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Machine Learning in Taiwan: Ecosystem, Industrial Applications, Governance, and Future Directions

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Abstract

Machine learning (ML) has moved from a specialized computational technique to a general-purpose technology that increasingly shapes manufacturing, healthcare, finance, public administration, logistics, and scientific research. Taiwan provides an especially important context for examining this transformation because its economy combines a globally significant semiconductor ecosystem, advanced information and communications technology capabilities, dense university and research networks, export-oriented manufacturing, and an expanding national policy agenda for artificial intelligence (AI). This article reviews the foundations, applications, enabling conditions, constraints, and future directions of machine learning in Taiwan. It adopts an integrative literature-review and policy-analysis approach, drawing on foundational ML literature, peer-reviewed studies, Taiwan government documents, and recent sectoral research. The review shows that Taiwan's comparative opportunity is not limited to developing software models: it lies in connecting algorithms with semiconductor production, edge computing, industrial equipment, healthcare data, smart infrastructure, and domain-specific engineering. Evidence from wafer testing and wafer-defect studies illustrates how supervised learning can support yield improvement and process diagnosis, while healthcare research demonstrates opportunities in clinical prediction, imaging, workflow support, and smart-healthcare value chains. At the policy level, Taiwan has established initiatives addressing computing resources, data, talent, investment, industrial adoption, and AI governance, including the Ten AI Initiatives Promotion Plan and the AI Basic Act. Nevertheless, significant challenges remain: data quality and interoperability, privacy and cybersecurity, model interpretability, external validation, shortage of advanced interdisciplinary talent, high deployment costs, energy consumption, organizational resistance, and the difficulty of transferring models between plants, hospitals, and operating environments. The article proposes a Taiwan-oriented ML development framework based on trusted data infrastructure, domain-specific foundation models, edge and industrial AI, responsible evaluation, university-industry collaboration, and continuous workforce development. The central conclusion is that Taiwan's ML trajectory will depend less on algorithmic novelty alone than on its ability to integrate trustworthy learning systems with real-world production and public-service environments.

Keywords: Machine learning; Taiwan; artificial intelligence; semiconductor manufacturing; smart manufacturing; healthcare AI; industrial AI; AI governance; edge AI; digital transformation

1. Introduction

Machine learning refers to computational methods that enable systems to infer patterns, make predictions, or improve decisions from data rather than relying exclusively on manually specified rules (Mitchell, 1997; Jordan & Mitchell, 2015). The field encompasses supervised, unsupervised, semi-supervised, self-supervised, reinforcement, and increasingly foundation-model-based learning. Recent advances in deep neural networks have expanded ML from conventional prediction tasks toward computer vision, natural language processing, speech recognition, generative systems, robotics, and multimodal reasoning (LeCun et al., 2015; Goodfellow et al., 2016).

Taiwan is a particularly valuable setting for studying ML because computation, electronics, manufacturing, and digital services are deeply interconnected. The island's semiconductor capabilities provide both an industrial application domain and an enabling hardware base for AI. Government strategy increasingly treats AI as a cross-sector technology, while industrial policy links AI with semiconductors, next-generation communications, security, and other strategic sectors (National Development Council [NDC], 2025a, 2025b). The government's Ten AI Initiatives Promotion Plan for 2025–2028 explicitly positions AI as a tool for upgrading individuals, industries, and the nation, including in response to demographic and labor-market pressures (NDC, 2026).

The research question guiding this article is: How can Taiwan's technological and institutional capabilities support the development and responsible deployment of machine learning, and what constraints must be addressed for ML to produce sustained economic and social value? Rather than treating Taiwan simply as an adopter of foreign AI technologies, this review examines Taiwan as a potential site of co-evolution between algorithms, semiconductor hardware, industrial processes, data infrastructures, research institutions, and public policy.

