AI APPLIED

ABAC

Successful Use-Cases in APEC's Traditional Industries



A report of the APEC Business Advisory Council
A joint project of ABAC Canada and ABAC China
Authored by the Asia Pacific Foundation of Canada

ASIA PACIFIC FOUNDATION OF CANADA
FONDATION ASIE PACIFIQUE DU CANADA

ABAC

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FOREWORD

Artificial intelligence is becoming an integral part of the economic infrastructure that supports growth, competitiveness, and inclusion across our region. The question is no longer whether AI will transform our economies. The question is which economies, and which businesses, will be ready to harness its benefits.

AI adoption is accelerating across APEC, but it is not accelerating evenly. Some economies and large firms are moving quickly, while many smaller businesses have yet to begin. For the traditional industries that employ much of the region's workers, from mining and shipping to agriculture, health care, and aquaculture, the practical challenge is not simply gaining access to AI. It is putting AI to work.

Over the past year, ABAC examined 13 AI deployments across nine APEC economies to understand how to put AI to work. The central finding is clear: successful AI adoption depends more on the conditions around the technology than on the sophistication of the technology itself. The firms achieving meaningful results started with a defined business problem, usable data, a workforce equipped to adapt, and a policy environment that enables deployment. Their gains came not from having the most advanced AI, but from getting the fundamentals of adoption right.

That lesson matters especially for micro, small, and medium-sized enterprises. Most will not build AI themselves. They will adopt AI through the business tools and platforms they already use. The challenge for APEC is therefore to ensure that businesses of every size, and economies at every stage of digital development, have the capacity to participate.

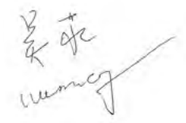
The next phase of the AI opportunity is not simply about developing more powerful technology. It is about enabling more businesses to put that technology to work.

We offer this report to APEC Leaders and Digital Ministers, and to businesses across the region, as a practical guide to what is already working and to the conditions needed to turn AI ambition into AI adoption.



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Acknowledgments

This report was commissioned by the APEC Business Advisory Council (ABAC) as a joint project between ABAC Canada and ABAC China, authored by the Asia Pacific Foundation of Canada. The team is grateful to the firms that gave their time to be interviewed and to ABAC China and the APEC Study Center at Nankai University for their partnership.

The project team thanks the ABAC members and staffers who supported the work, and the partner organizations, especially the Kadin Indonesia Institute, that made introductions across the region.

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USE OF AI

The lead author used AI tools to assist with drafting and editing. The research, analysis, and findings are the lead author's own. The lead author verified all figures and quotations against interview records and firm-approved text.

APEC Business Advisory Council
Canada

About ABAC

Recognizing the integral role of business and the value of representative business advice on key issues, APEC leaders established the APEC Business Advisory Council (ABAC) in November 1995. ABAC is the sole private-sector arm of APEC with a mandate to advise leaders and other APEC officials on issues of interest to business.

This private-sector body presents recommendations to APEC leaders in an annual closed-door dialogue and advises APEC officials on business-sector priorities and concerns. ABAC meets four times a year; ABAC representatives also attend senior officials' meetings, the annual ministerial meeting and, the sectoral ministerial meetings. ABAC members are appointed by their respective economic leaders and represent a range of business sectors, including micro, small, and medium-sized enterprises (MSMEs).

Visit the ABAC Website ▸

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About the Asia Pacific Foundation of Canada

The Asia Pacific Foundation of Canada (APF Canada) is an independent not-for-profit organization focused on Canada's relations with Asia. Our mission is to be Canada's catalyst for engagement with Asia and Asia's bridge to Canada.

APF Canada is dedicated to strengthening ties between Canada and Asia through its research, education, and convening activities, such as the Canada-in-Asia Conferences series, our Women's Business Missions to Asia, and the APEC-Canada Growing Business Partnership project. APF Canada serves as Canada's Secretariat for several APEC networks, including the APEC Business Advisory Council and the Pacific Economic Cooperation Council, and serves as one of Canada's designated APEC Study Centers.

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Executive Summary



Rio Tinto smelter in Kitimat, British Columbia. Photo by Province of British Columbia via Flickr.

Artificial intelligence is creating new opportunities for productivity and competitiveness across APEC's traditional industries. From mining and manufacturing to logistics, agriculture, and health care, businesses are demonstrating measurable improvements in efficiency and operational performance.

Yet the ability to capture these benefits remains uneven. The emerging divide is increasingly about whether businesses have the data, skills, infrastructure, and enabling conditions required to put AI to work.

For APEC, the challenge is to move from individual successes to widespread adoption that strengthens productivity, competitiveness, and inclusive growth across the region.

This report finds that successful AI adoption depends more on the conditions around the technology than on the sophistication of the technology itself.

Drawing on 13 case studies across nine APEC economies, the report examines how businesses in traditional sectors are putting AI to work, what is producing measurable value, and what governments and businesses can do to accelerate adoption.

AI is already delivering results

Across APEC's traditional industries, businesses are achieving measurable gains in productivity, efficiency, and operational performance.

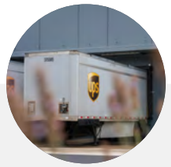


EverEx

KOREA

Improved

Outcomes in randomized controlled trial of more than 200 patients.



UPS

UNITED STATES

~99%

Customs clearance rate recovered.



Xiaomi

CHINA

90%

Reduction in automotive inspection time.
20 seconds ▸ 2 seconds.



eShepherd

NEW ZEALAND

4 weeks ▸ 5 days

Warranty processing time reduced.

The results are tangible. Antofagasta Minerals (Chile) uses AI-based recommendation systems to optimize key processing steps, such as leaching and grinding. UPS (United States) recovered customs clearance rates to around 99 per cent. EverEx (Korea) demonstrated significantly improved pain, function, and quality-of-life outcomes compared with usual treatment in a randomized controlled trial of more than 200 patients. eShepherd (New Zealand) reduced warranty processing from four weeks to five days. Xiaomi (China) reduced automotive inspection time from 20 seconds to two seconds while achieving inspection accuracy above 99.9 per cent.

Five conditions for successful AI adoption

Our research shows that successful AI adoption depends on five mutually reinforcing conditions, rather than technology alone.

1 **Business Problem**

Clear, well-defined business challenge with measurable value potential.

2 **Data Readiness**

Access to high-quality relevant data with appropriate governance.

3 **Enabling Environment**

Supportive regulatory, assurance, and infrastructure conditions.

4 **Workforce Capability**

People with the skills and industry expertise to apply AI effectively.

5 **Capacity to Adopt**

Organizational capability to integrate AI into operations and scale its use.

Successful AI adoption

How AI reaches MSMEs

For micro, small, and medium-sized enterprises (MSMEs), the pathway to adoption will often be different from that of large firms. Most MSMEs will not build AI. They will adopt AI through the software, platforms, and business tools they already use.

Online marketplaces, booking platforms, cloud services, and other business platforms are increasingly embedding AI directly into the tools used by smaller businesses. In this model, the platform is the AI enabler and the MSME is the adopter. A small business does not need to develop its own AI capability; it needs access to affordable and trusted tools, the skills to use them, and the ability to reorganize work around them.

This has an important implication for APEC. Scaling AI adoption across millions of MSMEs is not primarily about helping every small business build AI. It is about creating the conditions that allow them to adopt proven AI-enabled tools at scale.



Container ship MOL Tribute, on the Elbe, bound for the port of Hamburg. Photo by Hummelhummel via Wikimedia Commons.

From AI ambition to AI adoption

APEC Leaders have already established a regional ambition through the APEC AI Initiative (2026–30). The next challenge is implementation: creating the conditions that allow businesses across all APEC economies to translate advances in AI into productivity, competitiveness, and growth.

ABAC therefore calls on APEC Leaders and Digital Ministers to focus co-ordinated regional action on four priorities:

1 **Build the data foundations for AI.** Advance common data standards and interoperability, modernize data legislation, and improve access to high-quality industrial, local, and culturally relevant data.

2 **Create regulatory and reimbursement pathways that enable adoption.** Establish predictable regulatory pathways for AI-enabled products and services, work toward mutual recognition where appropriate, and co-ordinate safety and assurance frameworks that allow proven applications to scale.

3 **Invest in the workforce that AI depends on.** Expand upskilling, apprenticeships, and on-the-job pathways that combine AI capabilities with deep sector expertise.

4 **Make AI adoption inclusive.** Support targeted pilots, shared infrastructure, and capacity-building that lower the cost and complexity of adoption for MSMEs and traditional sectors in less AI-ready economies. Harness AI-enabled platforms and existing business tools as an important pathway for bringing AI capability to smaller firms at scale.

The next phase of the AI opportunity is not simply about developing more powerful technology. It is about enabling more businesses, in more sectors and across more economies, to put that technology to work.

Introduction

01

AI is moving rapidly from experimentation to deployment across APEC. But its benefits are not spreading evenly.

In the first quarter of 2026, the share of the working-age population using generative AI ranged from more than 60 per cent in APEC's leading economy to less than 10 per cent in the least connected (Figure 1). A similar divide exists between firms. Large businesses often have the data, skills, infrastructure, and capital needed to adopt AI, while many smaller businesses and grassroots producers do not.

The challenge for APEC is therefore not simply advancing AI technology. It is broadening the capacity to adopt it.

APEC Leaders established that ambition in October 2025 through the APEC AI Initiative (2026–30), adopted in the Gyeongju Declaration. The Initiative focuses on advancing AI transformation and resilient growth, building AI capacity and participation across economies, and cultivating investment in resilient AI infrastructure.

Translating ambition into implementation

For businesses in traditional industries, the question is increasingly practical: Where can AI create value, what does it take to deploy successfully, and how can proven applications be scaled?

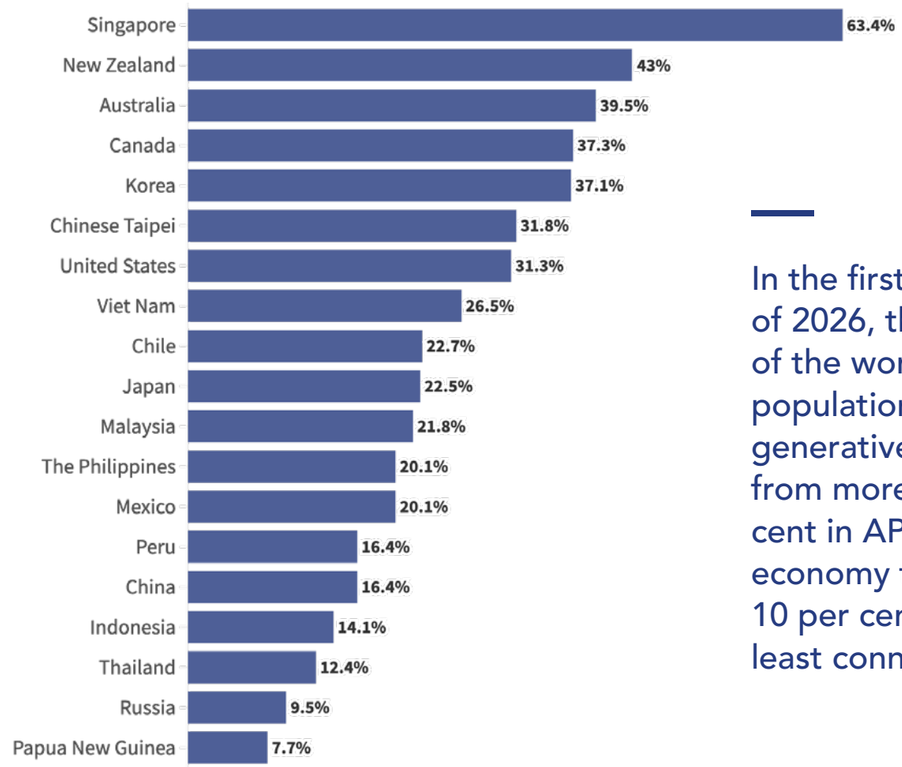
This report addresses those questions through the experience of firms already putting AI to work across mining, manufacturing, logistics, maritime, health care, agriculture, aquaculture, forestry, and other traditional sectors.

The cases point to an important distinction. Access to increasingly capable AI models does not by itself produce adoption. Businesses also need usable data, workers capable of applying the technology, clear regulatory and commercial pathways, and a business problem or opportunity worth solving.

These conditions are not evenly distributed. This warrants attention because firms and economies best positioned to adopt AI today are also often those best positioned to capture its productivity gains tomorrow.

Figure 1: AI adoption across APEC economies, Q1 2026

Share of working-age population using AI, %



Source: Microsoft AI Economy Institute, AI Diffusion Index, Q1 2026 release (method described in arXiv 2511.02781). **Note:** The source does not report data for Brunei Darussalam or Hong Kong, China.

In the first quarter of 2026, the share of the working-age population using generative AI ranged from more than 60 per cent in APEC's leading economy to less than 10 per cent in the least connected

According to Microsoft's 2026 AI Diffusion Index, Singapore leads APEC at 63.4 per cent in the share of working-age population using AI, followed by New Zealand, Australia, Canada, and Korea. At the other end of the distribution, several economies remain below 20 per cent, with Papua New Guinea at 7.7 per cent.

These figures measure individual use rather than business adoption, but they illustrate the very different environments in which APEC firms are operating. Workers' familiarity with AI, digital connectivity, and skills all influence how readily businesses can put new technologies to work.

The same challenge is visible at the firm level. Large enterprises can invest in data infrastructure, specialist talent, and customized AI applications. Smaller businesses are more likely to depend on AI capabilities embedded in the platforms, software, and business tools they already use.

For most MSMEs, the path to AI will therefore be adoption, not development.

The challenge is to make that pathway affordable, accessible, and trusted across APEC.

Why APEC action matters

The private sector will develop and deploy much of the technology. But businesses cannot create all of the conditions for adoption on their own.

Data interoperability, regulatory and reimbursement frameworks, workforce development, digital infrastructure, and measures that enable smaller firms to participate all have a public-policy dimension. Co-operation across APEC can also help economies learn from successful deployments rather than each starting from scratch.

The opportunity is to turn uneven experimentation into broad-based adoption, allowing more businesses, in more traditional sectors and across more APEC economies, to translate AI into productivity, competitiveness, and growth.

This report examines what is already working and identifies the practical lessons for businesses and policymakers seeking to make that transition.



Centinela. Photo by Antofagasta Minerals via Flickr.

THE AI DIVIDE

As in the wider digital economy, the divide in AI is less about access to the technology and more about the conditions for using it: data, skills, connectivity, and capital required for adoption. Closing that gap is where co-ordinated APEC action can do the most for regional economic growth.

Methodology: 02

Learning from AI in Practice

This report documents 13 AI case studies across nine APEC economies, spanning traditional sectors including mining, logistics and maritime transport, health care, agriculture and aquaculture, forestry, manufacturing, and new energy.

The cases were deliberately selected to capture a range of economies, sectors, firm sizes, and approaches to AI adoption. They include large enterprises deploying AI at scale, smaller businesses and producers adopting AI-enabled solutions, and technology providers developing applications for traditional industries.

Each case study was developed primarily through interviews with participating firms, supplemented by publicly available information where relevant. Participating firms reviewed and approved their respective case studies for accuracy.

The analysis focuses not simply on the technology deployed, but on the business problem or opportunity being addressed, the conditions required for adoption, the results achieved, and the lessons that can be applied elsewhere across APEC.

The cases are not intended to provide a statistically representative assessment of AI adoption across the region. Rather, they provide practical evidence of how AI is being deployed today, what is enabling successful adoption, and where barriers remain.

Taken together, the cases provide a window into what it takes to take AI from technological possibility to practical business value.

Two cases, Banyu and FisTx, were developed with the Kadin Indonesia Institute, covering seaweed and shrimp aquaculture. Three cases were developed with the APEC Study Center at Nankai University, covering manufacturing, low-altitude drone logistics, and new energy. These are woven through the analysis rather than treated separately. They illustrate patterns that recur across the wider set, including the distinction between firms that adopt AI and firms that build it.

A note on evidence

The findings rest on what firms reported in interview, corroborated by public sources where available. Quantified outcomes of AI adoption are attributed to their source and, where a figure could not be traced to an approved source, it is described qualitatively rather than stated as confirmed. The full case studies, with their evidence and sourcing, are provided in the annex.

