	Cloud & Enterprise Tech	Digital Economy
Singapore	85	75	65	85	75	85
India	75	75	65	75	65	75
South Korea	78	75	45	75	75	65
Australia	75	65	55	65	75	65
Malaysia	65	72	55	65	55	75
Japan	72	72	45	65	72	55
Thailand	72	65	45	58	65	65
Vietnam	65	65	45	65	55	72
Hong Kong	75	55	45	75	45	65
New Zealand	75	65	35	55	65	65
Indonesia	58	55	45	45	55	75
Philippines	65	45	35	55	55	65

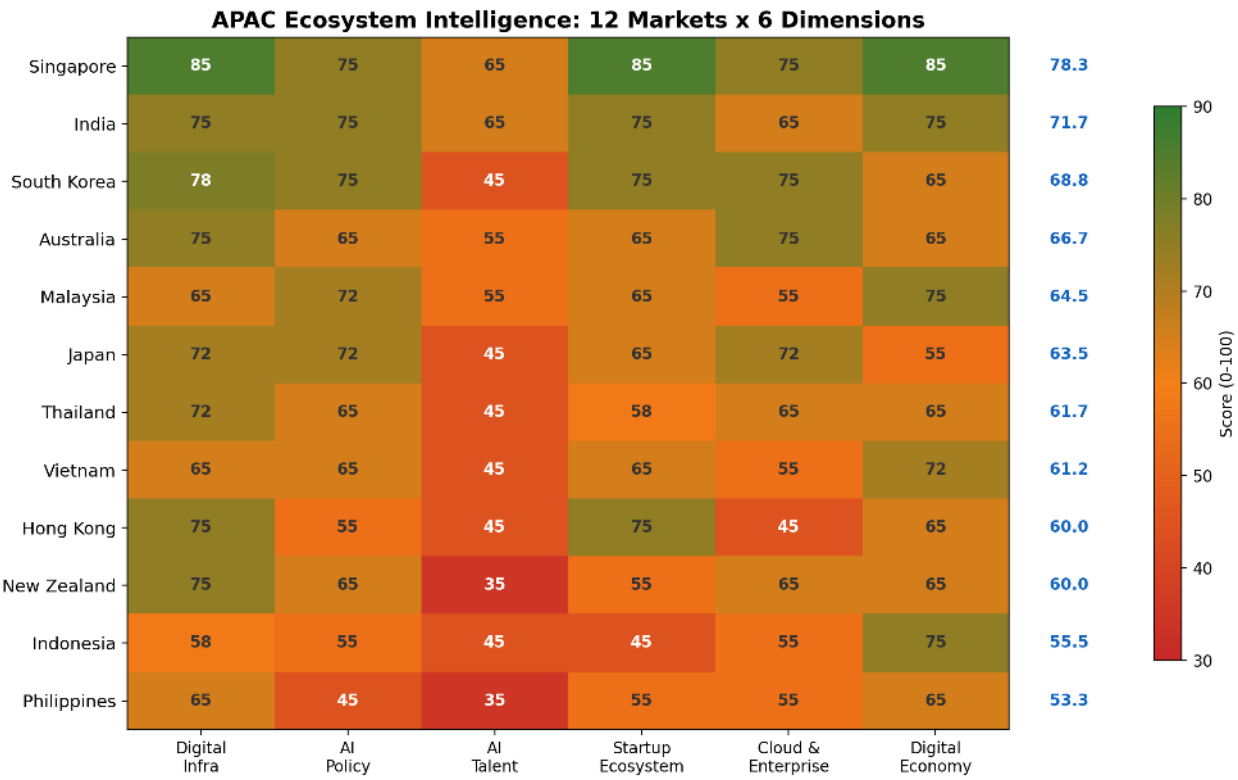

Figure 2: APAC Ecosystem Heatmap – country-level regional context across 12 APAC markets, 6 dimensions (0–100). Scores shown as produced by the pipeline; Korea and Japan Talent scores are flagged as understated elsewhere but not numerically adjusted. Note: ecosystem scoring only; companies outside the 5 scored markets are not part of the Index.

AI Talent Pool is the weakest observable dimension across APAC: no market exceeds 65 on this dimension (Singapore, India, ceiling). This is the **strongest observable constraint in the ecosystem dataset**, consistent with what the company-level Index surfaces. Digital infrastructure, by contrast, scores consistently high – most APAC markets have built the physical and connectivity foundations for AI, but the human capital to exploit them is thinner in the signal set available to us. Country ranks within a ±5-point band should be treated as statistically indistinguishable; ecosystem scoring is directional context, not a precision league table.

5. Index Findings: Measuring the Gap

> **510 companies** scored across 5 APAC markets and 6 sectors
> **+96%** increase in mean TRS for the same 117 companies (V1 → V2)

5.1 Before and After: The Enrichment Impact

The V2 pipeline expanded coverage from 229 to 510 companies. To isolate the methodology impact from the composition change, the table below compares the same 117 companies scored under both V1 (Apollo-only) and V2 (multi-source):

Metric	V1 (Apollo Only)	V2 (Multi-Source)
Companies (matched set)	117	117
Mean TRS	14.7	28.7
Companies at TRS floor (3.0)	62	31
High confidence	3 (2%)	28 (23%)
Low confidence	88 (75%)	41 (35%)
Full V2 universe		**510**
Full V2 mean TRS		17.3
Full V2 max TRS		73.2