The article contributes in four ways. First, it synthesizes the technical foundations of ML in language accessible to interdisciplinary readers. Second, it maps major application domains in Taiwan. Third, it connects industrial evidence with the country's emerging AI governance and talent policies. Fourth, it proposes a practical research and deployment agenda for trustworthy, domain-specific ML.

2. Review Methodology

This study uses an integrative literature-review and policy-analysis design. It is not a statistical meta-analysis and does not claim to estimate an aggregate effect size for ML in Taiwan. Sources were selected to cover three layers: (1) foundational and methodological ML scholarship; (2) empirical and review literature concerning semiconductor manufacturing, healthcare, and industrial AI; and (3) official Taiwan policy and governance documents available through September 2026. Particular attention was given to sources that document concrete ML applications or institutional conditions rather than promotional claims.

The synthesis is organized thematically around technological foundations, industrial applications, data and talent, governance, implementation barriers, and future research. Where evidence concerns Taiwan specifically, the text identifies the Taiwan context. Where evidence comes from the broader ML literature, it is used to explain mechanisms or methodological principles rather than to imply that an identical result has already been demonstrated in Taiwan.

Table 1. Scope and evidence categories used in the review

Evidence category	Examples	Purpose in this article
Foundational ML literature	Mitchell; Breiman; LeCun et al.; Goodfellow et al.	Define methods, capabilities, and methodological limits

Taiwan policy documents	NDC, MODA, Executive Yuan, AI Basic Act	Assess strategic priorities, infrastructure, governance, and talent
Taiwan empirical studies	Wafer defect/yield studies; healthcare AI studies	Document concrete applications and deployment issues
Recent sector reviews	Semiconductor ML and smart healthcare reviews	Identify emerging trends and research gaps
Synthesis	Cross-sector comparison	Develop Taiwan-oriented research and deployment framework

3. Machine Learning: Concepts and Technical Foundations

ML systems learn a mapping between inputs and outputs, a representation of structure in data, or a policy for acting in an environment. In supervised learning, a model is trained using labeled examples, such as process measurements paired with product-quality outcomes. Regression predicts continuous quantities, while classification assigns observations to categories. Unsupervised learning identifies structure without target labels, including clusters, latent representations, and anomalies. Reinforcement learning instead optimizes sequential decisions using rewards or costs (Sutton & Barto, 2018).

Classical algorithms remain highly relevant to industrial and public-sector ML. Linear and logistic regression provide interpretable baselines; decision trees represent nonlinear decision rules; random forests and gradient-boosting methods often perform well on structured tabular data; and support-vector machines can be effective in high-dimensional settings (Breiman, 2001; Cortes & Vapnik, 1995). Deep learning is particularly powerful where data contain complex spatial, temporal, or linguistic structure. Convolutional neural networks have been central to image analysis, recurrent and transformer architectures have supported sequence modeling, and attention-based transformers now dominate many language and multimodal applications (LeCun et al., 2015; Vaswani et al., 2017).

Performance, however, is not determined by algorithm choice alone. Data representativeness, label quality, feature engineering, hyperparameter selection, class imbalance, train-test leakage, and distribution shift can substantially alter results. In production environments, the most important question is therefore not whether a model achieves a high score on a benchmark but whether it remains reliable when operating conditions change. This distinction is particularly important for Taiwan's manufacturing sector, where equipment, recipes, materials, and product generations may change over time.

Table 2. Major machine-learning paradigms and Taiwan-oriented uses

Paradigm	Typical methods	Potential Taiwan applications	Key limitation
Supervised learning	Regression, random forest, boosting, SVM, neural networks	Yield prediction, defect classification, demand forecasting	Requires reliable labels
Unsupervised learning	Clustering, PCA, autoencoders	Anomaly detection, process-state discovery	Harder to validate without labels
Deep learning	CNNs, transformers, multimodal networks	Visual inspection, language, medical imaging	Data/computing demands and interpretability
Reinforcement learning	Q-learning, policy gradients, actor-critic	Process control, robotics, scheduling	Safety and reward-design challenges
Self/semi-supervised learning	Contrastive learning, masked prediction	Learning from large unlabeled industrial/medical data	Evaluation and representation drift
Federated learning	Distributed model training	Cross-hospital or cross-factory collaboration	Communication, privacy, heterogeneity