Table 1: The 13 firms studied

FIRM	ECONOMY	SECTOR	SIZE	WHAT THE FIRM DOES
Rio Tinto	Australia	Mining	Very large	Leading global mining and materials company
Antofagasta Minerals	Chile	Mining	Very large	Top 10 copper producer, using AI to optimize processing and lift recovery
Mitsui O.S.K. Lines	Japan	Maritime	Very large	Global shipping company, using AI for voyage optimization and knowledge transfer
UPS	United States	Logistics	Very large	Global express and supply chain provider, using machine learning for customs classification
EverEx	Korea	Health care	Mid-sized	Digital health firm providing AI-guided home rehabilitation through a phone camera
Banyu	Indonesia	Aquaculture (seaweed)	Small	Grassroots seaweed producer breeding improved seedlings for smallholder farmers
FisTx	Indonesia	Aquaculture (shrimp)	Small	Aquaculture firm applying AI inside the company before placing it in farmers' hands
Lumber Pricing (Yeji Data Lab)	Canada	Forestry	Mid-sized	AI provider that built a pricing module for a mid-sized lumber business
Container Terminals (Yeji Data Lab)	Canada	Ports	Mid-sized	AI provider that built predictive maintenance for a container terminal operator
eShepherd by Gallagher	New Zealand	Agriculture	Mid-sized	Virtual fencing platform for cattle, using AI across support, warranty, and product
Xiaomi Corporation	China	Manufacturing	Very large	Technology manufacturer applying industrial AI models in automotive production
Phoenix Wings (Shenzhen) Co., Ltd.	China	Drone logistics	Mid-sized	Low-altitude logistics operator using AI for perception and flight support
Shenzhen SmartMore Technology Co., Ltd.	China	New energy	Mid-sized	Industrial AI firm building inspection models and devices that other factories adopt


CANADA
Lumber Pricing, Container Terminals
(Yeji Data Lab)
UNITED STATES
UPS
CHILE
Antofagasta Minerals
CHINA
Xiaomi, Phoenix Wings, SmartMore
KOREA
EverEx
JAPAN
Mitsui O.S.K. Lines
INDONESIA
Banyu, FisTx
AUSTRALIA
Rio Tinto
NEW ZEALAND
eShepherd by Gallagher

How Businesses Are Adopting AI

03



Drone delivery. Photo by Zyanya Citlalli via Unsplash.

Across the 13 case studies, AI adoption is underway but far from uniform. Firms are putting AI to work in different ways depending on the business problem, their internal capabilities, the readiness of their data, and the availability of suitable technology.

In the most AI-ready settings, AI is increasingly integrated into longer-term business strategies and governance. Mitsui O.S.K. Lines treats AI as an enabling capability within its 13-year BLUE ACTION 2035 management plan. Rio Tinto is progressively developing its AI capabilities, applying the technology to specific operational and business needs while taking a considered approach to safety, risk, and governance. In less AI-ready settings, adoption is more likely to begin with a specific problem and progress incrementally, often after more fundamental business and data capabilities have been established. Banyu and FisTx illustrate this approach in Indonesian aquaculture.

The cases demonstrate that businesses do not need to build AI themselves to benefit from it. What matters is finding the right pathway to adoption.

Three pathways to AI adoption

Businesses in APEC are adopting AI through three main pathways, often using a combination.

1

Existing platforms

- Adopting AI capabilities through established software platforms and tools
- Lower cost and faster implementation (often relevant for MSMEs)

2

Internal development

- Building in-house capabilities tailored to specific business needs
- Greater control and customization (typically larger organizations)

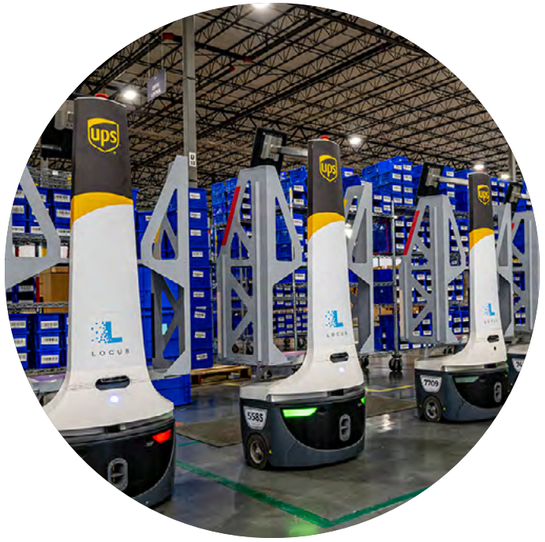
3

Specialist providers

- Working with specialized AI companies and technology partners
- Access to deep expertise and sector-specific solutions

What matters is not who builds the AI, but whether the approach matches the business need and whether the organization has the conditions required to put it to work.

Successful AI adoption



Automated warehouse robots. Photo by UPS.

For smaller businesses in particular, the ability to draw on external AI capability can reduce the cost, complexity and expertise required for adoption.

Two roles: AI adopters and AI enablers

The cases also reveal two distinct but complementary roles in the AI economy: **AI adopters** and **AI enablers.**

AI adopters use AI to improve their own operations, products, or services. Rio Tinto, Mitsui, and UPS are examples, applying AI to problems within their existing industries.

AI enablers develop the models, applications, platforms, or services that allow other businesses to adopt AI. SmartMore, for example, develops IndustryGPT and inspection systems that other manufacturers can deploy. EverEx has developed an AI-enabled rehabilitation platform used by health care providers. Some firms can play both roles: Xiaomi develops industrial AI capabilities while also deploying them within its own automotive manufacturing operations.

This distinction matters because AI adoption at scale will depend on connecting the two.

Adopters need affordable, trusted solutions suited to their business and sector. Enablers need market demand, sector knowledge, and access to the data required to develop useful applications.

For smaller businesses in particular, the ability to draw on external AI capability can reduce the cost, complexity, and expertise required for adoption. Rather than every firm developing its own AI capability, specialist providers and platforms can spread proven applications across many businesses.

Government can help both sides meet, particularly for the smaller firms that lack the resources to find each other, which connects this distinction directly to the inclusion theme.

For most MSMEs, adoption will happen through platforms

Most MSMEs will not build AI. They will adopt better business tools powered by AI.

For many smaller businesses, the most practical pathway to AI will be through software and platforms they already use. Accommodation and booking platforms, online marketplaces, cloud services, and search providers increasingly embed AI capabilities directly into their products. In this model, the platform acts as the AI enabler and the small business becomes the adopter.

This changes the way the MSME adoption challenge should be understood. A small business does not necessarily need its own AI models, specialist technical team, or large technology budget. It needs access to affordable and trusted AI-enabled tools, the skills to use them effectively, and the ability to adapt its business processes to take advantage of them.

Platforms and other AI enablers can therefore become force multipliers for adoption, allowing AI capabilities to reach many businesses without each having to build those capabilities independently.

This has important implications for APEC. Supporting MSME adoption is not simply a matter of helping individual businesses develop AI expertise. It also means strengthening the digital and data foundations that allow them to use AI-enabled tools, building confidence and skills, and enabling competitive markets in which trusted solutions can reach smaller firms across economies.

Different firms, different starting points

The case studies also show that the pathway to adoption varies with the resources and capabilities of the firm.

Large enterprises such as, Antofagasta Minerals, Mitsui, and UPS can govern AI at the enterprise level, invest in their own data foundations, and develop or customize applications around defined business opportunities.

Mid-sized and scaling firms such as EverEx, Yeji Data Lab, and eShepherd tend to begin with narrower applications and well-bounded business problems, allowing them to demonstrate value before expanding deployment.

At the grassroots level, Banyu and FisTx illustrate a different starting point. Both work with producers for whom basic operating practices, data collection, and digital capability may need to be strengthened before more advanced AI applications can add value. In these circumstances, adoption may need to be sequenced behind foundational capacity-building and supported by external partners.

The pathway may differ, but the lesson across the cases is consistent:

Successful AI adoption is not determined by access to the most advanced technology. It depends on matching the technology to a defined business need and creating the conditions to put it to work.

Section 4 examines those conditions in greater detail.

Findings: 04

Five Conditions for Successful AI Adoption

Across sectors, economies, and firm sizes, the cases point to five conditions that consistently determine whether AI moves from technological possibility to practical business value.

No single condition is sufficient on its own.

Successful adoption occurs when AI is matched to a defined business need and supported by the data, people, and enabling environment required to put it to work.

The five conditions at a glance

	CONDITION	WHAT THE CASES SHOW	ILLUSTRATIVE CASES
1	Start with the business problem or opportunity	AI creates value when it is tied to a defined business need and measurable outcome.	Rio Tinto; UPS; eShepherd
2	Get the data ready	Data quality, accessibility, and consistency determine how much value AI can add.	Mitsui; Rio Tinto; Yeji Data Lab
3	Create an enabling environment	Regulation, approvals, reimbursement, and assurance can determine whether technically viable AI can be deployed and scaled.	EverEx; UPS
4	Prepare the workforce	AI changes tasks and increases demand for workers who combine sector expertise with digital and AI capabilities.	Antofagasta; Rio Tinto; eShepherd
5	Expand the capacity to adopt	Smaller firms and less AI-ready economies often lack the data, skills, capital, and infrastructure available to larger firms.	Banyu; FisTx; eShepherd

Firms may be attracted by increasingly capable AI models, but sophisticated technology cannot compensate for fragmented, inaccessible, or poorly defined data.

Start with the business problem or opportunity

The strongest deployments began with a business outcome, not an AI ambition.

Successful adopters first identified a problem to solve or an opportunity to capture and then assessed whether AI was the appropriate tool. This gave firms a clear objective against which the value of deployment could be measured.

The company therefore focuses on applying AI to defined business needs, with applications spanning areas including productivity, operational performance, equipment reliability, and mine planning.

UPS followed the same principle from a different starting point. Changes in customs requirements created an operational problem that made manual classification increasingly difficult to sustain. Machine learning was deployed in response to that need, helping customs clearance recover to around 99 per cent.

The lesson is straightforward:

AI adoption should begin with the value a business is trying to create, not with the technology it wants to deploy.

Get the data ready

Data readiness sets the ceiling on AI value.

Across the cases, the quality, accessibility, and consistency of data determined what AI could achieve. In several instances, preparing the data required as much attention as selecting or developing the technology itself.

Mitsui described data readiness, rather than the availability of AI tools, as setting the pace of adoption. Rio Tinto faces the challenge and opportunity of applying AI across decades of operational and legacy data. Yeji Data Lab found that operational metrics first had to be consistently defined and re-engineered before effective modelling could begin. eShepherd similarly rebuilt its inquiry database before applying AI to customer support and warranty processes.

These experiences point to a practical sequencing issue. Firms may be attracted by increasingly capable AI models, but sophisticated technology cannot compensate for fragmented, inaccessible, or poorly defined data.

For many businesses, the most important first investment in AI may therefore be the data foundations that make AI usable.

Create an enabling environment

Technically viable AI does not automatically translate into commercially viable adoption.

The cases demonstrate the importance of the policy and market environment surrounding the technology. Regulation, approval processes, reimbursement, and assurance frameworks can determine whether an AI application can progress from successful demonstration to sustained deployment.

EverEx provides the clearest example. Its AI-enabled home rehabilitation technology had demonstrated technical and clinical potential, but adoption depended on regulatory approval and a mechanism to reimburse the clinical activity supporting the service. Once a reimbursement pathway became available in the United States, its revenue there overtook its Korean revenue in 2024.

UPS similarly identified regulatory complexity and incomplete adoption of paperless customs processes as constraints on further automation.

The implication extends beyond these individual cases.

When policies, regulations, or frameworks do not evolve alongside technology, viable AI applications can remain stranded between innovation and adoption.

Governments therefore have an important role not in choosing the technologies businesses should use, but in creating predictable conditions in which proven applications can be responsibly deployed and scaled.



Rio Tinto Nerva Mining Basin Heritage Area. Photo by Junta Informa via Wikimedia Commons.

Prepare the workforce

AI adoption is not simply a technology investment. It changes how work is performed, how decisions are made, and how employees contribute value.

Successful adoption depends on combining AI capabilities with deep industry knowledge. The challenge is not simply to develop more AI specialists, but to equip people who understand their industries to apply AI effectively.

Across the cases, AI reduced or automated some routine tasks while increasing demand for workers able to combine sector knowledge with digital and AI capabilities.

At UPS, machine learning substantially reduced reliance on specialist manual customs classification. Rio Tinto identifies one of the constraints on adoption in the resources sector as the availability of people who understand both complex industrial operations and AI. eShepherd developed new data-science capabilities as AI became more deeply integrated into its operations.

Antofagasta Minerals illustrates how firms can respond deliberately. Its Digital Academy provides employees with new capabilities as digital tools and AI become integrated into mining operations.

The cases therefore point primarily to task redesign, augmentation, and redeployment, while also demonstrating the need for substantial upskilling. The challenge is not simply to teach workers how to use AI tools. It is to develop people who can combine AI capability with the deep sector expertise required to apply those tools effectively.

For traditional industries, this combination of operational experience and digital capability will become an increasingly important source of competitive advantage.



A solar-powered GPS neckband that holds and moves cattle with audio-first cues, no posts and no wire. Photo by eShepherd.

Expand the capacity to adopt

The most consequential finding for APEC is the divide in the capacity to adopt AI.

Large enterprises generally have greater access to the data, specialist skills, infrastructure, and capital needed to experiment with and deploy AI. The experience of Rio Tinto, Mitsui, UPS, and Antofagasta demonstrates what becomes possible when these foundations are already present.

The starting point is very different for many smaller businesses and grassroots producers.

Banyu and FisTx work with Indonesian aquaculture producers where connectivity, data collection, and digital capability may need to be strengthened before AI can add value. Their experience demonstrates why AI sometimes needs to be sequenced behind more fundamental capacity-building rather than introduced as the first intervention.

The challenge also exists in more AI-ready economies. eShepherd identified affordability, understanding of the technology, and limited public support for initial deployment as barriers for smaller agricultural producers.

The cases therefore suggest that the emerging AI divide is not simply about access to technology. It is increasingly about whether businesses have the capacity to put that technology to work.

This distinction matters particularly for MSMEs. As Section 3 shows, many smaller firms will access AI through platforms, software, and specialist providers rather than developing it themselves. That can significantly lower the technical barrier to adoption, but it does not eliminate the need for digital capability, skills, appropriate data, and the resources to change business processes.

Without those foundations, the firms and economies already best equipped to adopt AI are likely to capture its benefits faster than those starting further behind.

Closing the adoption-capacity gap is therefore central to ensuring that AI contributes to broad-based productivity and growth across APEC.

From technology readiness to adoption readiness

Taken together, the five findings shift the focus of the AI debate.

The availability and capability of AI technology will continue to advance rapidly. But the cases in this report suggest that technology alone is not the principal determinant of whether businesses capture its value.

The cases therefore suggest that the emerging AI divide is not simply about access to technology. It is increasingly about whether businesses have the capacity to put that technology to work.

The critical question is increasingly one of adoption readiness: Does the business have a problem worth solving, data that can support the solution, an enabling policy environment, people equipped to use it, and access to the capabilities required to deploy it?

These conditions are mutually reinforcing. Strong data without skilled people will not produce sustained adoption. A technically successful application may not scale without an appropriate regulatory or commercial pathway. And smaller firms may struggle to participate even when proven AI solutions are readily available.

The next phase of AI adoption across APEC will therefore depend not simply on making AI more powerful, but on making more businesses ready and able to use it.

Section 5 examines how these conditions play out across individual sectors before Section 6 turns to the actions APEC Leaders and Digital Ministers can take to accelerate adoption.



Eco-friendly seaweed farming to support sustainable economy. Photo by Satwika02 via Wikimedia Commons.

How AI Adoption Differs by Sector

05

The conditions for successful AI adoption are broadly consistent across the case studies, but how those conditions are applied differs significantly by sector.

In mining and heavy industry, safety, accountability, and operational resilience are critical. In logistics and maritime transport, interoperability and the movement of data across complex systems matter greatly. In health care, regulation and reimbursement can determine whether adoption is commercially viable. In agriculture and aquaculture, affordability, connectivity, and producer readiness set the pace of uptake. In manufacturing and other industrial applications, AI is increasingly being embedded directly into production systems.

There is therefore no single model for AI adoption across APEC. The common conditions identified in Section 4 need to be applied to the operational realities of individual sectors.

Mining: Productivity gains require strong operational guardrails

Mining demonstrates both the potential value of AI in complex industrial environments and the importance of governing where and how it is used.

Antofagasta Minerals provides a clear example of AI applied at scale in mining. Its SIRO recommendation systems support the optimization of processing steps, such as leaching and grinding. Its Digital Academy also illustrates the workforce dimension of adoption, helping operators develop the capabilities needed to work alongside new digital systems.

Rio Tinto is building on decades of automation and technological innovation to apply AI across mining operations. Applications include modernization of systems, machine learning to support mineral exploration, AI to optimize equipment dispatch and autonomous truck movements, and predictive analytics to improve equipment reliability. These examples demonstrate how AI can support value creation and productivity improvements in complex industrial environments where safety and risk management are critical.

The sector lesson is that AI can create significant value in heavy industry, but adoption must be matched by governance appropriate to the operational consequences of failure.