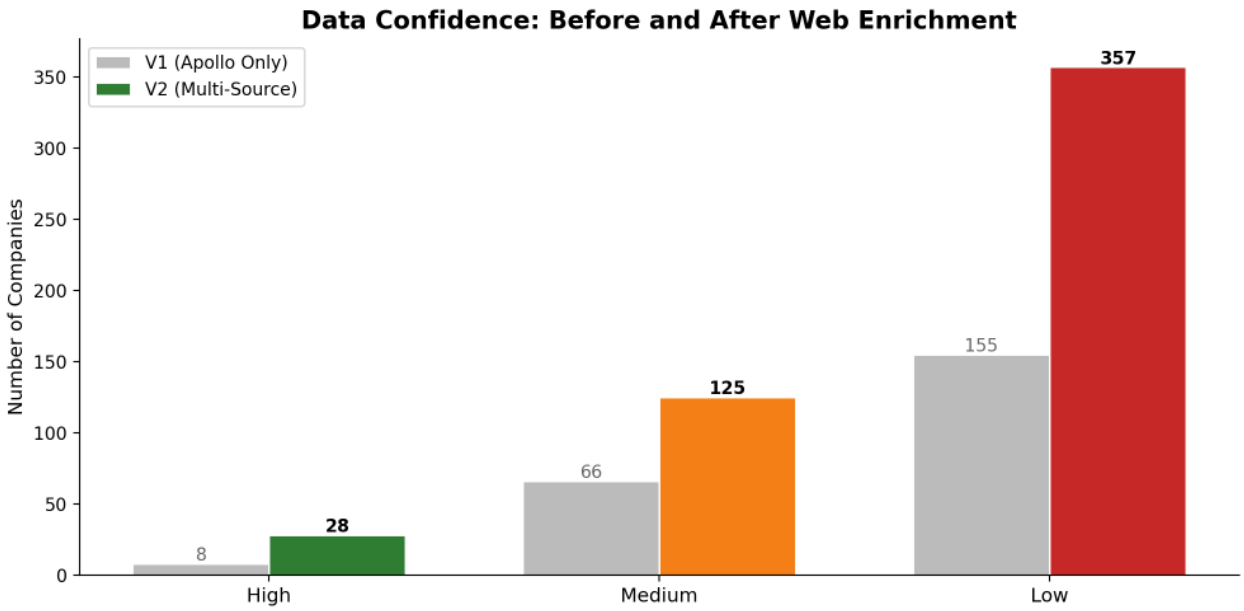

Figure 3: Data confidence improvement from V1 (Apollo only) to V2 (multi-source pipeline)

5.2 Tier Distribution

Tier	Companies
Pacesetter	51 (10%)
Developing	153 (30%)
At Risk	306 (60%)
Critical	0 (0%)

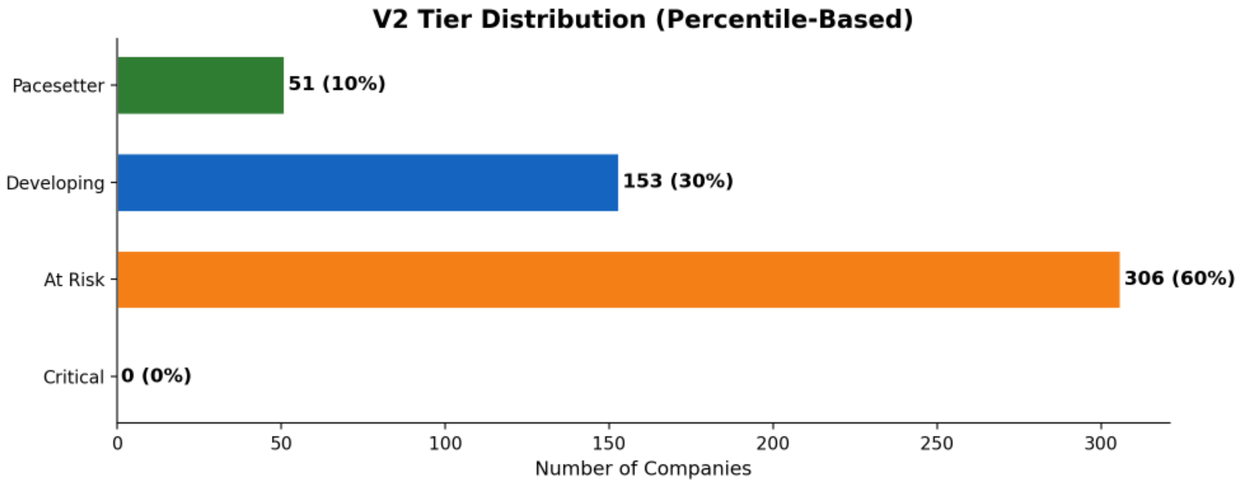

Figure 4: Tier distribution using cohort-relative percentile assignment

5.3 Market-Level Results

The relationship between data coverage and scoring reveals a critical pattern: markets with higher data coverage (Australia, Singapore) score higher, while markets with persistent data gaps (Thailand, Malaysia) score lower. This raises an important question: are these companies less ready, or are they less visible? **Differences across markets reflect both underlying readiness and variation in data coverage; these effects cannot be fully disentangled in the current dataset.** Mean TRS differences between, for example, Malaysia and Singapore should be read as a composite of capability and observability, not as a pure capability ranking.

Market	Companies	Low Confidence (V2)	Confidence Change (V1→V2)
Australia	112	56 (50%)	50% → 50%
Indonesia	97	68 (70%)	100% → 70%
Malaysia	100	82 (82%)	89% → 82%
Singapore	110	71 (64%)	48% → 64%
Thailand	91	80 (87%)	95% → 87%

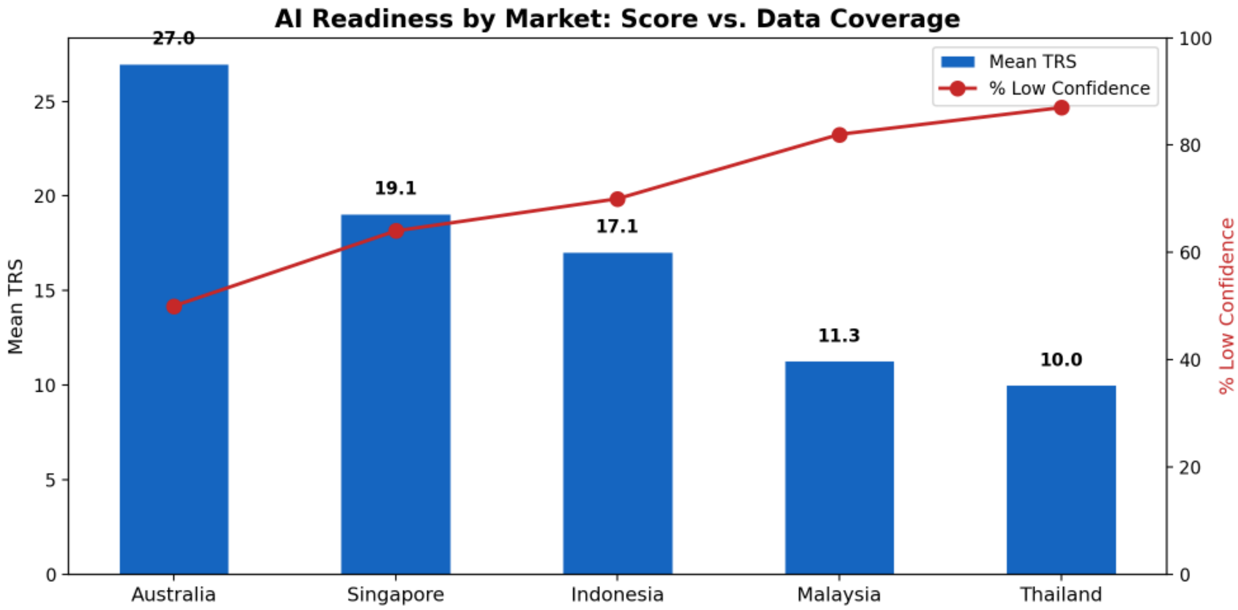

Figure 5: Mean TRS by market (blue bars) vs. percentage of Low confidence companies (red line)