4. Taiwan's Machine-Learning Ecosystem

Taiwan's ML ecosystem is supported by the interaction of government agencies, universities, research institutes, technology companies, manufacturers, hospitals, startups, and infrastructure providers. The Ministry of Digital Affairs (MODA) has described five policy pillars for AI development: computing power, data, talent, marketing, and funding. Measures include AI computing resources, data initiatives, talent programs, and support for industry adoption (MODA, 2025a). The National Development Council's Ten AI Initiatives Promotion Plan, approved in January 2026, places AI within a broader national transformation strategy (NDC, 2026).

The ecosystem also benefits from Taiwan's semiconductor cluster. Semiconductor manufacturing generates large volumes of process, equipment, inspection, metrology, test, and yield data, creating a natural environment for supervised and unsupervised learning. Conversely, AI creates demand for advanced processors, memory, networking, packaging, and energy-efficient computing. This creates a feedback relationship in which Taiwan can apply ML to semiconductor production while also producing hardware used to train and deploy ML systems globally.

Talent development is another central element. Taiwan has expanded AI-oriented training and interdisciplinary programs. The Ministry of Education's Taiwan Artificial Intelligence College Alliance (TAICA), for example, is designed to build a nationwide platform for AI education and interdisciplinary talent development (Ministry of Education, 2025). Such programs are important because industrial ML requires more than data-science skills: successful projects often require simultaneous knowledge of process engineering, statistics, software, cybersecurity, and organizational workflows.

Table 3. Enabling components of Taiwan's ML ecosystem

Component	Taiwan strength/opportunity	Implication for ML
Semiconductors	Dense manufacturing and R&D ecosystem	Large industrial data sources and AI hardware capabilities
ICT and electronics	Strong hardware/software integration	Supports edge AI and intelligent devices
Universities and research institutes	Broad technical research capacity	Provides algorithms, talent, and applied research
Healthcare infrastructure	Large-scale digital health ecosystem	Potential for clinical and administrative ML
Government policy	Dedicated AI plans, infrastructure and governance	Coordinates investment and standards
Talent programs	AI education and industry-oriented training	Builds interdisciplinary workforce
Industrial clusters	Manufacturing concentration and supplier networks	Facilitates pilot-to-production deployment

5. Machine Learning in Semiconductor Manufacturing

Semiconductor manufacturing is arguably the most strategically distinctive ML application domain in Taiwan. Modern fabrication involves hundreds or thousands of process steps, complex equipment interactions, strict quality constraints, and extremely expensive failures. ML can support fault detection and classification, virtual metrology, predictive maintenance, yield prediction, process optimization, defect inspection, and root-cause analysis.

Research illustrates the feasibility of these approaches. Cheng et al. (2021) developed ML methods for detecting wafer-test-induced defects and reported average prediction accuracy above 97% across six real

products. The study is particularly relevant because it connects ML to yield learning and the distinction between test-induced and fabrication-induced defects. A more recent Taiwan case study examined white-pixel defects in silicon-wafer manufacturing and found that classification and regression tree and random-forest models achieved approximately 95.18% prediction accuracy under the study's default settings, while also identifying grinding load and torque as important factors (Wang et al., 2024).

These examples illustrate a broader principle: the value of industrial ML is not only predictive accuracy. Models can also provide process knowledge by identifying variables associated with defects. However, production deployment requires careful validation because process distributions can shift, rare defects create severe class imbalance, and a false alarm can be costly. A recent review of ML-powered semiconductor vision inspection reports strong performance in published experiments but notes that only a minority of reviewed studies report full-scale high-production deployment, emphasizing the gap between laboratory performance and operational robustness (Array review, 2026).