Logistics and maritime transport: Interoperability is central to scaling adoption

Logistics and maritime transport demonstrate the value of AI in managing complex flows of goods, information, and decisions across organizations and borders.

UPS introduced machine learning into customs classification as United States import requirements became more complex, helping customs clearance recover to around 99 per cent. The company also reports that 97 per cent of its shipments clear customs on the first day of entry. UPS identifies greater adoption of paperless customs as an important means of enabling further automation across international logistics.



UPS plane. Photo by Lukas Souza on Unsplash.



Xiaomi Store in Loulé, Portugal. Photo by Justin Sijbolts via Wikimedia Commons.

Health care provides the clearest example in the study of technically successful AI depending on the surrounding regulatory and financial environment.

Mitsui O.S.K. Lines takes a broader transformation approach. AI is set within its long-term management strategy, with applications including voyage optimization and knowledge transfer. The company has set a target of reducing time spent on repeated tasks by 20 per cent by 2030 as part of efforts to transfer knowledge from experienced crews to younger employees.

These cases point to a broader sector issue. Logistics and maritime transport are inherently interconnected and cross-border. The value of AI therefore depends not only on what an individual firm can automate, but also on the quality and interoperability of the data and processes connecting firms, ports, customs authorities, and other parts of the supply chain.

In logistics, AI adoption can progress only as fast as the systems around it allow.

Health care: The adoption bottleneck may lie outside the technology

Health care provides the clearest example in the study of technically successful AI depending on the surrounding regulatory and financial environment.

EverEx's MORA platform uses AI-based pose estimation through the camera of a phone or tablet to guide and monitor home rehabilitation without additional hardware. A randomized controlled trial involving more than 200 patients in Korea showed significantly improved outcomes compared with usual treatment.

The technology alone, however, did not determine commercial viability. Adoption depended on a reimbursement pathway that funded the clinician effort supporting the service. Once such a pathway became available, it helped turn a technically and clinically viable application into a viable delivery model.

The health care lesson is particularly important: successful innovation can stall if regulation, approval, and payment models do not evolve alongside the technology.

For AI-enabled health care, adoption therefore depends not only on technical performance and clinical evidence, but also on regulatory pathways, assurance, and mechanisms that allow providers to be compensated for providing the service.

Agriculture and aquaculture: Adoption must start from the producer's reality

Agriculture and aquaculture show both the potential for AI to reach grassroots producers and the importance of understanding their starting conditions.

eShepherd demonstrates how AI can be integrated into an existing agricultural platform. It uses AI across customer support, warranty assessment, and multilingual onboarding as it scales its virtual-fencing platform internationally. Warranty processing fell from four weeks to five days, while the platform supports farmers in more than 10 languages.

Banyu and FisTx illustrate a different adoption pathway in Indonesian aquaculture. Banyu sequenced AI behind more fundamental work on seaweed biotechnology and improved seedlings, which raised farmer yields by about 20 per cent. FisTx first applied AI internally in areas such as budgeting, procurement, and product research before placing AI-supported tools in farmers' hands. Its farm success rate rose by roughly 20 percentage points.

Both cases involve producers with limited connectivity and relatively little prior exposure to digital tools. Their experience shows why adoption may need to begin with foundational capability, demonstration of value, and trusted support rather than with the technology itself.

In grassroots sectors, the first barrier to AI adoption may not be AI at all. It may be connectivity, data, skills, affordability, or confidence in the value of the technology.

This makes agriculture and aquaculture particularly important to the report's inclusion argument. The businesses and producers that could benefit significantly from AI may also be those least able to adopt it without external support or enabling platforms.

Manufacturing, drone logistics, and new energy: AI is moving into core operations

The manufacturing, drone logistics, and new-energy cases show AI moving beyond experimentation and into daily industrial operations.

Xiaomi applies AI across materials discovery, quality inspection, and production control in automotive manufacturing. Its quality-inspection process reduced inspection time from 20 seconds to two seconds, achieved accuracy above 99.9 per cent, and contributed to an approximately eight per cent increase in manufacturing efficiency.

Phoenix Wings applies deep-learning perception, vision-language models for scene understanding, and a large-language-model-based flight assistant in low-altitude drone logistics. SmartMore develops IndustryGPT and industrial inspection systems for new-energy battery production, including blue-film inspection operating at 0.5 seconds per unit and reducing the key-defect miss rate from about 0.3 per cent to near zero.



Transport division providing rail and road cargo services in northern Chile predominantly to mining customers. Photo by Antofagasta plc.

These examples illustrate a different stage of adoption. AI is no longer simply an isolated tool or pilot; it is increasingly being integrated directly into production, inspection, and operational systems.

At an industrial scale, the value of AI comes increasingly from embedding it into the workflow rather than treating it as a standalone technology project.

Sector differences, common foundations

The cases demonstrate that the fundamentals of successful adoption are consistent, but their relative importance varies by sector.

Safety and accountability are particularly important in mining and industrial operations. Interoperability and cross-border processes dominate logistics and maritime transport. Regulatory and reimbursement pathways can determine viability in health care. Affordability, connectivity, and digital readiness are especially important in agriculture and aquaculture. In manufacturing and new-energy applications, integration into operational systems becomes increasingly important as AI moves to scale.

APEC's challenge is therefore to establish common conditions for AI adoption while allowing those conditions to be applied in ways that reflect the realities of individual sectors.

This sector perspective also reinforces a broader conclusion from the case studies: adoption policy should not assume that every industry will follow the same pathway or face the same bottleneck. What is common is the need to identify and address the constraint that prevents proven technology from being put to productive use.

Table 2: Selected outcomes and performance measures from the case studies

FIRM (ECONOMY)	MEASURE	RESULT
UPS (United States)	Customs clearance	Recovered to around 99 per cent; 97 per cent first-day clearance reported publicly
EverEx (Korea)	Clinical effectiveness	Significantly improved pain, function, and quality-of-life outcomes versus usual treatment in a controlled trial of 200+ patients (Korea)
Mitsui (Japan)	Repeated-task time	Target of 20 per cent reduction by 2030
FisTx (Indonesia)	Farm success rate	Up about 20 percentage points, from roughly 60 to mid-80s per cent
Banyu (Indonesia)	Farmer yield	About 20 per cent gain
Container Terminals, Yeji Data Lab (Canada)	Equipment availability	Predicted at 96.5 per cent accuracy
eShepherd (New Zealand)	Warranty processing	Reduced from four weeks to five days
Xiaomi (China)	Inspection and process	Accuracy over 99.9 per cent; inspection time from 20 seconds to 2 seconds; about 8 per cent manufacturing-efficiency gain
SmartMore (China)	Blue-film inspection	0.5 seconds per unit; key-defect miss rate reduced from about 0.3 per cent to near 0.0 per cent

Source: Firm interviews conducted for this report, corroborated by public sources where available. Antofagasta Minerals, Rio Tinto, Phoenix Wings, and Lumber Pricing (Yeji Data Lab) are not listed here because none of the cases reports a single headline metric.

Recommendations to APEC Leaders and Digital Ministers

06

Supply chains cross borders, businesses operate across multiple economies, and successful applications developed in one market can often be adapted for another.

APEC has already established its ambition on AI. The next priority is adoption.

The evidence from these case studies points to a clear priority for APEC: accelerating the capacity of businesses to adopt AI at scale.

While the private sector will drive much of the innovation and deployment, governments have an important role in creating the conditions for adoption. Data interoperability, regulatory and reimbursement pathways, workforce capability, digital infrastructure, and access for smaller firms all have a public-policy dimension.

These challenges are also regional. Supply chains cross borders, businesses operate across multiple economies, and successful applications developed in one market can often be adapted for another. Regional co-operation can reduce fragmentation, share proven approaches, and help smaller businesses and less AI-ready economies participate.

ABAC calls on APEC Leaders and Digital Ministers to move from AI ambition to implementation through co-ordinated action in four priority areas.

The recommendations below build on the joint ABAC position endorsed at the Third ABAC Meeting in Thailand in July 2026 and the evidence from the case studies in this report.



Centinela. Photo by Antofagasta Minerals.

Recommendation 1: Data foundations

Advance interoperable data standards, modernize data governance, and improve access to high-quality, sector-relevant datasets; explore shared data infrastructure that lowers MSME adoption barriers.

AI can only be as effective as the data available to support it.

Across the cases, fragmented, inaccessible, or poorly defined data constrained what AI could achieve. Mitsui O.S.K. Lines identified data readiness rather than the availability of AI tools as determining the pace of adoption. Rio Tinto faces the challenge and opportunity of applying AI across decades of operational data, while Yeji Data Lab found that operational metrics first had to be consistently defined before effective modelling could begin.

APEC economies should advance common approaches to data standards and interoperability, particularly in sectors and supply chains where information needs to travel across businesses and borders. Leaders and Ministers should modernize data frameworks to enable responsible use and encourage access to diverse, high-quality datasets, including industrial, local, and culturally relevant data that global models may not adequately capture.

For MSMEs, governments should also support shared data infrastructure and practical mechanisms that allow smaller firms to benefit from AI without having to develop sophisticated data capabilities independently.

The objective should be to make data a foundation for adoption rather than a barrier to it.

Recommendation 2: Enabling regulation

Establish predictable, proportionate approval and assurance pathways for commercial deployment, including appropriate mutual recognition and health-care reimbursement.

Technical viability does not guarantee adoption.

Several cases show that regulation, approval processes, reimbursement, and assurance requirements can determine whether proven AI applications can progress from demonstration to sustained deployment.

APEC economies should identify priority sectors where these barriers are constraining adoption and establish predictable pathways for AI-enabled products and services. Where appropriate, economies should work toward mutual recognition and greater alignment of regulatory, safety, and assurance frameworks, reducing unnecessary barriers to deployment across markets.

The EverEx case demonstrates why this matters. Its AI-enabled rehabilitation platform had demonstrated clinical value, but a reimbursement pathway was needed to make the service commercially viable. Once reimbursement became available in the United States, the United States revenue overtook Korean revenue in 2024.

UPS points to a related challenge in cross-border logistics, where regulatory complexity and incomplete adoption of paperless customs processes can constrain further automation.

The role of government is not to choose the technology, but to create predictable conditions in which proven technologies can be responsibly deployed and scaled.

Recommendation 3: Workforce

Prioritize industry-led upskilling and workplace learning that combine AI with sector expertise and business-process redesign.

The workforce challenge is not simply to create more AI specialists. It is to equip people with the combination of sector expertise and AI capability required to apply the technology in working environments.

Across the cases, AI changed the nature of work while increasing demand for cross-disciplinary capabilities. Firms need people who understand the underlying business or industrial process and can identify where AI can improve it, interpret its outputs, and integrate it into everyday work.

APEC economies should expand industry-led upskilling, apprenticeships, and workplace-based learning that combine AI capabilities with sector expertise. Governments, businesses, and educational institutions should work together to create practical pathways that allow existing workers to adapt as AI changes their roles.

Antofagasta Minerals' Digital Academy provides one model of how firms can develop these capabilities internally. The existing case evidence also identifies shortages of people able to combine deep sector knowledge with AI expertise.



Asia at night assembled from data acquired by the Suomi NPP satellite. Photo by NASA via NASA Image and Video Library.

This is particularly important in traditional industries, where deep operational knowledge often resides with experienced workers.

Successful adoption will depend not only on bringing AI skills into traditional sectors, but on bringing AI capability to the people who already understand those sectors.

Recommendation 4: Inclusion

Expand access to affordable, trusted AI-enabled tools and platforms; support shared infrastructure and exchange of proven practices across economies.

The greatest inclusion challenge is not access to AI technology alone. It is the capacity to adopt it.

Large enterprises generally have greater access to data, specialist talent, infrastructure, and capital; smaller firms and grassroots producers often do not. This recommendation calls for targeted pilots, capacity-building, shared infrastructure, and support for initial deployment to address this gap.

But the pathway for MSMEs will often be different from that of large firms.

Most MSMEs will not build AI. They will adopt better business tools powered by AI.

As the cases and analysis in Section 3 show, smaller businesses will increasingly access AI through software, platforms, and sector-specific applications developed by others. Existing business platforms can therefore become important AI enablers, allowing new capabilities to reach many smaller firms without each business having to develop its own AI expertise.

APEC economies should therefore focus not only on building AI capability within individual MSMEs, but also on expanding access to affordable, trusted, and proven AI-enabled tools. This should include targeted demonstrations and adoption programs, shared infrastructure, practical capacity-building, and partnerships with technology providers and platforms capable of reaching large numbers of smaller businesses.

Initial public support can also help firms test proven applications, understand their value, and build the confidence and capability to continue adoption commercially. The eShepherd case suggests that even partial support for initial deployment can help smaller producers experience the benefits and subsequently continue on their own.

The objective should be to shift from supporting individual AI pilots to creating pathways through which proven solutions can reach thousands of businesses.

Examples such as the Thai government's AI Centres of Excellence illustrate how co-ordinated public investment can create capabilities and infrastructure that smaller firms can draw upon rather than requiring every business to build them independently.

Similar approaches across APEC could help address the adoption-capacity gap while allowing the private sector to remain the primary developer and supplier of AI technologies and services.

APEC PRACTICE IN ACTION: THAILAND

Thailand provides an example of how public policy can build shared AI capability. The Thai government has announced AI Centres of Excellence across 10 priority sectors as part of its ambition to develop the economy into a regional AI hub.



Cattle farmer. Photo by eShepherd.

From recommendations to implementation

The next step is to turn these recommendations into practical co-operation.

ABAC encourages APEC to build on the AI Applied work through an ongoing focus on practical adoption. This could include expanding ABAC's work with participating economies and industry partners to identify practical opportunities for sector-specific adoption playbooks, MSME demonstrations, and connections between AI adopters and technology providers.

This need not require a new institution. It can build on existing APEC and ABAC mechanisms and the work already undertaken through the APEC AI Initiative (2026–30).

APEC does not need 21 economies independently solving the same adoption problems. Regional co-operation can help proven approaches spread more quickly across sectors and borders.

APEC's AI agenda should therefore focus not only on advancing the technology, but on expanding the capacity to use it. By strengthening data foundations, enabling pathways to deployment, developing the workforce, and creating practical routes to adoption for MSMEs, APEC can help ensure that AI-driven productivity and growth extend beyond the firms and economies already best positioned to capture them.

Conclusion:

From AI Potential to Widespread Adoption

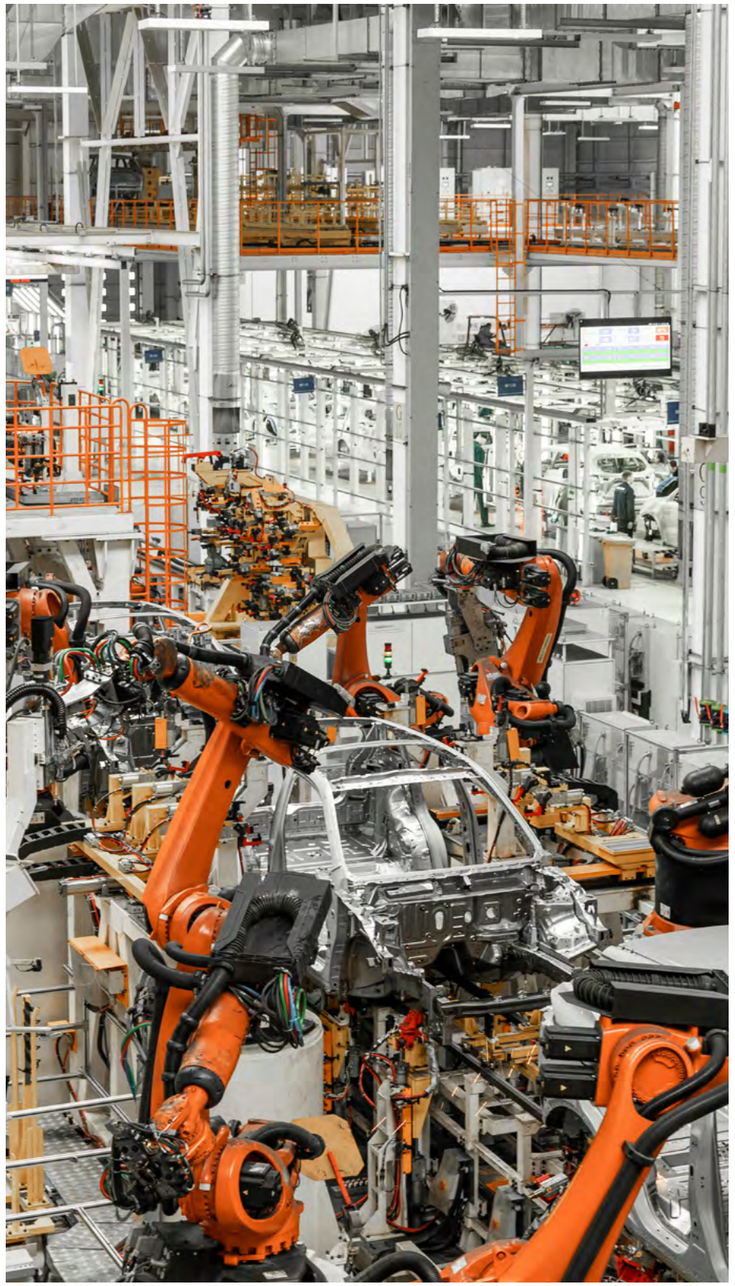
The next phase of AI-driven economic growth will be determined not simply by advances in technology, but by how effectively businesses and economies put those advances to work. The experience of firms across APEC demonstrates that AI can already deliver measurable value in traditional industries. The challenge now is to move beyond individual success stories and create the conditions for adoption at scale.