5.4 Sector Analysis

Sector differences in AI readiness are meaningful and persistent. Tech/Fintech companies lead with the highest mean TRS, driven by deeper AI talent pools and stronger digital infrastructure. Manufacturing lags significantly, reflecting the structural reality that labour-intensive industries have lower ratios of specialist to total staff. **A sector-level visibility caveat:** lower-scoring sectors such as Manufacturing and Logistics may reflect both structural readiness gaps and lower digital visibility, particularly where AI capability is embedded in proprietary operational systems, shop-floor automation, or OEM-partner stacks rather than externally signalled. The same failure mode that understates North Asian ecosystems at the country level (Section 4) applies to industrial sectors at the company level: quiet, internalised execution is penalised by an observable-signal methodology.

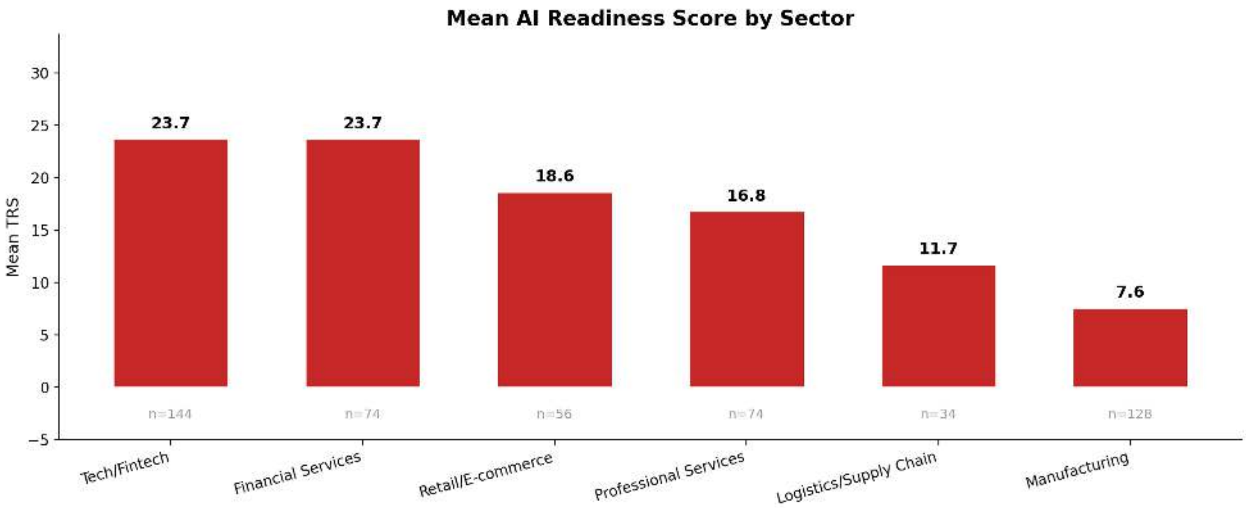

Figure 6: Mean AI Readiness Score by sector

Sector	Companies	Mean TRS	Max TRS	Pacesetters
Financial Services	74	21.5	67.4	14
Tech/Fintech	144	21.2	69.5	21
Retail/E-commerce	56	17.5	73.2	5
Professional Services	74	16.0	55.9	6
Logistics/Supply Chain	34	10.9	55.3	1
Manufacturing	128	7.3	57.6	3

5.5 Top 15 Companies

Top 15 Companies by Total Readiness Score

All Pacesetters have High or Medium data confidence · Bars scaled to max TRS (73.2)

#	Company	Market	Sector	TRS	Tier	Confidence
1	Secretlab	Singapore	Retail/E-commerce	73.2	Pacesetter	High
2	Coda	Singapore	Tech/Fintech	69.5	Pacesetter	High
3	ShopBack	Singapore	Retail/E-commerce	68.4	Pacesetter	Medium
4	THE ICONIC	Australia	Retail/E-commerce	68.3	Pacesetter	High
5	Zip Co	Australia	Financial Services	67.4	Pacesetter	Medium
6	Titansoft Pte Ltd	Singapore	Tech/Fintech	64.1	Pacesetter	High
7	Mindsprint	Singapore	Tech/Fintech	63.6	Pacesetter	Medium
8	humm group	Australia	Financial Services	62.1	Pacesetter	High
9	Pet Circle	Australia	Retail/E-commerce	60.9	Pacesetter	High
10	Buildkite	Australia	Tech/Fintech	58.0	Pacesetter	High
11	Pentamaster Corporation Berhad	Malaysia	Manufacturing	57.6	Pacesetter	Medium
12	Fazz	Indonesia	Financial Services	56.9	Pacesetter	High
13	ADVANCE.AI	Singapore	Tech/Fintech	56.1	Pacesetter	Medium
14	Employment Hero	Australia	Professional Services	55.9	Pacesetter	High
15	Megaport	Australia	Tech/Fintech	55.9	Pacesetter	Medium

Disclosure on named companies. All company information published in this Index is derived exclusively from publicly available or licensed sources – corporate websites, press releases, public job postings, regulatory filings, and commercial business-intelligence platforms operating under their own terms of service. No proprietary, confidential, or personal data (as defined under Singapore's PDPA or equivalent regional frameworks) is republished here. Companies named in this Index were not contacted in advance to seek consent to publication, as the Index is a research publication analysing publicly observable signals of organisational readiness, not of individuals. Rankings are algorithmic outputs of the scoring methodology in Section 2 and are not endorsements or adverse assessments of any named company. Any company wishing to request correction, additional context, exclusion from future editions, or a copy of the signals underlying its score may contact info@airapac.org; corrections supported by evidence will be reflected in the next scheduled refresh.