Taiwan's semiconductor position also creates opportunities for machine learning across the entire value chain: materials selection, equipment maintenance, process control, packaging, testing, supply-chain forecasting, and energy optimization. Recent reviews indicate growing use of deep learning, reinforcement learning, generative approaches, and physics-informed methods in wafer fabrication and advanced packaging (Rafiee & Saini, 2026; AI-powered wafer fabrication review, 2026).

Table 4. ML use cases in semiconductor manufacturing

Use case	Input data	ML task	Potential operational value
Defect classification	Wafer maps, images, test results	Classification/vision	Faster screening and yield learning
Predictive maintenance	Equipment sensors and logs	Time-series prediction	Reduced unplanned downtime
Virtual metrology	Process parameters and sensor streams	Regression	Reduced measurement time and cost
Yield prediction	Process history and test data	Classification/regression	Early intervention and production planning
Root-cause analysis	Multivariate process data	Feature importance/anomaly detection	Faster troubleshooting
Process optimization	Recipe and outcome data	Optimization/reinforcement learning	Improved process stability
Packaging optimization	Thermal/electrical/mechanical simulation	Surrogate modeling	Faster design-space exploration

6. Smart Manufacturing and Industrial AI

Beyond semiconductor fabrication, Taiwan's broader manufacturing base provides a large potential field for industrial ML. Factories can combine sensors, industrial cameras, machine logs, enterprise-resource-planning records, and maintenance histories to create digital representations of production. ML can then estimate machine health, identify anomalies, predict quality, optimize schedules, and assist workers.

The main challenge is integration. Industrial data are frequently fragmented across machines and software systems. Different vendors may use incompatible protocols, timestamps can be inconsistent, and production engineers may prioritize physical interpretability over black-box accuracy. Consequently, successful industrial AI often requires a hybrid approach that combines statistical learning with domain knowledge, physics-based constraints, and human oversight.

Digital twins provide a useful framework for such integration. A digital twin links physical assets with data and models so that system states can be monitored and simulated. ML can serve as a fast surrogate for expensive simulations or as a component that detects deviations between expected and observed behavior. Recent reviews of smart semiconductor manufacturing emphasize the growing importance of deep learning, digital twins, and high-performance computing in system-level optimization (Smart manufacturing review, 2026).

7. Healthcare and Biomedical Applications

Healthcare is another important Taiwan ML domain because digital health combines large-scale data, sophisticated hospitals, strong ICT capabilities, and national-scale health insurance infrastructure. A 2026 review describes Taiwan's smart-health ecosystem as involving government policy, universities, hospitals, ICT firms, and the National Health Insurance environment (Giansanti et al., 2026).

ML applications include medical-image analysis, disease-risk prediction, triage, clinical decision support, patient monitoring, hospital operations, natural-language processing of clinical documents, and drug discovery. A Taiwan-specific review of emergency medicine reports applications in disease prediction, diagnostic imaging, and workflow enhancement, while highlighting interpretability, dataset quality, external validation, and ethical issues as major challenges (Shih & Yeh, 2024). Earlier research on healthcare-AI deployment in a Taiwanese medical center similarly emphasized that successful scaling depends on stakeholders, workflow integration, regulation, and organizational conditions rather than algorithm performance alone (Yang et al., 2021).

Healthcare ML therefore requires particularly strong governance. Clinical datasets may contain sensitive personal information, and models trained at one institution may perform differently elsewhere because of differences in patient populations, equipment, clinical protocols, and coding practices. Taiwan's AI governance principles explicitly include privacy and data governance, cybersecurity and safety, transparency and explainability, fairness and non-discrimination, and accountability (MODA, 2026a).