The more important lesson, however, is that successful AI adoption depends more on the conditions around the technology than on the sophistication of the technology itself.

Those conditions are unevenly distributed. Some businesses have the data, skills, infrastructure, and resources to act quickly; others do not. As AI capabilities become more widely available, this difference in the capacity to adopt risks becoming an increasingly important source of economic advantage, both between businesses and across economies.

For APEC, this is both a competitiveness imperative and an inclusion opportunity. Co-ordinated action on data, regulation, workforce capability, and access to AI-enabled tools can help ensure that the benefits extend beyond the largest firms and most digitally advanced economies.

The opportunity is not simply to build more powerful AI. It is to enable more businesses, in more sectors and across more economies, to use AI to drive productivity and sustainable economic growth.



Industrial automation. Photo by Getty via Unsplash.

ANNEX

The case studies at a glance

The following matrix lists the case studies for this report. The full case studies follow; each built from an interview with the firm and reviewed by it before publication.

Full case studies

The full case studies follow in the order of the matrix above: Rio Tinto (Australia); Antofagasta Minerals (Chile); Mitsui O.S.K. Lines (Japan); UPS (United States); EverEx (Korea); Banyu (Indonesia); FisTx (Indonesia); Yeji Data Lab, lumber pricing and container terminals (Canada); eShepherd by Gallagher (New Zealand); and Xiaomi, Phoenix Wings, and SmartMore (China).

ECONOMY	SECTOR	FIRM	AI APPLICATION AND HEADLINE RESULT
Australia	Mining	Rio Tinto	AI applications in exploration, mine planning, equipment reliability, and operational productivity
Chile	Mining	Antofagasta Minerals	SIRO process optimization in leaching and grinding; Digital Academy upskilling
Japan	Maritime	Mitsui O.S.K. Lines	Voyage optimization within BLUE ACTION 2035; 20 per cent task-time target by 2030
United States	Logistics	UPS	ML customs classification; clearance recovered to around 99 per cent
Korea	Health care	EverEx	AI home rehabilitation; reimbursement the unlock; improved outcomes in controlled trial
Indonesia	Aquaculture (seaweed)	Banyu	AI sequenced behind seedlings; 20 per cent farmer yield gain
Indonesia	Aquaculture (shrimp)	FisTx	AI inside the company first; success rate up about 20 percentage points
Canada	Forestry	Lumber Pricing (Yeji Data Lab)	ML pricing module supporting the commercial team
Canada	Ports	Container Terminals (Yeji Data Lab)	Predictive maintenance; availability prediction at 96.5 per cent accuracy
New Zealand	Agriculture	eShepherd by Gallagher	AI across support, warranty, and product; warranty four weeks to five days
China	Manufacturing	Xiaomi	Industrial AI models for materials, quality inspection, and process control
China	Drone logistics	Phoenix Wings	Deep-learning perception; vision-language models; LLM flight assistant
China	New energy	SmartMore	IndustryGPT; blue-film battery inspection

CASE STUDY: AUSTRALIA, MINING

RioTinto

Capability before novelty: disciplined AI adoption in a 150-year-old asset base

Snapshot

ECONOMY	Australia
SECTOR	Mining; metals and minerals
FIRM	Rio Tinto (aluminum and central IST functions represented in interview)
AI FOCUS	End-user productivity tools, bespoke function-specific models, and return-on-investment-intensive big-bet studies; AI applications in exploration, mine planning, equipment reliability, and operational productivity
MATURITY	End-user and embedded AI widespread; bespoke models in selected functions; standalone AI in production environments still rare; no AI in core control systems
EVIDENCE	High (interview with Jenny Johnson, GM Enterprise Platforms and Services, and Brad Tomlinson, Aluminum)

In plain terms: Rio Tinto uses AI across performance optimization, safety analytics, and decades of legacy engineering data, while keeping people in charge of core control decisions.

Based on an interview in June 2026 with Ms. Jenny Johnson, General Manager Enterprise Platforms and Services, and Mr. Brad Tomlinson Senior Manager, Digital & Technology, Rio Tinto Aluminum, Rio Tinto. Recorded with permission; full transcript on file. Reviewed by Rio Tinto before publication.

The opportunity

Rio Tinto is a leading global mining and materials company, with three core product groups: Iron Ore, Aluminum & Lithium, and Copper. The company has long been an early adopter of technology and automation, with AI representing the next step in that journey.

AI is creating opportunities across the business, from helping employees work more productively and improving business processes to supporting mining operations, including exploration, operational productivity, safety, and environment.

In exploration, Rio Tinto is using machine learning and advanced data analysis to make geological information easier to access and analyze, helping accelerate the mineral discovery process.

Aluminum in particular is an intensely competitive, energy- and capital-intensive industry that has had more than a century to optimize its legacy processes. As the interview put it, Rio Tinto is applying AI and advanced analytics to improve operational performance and efficiency, building on its existing technology and automation capabilities.

Rio Tinto's long operating history has generated significant technical expertise and operational data. AI and advanced analytics provide opportunities to make better use of this information, supporting knowledge sharing, operational improvements, and productivity across the business.

Rio Tinto is explicit that it is not trying to win an AI race. Its leadership frames the core business as providing the materials the world depends on. Being the best at AI is not the goal. AI is pursued where it serves the business. The company positions itself as a cutting-edge rather than bleeding-edge adopter.

The AI strategy

Rio Tinto is developing its AI capabilities across three broad areas: supporting personal productivity through better access to information and analysis; improving and automating business processes; and applying AI to mining activities, from exploration and mineral discovery through to operational productivity and safety.

The company is continuing to build on its existing technology and data capabilities, learning from individual applications and looking at how successful approaches can be applied more widely across its global operations.

RIO TINTO

Rio Tinto recognizes the opportunities and risks associated with AI, with its approach supported by governance processes, monitoring, and internal capability development. The company reports consistent appetite across central teams and product groups, with CFOs and managing directors engaged and supportive. The biggest governance challenge is keeping effort tied to demonstrated capability rather than technology for its own sake, especially given a hype curve that creates demand faster than the organization can absorb.

AI in practice

Rio Tinto is applying AI and advanced analytics across a range of operational activities, from exploration and mineral discovery to mine planning, equipment reliability, safety, and environment.

In exploration, advanced drill core scanning and machine learning are helping geologists analyze mineralization data more quickly and consistently. At the Winu copper-gold project in Western Australia, Rio Tinto is testing AI-enabled core scanning technology to accelerate geological analysis.

Rio Tinto is also using AI for orebody modelling, equipment dispatch and autonomous truck optimization, and predicting equipment failures at Oyu Tolgoi in Mongolia to help prevent unplanned downtime.

These applications build on Rio Tinto's longstanding investment in automation, data, and technology, with the opportunity to apply successful approaches more widely across the business.

A distinctive theme was the use of AI on the company's own legacy technology. With 150 years of operating history and systems carrying tens of thousands of integrations, AI is being used to analyze what legacy systems are doing, to map integrations, and to support migration to new platforms, work that would otherwise be prohibitively slow for humans. The company also described using different models to check each other, for example, one model for specification, another for code generation, and another for testing; an approach that produces a more reliable result, with a human in the loop throughout.

Build, partner or buy

Rio Tinto's approach to AI draws on a combination of existing technology platforms, internal development, and external partnerships, depending on the application and business need.

Where a problem depends on captured numerical or scientific data unique to mining, such as ore concentration underground, Rio Tinto will look to partner with specialist data scientists or geologists. The company noted that some computer vision applications are so region-specific (e.g. modelling the Australian outback by geography and vegetation) that off-the-shelf solutions do not fit. It partners with universities and other organizations in these cases.

AI and core systems

Rio Tinto uses AI, automation, and advanced analytics to support its mining operations, including orebody modelling, equipment dispatch, and autonomous truck optimization. Safety and risk management remain central to its approach, with established processes for managing major hazards and verifying the effectiveness of critical controls.

At Oyu Tolgoi in Mongolia, AI is also being used to analyze safety data and help teams identify higher-risk activities and strengthen the checking of critical safety controls.

The workable pattern the company described is an AI system suggesting a set point, with a separate secondary system validating and integrating that change, supported by root-cause analysis techniques. Shift planning and forecasting are comfortable AI territory; an LLM setting equipment parameters directly is not and will not be realized until safety boundaries and assurances are resolved.

Implementation, outcomes, and workforce

One challenge with AI value realization across the sector is making the transition from proofs of concept to embedded, high-value operational use. There are three main considerations. First, the product-versus-project gap: turning a minimum viable product into a supported, sustained operational capability is difficult and requires a deliberate mechanism. Second, data sustainability: models that look strong against "static" data can struggle to perform in live operations, and hardening sustainable products is an order of magnitude more challenging than the initial AI projects. Third, trust and adoption: in an operational environment, trust in the technologies and effective change management are the binding constraints.

The company was candid that operational tolerance for system faults is very low. Where consumers choose the technology they use and forgive its failures, in a business-to-business operational setting the technology is given to users who did not ask for it, so the tolerance for degradation is far lower. One or two bad shifts can cause a tool to be abandoned in favour of the whiteboard that reliably worked before. This is why the company's clearest productivity wins have come from improving existing processes with AI rather than introducing standalone products, and why, when people choose where to invest, they tend toward automation as more predictable, lower risk, and more reliably returning value.

On workforce, the company runs extensive internal upskilling. Its main challenge is the external talent pipeline: the resources sector struggles to find candidates who are passionate about mining, and skilled in both mining technologies and AI. It noted that this is an exciting challenge for training organizations to meet the unique, multi-disciplinary profile mining needs. It called for more opportunities to address these unique development pathways to fill the gaps.

Lessons and best practices

- Capability first, not technology for its own sake. Tools tied to tangible production, safety, and business outcomes endure; a generic AI deployment decays quickly once people forget what it connects to.

- Start with the business opportunity, not a technology driver such as AI. The hype around AI can result in the right solution for the wrong problem; this inverts the correct order. Be prepared to revert to a basic script if AI is the wrong solution.

- Use AI to revisit long-unsolved problems. The most exciting opportunities are long-standing problems that were previously intractable, such as surveying entire markets and data to identifying consumer sentiment across multiple continents or running ensemble scenario modelling in parallel.

- Keep a human in the loop. Given the limits on traceability, AI outputs need human review, particularly for any safety or operational decisions.

Implications for policy

Rio Tinto offered a wide set of recommendations for APEC Digital Ministers:

- Co-ordinate industry work on safety and assurance for AI in heavy industry. No single firm is solving the entirety of the assurance challenge for AI in operational environments; co-ordinated, cross-industry efforts would be valuable.
- Address the talent pipeline. Partner with industry and universities to define a modern, cross disciplinary profile blending mining, engineering, and AI. It is a priority to invest in policy and curricula to best support adoption of emerging technologies.
- Modernize data and adoption legislation. Update legislation to make responsible adoption and use of data easier, recognizing the pace gap between technology and policy.
- Clarify AI accountability and ethics. Clearer expectations around governance, oversight and accountability for AI applications would help businesses manage risks and adopt the technology responsibly.
- Support responsible use of diverse and locally relevant data in AI. Greater collaboration on AI research could help develop applications suited to industrial and local contexts, while ensuring that culturally sensitive information is managed appropriately and in partnership with relevant communities.

ANTOFAGASTA MINERALS

CASE STUDY: CHILE, MINING

ANTOFAGASTA MINERALS

AI as a board-level commitment to copper production optimization

Snapshot

ECONOMY	Chile
SECTOR	Mining (copper production)
FIRM	Antofagasta Minerals (Antofagasta plc subsidiary); one of the world's top 10 copper producers; second-largest private copper producer in Chile
AI FOCUS	Process optimization across mining and processing, with applications spanning recovery, predictive analytics, computer vision for operations (oversize rocks and shovel-truck operation), and digital twins
MATURITY	Scaled across operations; deployment journey began approximately eight years ago
INVESTMENT DISCIPLINE	3.5x return-on-investment threshold required for all AI investments at group level
EVIDENCE	High (interview with Antofagasta Minerals in May 2026; reviewed and confirmed by the company)

In plain terms: Antofagasta uses AI to optimize its mineral processing, which raises copper recovery, and develops the skills of its people through its own Digital Academy.

This case study is based on an interview with Antofagasta Minerals conducted on May 6, 2026 (recorded with permission; full transcript on file), supplemented by public company communications referenced inline. Reviewed and confirmed by Mr. Héctor Flores, Vice President of Business Development and Innovation, Antofagasta Minerals, before publication.

The opportunity

Antofagasta Minerals applies AI to concrete operational challenges. Each initiative starts from a problem and a business KPI defined from the beginning. For the company, the question is not where to use AI, but what limits the operation today and what is the best way to solve it.

The motivating drivers were operational cost reduction and productivity gains across copper production. Each initiative addresses a specific constraint in the operation and is prioritized by its impact on business KPIs. Every AI deployment is benchmarked against the corresponding operational performance without AI tools, making the comparison continuous and quantifiable.

This framing matters for replication across the sector. Antofagasta's experience suggests starting from a clear operational problem with a business KPI, and then finding the best way to solve it, with AI as one of the tools.

The AI solution

AI is now part of some decision-making processes at Antofagasta Minerals at the company level. The company has identified specific areas across mining and processing where AI can improve efficiency, reduce costs, and increase productivity, and has allocated dedicated teams of data scientists and technical leaders to each.

The technical architecture rests on three layers. First, sensors are deployed across operations to capture process data at scale, with deployment continuing as part of an active sensor program. Second, all sensor data flows into a central data lake covering operations across the group. Third, analytical methods including machine learning and digital twins are applied to this data to generate insights and recommendations.

Machine learning is used in part for retrospective analysis, examining past operational decisions to identify whether outcomes could have been better with different choices. Digital twins run alongside live operations, providing operators with live recommendations grounded in current process state. The combination produces both diagnostic learning and operational guidance.

Antofagasta Minerals manages the operations of two of its four mining companies through the Integrated Remote Operations Centre (IROC), the company's centralized operations function. Within IROC, advanced analytics teams continuously feed insights into operational decision-making across these operations. The company runs four mining companies in Chile, each with its own data science capacity at site level, complementing the corporate-level capability based at the Santiago headquarters. This structure allows AI applications to be developed at corporate level and deployed consistently across sites, rather than being built and maintained in isolation at each operation.

Public communications from the company illustrate the depth of deployment. At Antucoya, the SIRO system supports the optimization of acid dosing in leaching. At Los Pelambres, a SIRO module optimizes the SAG mills in closed loop.

Implementation

The company applies a build, partner, or buy decision to each AI initiative. The first step is a market scan to assess whether an existing solution meets the requirement. Where it does, the company partners with the provider; where it does not, internal teams develop the solution, drawing on data scientists from the corporate level in Santiago and individual operating companies.

Deployment follows a proof-of-concept, pilot, scale-up pathway. Scale-up decisions for the entire group are taken by a Data Analytics Committee comprising the CEO, other VPs, and the General Managers of operating companies. Project timelines from initial concept to scaled deployment range from three months to roughly one year, depending on the size of the application.

The hardest part of implementation has been the knowledge transfer required to integrate AI tools into operational decision-making. Once the inputs are correctly defined and the people using the tools understand them, deployment moves quickly.

One element that surprised the team during deployment was the capacity of machine learning models to identify patterns and correlations that human analysts had not detected, even in processes with decades of operational data.

Outcomes

AI deployment has produced measurable gains across four dimensions of copper production at Antofagasta Minerals.

Production at mining sites has increased through process optimization driven by AI tools. Copper recovery at processing plants has improved as a direct result of AI-supported decision-making. Computer vision systems are used to detect oversize rocks and improve shovel and truck operations. As a consequence of these gains, operational costs have also been reduced.

Beyond these direct outcomes, AI has produced second-order effects on environmental performance. The same optimization logic that improves production has also reduced energy consumption (electric and diesel), improved water management, and lowered the environmental footprint of operations.