#	Company	Market	Sector	TRS	Tier	Confidence
1	Secretlab	Singapore	Retail/E-commerce	73.2	Pacesetter	High
2	Coda	Singapore	Tech/Fintech	69.5	Pacesetter	High
3	ShopBack	Singapore	Retail/E-commerce	68.4	Pacesetter	Medium
4	THE ICONIC	Australia	Retail/E-commerce	68.3	Pacesetter	High
5	Zip Co	Australia	Financial Services	67.4	Pacesetter	Medium
6	Titansoft Pte Ltd	Singapore	Tech/Fintech	64.1	Pacesetter	High
7	Mindsprint	Singapore	Tech/Fintech	63.6	Pacesetter	Medium
8	humm group	Australia	Financial Services	62.1	Pacesetter	High
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12	Fazz	Indonesia	Financial Services	56.9	Pacesetter	High
13	Employment Hero	Australia	Professional Services	55.9	Pacesetter	High
14	SICEPAT EKSPRES INDONESIA	Indonesia	Logistics/ Supply Chain	55.3	Pacesetter	High
15	Hudson	Australia	Tech/Fintech	54.8	Pacesetter	Medium

5.6 Per-Market Quadrant Views

The quadrant framework is most useful when applied within a specific market, allowing companies to see their position relative to direct peers.

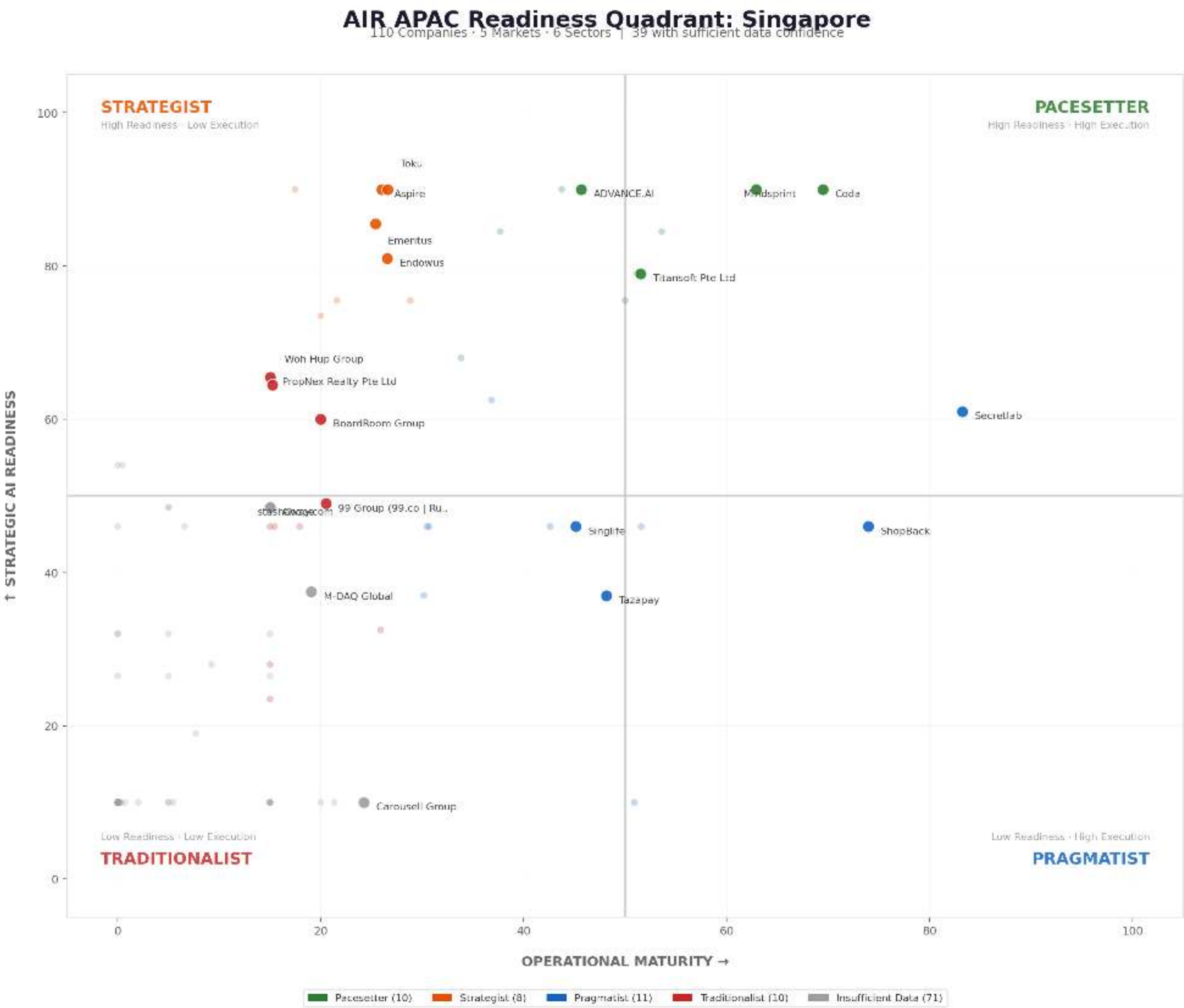

Figure: Readiness Quadrant, Singapore (110 companies)

Figure: Readiness Quadrant, Australia (112 companies)

Figure: Readiness Quadrant, Indonesia (97 companies)