8. Other Potential Applications in Taiwan

Taiwan's ML opportunities extend beyond semiconductors and healthcare. Smart logistics can use demand forecasting, route optimization, and anomaly detection. Financial institutions can apply ML to fraud detection, credit-risk modeling, customer service, and compliance monitoring. Agriculture can combine remote sensing, weather information, soil data, and crop imagery for precision farming. Energy systems can use load forecasting and predictive maintenance, while cities can apply ML to transportation, environmental monitoring, and emergency management.

These applications should not be assumed to have identical levels of maturity. In many domains, the technical feasibility of an ML model is easier to demonstrate than its institutional value. A model that predicts traffic or disease risk may require organizational changes before it produces measurable benefits. Consequently, Taiwan's future research agenda should evaluate not only model metrics but also implementation outcomes such as cost, reliability, user adoption, equity, explainability, energy consumption, and long-term maintenance.

Table 5. Cross-sector ML opportunities in Taiwan

Sector	Illustrative ML tasks	Primary data sources	Key deployment concern
Semiconductors	Defect detection, yield prediction, process optimization	Wafer maps, sensors, test data	Distribution shift and proprietary data

Healthcare	Risk prediction, imaging, workflow optimization	Clinical records, images, claims	Privacy, validation, safety
Logistics	Demand forecasting, routing	Orders, GPS, inventory	Real-time reliability
Finance	Fraud/risk detection	Transactions, customer data	Fairness and explainability
Agriculture	Crop monitoring, disease detection	Images, weather, soil	Data sparsity and rural connectivity
Energy	Load forecasting, maintenance	Smart meters, sensors	Cybersecurity and system resilience
Public services	Document processing, service demand prediction	Administrative records	Accountability and transparency

9. Data Infrastructure, Privacy, and Cybersecurity

Data are the essential input to ML, but more data do not automatically produce better models. Quality, representativeness, provenance, labeling, interoperability, and governance are equally important. Industrial data can be noisy and proprietary; health data can be fragmented and sensitive; public-sector data can contain inconsistent definitions across agencies.

Taiwan's AI strategy has therefore emphasized data infrastructure alongside computing and talent. MODA has described plans for AI training-data repositories and additional government-data releases, while also identifying data governance as an important policy issue (MODA, 2025a). The objective should be to enable useful data sharing without treating privacy as an afterthought.

Privacy-preserving techniques such as federated learning, differential privacy, secure multiparty computation, and carefully designed data trusts may become increasingly important. Federated learning is particularly relevant when multiple hospitals or firms wish to learn from distributed data without centralizing all raw records. Nevertheless, federated systems introduce new risks, including model leakage, heterogeneous data distributions, communication overhead, and governance complexity.

10. AI Governance and the Taiwan Regulatory Environment

Taiwan's AI governance has developed alongside its industrial strategy. The Legislative Yuan passed the Artificial Intelligence Fundamental Act on December 23, 2025. The framework establishes seven principles for government promotion of AI: sustainable development and well-being, human autonomy, privacy protection and data governance, cybersecurity and safety, transparency and explainability, fairness and non-discrimination, and accountability (MODA, 2026a; Executive Yuan, 2025).

These principles are significant for ML because many risks emerge not from the algorithm in isolation but from how it is used. A highly accurate model may still be inappropriate if its training data are biased, if users cannot understand its limitations, if it is deployed outside its validated population, or if responsibility for errors is unclear. Governance therefore needs to cover the entire ML lifecycle: problem definition, data acquisition, model development, validation, deployment, monitoring, incident response, and retirement.

For Taiwan, governance also has an international dimension. AI systems are increasingly embedded in globally traded products, semiconductor supply chains, healthcare services, and digital platforms. Compatibility with international technical standards and responsible-AI practices can therefore reduce barriers to global adoption. At the same time, Taiwan needs domestic evaluation capabilities so that imported models are tested against local language, culture, laws, clinical conditions, industrial processes, and user expectations.

11. Talent, Education, and University–Industry Collaboration

ML talent is multidimensional. A production-quality project may require data engineers, ML engineers, statisticians, domain specialists, cybersecurity professionals, product managers, and governance experts. Taiwan's semiconductor and manufacturing industries add another requirement: employees must understand physical processes and operational constraints.