The deployment journey began approximately eight years ago and has reached a stage of operational maturity. Impact is tracked weekly across operations. The group scorecard includes explicit data analytics commitments with associated investment levels, and each AI initiative is required to return at least 3.5 times the value of the underlying investment for the group to consider the deployment successful.

A significant transition is currently underway from information technology to operational technology integration. To date, AI systems have produced recommendations on the IT side, which then required human action to implement. The company is now in the process of connecting IT and OT directly, so that AI recommendations drive automated operational responses within defined limits and under human supervision, as in the SAG mills at Los Pelambres.

Workforce and upskilling

Workforce changes combine the creation of new roles with developing the skills of the existing workforce. Antofagasta Minerals has built advanced analytics teams within IROC, the centralized operations function. Data scientists are now employed at both the corporate level and within each of the four operating mining companies. These roles did not exist in the organization before the AI program began.

In addition to new analytics roles, in 2025 Antofagasta Minerals launched a Digital Academy to accelerate the development of critical skills for the future of mining. The integration of AI into decision-making has been driven primarily through the analytics teams at IROC, who feed insights and recommendations into operational decision-making rather than requiring frontline operators to interact directly with AI tools.

The long-run implications for the operational workforce merit examination, particularly as the IT-to-operational-technology integration progresses.

Enablers and barriers

ENABLERS

- Board-level commitment, demonstrated through site visits and direct engagement with deployed AI solutions, rather than executive-level championing alone.
- A formal Data Analytics Committee covering scale-up decisions for the whole group, including the CEO, other VPs, and operating company General Managers.
- A 3.5x return-on-investment threshold applied to all AI investments at group level, providing investment discipline and a clear basis for prioritization.
- A scorecard at group level that includes data analytics commitments alongside operational and financial metrics.
- Sensor and data infrastructure built deliberately as a prerequisite, with all data centralized in a group-wide data lake.
- A flexible build, partner, or buy approach that combines internal capability with external partnerships as appropriate to each initiative.
- IROC, the centralized operations function, concentrating analytics talent and providing a consistent platform for deployment across two of four operating mining companies.

BARRIERS AND CHALLENGES

Knowledge transfer to operational teams, identified as the hardest part of getting AI tools into production.

The IT-to-operational-technology integration, currently in active progress, where AI recommendations are being connected to automated operational responses within defined limits and under human supervision.

Replicability

The Antofagasta Minerals model is highly replicable for large-scale extractive operations with sufficient sensor data and centralized governance capacity. The core elements that enable replication are board-level commitment, a formal investment discipline, a consolidated data infrastructure, and a co-ordinated analytics team operating across sites.

For mid-sized mining firms considering AI for the first time, the practical lesson is to start with a clear business problem and the data infrastructure. Specifically, the entry point that has worked for Antofagasta Minerals begins with sensor deployment and data centralization, followed by the gradual layering of analytics on top. Without the underlying data infrastructure, AI investments tend to produce localized wins that do not scale.

The Chilean mining sector overall has reached a high level of AI maturity and has been recognized internationally for its AI deployment in mining operations. Large mining companies operating in Chile, such as Codelco and Anglo American, also follow a similar pattern, with advanced AI strategies across exploration, extraction, production, and processing. With the development and accessibility of innovative AI tools, the mining sector is undergoing tremendous change.

Best practices and lessons

- Start from the business problem, not from the technology, with business KPIs defined from the beginning (productivity, safety, water, energy).
- Anchor AI deployment in board-level governance and a formal cross-functional committee, with site visits as a mechanism for keeping the board substantively engaged.
- Establish a quantitative return-on-investment threshold for AI investments at the outset and apply it consistently across all initiatives at group level.
- Build the data infrastructure first. Sensor deployment and a central data lake are prerequisites for AI deployment at scale. The absence of either typically constrains the value of subsequent investments.
- Use a proof-of-concept to pilot to scale-up pathway, with scale-up decisions taken at group level rather than at site level.
- Combine internal data science capacity with selective external partnerships, deciding on each initiative through a market scan rather than committing to a single sourcing approach.
- Concentrate analytics talent in a centralized operations function that feeds insights into site-level decision-making, rather than distributing data scientists across sites without co-ordination.
- Plan for the IT-to-operational-technology integration from the outset. AI recommendations have limited operational value without a path to direct integration with control systems. The transition itself is a non-trivial program of work.

Implications for policy

Antofagasta Minerals' experience offers two policy-relevant observations.

First, government and APEC support for AI adoption in traditional sectors can be most useful through the publication and dissemination of well-documented case studies. Public sector investment in case study production, regional knowledge exchange, and sector-specific peer learning would directly support the diffusion of practices that have been proven at scale by leading firms.

Second, the IT-to-operational-technology transition represents a generic challenge across traditional industries, with implications for cybersecurity, workforce, and standards. Co-ordinated APEC-level work on operational technology integration would benefit not only mining but also other sectors at similar stages of AI deployment, including manufacturing, oil and gas, and infrastructure.

MITSUI O.S.K. LINES

CASE STUDY: JAPAN, MARITIME LOGISTICS

AI as an enabler within a long-horizon transformation toward social infrastructure

Snapshot

ECONOMY	Japan
SECTOR	Maritime logistics
FIRM	Mitsui O.S.K. Lines, Ltd. (MOL); one of the world's largest shipping companies, 140+ years of operating history
AI FOCUS	Operational decision support through voyage optimization, AI-ready knowledge management, and governed automation of repeatable business processes
MATURITY	Machine learning since around 2016; generative AI since 2023; MOL has historically started AI use cases through controlled pilots and proofs of concept, and is now moving toward scaled implementation in selected priority areas
ANCHOR	BLUE ACTION 2035 management plan, Phase 2 (FY2026 to FY2030), with Digital Transformation as one of four thematic visions
EVIDENCE	High (written response and interview with MOL's Headquarters of Technological and Digital Transformation)

In plain terms: MOL uses AI built into its existing software to optimize vessel voyages and reduce repeated manual tasks for its crews.

Based on the written response provided by Mitsui O.S.K. Lines on May 11, 2026, followed by an interview with Ms. Kelly Takano and Mr. Yuya Inoue of MOL's Headquarters of Technological and Digital Transformation on May 14, 2026 (recorded with permission; full transcript on file), supplemented by public company communications referenced inline. Reviewed and revised by MOL on June 18, 2026. Name and title of President and CEO confirmed by MOL.

The opportunity

Mitsui O.S.K. Lines (MOL) treats AI as an enabling capability within its 13-year BLUE ACTION 2035 management plan, rather than as a response to a single business problem. Launched in April 2023, the plan entered Phase 2 (FY2026 to FY2030) in April 2026 under President and CEO Jotaro Tamura, shifting the focus from transformation and expansion to value realization across four thematic visions: Environment, Safety, Human Capital, and Digital Transformation.

MOL describes itself as a shipping and social infrastructure company rather than a technology company and deploys AI where it helps the business make better operational decisions. Two opportunities have anchored recent investment. The fragmentation of operational data across the complex group created a need for centralization before AI could be applied. The demographic challenge of transferring the tacit knowledge of seniors to younger colleagues created a need for structured documentation that AI can produce and search. MOL aims to make institutional knowledge easier to document, structure, search, and update through AI, so that expertise is not overly dependent on individual employees.

For long-horizon traditional industry leaders, AI is often integrated into an existing transformation strategy rather than adopted on its own. The maturity of that strategy, and the data and governance work that precedes deployment, is a precondition for AI to add value.

The AI solution

MOL's deployment spans three layers. Machine learning has been used since around 2016, principally for forecasting and modelling, with generative AI added from 2023.

AI is increasingly embedded within the Software as a Service (SaaS) tools MOL already uses, as vendors add generative capabilities into their existing offerings, often invisibly to the customer. This arrival of AI by absorption into the software stack, rather than through dedicated deployment projects, is a notable feature of how AI reaches traditional industries today.

On build, partner, or buy, MOL prefers ready market solutions where they exist, partners with specialists where in-house work is not justified, and develops internally only where the use case warrants it, while managing the risk of over-reliance on any single partner. MOL manages AI use through internal governance policies and review processes, particularly where proprietary, personal, or confidential data may be involved.

Implementation

MOL has historically started AI use cases through controlled pilots and proofs of concept and is now moving toward scaled implementation in selected priority areas. Governance has evolved alongside the technology: oversight rests with the Chief Digital Information Officer, whose authority expanded with the arrival of generative AI. The April 2026 transition to Phase 2 brought stronger top-down support for AI and data utilization as a corporate priority.

AI-related approvals are handled through cross-functional review processes rather than a single standing AI committee and are supported by MOL's AI governance framework and internal policies.

The hardest part of moving AI into production at MOL is demand-side awareness: helping business users understand what AI can do and what to expect from it. The technology is not usually the binding constraint. The clarity of the business question is what limits progress. MOL also noted that the rapid fall in generative AI costs means a use case that needed substantial investment a year ago can now be addressed at roughly 10–30 per cent of the cost, so for marginal cases, patience is often the right strategy.

Outcomes

MOL tracks outcomes against value-creation key performance indicators (KPIs) rather than individual AI projects. The flagship Phase 2 target is a 20 per cent reduction by 2030 in the time required to complete repeated tasks, to which AI contributes alongside other initiatives. Voyage optimization is the clearest measurable contribution, reducing fuel use and associated emissions, and linking the Environment and Digital Transformation visions in practice. Current AI priorities are focused on internal and operational transformation, including office- and vessel-related processes, before direct customer-facing applications.

Workforce and upskilling

Knowledge retention is central to MOL's workforce strategy. The company is documenting institutional knowledge in forms that AI can search and update, so knowledge is accessible across the organization rather than tied to individuals. More broadly, MOL encourages employees to start using AI tools regardless of skill level, drawing first on tools provided by the company, which lowers cost and the barrier to entry.

Enablers and barriers

- Embedment within a 13-year management plan gives AI strategic stability across short-term commercial cycles.
- Top-down support from group leadership, reinforced at the April 2026 transition, makes AI a corporate rather than a departmental priority.
- Cross-functional approval governance reduces the risk of fragmented or duplicative AI investment.
- Data fragmentation across a complex group is the main barrier; data is not yet fully AI-ready, which constrains the pace of deployment.
- Demand-side awareness, helping users articulate what AI should do for them, remains the hardest part of reaching production.

Replicability

The MOL model is highly replicable for established, long-horizon traditional firms operating across complex group structures, through an explicit multi-year plan in which digital transformation is one of several visions, top-down support, cross-functional governance, and deliberate sourcing. For mid-sized maritime firms in APEC, the more important lesson is about prerequisites: data centralization, structured documentation of operational knowledge, and a clear strategic frame are the conditions that make AI work. MOL suggests that further maritime cases should examine shipbuilders, which it described as more traditional than shipping lines.

Best practices and lessons

- Anchor AI within an explicit multi-year management plan rather than treating it as a standalone investment.
- Treat data centralization as a precondition; the pace of AI uptake is set by data readiness, not by the availability of tools.
- Use AI as the mechanism for knowledge transfer between generations of staff, through documentation AI can search and update.
- Reframe the AI challenge as demand-side awareness; helping business users understand what AI can do is harder and more important than the technical deployment.
- Be patient with use cases at the cost frontier, where falling generative AI prices often make waiting more economical than deploying.

Implications for policy

MOL offered two policy-relevant observations for APEC. Supporting MSMEs in the maritime supply chain is the highest-priority lever: the sector is fragmented, with many small shipping agents and shipowners who lack the capital to invest in AI, and MOL recommended that APEC support these smaller actors through visibility and efficiency initiatives, standardized end-to-end supply chain data, and capacity building. Without this, the gap between large carriers and the rest of the ecosystem will widen, with consequences for resilience and decarbonization.

Data sharing standards are the second binding constraint. The instinct to protect proprietary data is in tension with the data sharing needed to reach net zero in shipping. APEC-level work on data-sharing standards, with clear protection of legitimate confidentiality and clear protocols for safe use, would unlock significant value and could support the maritime data centralization already being attempted within Japan.

CASE STUDY: UNITED STATES, LOGISTICS AND SUPPLY CHAINS

AI to support trade compliance and border clearance amid rising complexity in trade regulations

Snapshot

ECONOMY	United States
SECTOR	Logistics and supply chains
FIRM	United Parcel Service (UPS); global express and supply chain provider operating across all APEC economies
AI FOCUS	Machine learning embedded in customs declaration systems to support data entry of goods descriptions and Harmonized Tariff Schedule (HTS) codes
MATURITY	Deployed and actively used by traders; the lead customs clearance solution scaled in under six months
DRIVER	Trade compliance, a better customer experience, and cost savings from additional manpower required were major drivers.
EVIDENCE	Medium to high (interview with Vice President, Corporate Affairs, Asia Pacific Region; corroborated by published research and the public regulatory record)

In plain terms: UPS uses machine learning to classify customs paperwork automatically, so more shipments attain pre-arrival clearance and immediate release.

Based on an interview with Ms. Shiumei Lin, Vice President, Corporate Affairs, Asia Pacific Region, UPS, on May 13, 2026 (recorded with permission; full transcript on file), supplemented by public sources referenced inline. Reviewed and revised by UPS on June 19, 2026, with publicly released figures incorporated on June 22, 2026.

The opportunity

UPS turned to AI to support trade compliance and efficient border clearance in response to a steep rise in complexity for United States imports. From late 2024 into 2025, the United States Customs and Border Protection (CBP) began requiring substantially greater specificity in the description of goods prior to departure from origin. In 2025, new tariffs specific to individual economies were issued, creating greater complexity for inputting against complex Harmonized Tariff Schedule (HTS) requirements. This was further exacerbated by reform of the de minimis regime, creating a spike in detailed formal declaration submissions.

AI adoption was driven by operational continuity in the face of a fast-moving regulatory environment that exceeded what manual intervention and conventional automation could sustain. For logistics firms across APEC, AI adoption is increasingly becoming a necessity as the external trading environment becomes more complex.

The AI solution

The AI solution is embedded in UPS's declaration systems for shippers. Machine learning converts imprecise customer-supplied descriptions into the specificity CBP now requires: where a customer describes an item simply as a T-shirt, the system infers the attributes needed for accurate HTS classification, including fabric composition, man-made or natural fibres, and the apparel category by gender and age. This technology now runs between the customer-facing declaration interface and CBP's electronic submission and has largely displaced the specialist customs rater role. As Ms. Lin observed, AI has resolved the lack of available talent to support customs HTS code raters while supporting efficient Customs brokerage operations.

Implementation

UPS builds, partners, or purchases solutions: where a market solution exists, it partners or purchases; where no solution meets its specific needs, it builds. All solutions require a business case to be considered. The customs tool was developed to meet specific UPS system and customer needs. The operational disruption drove implementation in under six months. To raise trade compliance levels, the solution was deployed globally to support United States imports regardless of origin.

UPS

Outcomes

The clearest measurable outcome is on clearance rates. In the period immediately after the new CBP requirements took effect, before the machine-learning solution was implemented, clearance rates fell materially due to the disruption; once the AI-supported declaration system was deployed, clearance rates recovered to around 99 per cent. UPS described this as one of its most successful technology deployments.

In a public statement on June 18, 2026, UPS reported that 97 per cent of its shipments clear customs on the first day of entry, corroborating the scale of the clearance improvement described in the interview. The public statement also described the AI-enabled brokerage capabilities behind this, including next-generation brokerage services, more accurate product classification through UPS Export Assure, and digital trade documentation through UPS Paperless Invoice.

Second-order but equally important outcomes include reduced reliance on additional manpower resources and on an already constrained customs rater talent pool, and a better customer experience.

Workforce and upskilling

UPS indicated it is too early to draw firm conclusions on the workforce implications and is still working through how AI solutions will affect roles, required skills, and training to accompany deployment and redeployment. One clear conclusion is that AI can now conduct rating at greater speed and accuracy. Customs brokers can now focus on higher-value advisory services beyond HTS code categorization and rating.

Enablers and barriers

- Regulatory urgency acted as a deployment accelerator, compressing normal procurement and development cycles.
- The network business model justifies consistent global deployment. Customs requirements apply regardless of origin economy.
- Cross-functional leadership engagement followed from the fact that customs clearance is an important component of the core service provided.
- Paperless capability gaps across APEC are the main barrier: many shippers still rely on paper air waybills, so data must be digitized manually before AI can act on it.

Data localization is, in practice, not a significant barrier here: the operational data crossing borders for clearance is for government use only, in this case for customs clearance purposes only. The data typically contains no personal or sensitive information, a useful distinction for policymakers.