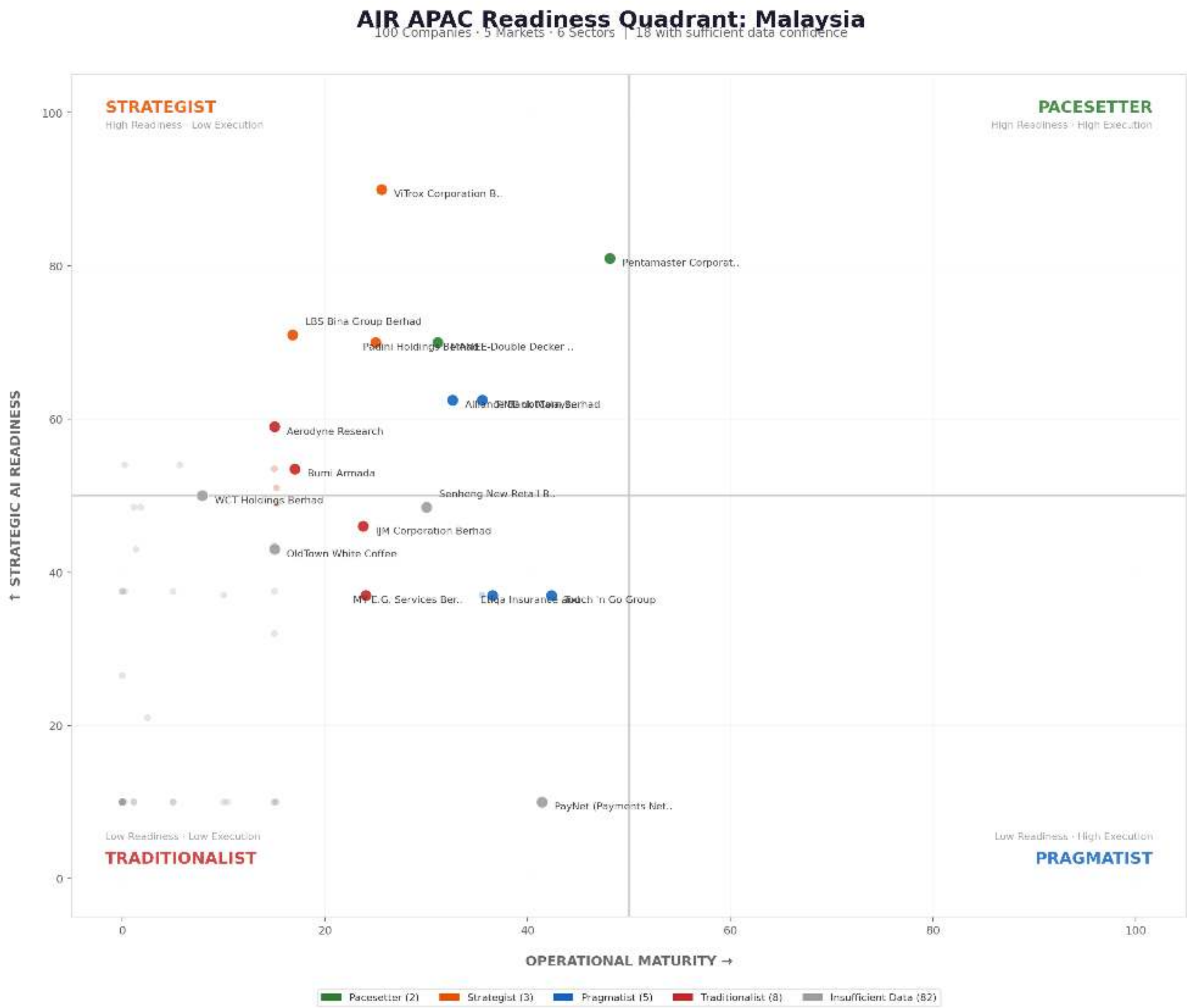

Figure: Readiness Quadrant, Malaysia (100 companies)

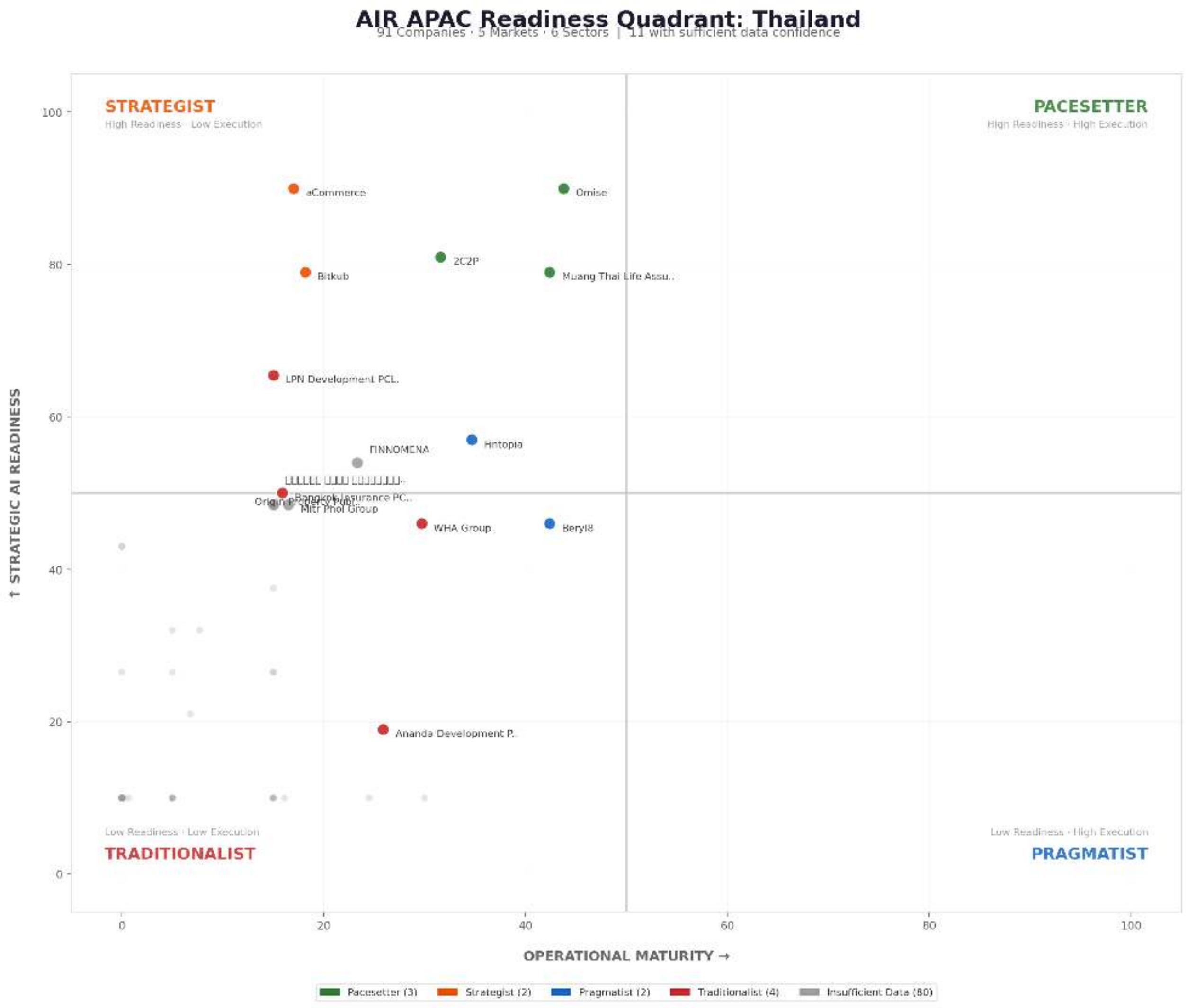

Figure: Readiness Quadrant, Thailand (91 companies)

5.7 Company Spotlights

Pacesetter: Secretlab

Secretlab leads the Index with a TRS of 73.2, scoring strongly across all three layers. With a Digital Footprint score of 100, Talent score of 66.5, and Strategy score of 61.0, the company demonstrates the combination of infrastructure investment, specialist talent, and strategic commitment that defines a Pacesetter.

Data Desert Rescue: Pentamaster Corporation Berhad

Pentamaster Corporation Berhad (Malaysia) exemplifies the Data Desert rescue. In V1, this company scored at the TRS floor of 3.0 with Low confidence – Apollo returned zero usable data. The V2 web enrichment pipeline discovered cloud platforms, hiring activity, and business systems through localised web search, producing a TRS of 57.6 with Medium confidence. The company was not unready – it was unmeasured.