Government programs increasingly emphasize this interdisciplinary requirement. MODA has supported AI talent initiatives and industry-oriented training, while the Ministry of Education has promoted the Taiwan Artificial Intelligence College Alliance as a nationwide platform for AI education (MODA, 2025b; Ministry of Education, 2025).

Universities can strengthen the ecosystem by moving beyond isolated AI courses toward joint laboratories and shared datasets with manufacturing, healthcare, logistics, and public-sector partners. Industry placements, capstone projects, open benchmarking challenges, and co-supervised doctoral research can help bridge the gap between academic model development and operational deployment.

12. Key Challenges to ML Adoption in Taiwan

Despite strong enabling conditions, Taiwan should not assume that technological capability automatically translates into successful ML adoption. Several structural challenges deserve attention.

- Data fragmentation and interoperability: valuable datasets may remain locked in organizational silos or use incompatible schemas.
- Limited high-quality labels: rare failures and expensive expert annotation can make supervised learning difficult.
- Distribution shift: equipment changes, new product generations, demographic changes, and changing clinical practice can reduce model reliability.
- Explainability and accountability: high-stakes users often need reasons, uncertainty estimates, and clear responsibility for decisions.
- Cybersecurity: connected ML systems expand the attack surface through data pipelines, APIs, edge devices, and model interfaces.
- Compute and energy demand: large models can require substantial infrastructure and electricity, creating cost and sustainability concerns.
- Interdisciplinary talent shortages: algorithmic expertise must be combined with domain knowledge and deployment skills.
- Procurement and organizational barriers: public agencies and firms may struggle to evaluate vendors, manage pilots, and sustain systems after initial funding.
- Benchmarking and reproducibility: published accuracy does not necessarily indicate robustness under real-world operating conditions.
- International exposure: Taiwan's globally integrated technology sector must manage export controls, supply-chain shocks, standards, and cross-border data issues.

13. A Taiwan-Oriented Framework for Responsible ML Deployment

Based on the literature and policy evidence, this article proposes a six-layer framework for Taiwan. The framework is intended as a synthesis rather than a government policy proposal.

Table 6. Six-layer framework for responsible ML deployment in Taiwan

Layer	Core question	Recommended practice
1. Problem	Is ML the right intervention?	Define measurable operational or social objectives before selecting an algorithm.
2. Data	Are data fit for purpose?	Document provenance, quality, representativeness, labels, privacy, and access rights.
3. Model	Does the model generalize?	Use strong baselines, external validation, uncertainty analysis, and drift testing.
4. System	Can it operate reliably?	Integrate monitoring, cybersecurity, human oversight, fail-safe procedures, and version control.
5. Governance	Who is accountable?	Define responsibility, auditability, fairness checks, documentation, and incident response.
6. Value	Does deployment create durable value?	Measure cost, productivity, quality, safety, user adoption, equity, and environmental impact.

At the industrial level, this framework suggests moving from isolated proof-of-concept projects toward ML platforms that support repeated deployment. A factory, hospital, or public agency should maintain common data standards, model registries, monitoring infrastructure, validation protocols, and governance procedures. This reduces the cost of deploying each new ML application and makes institutional learning cumulative.

Taiwan can also pursue domain-specific foundation models. Instead of relying exclusively on general-purpose models, researchers and firms could develop models adapted to semiconductor process data, Traditional Chinese and Taiwanese language contexts, industrial documentation, medical records, and engineering knowledge. Such models could be smaller, more efficient, and easier to govern than very large general-purpose systems when the task is domain-specific.

14. Future Research Agenda

Future research should move beyond demonstrations of predictive accuracy toward longitudinal evidence of operational impact. First, studies should report external validation across factories, hospitals, product generations, and time periods. Second, researchers should evaluate uncertainty and failure modes rather than accuracy alone. Third, economic analysis should estimate the total cost of ownership, including data preparation, computing, integration, monitoring, retraining, cybersecurity, and staff time.