Replicability

The model is highly replicable for logistics companies operating into markets with high regulatory complexity, through a clear externally driven problem, the network model that justifies global deployment, machine learning applied to a constrained classification task with abundant historical data, and cross-functional alignment. For mid-sized APEC firms, the most replicable element is the narrow, targeted deployment: UPS started with one well-bounded problem with a clear trigger and measurable consequences rather than enterprise-wide transformation. The barriers to replication are upstream of the carrier, in paperless data capture and consistent customs data standards across economies.

Best practices and lessons

- Frame AI deployment around specific external problems with measurable consequences and well-defined inputs and outputs.
- Compress deployment timelines where the business case is clear; UPS reached production in under six months.
- Deploy as a network, so solutions work consistently across all origin and destination markets.
- Use machine learning and AI to relieve talent constraints, as with the customs rater function.

Implications for policy

UPS offered three observations for APEC. Paperless trade is the most direct lever for accelerating AI adoption in logistics: where shippers still rely on paper documentation, the value of downstream AI is reduced and the cost of manual digitization falls on carriers, so government efforts to require, support, or incentivize paperless declarations would have an immediate effect, particularly in emerging economies.

Data localization should not be treated as a generic barrier to cross-border logistics AI. The operational data exchanged for clearance typically contains no personal or sensitive information, and conflating the two slows deployment without protective benefit.

APEC Digital Ministers can pave the way for accelerated AI adoption by customs administrations through resource prioritization, common data governance frameworks, and establishing interoperability.

CASE STUDY: KOREA, HEALTH CARE

EverEx

AI-guided home rehabilitation for musculoskeletal care, unlocked by reimbursement reform

Snapshot

ECONOMY	Korea
SECTOR	Health care; musculoskeletal rehabilitation
FIRM	EverEx (founded 2019; multidisciplinary clinical and AI team)
AI FOCUS	Proprietary AI pose-estimation model for functional assessment via smartphone camera; individualized home rehabilitation through the MORA platform; clinician dashboard for remote monitoring
MATURITY	Deployed across more than 100 care sites globally; MORA Cure approved as a digital therapeutic; EverEx Rehab listed as a United States FDA Class II medical device in 2023
EVIDENCE	High (interview with Dr. Chan Yoon, founder and CEO)

In plain terms: EverEx uses AI pose-estimation through a phone camera to assess a patient's movement and guide home rehabilitation, with a clinician monitoring progress remotely.

Based on an interview on June 3, 2026, with Dr. Chan Yoon, founder and Chief Executive Officer of EverEx. Recorded with permission; full transcript on file. Reviewed by EverEx before publication.

The opportunity

Musculoskeletal conditions affect around one-third of the population. These conditions are not usually life-threatening, so patients live with them for a long time. The patient pool continues to grow. The central treatment is exercise-based therapy, which should form part of the treatment course for more than 90 per cent of musculoskeletal patients. Yet the traditional delivery model, in-person physical therapy where the patient goes to a clinic to work with a therapist, cannot reach the majority of those patients. In practice, only urgent cases, such as post-operative patients, receive proper rehabilitation; most others go without due to limited medical resources.

Dr. Yoon, an orthopedic surgeon at Seoul National University Hospital, saw this gap over a decade of clinical practice. Clinicians do recommend home rehabilitation, but the usual aids, including printed handouts or recorded video clips, are not individualized, patients cannot ask questions or get feedback, and compliance collapses. Around 80 per cent of the information given in a clinic is forgotten by the patient once they leave. EverEx was founded in 2019 to make home rehabilitation work: individualized, monitored, and connected back to the clinician.

Why now: technology and reimbursement

While the idea of digital home rehabilitation had been attempted for years, it failed for two reasons. First, the technology was not ready; AI features and application UX were not good enough for patients to use easily and stay engaged at home. Second, and more important, there was no approval or reimbursement pathway. Adoption requires clinician effort to educate patients, run the program through the tool, and monitor progress, and without a way to reimburse that effort, clinicians cannot sustain it. As a result, digital home rehab stayed in research and never reached practical use.

Two policy changes removed that barrier. After COVID-19, the digital therapeutics category created an approval and reimbursement pathway for digital tools used in home rehabilitation. In the United States, the introduction of Remote Therapeutic Monitoring (RTM) reimbursement allowed clinician effort for musculoskeletal home rehab to be reimbursed. These changes are what made EverEx viable as a business rather than only a research project.

The AI solution: the MORA platform

The patient experiences two main functions: assessment and rehabilitation.

EVEREX

Assessment mimics an in-person clinician. EverEx built its own AI pose-estimation model that runs in the camera of a smartphone or tablet, with no additional hardware or sensors, capturing 24 joint locations and tracking their movement. It measures maximum range of motion and supports common functional tests such as the single-leg squat, squat, and sit-to-stand, alongside questionnaires. Together, the information provides an accurate picture of the patient's current functional status and the basis for an individualized program.

Rehabilitation draws on a library of close to 3,000 individual exercises, covering most musculoskeletal conditions as well as neurological and post-cancer rehabilitation, which a clinician uses to build an individualized curriculum. A clinician dashboard then lets the care team monitor each patient's home-based assessments, exercise adherence, and symptom change as a patient-reported outcome, and communicate with the patient through an in-app chat, including swapping out exercises a patient finds difficult.

On clinical-grade evaluation from a single camera, Dr. Yoon explained that functional assessment was previously done either by manual physical examination, which is expensive in clinician time and subjectively variable between practitioners, or by sophisticated multi-camera, marker-and-sensor motion-capture setups that few clinics can afford and that only work for limited indications. EverEx reports validation studies comparing aspects of its camera-based functional assessment with clinician evaluation, conventional motion-analysis approaches, and X-ray-based measures, supporting its use for remote functional assessment in selected rehabilitation workflows.

Outcomes, regulation, and market

EverEx has two distinct regulatory milestones. EverEx Rehab, a remote monitoring solution, was listed as a United States FDA Class II medical device in 2023, supported by clinical validation and accuracy data related to objective patient monitoring. MORA Cure, a digital therapeutic, required a clinical trial for its indication to show clinical effectiveness and safety. EverEx ran a randomized, controlled, multicenter trial in Korea with more than 200 patients. The results, published in the British Journal of Sports Medicine, showed significantly improved outcomes in the evaluated indication across pain, function, and quality-of-life-related measures, alongside high adherence compared to usual treatment.

The platform is used across more than 100 care sites globally, including hospitals and rehabilitation providers. It performs especially well in two settings. Post-surgical patients are highly motivated to rehabilitate, but in rural areas accessibility to physical therapy is low and wait times can run four to six weeks, past the golden period when early rehabilitation matters most; the tool provides rehabilitation in that window. For chronic pain conditions such as chronic lower back and knee pain, patients often cannot attend clinics regularly and face a cognitive distortion toward pain that lowers adherence; EverEx addresses this by combining cognitive behavioural therapy with the rehabilitation exercises so that these patients benefit from psychological treatment alongside the physical program.

EverEx's United States revenue surpassed its Korean revenue in 2024. This is attributed to the United States RTM reimbursement pathway, which is significantly advanced and commercially important relative to most other markets. RTM is strategically important because it reimburses clinician monitoring of home rehabilitation across a broad range of musculoskeletal conditions, whereas digital therapeutics often require indication-specific clinical evidence and regulatory work before expansion into new use cases.

Workforce and the role of AI

EverEx employs a multidisciplinary clinical team spanning orthopedics, rehabilitation medicine, psychiatry, and physical therapy, working alongside its AI team. Dr. Yoon distinguished between task-specific machine-learning models used in functional assessment and newer generative AI tools. In EverEx's view, generative AI currently has clearer near-term applications in workflow support, patient engagement, and administrative operations than in autonomous diagnosis or treatment decisions, where human oversight remains essential. EverEx therefore keeps a human in the loop, with clinicians verifying any generative AI-supported recommendations before they affect patient treatment or engagement.

Lessons and best practices

- Know the clinical workflow deeply. Workflow differs by economy, hospital, and clinic. A deep understanding of it is the most important factor in building a solution that is used in the clinical setting. This applies in every market.
- Build a solid business model that helps the hospital or clinician. The solution must either make money for the provider or demonstrably save costs; one of these must be unambiguous for adoption in a hospital setting.
- Sequence on reimbursement, not only on technology. The decisive unlock for EverEx was the emergence of digital therapeutics approval and RTM reimbursement, not the technology alone.
- Keep a human in the loop for clinical AI. Given the opacity of generative models, clinicians verify AI recommendations before they affect care.
- Design for adherence. Individualized programs, in-app feedback, and, for chronic pain, integrated cognitive behavioural therapy are what complete a patient's home rehab tool.

Implications for policy

The policy case should be framed around the scale of the musculoskeletal burden across APEC economies. Many economies face this burden: large patient numbers, reduced ability to work, reduced mobility, and dependence on others for daily activities, all of which impose heavy economic cost. Musculoskeletal care is among the largest areas of health spending, with around 600 billion US dollars spent annually in the United States alone. To reduce these costs, technology adoption that improves early access to care is imperative, so patients are well-managed before they deteriorate and treatment becomes expensive.

FOR GOVERNMENTS ACROSS APEC

- Establish reimbursement pathways for digital therapeutics and for remote monitoring of clinician effort. The absence of these pathways is what kept digital rehabilitation out of practice. The technology was not the obstacle; the United States RTM model is a reference that other economies could adopt.
- Support early screening and prevention through digital, exercise-based tools that are scalable to manage musculoskeletal patients before their conditions worsen and drive up costs.

FOR APEC DIGITAL MINISTERS

- Encourage adoption of remote therapeutic monitoring reimbursement across member economies. A broad billing pathway lets proven digital health tools scale across conditions far faster than indication-by-indication approval.
- Treat improved early access to musculoskeletal care as a cost-control measure for aging populations, given the scale of spending and workforce impact across the region.

BANYU

CASE STUDY: INDONESIA, OCEANS AND FISHERIES

Sequencing AI behind biotechnology in Indonesia's seaweed value chain

Snapshot

ECONOMY	Indonesia
SECTOR	Oceans and fisheries; seaweed aquaculture
FIRM	Banyu (founded December 2023; ~30 staff; three sites in eastern Indonesia)
AI FOCUS	Disease monitoring, drone surveillance, and buyer-to-farmer translation, all at minimum viable product stage; partnership-sourced rather than in-house
DRIVER	20 per cent yield improvement at farmer level achieved through seedling and good aquaculture practice; AI sequenced as the next phase to support expansion
EVIDENCE	Medium to high (founder interview)

In plain terms: Banyu uses AI to support its seaweed breeding and seedling program, applying it behind the biological work rather than ahead of it.

Based on an interview with Mr. Dodon Yamin, CEO of Banyu, on May 19, 2026, led by Iga Andita Lestari (Kadin Indonesia Institute) on behalf of the ABAC AI Applied research team. Recorded with permission; full transcript on file. Reviewed by Banyu before publication.

The opportunity

Indonesia is the world's second-largest seaweed exporter, yet the sector remains structurally traditional: fragmented supply chains with up to nine intermediaries between farmer and buyer, unclear policy, weak technology adoption, and unresolved seedling quality. Other aquaculture commodities like shrimp and tilapia have grown faster and adopted technology more readily.

Mr. Yamin, who has spent close to a decade in seaweed, founded Banyu in December 2023 around a deliberate bet: that the most consequential intervention is the seedling. Unlike shrimp or tilapia, where farmers need seed, feed, and fertilizer, in seaweed, the only input is the seed. Banyu patented its own seedling production and propagation, and raised funding against its thesis to build the business around biotechnology first.

AI is sequenced behind this strategy. As a capital-constrained startup, Banyu has been deliberately cautious about premature AI claims. The aim is to be profitable and to function as a benchmark for serious seaweed businesses, which means getting the manual and biotechnological foundations right before layering AI on top. The case is the clearest evidence that for grassroots traditional sectors in developing APEC economies, AI works best as a follow-on capability supporting expansion instead of as the starting point.

The AI solution

Today, AI plays two roles at Banyu. In everyday operations, AI tools are used across company management, analysis, and cloud-based workflows. On the product side, three applications are at the minimum viable product stage, all sequenced behind the biotechnology work:

- Disease management as early warning: On-site sensors feed environmental indicators to a data logger; AI analyzes the data and sends alerts and directions to farmers.
- Drone monitoring of cultivation sites: AI-analyzed drone footage replaces the daily in-person site visits that currently define the farmer's working day.
- Buyer-to-farmer translation: AI converts incoming purchase orders into specific actions for farmers, compressing intermediary friction.

All three AI uses target the same underlying cost: daily, in-person, manual labour. The hypothesis is that AI-supported monitoring is the lever that turns the 20 per cent yield gain at a single site into a scalable model across thousands of remote farmer sites.

On build, partner, or buy, Banyu prioritizes partnerships. Hardware sensors come from Seliam Waters; cloud infrastructure is being planned with a partner. Banyu's own intellectual property is the flow of information and the operating model. It does not own the AI components. As Mr. Yamin put it: *partnership is the key, especially for AI*.

Implementation and outcomes

Banyu is structured around three co-founders (the founder, his former operations manager, and a Purdue industrial engineering and venture capital colleague) and employs roughly 30 staff: 30 per cent in biotechnology, 20 per cent in marketing, and 50 per cent in operations. There is no dedicated technology team. AI capability is sourced through partnerships, with cost-benefit analysis applied to every spending decision.

Operations span three locations in eastern Indonesia, where 99 per cent of Indonesian seaweed is produced: North Kalimantan, South Sulawesi (both Bugis), and East Nusa Tenggara (culturally distinct). Farmer acquisition is built around co-operatives (Poktan) rather than individuals. Banyu engages the Ministry of Marine Affairs and Fisheries, operates a laboratory with BRIN, the Indonesian national research agency, and recruits research staff for its biotechnology team.

The reported 20 per cent yield improvement comes through a closed loop, where farmers are trained for one to two days, receive a certificate, are supplied with Banyu's improved seedlings, and have their harvest bought back by Banyu. AI is not part of this lift yet. Other reported outcomes include better farmer prices, a more balanced supply chain, and the early traceability story international buyers now request, including for carbon sequestration claims.

Bridging the digital readiness gap

Closing the digital gap with farmers in remote eastern Indonesia is the single biggest open question for Banyu's AI strategy. Outside Greater Jakarta and Surabaya, smartphone use is limited, with the majority of seaweed farmers having only elementary or junior high school education.

Banyu's working approach is progressive technology dissemination through familiar platforms first:

- Stage one (WhatsApp/Facebook groups): Farmers self-organize, share daily life beyond aquaculture. Social context comes first.
- Stage two (structured aquaculture content in the same groups): Typical drop-off of around 20 per cent.
- Stage three (web-based monitoring tools): Further drop-off of around 25 per cent.

From an earlier 50-farmer pilot at Mario Science, around 30 were retained at stage three. These drop-off rates are accepted as the realistic baseline.

Enablers, barriers, and replicability

ENABLERS

- Patented biotechnology thesis (seedling quality) that creates value independent of AI.
- Co-operative-based farmer engagement model that aggregates the unit of intervention.
- Working partnerships with the Ministry of Marine Affairs and Fisheries, BRIN, and selected European research agencies.

BARRIERS

- Limited smartphone use and digital literacy in eastern Indonesia.
- Inverted logistics: cheaper to transport seaweed from Makassar to Shanghai than from Makassar to Surabaya.
- Farmer cohorts with 20 years of habitual practice and little exposure to innovation, against a backdrop of climate-driven variability.
- Government role confusion: the Indonesian government has at times tried to be part of the supply chain (including by providing seedlings) rather than playing the regulator role for which it is best suited.

The Banyu model is highly replicable for agri-tech and marine-tech startups serving traditional sectors in developing APEC economies. Transferable elements include: a clear biotechnology or operational thesis that creates value without AI; co-operative-based farmer aggregation; partnership-first technology sourcing; and a staged digital adoption path that meets farmers where they are. The founder's direct lesson for others is to be honest, transparent, and step-by-step. Agri-tech in Indonesia means being honest about what works in the field, not what sounds good in Jakarta.

Implications for policy

FOR THE INDONESIAN GOVERNMENT

- Be honest with the data. Actual education levels, technology adoption rates, and operating realities in the field are often unclear to decision-makers. Honest data is the precondition for sensible policy.
- Fix the manual process before designing for AI. Business processes, regulations from local and central government, and policy stimulus for smallholder farmers need to be coherent before AI is introduced.
- Be a regulator, not a supplier. The government has at times tried to be part of the supply chain itself. The recommendation is to step back, leave supply to the private sector, and concentrate capacity on policy and regulation.

FOR APEC DIGITAL MINISTERS

- Invest in knowledge transfer to the policymakers who will set AI policy in member economies. Policy is too often made in the absence of clarity about how AI works in the field.
- Support pilots and provide technical assistance to AI projects in traditional sectors in lower-income APEC economies. As the founder framed it: if it succeeds in Indonesia, it succeeds anywhere.