Strategist: Buildkite

Buildkite (Australia) represents the Strategist archetype: strong strategic commitment (Strategy score: 90.0) but limited operational maturity (Digital Footprint: 60, Talent: 35.7). Leadership is communicating transformation intent, but the company has not yet built the infrastructure and talent to execute.

Methodology Stress Test: The Klook Case

One of the most instructive cases in the Index is Klook, the Hong Kong-headquartered travel experiences platform. On the surface, Klook's profile appears anomalous: a Strategy score of 90 but an Operational Maturity score of just 6.12 – placing it deep in the Strategist quadrant with high ambition but near-zero measurable execution.

Three layers of the methodology's quality controls flagged this case correctly:

1. **Data Confidence:** Klook scored Low confidence (5 of 9 signal points). The cross-layer check prevented the high Strategy score from masking the absence of operational evidence.
2. **Score integrity:** The TRS of 30.5 correctly reflects the imbalance. A company with strong press coverage but no detectable cloud infrastructure should not score as a Pacesetter.
3. **Scope validation:** Post-scoring research revealed that Klook is a venture-backed unicorn (valued >$1 billion, $417M annual revenue, active NYSE IPO filing). While its 2,000 headcount is mid-market, every other metric places it firmly in the enterprise segment. The data quality screening correctly identified Klook as out of scope.

The honest caveat. Outlier cases like Klook illustrate both the strength of the confidence system and the limits of observable-signal scoring in complex, high-growth firms. The quality controls caught Klook; they will not catch every comparable case on the first pass, and some companies with genuinely strong internal AI capability but unusual external footprints will sit in Low confidence for reasons that are methodological rather than substantive. This is a known property of the pipeline, not a bug to be engineered away.

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6. The Data Desert: A Structural Barrier to Bridging the Gap

Most readiness indices treat data gaps as a methodological inconvenience to be minimised. The Center for AI Readiness treats them as the primary finding – and as a structural barrier that governments and development agencies must address before the readiness gap can be meaningfully closed.

Causal boundary. The Data Desert is a barrier to *measurement, targeting, and investment allocation*, not a direct causal barrier to AI adoption itself. A company that becomes visible does not automatically become ready; a government that can see its mid-market clearly does not automatically close the readiness gap by seeing it. The Data Desert, once corrected, is a necessary but not sufficient condition for effective intervention. Fixing visibility does not fix capability – but the reverse is also true: capability that cannot be measured cannot be supported.

Falsifiability. The Data Desert hypothesis is not a post-hoc explanation for every low score – it is a testable claim. As visibility improves through multi-source enrichment, native-language signal collection in Korean, Japanese, Indonesian, Thai, and Malay, and broader data-infrastructure investment, TRS for affected markets should converge upward and the TRS–DVS gap should narrow in markets currently flagged as under-detected. If this does not happen across successive Index iterations, the Data Desert thesis is weakened and other explanations (genuine readiness deficit, structural economic drag, absence of policy traction) would dominate the interpretation. This convergence test will be evaluated explicitly in the H2 2026 refresh and in each subsequent edition.

6.1 What the Data Desert Means for Policy and Markets

The systematic invisibility of APAC mid-market companies to global data platforms creates cascading problems:

- **Misallocation of technology investment.** Vendors relying on Apollo, LinkedIn, or BuiltWith to identify targets will systematically overlook companies in Indonesia, Thailand, and parts of Malaysia. These companies are not unready – they are unmeasured.
- **Misleading market intelligence.** Any competitive analysis that treats "no data" as "no capability" will undercount the addressable market in Southeast Asia by 40–60%.
- **Self-reinforcing exclusion.** Companies invisible to data platforms are less likely to be approached by vendors, appear in benchmarks, or attract partnerships. The Data Desert perpetuates itself.
- **Blind spots in national policy.** Governments designing AI capability programmes without accurate mid-market data risk targeting the wrong segments.

6.2 The Two Forms of the Data Desert

The v2.1 edition of this Index formalises the Data Desert as a two-form framework:

- **Coverage gaps** – companies simply absent from Western data platforms. Most acute in Indonesia, Thailand, and parts of Malaysia. Mitigated by multi-source enrichment and localised search queries.
- **Representation gaps** – companies present but systematically mis-measured because their talent and technology signals travel in non-English channels or within internalised

corporate structures (chaebol, keiretsu). Most acute in Japan and South Korea. Acknowledged in v2.1 via "understated (visibility bias)" flags and an explicit methodology note; *no numeric correction is applied* – a formal per-capita density overlay across all 12 markets is planned for the H2 2026 refresh.

6.3 The Distinction: 'Not Found' vs. 'Found Nothing'

"Not found": The data source could not locate the company at all. This is a data coverage problem, not a readiness signal.

"Found nothing": The pipeline located the company, searched multiple sources, and confirmed that no AI/digital signals exist. This IS a readiness signal – the company has been measured and found wanting.

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7. Recommendations: Bridging the Gap

The recommendations below are *consistent with the constraints observed in the Index dataset*, but they are not causal claims derived from the Index alone; they draw on broader AI policy and industry literature for the design of specific instruments (grants, sandboxes, apprenticeships). The Index identifies where to act and who to prioritise; it does not, on its own, prove which instruments will close the gap.

> The readiness gap is bridgeable. The tools exist. The question is whether governments, industry bodies, and enterprise leaders will act with sufficient urgency and coordination.

7.1 For Governments and Policy-Makers

Segment interventions by visibility as well as readiness. The TRS–DVS framework (Section 2.6) implies a two-axis segmentation of policy instruments: low-visibility markets and sectors require *data infrastructure investment first* (public business registries with enriched digital profiles, open company-data APIs, localised standard identifiers) before capability programmes can be effectively targeted or evaluated; high-visibility but low-readiness markets already have the measurement infrastructure and require *talent and adoption interventions* (skills programmes, AI adoption grants, regulatory sandboxes). Applying the wrong instrument to the wrong segment – capability programmes to markets that cannot yet be measured, or data infrastructure to markets whose mid-market is already visible – wastes public investment and produces unmeasurable outcomes.

A. Establish National Mid-Market AI Readiness Baselines

No government in the five scored markets currently maintains a systematic, evidence-based view of mid-market AI readiness. We recommend that ministries responsible for digital economy or trade & industry commission annual readiness baselines grounded in observable behavioral signals, rather than self-reported surveys.