Fourth, more research is needed on human–AI collaboration. In manufacturing, the relevant question may be whether an engineer using an ML system identifies faults faster or makes fewer errors, rather than whether the model alone has a particular accuracy score. In healthcare, studies should assess clinician workflow, patient safety, and equity. In public administration, research should examine transparency and procedural fairness.

Fifth, Taiwan is well positioned to investigate hardware–algorithm co-design. AI workloads influence semiconductor architecture, packaging, memory, interconnects, and energy efficiency, while Taiwan's hardware capabilities can shape the practical economics of ML deployment. Research connecting ML algorithms with edge devices, advanced packaging, photonic interconnects, and energy-aware computing could create value across both the AI and semiconductor ecosystems.

15. Discussion

The evidence reviewed in this article suggests that Taiwan's ML opportunity is best understood as an ecosystem problem rather than a narrow software problem. Taiwan possesses several complementary assets: semiconductor manufacturing, ICT engineering, industrial clusters, universities, hospitals, public digital infrastructure, and an increasingly explicit AI policy framework. The combination is particularly relevant for industrial AI, where success depends on integrating models with physical systems and domain expertise.

At the same time, the review cautions against equating national AI ambition with guaranteed technological outcomes. Government strategies can create infrastructure and incentives, but durable ML value depends on the quality of projects, data governance, workforce capabilities, organizational adoption, and continuous evaluation. Evidence from semiconductor and healthcare applications demonstrates both the technical promise of ML and the practical importance of validation, interpretability, and deployment conditions.

Taiwan's governance direction is also notable because it combines innovation objectives with explicit principles concerning human autonomy, privacy, security, transparency, fairness, and accountability. These principles are especially relevant as ML moves from laboratory prediction into operational decision-making. The challenge for implementation will be to translate high-level principles into technical controls, documentation requirements, evaluation protocols, procurement standards, and clear responsibility.

16. Conclusion

Machine learning is becoming an important component of Taiwan's technological and industrial transformation. Its relevance extends from semiconductor manufacturing and smart factories to healthcare, logistics, finance, agriculture, energy, and public services. Taiwan's semiconductor ecosystem gives it a distinctive opportunity to develop ML not only as software but as an integrated technology linking algorithms, sensors, processors, manufacturing systems, and domain expertise.

The review identifies three priorities. First, Taiwan needs trustworthy data and evaluation infrastructure so that models can be validated beyond laboratory conditions. Second, it needs interdisciplinary talent and stronger university–industry collaboration to connect ML methods with real operational problems. Third, it needs governance and lifecycle-management practices that protect privacy, security, fairness, transparency, and accountability while enabling innovation.

The next phase of Taiwan's ML development should therefore be measured not simply by the number of models developed, AI startups created, or computing resources installed, but by the reliability and measurable value of ML systems in real environments. If Taiwan successfully connects its semiconductor and ICT strengths with trustworthy data, domain-specific research, responsible governance, and sustained talent development, it can deepen its role in the global machine-learning ecosystem while addressing domestic industrial and social needs.

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Appendix A. Suggested Research Questions for Taiwan-Focused ML Studies

- How stable are semiconductor ML models when transferred across fabs, tools, recipes, and product generations?
- Can federated learning enable useful cross-hospital learning while preserving patient privacy and institutional control?
- What combinations of physics-informed models and data-driven learning produce the most reliable industrial digital twins?
- How should Taiwan measure the total economic and environmental cost of large-scale AI training and inference?
- What evaluation protocols should public agencies use before deploying ML systems in high-impact decisions?
- How can AI education combine statistical foundations, software engineering, domain expertise, ethics, and cybersecurity?
- Which edge-AI architectures provide the best trade-off among latency, accuracy, energy consumption, privacy, and maintainability?