CASE STUDY: INDONESIA, OCEANS AND FISHERIES

AI inside the company first: a disease-led approach to Indonesian shrimp farming

Snapshot

ECONOMY	Indonesia
SECTOR	Oceans and fisheries; shrimp and fish aquaculture
FIRM	FisTx, founded in Yogyakarta; around 1,000 farmer partners across 21 provinces, with partners in several other economies
AI FOCUS	AI across internal operations (budgeting, procurement, reverse engineering, product research, and marketing); AI-supported water-quality reading and farm assessment, with a human in the loop; product-embedded AI planned within the next quarter
MATURITY	AI well established inside the company; customer-facing AI mostly complementary today, with embedding into the FisTx app planned
EVIDENCE	High (founder interview)
In plain terms: FisTx uses AI inside the company first, across budgeting, procurement, and product research, before placing it in farmers' hands.	

Based on an interview with Mr. Rico Wibisono, founder of FisTx, on June 3, 2026, led by Iga Andita Lestari (Kadin Indonesia Institute) on behalf of the ABAC AI Applied research team. Recorded with permission; full transcript on file. Some figures, including farmer and province counts and yield, were given verbally and confirmed with FisTx on review. Reviewed by FisTx before publication.

The opportunity

FisTx, founded in Yogyakarta, Indonesia, began with water management, which Mr. Wibisono describes as the key to fish and shrimp health across the industry. The company built its early business around water disinfection, including a UV disinfection product and a copper-and-silver nanotechnology developed from the founder's background in education and materials science, positioning itself as one of the leading water disinfection providers in Indonesia.

The deeper problem FisTx set out to address is disease, the single largest source of loss in shrimp farming, at around one billion US dollars in Indonesia in 2024. The sector is characterized as facing a new disease challenge on a recurring basis, forcing farmers to adapt their practices continually. This is what drew FisTx to expand disinfection into a wider model. Solving disease requires attention across the whole production cycle rather than at a single point.

For grassroots aquaculture in Indonesia, the FisTx case shows AI working first as an internal capability that lowers the company's own costs and improves its decisions, and only then beginning to reach the farmer through products and guidance. The sequencing echoes other Indonesian cases, where the foundational work in the field comes before AI is placed in farmers' hands.

The FisTx 360 model and the AI solution

FisTx describes its offer as a 360-degree model spanning the full cultivation cycle, built on systems thinking rather than a single on-farm fix. It begins upstream with pond construction, an area the founder considers underserved by aquaculture engineering expertise in Indonesia, on the basis that good construction saves costs and loss later. It then covers farm preparation, the critical early stages of the cycle when feed and water control matter most, and harvest, with data collected at each stage to inform the next cycle.

AI is used most heavily inside the company. FisTx applies AI to budgeting, supplier and procurement work, reverse engineering of its own products, product research across laboratory and field trials, and marketing and content. The founder's stated philosophy is that AI must add value internally before it can add value for customers. New staff are expected to gain AI certifications, including in agentic AI, so that the team can build and manage AI agents.

For customers today, AI is largely complementary rather than embedded in the products. Farmers receive guidance through a WhatsApp channel that draws on the company's accumulated knowledge, available at any hour, which the founder reports farmers value highly. FisTx plans to embed AI into its own application within the next quarter to make farm analysis easier, drawing on its own farm operations and assessment work.

On the sensing side, FisTx uses a simple, low-cost approach rather than physical sensor hardware: chemical titration read through colour, so a farmer can use a phone to capture the colour. The system can identify a water problem and recommend a corrective method. The founder stressed that interpreting the data matters more than collecting it, which is where machine

FISTX

learning adds value. Decision-making is AI-supported but keeps a human in the loop. The founder wants errors checked rather than acted on automatically. The one-hour disease rapid test is run with a Singapore-based partner and is not yet AI-integrated; integration is planned once the app can analyze the data. Sourcing across these capabilities is a combination of in-house expertise and trade partners connected through open APIs.

Outcomes

The clearest reported outcome is the success rate, which has risen by around 20 percentage points, from roughly 60 per cent to the mid-80s. This is linked to AI-supported stocking-density planning, where a medium, well-planned density produces strong yields without the cost of the highest densities. The yield figure is above the common traditional farm benchmark of around 20 tonnes per hectare, and cost control, particularly around pumping and the high cost of failure mid-cycle, is as important as yield, because a higher success rate is what allows a farmer to keep more of the harvest.

FisTx measures impact in two ways: the FisTx phone app, which shows final harvest results, and repeat orders, which are regarded as the truest measure. A farmer buying again confirms value. For farmers, the most important outcomes are productivity and, above all, cost and profit, given a thin market and heavy exposure to United States demand and regulation for Indonesian shrimp.

Bridging the digital gap

The adoption of AI tools by farmers is framed around the "second-generation farmer," who is already on social media and exposed to AI daily, rather than the older farmer. FisTx reaches these farmers through social media, webinars, and offline meetings with customers, prioritizing early adopters and letting the broader base follow.

Proof is the precondition for adoption. Data alone does not convince a farmer. A product has to demonstrate a visible result, such as visibly clean water and a pathogen reading at zero after treatment in the reactor, before a farmer will buy. Three design choices drive adoption: a product that proves itself visibly, a clear willingness to pay (without which there is no impact), and an affordable price suited to a price-sensitive Indonesian market, which FisTx reached partly by redesigning products with AI to match what customers can pay. Endorsement from large farms also matters. Their trust draws smaller farmers to follow.

Two programs support this transition. The Omah community is a free WhatsApp community of farmers, buyers, and sellers for sharing updates and new technology. The Tampan program (Tambak Mapan) is an AI-supported tool that lets a technician review many ponds in around 10 minutes by surfacing which ponds need priority attention. The app is currently limited to the company's own customers and the Tampan base rather than the whole community. Some technicians fear AI will replace people, a view the company rejects on the grounds that AI frees up time for higher-value work.

Workforce, scaling, and barriers

FisTx has added technical and data science roles as it has built its agentic AI capability, which the founder describes as central to letting the team focus rather than be distracted by routine analysis and reporting. He sees reducing distraction as a clear competitive advantage.

On scaling, the founder framed the main constraint as focus rather than any external barrier. FisTx intends to concentrate on the Indonesian market through to around 2028, on the view that Indonesia has the resources and conditions to become a leading global shrimp producer, and that winning at home matters more than early expansion, even though the company already has partners and offtake relationships in several other economies. He noted that a depreciating rupiah against the dollar has raised the cost of imported inputs, which has pushed FisTx toward producing more of its own products through reverse engineering, with support from its customers.

FisTx works with universities, government, and research partners, including BRIN, Indonesian ministries on coastal and mangrove restoration work, a probiotics collaboration in the Netherlands, the Singapore-based rapid-test partner, and nanotechnology work with National Taiwan University. The founder framed the company as small but aiming for large impact through these partnerships.

Lessons and best practices

- Know the customer before the idealism. The founder's central lesson is that the market does not need pure founder idealism; products should be built by listening to customers and treating early customers as mentors, then made affordable for the market.
- Lead with proof. A visible, demonstrable result is what converts a traditional, price-sensitive farmer, more than data or argument.
- Make AI add value internally first. FisTx applied AI to its own budgeting, procurement, research, and reverse engineering before placing it in customers' hands, on the principle that AI must work for the company before it can work for others.
- Keep a human in the loop. Decisions are AI-supported but checked by a person, given the cost of an error in the field.
- Use affordability as a design constraint. Redesigning products with AI to match what customers can pay was decisive in a price-sensitive market.

Implications for policy

FOR THE INDONESIAN GOVERNMENT

- Expand internet connectivity and democratize access. The founder's first recommendation is connectivity. AI is of little use to a farmer or fisher without reliable internet, and coverage is uneven, especially in coastal and remote areas.
- Make capable AI affordable for farmers and fishers. He noted that the cost of advanced, current-generation AI tools (meaning the paid tools rather than only the free or basic ones) is heavy for Indonesian users paying in a strengthening dollar. He asked for support that makes these capable tools affordable.
- Strengthen AI education and skills. He argued that the value of AI depends on the knowledge of the user, so improving how AI is taught and learned is as important as access to the tools.

FOR APEC DIGITAL MINISTERS

- Fund people to promote and teach AI use among farmers and fishers. Adoption depends on human support, not only on tools.
- Invest in the enabling facilities and infrastructure, especially connectivity, which the founder identified as the root constraint on equal access to AI in the sector.
- Support affordable access to capable AI across the region, recognizing the cost pressure that currency and pricing place on grassroots users in lower-income economies.

LUMBER PRICING

CASE STUDY: CANADA, FORESTRY

Machine learning for pricing confidence in a Canadian lumber business

Snapshot

ECONOMY	Canada
SECTOR	Forestry; lumber
FIRM	Anonymized client of Yeji Data Lab; large SME, few hundred employees, C$100M+ revenue, Eastern Canada
AI FOCUS	Machine learning pricing module that strengthens confidence in day-to-day lumber pricing targets
MATURITY	In production; proof-of-concept took a few months before MVP
EVIDENCE	Medium (Yeji-provided case material and follow-up responses)

In plain terms: Yeji Data Lab built a machine-learning module that recommends lumber prices, so the commercial team can decide faster and more consistently.

Based on case material and follow-up responses provided by Yeji Data Lab (David Lederhendler, CEO) in April 2026 for the ABAC AI Applied research project. The client is anonymized at the contributor's request. Reviewed before publication.

The opportunity

Lumber is a commodity sector where pricing is volatile, margins are thin, and pricing decisions are made frequently against shifting market conditions. The client, a large Canadian SME in Eastern Canada with a few hundred employees and over C$100 million in revenue, relied on a small commercial team to set day-to-day pricing targets. AI provided the opportunity to give the team stronger, data-driven confidence in pricing decisions that were previously made largely on judgment and experience.

Yeji Data Lab, a Canadian AI firm contributing case studies to this project, built and deployed the solution. The framing is a useful contrast with the larger firm cases: this is a mid-sized firm in a traditional commodity sector applying a focused, single-purpose AI tool rather than an enterprise-wide transformation.

The AI solution

The solution is a machine-learning pricing module integrated into the client's commercial workflow. Rather than replacing the commercial team, the module provides support by improving the confidence and consistency of day-to-day pricing targets. The module is narrow by design: it addresses one well-defined decision (e.g. pricing) with measurable inputs and outputs, which is consistent with the pattern of successful AI adoption in mid-sized firms.

Implementation and outcomes

The proof-of-concept phase took several months before reaching minimum viable product, after which the module moved into production. A small commercial team of three to four people in sales and commercial leadership uses, or is expected to use, this tool.

The module is now in production and producing realized outcomes. The principal benefit is stronger confidence in day-to-day pricing targets, which supports more consistent margin management in a volatile commodity market. The deployment was supported in part by public-sector funding, a feature shared by several Canadian AI adoption cases and relevant to the policy discussion on how governments can de-risk AI adoption for mid-sized firms.

Workforce and replicability

The workforce impact is concentrated in the small commercial team, whose pricing decisions are now augmented rather than replaced by the model. The tool changes how pricing judgment is exercised rather than eliminating the role, a pattern of augmentation rather than displacement that recurs across several cases in this report.

The model is highly replicable for other commodity sectors where pricing is frequent, volatile, and margin-sensitive, including other forestry products, agricultural commodities, and building materials. What is transferable is the architecture of a narrow, decision-support pricing model trained on the firm's own commercial data; what is specific to the client is the data model and the particular dynamics of the lumber market.

Best practices and policy implications

- Start narrow. A single, well-defined decision (e.g. pricing) with measurable inputs is a more reliable entry point for a mid-sized firm than enterprise-wide AI transformation.
- Augment rather than replace. Positioning the model as decision support for the commercial team eased adoption and preserved the value of human market judgment.
- Public-sector funding can be a meaningful enabler for mid-sized firms. The role of public co-funding in de-risking early AI adoption is directly relevant to APEC policy on supporting MSME and mid-market AI uptake.

CONTAINER TERMINALS

CASE STUDY: CANADA, PORTS AND LOGISTICS

Predictive maintenance and availability planning at a container terminal

Snapshot

ECONOMY	Canada
SECTOR	Logistics; ports and terminal operations
FIRM	Anonymized container terminal operator (private SME); solution by Yeji Data Lab
AI FOCUS	Predictive maintenance and equipment availability planning: forecasts failure risk, predicts short-term availability, and ranks maintenance actions
MATURITY	Models validated and put into production through a dashboard; strong reported test accuracy
EVIDENCE	Medium to high (detailed Yeji-provided case material)

In plain terms: Yeji Data Lab uses AI to predict when terminal equipment will need service, so maintenance can be planned before a breakdown.

Based on detailed case material provided by Yeji Data Lab (David Lederhendler, CEO) in May 2026 for the ABAC AI Applied research project. The client is anonymized at the contributor's request. Reviewed before publication.

The opportunity

Container terminals are asset-intensive operations where equipment availability directly determines throughput. At the client terminal, maintenance and operations planning relied on historical reporting, manual interpretation, and weekly co-ordination between two teams with competing needs: Operations needed to know which machines would be available for vessel, yard, and container-handling work, while Maintenance needed to schedule preventive and corrective work without leaving Operations short of critical equipment.

The pressure on the maintenance function had been rising. Maintenance work increased over the five years to 2023, with nearly 75 per cent of machines requiring more work. The total length of work required in 2022 and 2023 ran 26–51 per cent above the five-year average, with machine availability falling over the same period. The case does not attribute this rise to a single cause. Aging equipment and rising utilization are typical drivers in terminal operations. The opportunity was to close the information gap between Operations and Maintenance with predictive, data-driven decision support.

The AI solution

Yeji Data Lab built a predictive maintenance and availability decision-support system with three integrated layers:

- Equipment availability prediction: machine learning models forecast whether each asset will be available over the next two, four, and seven days, supporting near-term resource allocation by Operations.
- Failure-risk prediction: a 10-day model identifies whether an asset is likely to fail within a forward-looking maintenance window for Maintenance planning and weekly committee decisions.
- Maintenance-priority ranking: converts predictions into a ranked action list, combining failure probability, equipment criticality, open work orders, reliability and downtime metrics, spare-part availability, operational demand, and the cost of failure versus preventive maintenance.

The ranking layer is the critical design choice. Maintenance teams need to know what to do first, so the system translates model output into prioritized action.

Implementation and outcomes

Implementation proceeded in phases. The first validated the maintenance data model and re-engineered the definitions for mean time to repair (MTTR), mean time between failures (MTBF), and uptime. It also redefined reliability, downtime, and the two out-of-service measures, being out-of-service time and unplanned downtime. This work was a necessary foundation. The second built the training dataset around seven key inputs and explicitly addressed the rarity of failures using synthetic minority oversampling. The third compared model types and selected on operational usefulness rather than statistical accuracy alone. The final phase presented the output through a dashboard showing predicted availability, failure-risk scores, and priority rankings. The dashboard also displays open work orders, shortage risk, and a recommended action with its confidence level.

In testing, the 2/4/7-day availability model reported mean overall accuracy of 96.5 per cent and failure accuracy of 94.2 per cent; the 10-day model reported 94.6 per cent overall and 76.4 per cent failure accuracy. The reported business outcomes are reduced unexpected downtime, better equipment allocation, fewer equipment shortages, more efficient maintenance planning, and improved visibility into maintenance performance.

Workforce and replicability

The system required upskilling across four groups: maintenance planners (interpreting risk and availability forecasts), operations planners (using availability in daily and weekly allocation), the weekly maintenance committee (decision governance and capturing whether recommendations were used), and a technical and analytics team (data pipelines, dashboard maintenance, model retraining and monitoring). This is a richer workforce story than most cases in the report, with new analytical roles created rather than displaced.

The use case is highly replicable across ports, terminals, and intermodal yards. It applies equally to warehouses, airports, and mining sites. Transferable elements are the architecture, meaning the availability model, the failure-risk model, and the priority ranking. The dashboard, the feedback loop, and machine learning operations governance also transfer. Specific to the client are the equipment mix, ERP data model, and fleet-specific failure patterns. For other SMEs, the recommended approach is to start with one fleet (such as yard tractors or RTGs) targeting a well-defined, measurable pain point before expanding.

Best practices and policy implications

- Define KPIs before modelling. Predictive maintenance fails if availability, downtime, and reliability are not consistently defined. The same applies to MTBF and MTTR. Treat the KPI re-engineering as a foundation.
- Separate availability prediction from failure prediction. An asset may be unavailable for planned maintenance, corrective work, or operational assignment, and the model should distinguish among these.
- Rank recommendations rather than displaying probabilities. Maintenance teams need a prioritized action list that combines model risk with operational importance and spare-part availability.
- Embed AI into an existing decision forum. The weekly Operations-Maintenance committee provided a ready home for AI recommendations, avoiding the need to invent a new process.
- Connect predictive maintenance to inventory. A predicted failure is less useful if the required part is unavailable, which links predictive maintenance to spare-parts forecasting and procurement lead times. This dependency is a useful signal for APEC policy on data and supply chain readiness.