B. Fund Targeted AI Skills Programmes for the Mid-Market

- Subsidised AI upskilling for existing mid-market technology staff
- Employer-linked AI apprenticeship schemes with co-funded salary support for 12–24 months
- AI literacy programmes for mid-market C-suite and board members
- Industry-specific AI competency frameworks tied to national qualifications

C. Create AI Adoption Grants and Regulatory Sandboxes

- Matched-funding grants for mid-market AI proof-of-concept projects (US$50K–200K range)
- Regulatory sandboxes for mid-market firms in regulated sectors
- Tax incentives for AI-related capital expenditure at the mid-market headcount band
- Government procurement frameworks that include AI readiness criteria

D. Invest in Regional Data Infrastructure

Governments should consider investing in regional data infrastructure – public business registries with enriched digital profiles, open APIs for company data, and standardised digital identity frameworks.

E. Coordinate Regional Standards Through ASEAN and APEC

ASEAN and APEC working groups should develop harmonised AI readiness standards and mutual recognition frameworks for AI governance certifications.

7.2 For Industry Associations and Development Agencies

- **Sector-specific readiness benchmarks** using the Index methodology
- **Peer learning networks** using the quadrant framework as a natural segmentation
- **Capacity-building programmes** with the Center for AI Readiness; development agencies (ADB, World Bank, bilateral donors) should embed AI readiness diagnostics into SME programmes
- **Advocacy for mid-market inclusion** in national AI strategy consultations

7.3 For Mid-Market Enterprise Leaders

- **Traditionalists:** Priority is not AI – it is digital infrastructure. Invest in cloud migration and modern ERP before pursuing AI use cases.
- **Strategists:** Most important investment is talent. Evaluate managed AI services; ensure strategic commitment translates into funded initiatives.
- **Pragmatists:** Gap is organisational. Present your board with peer benchmarking; frame AI as risk management; appoint a senior executive sponsor.
- **Pacesetters:** Your opportunity is to shape the market. Publish case studies, contribute to regulatory consultations, consider open-sourcing non-competitive tools.
- **All Tiers:** Build basic AI governance capabilities now. MAS's guidelines and South Korea's AI Basic Act create near-term compliance obligations.

7.4 For Technology Vendors and Partners

Vendors relying on Western data platforms to identify APAC targets are missing 40–60% of the addressable mid-market in Indonesia, Thailand, and Malaysia. Multi-source intelligence is not optional for APAC market coverage. It is the minimum requirement.

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8. Methodology Integrity and Limitations

The Center for AI Readiness is committed to methodological transparency. To use this Index for resource allocation or peer comparison, stakeholders must understand the trade-offs inherent in behavioral signal analysis. By moving away from self-reported surveys, we eliminated social desirability bias, but introduced observability bias. This section preemptively states where that trade lands.

A first-generation measurement system. This Index should be understood as a first-generation measurement system, designed to improve with each iteration as data coverage, native-language signal collection, and longitudinal outcome data expand. The 2026 inaugural edition (V2/v2.1) is a deliberate prior, not a settled fact. Readers who anchor on specific numeric scores rather than on the structural findings (the Data Desert, the visibility-as-observability link, the tier-level distribution of the mid-market) will over-interpret the precision of this first release.

Where the Index is most likely to be wrong. The model has two predictable failure modes. It is most likely to *understate* readiness in firms with high internal AI capability but low external visibility – proprietary industrial firms, internal AI teams inside conglomerates, research-heavy private companies that do not hire visibly or publish about their work. It is most likely to *overstate* readiness in firms with strong public narrative but limited execution depth – companies that have learned to talk about AI effectively without building the underlying capability. The cross-layer confidence check mitigates both cases but does not eliminate them. When the Index appears to disagree with an informed local view of a specific company, the failure mode is almost always one of these two; the cross-layer evidence trail is the fastest way to identify which.

8.1 What the Index Measures: Proxies for Maturity

The Index does not measure absolute, internal AI deployment or realised business impact. It measures *observable proxies* of AI readiness: cloud detection, specialised hiring activity, and public strategic narrative. It is best understood as a **visibility-adjusted assessment of foundational digital maturity and intent**, not a definitive league table of enterprise AI capability.

8.2 Known Methodological Constraints

- **Talent visibility vs. embedded capability:** Our talent metrics rely heavily on platform data (LinkedIn, public job boards). Markets with high English-language platform adoption (Singapore, Australia) will naturally score higher in talent density than markets with alternative professional networks or internalised, low-turnover engineering cultures (Japan, South Korea). We are measuring *visible talent*, not total national capability. No numeric correction for this bias is applied in v2.1 at either the country or company level (see Section 4); ad-hoc correction of selected markets would introduce post-hoc bias of its own. A formal per-capita density overlay across all 12 markets is planned for the H2 2026 refresh.
- **The PR/execution gap in LLM scoring:** Signals F (Strategic Narrative) and G (Digital Commitment) utilise LLM-based structured extraction to quantify a company's public communications. This measures *external articulation of intent*, which can be skewed by strong marketing and PR, rather than internal operational reality. We mitigate this via the

cross-layer confidence check: companies cannot achieve a High-confidence score on narrative alone without corroborating infrastructure or talent evidence.

- **Weighting as a hypothesis, not a constant:** The 25/45/30 layer weightings reflect an analytical judgment that talent is the most reliable observable discriminator in the mid-market. These are hypothesis-driven baselines, not empirically derived constants, and will be recalibrated longitudinally as multi-year adoption and outcome data emerges.
- **Selection and survivorship bias:** Companies with virtually no digital footprint return Low-confidence scores and are excluded from the Pacesetter tier. Consequently, our scored universe inherently over-represents digitally active firms. The true readiness gap in the broader mid-market is likely *wider* than our data suggests; this Index should be read as a floor on the gap, not a ceiling.
- **From correlation to causation:** The Index identifies talent signals as the strongest observable constraint in the dataset. It cannot establish that talent is the single causal bottleneck for AI ROI; leadership alignment, data quality, use-case selection, and economic conditions all contribute and are only partly observable through this pipeline.
- **Score precision vs. tier robustness:** While the Index outputs decimal scores (e.g., 68.4), these are algorithmic artefacts of binary underlying signals. Downstream users should focus on **Quadrant Placement and Tier** (Pacesetter, Strategist, Pragmatist, Traditionalist) rather than small numeric differences. Differences of fewer than ~3 TRS points, or ~5 ecosystem points at the country level, should be treated as statistically indistinguishable.
- **Pacesetter is relative, not absolute:** Pacesetter status reflects the top 10% of *this specific cohort*, not absolute AI maturity on a global scale. A Pacesetter in the APAC mid-market cohort may score differently against a Fortune 500 benchmark. The tiers describe relative leadership, not graduation from the readiness journey.
- **Company-level vs. country-level scope:** The company-level Index (510 firms) and the 12-market ecosystem analysis use different methodologies and should not be read as directly comparable. A higher ecosystem score does not imply stronger company-level scores within that market; ecosystem scoring is directional context, not a predictor of company outcomes.