ESHEPHERD BY GALLAGHER

CASE STUDY: NEW ZEALAND, AGRICULTURE

Virtual fencing, and AI used with care to scale a farm technology worldwide

Snapshot

ECONOMY	New Zealand
SECTOR	Agriculture; livestock and primary industries
FIRM	eShepherd by Gallagher Animal Management; a virtual fencing platform for cattle, operating in more than 14 economies, available in more than 10 languages
AI FOCUS	AI across customer support, warranty assessment, software development and testing, multilingual onboarding, and value-added grazing insights
MATURITY	Deployed and in active use; AI central to operations and product development, with around 90 per cent of AI capability built in-house
EVIDENCE	High (interview with the GM/EVP of Strategy and New Ventures)

In plain terms: eShepherd uses AI chatbots to answer farmer questions, an AI agent to assess warranty returns, and AI to write and translate its software and materials.

Based on an interview with Ms. Sarah Adams, GM and EVP of Strategy and New Ventures, Gallagher Animal Management, on June 25, 2026 (recorded with permission; full transcript on file). Reviewed by eShepherd before publication.

The opportunity

eShepherd began as a startup in Australia, after its founder visited a family farming property and saw how difficult it was to herd, contain, and relocate animals with physical fencing. The idea was a better way to contain and manage livestock without building fences across the land. The platform replaces physical fencing with a solar-powered GPS neckband worn by cattle, so farmers define virtual paddocks through an app and the neckband guides animals by audio and then pulse cues. eShepherd helps farmers improve pasture utilization, lift cattle productivity, and improve environmental outcomes for the land.

Ms. Adams, GM and EVP of Strategy and New Ventures, framed the problem as the end point of a long evolution in fencing, from stone to wood to wire, then to the electric fence that Gallagher developed 88 years ago. Electric fencing let farmers rotate animals at lower cost, but it was expensive and labour-intensive to install, could fail in very dry conditions, and was impractical across the large rangelands of Australia and the United States. Virtual fencing addresses all of this. A rotational grazing system can be built on any terrain without a physical fence.

For grassroots agriculture across APEC, the eShepherd case shows a farm-technology firm using AI with care across the business to scale into new economies and languages with modest resources, while keeping a person available where judgment is needed.

The AI solution

AI adds value across two broad areas at eShepherd: supporting customers and building the product. The neckband hardware remains central, while AI runs through the operation around it.

CUSTOMER SUPPORT AND SUCCESS

An AI chatbot responds to customer inquiries and resolves a large share of issues without a person. The company rebuilt a database of its past inquiries and taught an AI agent to resolve them, now handling roughly 70–80 per cent of inquiries. The company's inquiry volume has risen by around 70 per cent while the share needing a person has fallen by around 50 per cent. Because it responds to many simple questions at any hour, the company can support farmers in other time zones and expand into new economies without training large support teams. When the assistant cannot answer, or a customer needs further assistance, the inquiry goes to a person, and the company keeps someone available at all hours.

WARRANTY ASSESSMENT

A second AI agent assesses neckbands returned for warranty, identifying what is wrong with each unit quickly and accurately. This feeds product development. The company can detect a poor batch early, alert affected farmers, and arrange a replacement before failures spread. The same agent reduced warranty processing time from four weeks to five days.

PRODUCT DEVELOPMENT AND VALUE-ADDED INSIGHTS

AI is used to write and test software, which the company reports has roughly doubled its development and testing speed for the same resource. The team built a website and landing pages through AI with no dedicated coder, working from spoken prompts. Beyond efficiency, the company is building subscription services on top of the hardware, including animal-behaviour and health algorithms, pregnancy detection, and camera-vision weighing that advises farmers when to shift animals to fresh pasture.

MULTILINGUAL REACH

As the company scaled into Europe, AI translated its onboarding, marketing, and video materials into more than 10 languages, and it is trialling tools that let an English-speaking team member and a farmer each hear and speak in their own language. This allowed the company to support customers in markets such as France and Serbia (countries where the company has no speaker of the local language) and keep those customers satisfied.

Around 90 per cent of the AI capability is built in-house, led by a head of technology strategy who continually trials new tools and brings them in. The one notable external piece is the camera-vision weighing algorithm, built with a partner who segmented the data and trained the model.

Implementation

Gallagher works to an open-innovation model, going faster by partnering or acquiring where a strong option exists and building in-house only where a needed capability does not yet exist. Expertise from the core business, such as pulse circuits and solar, transfers across to eShepherd.

On the engineering itself, the company uses AI to write and test code, building agents to do much of the testing, which lets it go considerably faster. It keeps security controls strict, then trials, tests, and iterates, working on the principle of progress over perfection. In one instance, there was a rewrite of more than 27,000 lines of the web application completed in under three months.

The hardest part was trust. Internally, staff worried AI would replace them, so the company kept headcount steady and used AI to remove disliked tasks, building confidence through a weekly habit of comparing what a sprint achieved before and after AI. Seeing work finished in three months that would once have taken nine did much to win the team over. Most farmers do not know they are speaking with the AI assistant, so little persuasion was needed.

Outcomes

For farmers, the shorter warranty turnaround means faster claims and earlier detection of an emerging issue. For the company, it turns a mundane, time-consuming job into one where staff help farmers solve the problem rather than diagnose it, and feeds results into product development more quickly.

The company prioritizes farmer satisfaction first, then the cost to serve, then self-service. A people-heavy model is hard to scale, and farmers prefer to act at a time of their choosing. It tracks customer satisfaction, how well inquiries are resolved or pre-empted, and churn, which it reports is very low and tied to customer success.

One outcome surprised the team. Many had expected support inquiries to fall once the assistant was in place; instead they rose, regarded as a positive outcome. Farmers who once assumed no one would answer late at night now get prompt replies and onboard faster. The contrast is that some customers still prefer a person and stay outside the digital channels, which then needs manual loading of their information.

Workforce and upskilling

The main new capability is a data science team. However, most changes came from a shift in mindset rather than a wave of new technical roles: the team is more open to new tools, more inclined to remove an annoying task with AI, and more willing to question how things have always been done. The result is higher efficiency, with people spending their time on higher-value work.

Scaling and barriers

The company identified several barriers to reaching more farmers and economies. Affordability matters, but the deeper barrier is that many farmers do not yet understand the value of rotational or managed grazing, so there is a large education task before adoption. Connectivity is a constraint in some places, though the company reports it largely solved in most. Manufacturing scale-up and having enough people on the ground to talk with farmers are practical limits.

Government support is a strong determinant of pace. Where governments support technologies like this, the company sees much faster scaling. It is suggested that support need not cover the full cost; even partial support for an initial set of neckbands would let farmers learn the value, discover they can afford it, and continue on their own.

Progress has been fastest where farmers already use related technology or understand managed grazing. In Southern Europe, a specialist partner reached customers who were already tracking animals with GPS and then wanted to control them. Progress is slowest among traditional farmers who are new to managed grazing and less comfortable with digital tools. Ms. Adams cited Northern Australia, where low farm returns and environmental shocks limit investment. She noted that markets with less digital familiarity, or stronger animal-welfare concerns, also take longer.

Lessons and best practices

- Start from the problem, not the technology. The central lesson is to find the friction points and the jobs to be done in the business, then ask whether AI fits, rather than adopting AI for its own sake.
- Use AI to relieve a pain or generate a gain. Customer-insight work to identify pains and gains should come first, then a view of all the options for solving them, with AI as one candidate.
- Bring the team along deliberately. Reassuring staff that headcount stays, removing disliked tasks, and a weekly habit of asking what the team won, learned, and changed built trust and adoption.
- Keep a person where judgment is needed. The assistant resolves routine inquiries at any hour, while a person remains available for what it cannot answer.

Implications for policy

FOR THE NEW ZEALAND GOVERNMENT

- Educate farmers on AI. Ms. Adams found at a recent Beef and Lamb event that many farmers have never used AI and few use it daily, so education on what AI can do and which tools suit which task is the single most important step.
- Set guidelines for responsible use, especially on animal welfare. She noted people using AI to detect animals breaching virtual-fence lines in ways that raise welfare concerns, so guidelines on where AI should and should not be used would help.
- Invest to show how AI improves efficiency. Investment that demonstrates to companies how AI can make them more efficient would accelerate responsible adoption.

FOR APEC DIGITAL MINISTERS

- Run practical AI workshops for farmers. It is suggested to bring farmers in with a problem and work through it with them, or letting them try AI tools to reach a solution.
- Encourage firms to build AI into products responsibly to improve productivity and return more value to farmers, so the region innovates faster.
- Establish data standards and support cross-sector collaboration to build the shared data resources that value-added agricultural AI depends on.

CASE STUDY: CHINA, MANUFACTURING

XIAOMI

Industrial AI models for material research, quality inspection, and process control in automotive manufacturing

Snapshot

ECONOMY	China
SECTOR	Manufacturing; automotive
FIRM	Xiaomi Corporation; a technology manufacturer that produces electric vehicles alongside consumer electronics
AI FOCUS	The MEE AI model for material discovery; a large visual model for die-casting quality inspection; a closed-loop large model for process control
MATURITY	Deployed across material research, quality inspection, and process optimization in automotive manufacturing
EVIDENCE	Contributed by the APEC Study Center at Nankai University

In plain terms: Xiaomi uses AI to discover new materials, to inspect die-casting parts for defects, and to control production processes in its automotive manufacturing.

Contributed by the APEC Study Center at Nankai University.

The opportunity

Integrated die casting lets a vehicle body that once needed dozens or hundreds of welded parts form in a single piece, which reduces welding, raises production efficiency, and lowers body weight. The constraint was the material. An alloy for ultra-large thin-walled die-casting parts needs very high fluidity to fill the mould, and at the same time high yield strength, tensile strength, and toughness so the body absorbs a collision without fracturing. These properties tend to work against each other, so most manufacturers reached a point where no existing alloy met all of them at once, which limited large-scale integrated die casting.

AI applications

Material research: Xiaomi shifted material research from an experiment-led approach to one led by a large model. The MEE AI model, also described as a Material Expert Ensemble, pairs performance prediction with formula optimization. The system used thermodynamic data as prior knowledge, pre-trained on simulation and literature data, then fine-tuned on a small amount of high-quality experimental data. It evaluated candidate formulas at scale and selected the alloy, Xiaomi Titanium Alloy. This shortened the material research cycle by about 50 per cent, and the alloy is in production for large die-casting parts.

Quality inspection: For internal defects in large die-casting parts, which come in small samples, tiny dimensions, and varied forms, Xiaomi applied a large visual model that predicts the mechanical properties of the parts. The system converts physical testing into X-ray image inspection, uses expert knowledge to pre-annotate data, and performs pixel-level segmentation of millimetre-scale defects through an integrated architecture that links perception, decision, and feedback control. The inspection process went from 20 seconds to two seconds, with quality inspection accuracy above 99.9 per cent.

Process optimization: Xiaomi developed its own large model that controls the process in a closed loop. The model studies the relationships between thousands of process parameters and final product quality. It evaluates and optimizes the process and co-ordinates hundreds of production and inspection machines, so the line adjusts on accumulated data rather than individual experience. AI-driven process improvements produced an eight per cent overall increase in manufacturing efficiency.

Approach and significance

Xiaomi introduced the models in stages from 2022 to 2025, beginning with material research, then full quality inspection, then process control. It keeps a human in the loop through an "AI suggestion, expert confirmation" procedure, where experts confirm model recommendations before use. The case shows that an industrial large model can bridge a traditional manufacturing process and frontier AI, lowering research cost while raising precision in inspection and control.

PHOENIX WINGS

CASE STUDY: CHINA, LOW-ALTITUDE AIR LOGISTICS

丰翼无人机 PHOENIX WINGS

Phased deep-learning perception, a vision-language model, and a flight assistant for low-altitude drone logistics

Snapshot

ECONOMY	China
SECTOR	Low-altitude air logistics; drone delivery
FIRM	Phoenix Wings (Shenzhen) Co., Ltd., a low-altitude logistics operator
AI FOCUS	Deep-learning perception and obstacle avoidance across takeoff, cruise, and landing; a vision-language model for scene analysis; a flight assistant based on a large language model and retrieval
MATURITY	Deployed in large-scale low-altitude logistics operations
EVIDENCE	Contributed by the APEC Study Center at Nankai University

In plain terms: Phoenix Wings uses AI so its delivery drones detect obstacles during takeoff, cruise, and landing, and so operators can query flight procedures in plain language.

Contributed by the APEC Study Center at Nankai University.

The opportunity

Drone logistics has shifted from pilot flights to regular, large-scale operations. The work is more than flying a parcel from one point to another. It spans the aircraft, the takeoff and landing sites, and the scheduling and safety control behind each delivery. As operations scale, the measure of success widens from a single successful flight to safe, punctual, and continuous fulfillment in open, changing environments. This raises the demand for safety perception, maintenance response, and adaptation to local conditions.

AI applications

Perception across the flight. Phoenix Wings trains separate deep-learning models for takeoff, cruise, and landing. At takeoff, an object-detection model checks the space around the drone and can abort if a risk enters the safe range. In cruise, small-object detection and semantic segmentation identify other drones, buildings, and power towers from about 100 metres away and separate sky, ground, and obstacles for early avoidance. At landing, a small-object detection model checks whether the landing area is clear.

Scene understanding: The firm added a vision-language model so the system reasons about the relationship between an object and the flight task rather than the object alone. The model raises a warning, such as a cargo frame entering the safety zone, judges whether to adjust the route for buildings or towers, and reads the motion of people or obstacles at landing. It also reasons about non-standard hazards such as standing water or temporary piles.

Flight assistant: Using a large language model with retrieval, the firm turns flight manuals and emergency procedures into a knowledge base. An operator can ask in plain language how to handle adverse weather and receive clear steps. The system combines vision, language, and voice, warns about low battery or an occupied landing zone, and accepts spoken commands after a safety check.

Significance

Phoenix Wings shows a shift from point-to-point automation to intelligent operation in complex settings. One operator can supervise more aircraft, and the drone becomes an operation unit that understands its environment. No single headline metric is reported for this case.

CASE STUDY: CHINA, NEW ENERGY

SmartMore 思谋
全球领先的工业AI智能体公司

An industrial multimodal model and turnkey inspection devices that other firms adopt, applied to new-energy battery production

Snapshot

ECONOMY	China
SECTOR	New energy; industrial AI
FIRM	Shenzhen SmartMore Technology Co., Ltd., an industrial AI firm that builds models and inspection devices other firms adopt
AI FOCUS	IndustryGPT, an industrial multimodal model; the ViMo vision platform and LrMo development platform; turnkey inspection devices
MATURITY	Deployed across more than 60 turnkey inspection devices in industrial use
EVIDENCE	Contributed by the APEC Study Center at Nankai University

In plain terms: SmartMore builds AI inspection systems that other factories adopt, including battery blue-film inspection and an industrial model called IndustryGPT.

The opportunity

In a lithium battery, a blue film wraps the cell to insulate and protect it, so a bubble, a scratch, or a foreign object on the film can cause a short circuit. Inspecting the film is hard for three reasons. A single cell needs every surface, edge, and corner checked at once. The film reflects strongly, so a bubble, a scratch, and a foreign object look alike under standard machine vision. The fast line makes manual inspection costly and prone to missed defects.

AI applications

Blue-film inspection: SmartMore built a dedicated optical and mechanism system that filters the stray reflections from anti-rust oil, then applied its ViMo deep-learning segmentation to extract micron-level features and recognize defects. Inspection is fully automated at a cycle time of 0.5 seconds per unit, which removes high-risk manual re-inspection.

IndustryGPT and synthetic defects: IndustryGPT is one of the first large-scale multimodal models built for complex industrial scenarios. Because high-end lines run very high yields, defect samples are scarce, which creates a cold-start problem for AI. IndustryGPT synthesizes realistic defect images from a small number of true examples. This reduced the missed-detection rate for key defects from an industry-typical 0.3 per cent to approximately 0.0 per cent.

Platforms and devices: The ViMo vision platform and the LrMo development platform use low-code and zero-code tools, so factory technicians without a programming background can train and deploy a model in one to two days. More than 60 turnkey inspection devices are in use across consumer electronics, new-energy batteries, and automotive components.

Significance

SmartMore is characterized as an enabler that packages industrial AI into standardized devices, which lowers the barrier for traditional factories to adopt it.

Contributed by the APEC Study Center at Nankai University.

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