8.3 Data Quality Screening

The published Index applies a rigorous data quality screening process. The following categories are excluded:

- Job boards, freelance marketplaces, recruitment agencies
- Educational institutions (universities and colleges)
- Media outlets and news publishers
- Non-profit organisations, charities, professional associations
- Confirmed entity mapping errors
- Duplicate domain entries and parent/subsidiary overlaps
- Companies that fall short of the mid-market headcount minimum for their sector

Multi-layer screening spanning 14 exclusion categories reduces a raw candidate pool of **769 entries** by removing 259 via the exclusion categories, yielding the final scored Index of **510 genuinely mid-market companies**. Full exclusion details are maintained in the audit trail (`output/final_index_v3_exclusions.txt`) for transparency.

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9. Conclusion: Bridging the Gap Together

The AI readiness gap in the APAC mid-market is real, it is measurable, and if left unaddressed, it will widen. But the central finding of this Index is not one of pessimism – it is one of actionable opportunity. The gap is bridgeable. The tools exist. The question is whether governments, industry bodies, and enterprise leaders will act with sufficient urgency and coordination.

The barriers to AI readiness in the APAC mid-market are not primarily technological. Cloud infrastructure is widely deployed. Costs for AI deployment are falling rapidly. What is missing is the combination of specialist talent, strategic commitment from leadership, and – critically – the institutional support structures that help mid-market firms bridge the gap between ambition and execution.

The Data Desert finding underscores a deeper structural issue: the global business intelligence ecosystem was not built for APAC. The tools, platforms, and data sources that drive market intelligence, investment decisions, and policy targeting in North America and Europe systematically undercount the APAC mid-market, whether through coverage gaps (Southeast Asia) or representation gaps (North Asia). Bridging this visibility gap is a prerequisite for bridging the readiness gap – you cannot help what you cannot see.

A Call to Coordinated Action

- **Governments:** Commission national mid-market AI readiness baselines. Fund targeted skills programmes and AI adoption grants. Invest in data infrastructure that makes your mid-market visible.
- **Industry associations:** Use the Index data to create sector-specific benchmarks and peer learning networks. Advocate for mid-market inclusion in national AI strategy consultations.
- **Development agencies:** Embed AI readiness diagnostics into SME development and digital economy programmes. The Data Desert is a development challenge, not just a business problem.
- **Enterprise leaders:** Use your Index placement as a starting point, not a verdict. Identify your specific gaps – talent, infrastructure, strategy – and build a prioritised roadmap.

The Index will be refreshed quarterly, with expanded market and sector coverage (including Taiwan and native-language North Asian signals) planned for H2 2026.

References

Third-party research and policy documents cited in this Index. Where a primary URL is unstable, the bracketed descriptor should guide readers to the most recent official publication.

Third-party research

1. IDC (2025). *Asia/Pacific Future Enterprise Resiliency & Spending Survey – AI Spending Intentions 2026*. IDC Asia/Pacific. [Finding cited: 96% of APAC enterprises plan to increase AI spending in 2026 by an average of 15%.] https://www.idc.com/ap
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1. Monetary Authority of Singapore (November 2025). *Guidelines on AI Risk Management for the Financial Sector*. MAS. https://www.mas.gov.sg/
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Index source data and audit trail

1. AIR APAC (2026). *Final Index v3 – Scored Dataset (510 companies), Exclusion Log (14 categories, 259 exclusions), and Signal-level Audit Trail*. Published alongside this report at the URLs below.
    - Scored dataset: `output/final_index_v3.csv`
    - Exclusion log: `output/final_index_v3_exclusions.txt`

- Country ecosystem profiles: `output/country_profiles.json`
- Re-scoring delta (v3 vs. rescored): `output/delta_v3_vs_rescored.md`

All third-party claims quoted in Sections 1, 4, and the *About* section of this paper correspond to the sources numbered above. Readers encountering a statistic without an adjacent in-text citation should treat it as corresponding to the numbered reference that contains the matching finding (e.g., the "95% zero-ROI" figure maps to reference 2; "96% of APAC enterprises plan to increase AI spending" maps to reference 1; "~30% of enterprise workflows mature enough for AI" maps to reference 3). Inline citation markers will be added in the H2 2026 refresh.

About the Center for AI Readiness – Asia Pacific

AIR APAC is the Center for AI Readiness in Asia Pacific – an independent research and advisory institution headquartered in Singapore, governed by an International Council, and dedicated to one mission: closing the AI readiness gap in the region's mid-market.

Why AIR APAC Exists

MIT's 2025 research confirmed what practitioners in the region had long suspected: 95% of AI initiatives deliver zero return on investment. Not because the technology fails – but because the organisation isn't ready. The barriers are human, not technical: leadership alignment, data governance, talent capability, process maturity, and organisational culture. AIR APAC calls this the **Human Layer** – the six dimensions of organisational readiness that determine whether AI creates value or destroys it.

The $50M–$500M companies driving APAC's economy have nowhere to turn. They are too mature for free government courses and online workshops. Too lean for McKinsey's $500K engagements. They face the same competitive pressure as large enterprises but with fewer resources, thinner management layers, and less tolerance for failed investments. AIR APAC exists to fill this gap.

What AIR APAC Does

- **Research:** The Mid-Market AI Readiness Index (this publication) and the AI Readiness Scorecard – a free diagnostic assessment that feeds the Index.
- **Programmes:** The AI Ready Leader executive cohort and specialised intensives delivered through the Center's Alliance of Fellows.
- **Advisory:** Strategic assessments, leadership alignment intensives, data readiness diagnostics, and transformation partnerships.

Independence and Neutrality

AIR APAC does not build AI. It does not sell AI technology. It does not take equity in client companies or accept technology vendor sponsorship.

> ***We are agnostic on the engine. We are opinionated on the steering wheel.***

Governance

The Center is governed by an International Council comprising senior executives, academic leaders, and policy practitioners across the Asia Pacific region. An Academic Council provides independent oversight of the Index methodology and research integrity.

Guiding Principles

- **Methodological transparency:** Every score is auditable. Every signal is documented. Every limitation is disclosed.

- **Intellectual honesty:** The Index reports what the data shows, not what stakeholders want to hear. Low confidence is flagged, not hidden. Limitations are stated before conclusions.
- **Actionable relevance:** Research that does not inform action is academic exercise. Every finding in this publication is designed to help a specific stakeholder make a better decision.

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