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Green by Design AI Entrepreneurship in Asia: A Techno Legal Framework for Computational Efficiency, Environmental Accountability and Sustainable Startup Innovation

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Abstract
Artificial Intelligence (AI) is rapidly transforming entrepreneurship across Asia by enabling new business models, improving resource efficiency and supporting innovation across diverse sectors. However, the growing computational intensity of AI also raises concerns regarding energy consumption, infrastructure requirements and environmental sustainability. This paper examines the emerging relationship between AI entrepreneurship, sustainability, law and computer science, with particular emphasis on the need to integrate environmental considerations into the governance of AI driven enterprises. It analyses the technological foundations of Green AI, including computational efficiency, model optimisation, energy consumption and sustainable AI infrastructure, and examines their implications for emerging entrepreneurial ecosystems. The paper further evaluates contemporary approaches to AI governance in Asia, with reference to developments in India, ASEAN and Singapore, while drawing upon broader regulatory developments concerning sustainable and responsible AI. It argues that existing governance frameworks remain insufficiently connected to measurable environmental impacts and that voluntary sustainability principles alone may not provide adequate accountability. The paper proposes a techno legal framework based on computational transparency, sustainability by design, lifecycle assessment, proportionate environmental accountability and innovation incentives. It concludes that Asian economies should move beyond the conventional conception of responsible AI towards sustainable by design AI entrepreneurship, where technological efficiency, environmental responsibility and entrepreneurial innovation operate as mutually reinforcing objectives.

Keywords: Artificial Intelligence; Green AI; Sustainable Entrepreneurship; AI Governance; Technology Law

1. INTRODUCTION: AI ENTREPRENEURSHIP AND THE SUSTAINABILITY IMPERATIVE IN ASIA

1.1 Introduction

Artificial Intelligence (AI) has become an important driver of technological entrepreneurship and digital transformation across Asian economies. Startups are increasingly using machine learning, deep learning, generative AI, predictive analytics and related technologies to develop new products, automate business processes and address sector-specific challenges. AI-based innovation is visible in financial technology, healthcare, education, agriculture, manufacturing, logistics, retail and other sectors.

The expansion of AI entrepreneurship creates significant economic opportunities, but it also raises an important sustainability question. AI applications can contribute to sustainable development by improving resource allocation, optimising transport systems, supporting renewable energy, monitoring environmental conditions and improving industrial efficiency. However, the development and operation of AI systems themselves require considerable computational and physical resources. Electricity, specialised processors, data storage, networking and cooling infrastructure are necessary for modern AI systems.

This creates a fundamental sustainability paradox. AI can be used to solve environmental problems while simultaneously generating environmental externalities through the computation required to operate it. The environmental footprint of AI can include energy consumption, carbon emissions, water use, hardware production and electronic waste. Therefore, evaluating AI entrepreneurship only through innovation, investment and economic growth provides an incomplete picture.

The central argument of this research is that AI can facilitate sustainable entrepreneurship, but the technology itself also creates environmental externalities that existing sustainability and entrepreneurial governance frameworks do not adequately capture. Sustainable AI entrepreneurship consequently requires attention to both the benefits produced by AI applications and the resources consumed in producing those benefits.

1.2 Rise of AI-Driven Entrepreneurship in Asian Economies

Asia has emerged as one of the major regions for AI

development, adoption and commercialisation. Economies such as China, India, Japan, South Korea and Singapore have developed significant technological capabilities, while other Asian economies are rapidly incorporating AI into their digital businesses and entrepreneurial ecosystems.

AI has changed the nature of entrepreneurial opportunity by enabling businesses to develop products based on automated prediction, data analysis, natural-language processing, computer vision and intelligent decision-making. Financial technology startups can use AI for fraud detection and risk assessment, healthcare ventures can develop AI-assisted diagnostic systems, agricultural enterprises can apply predictive technologies to crop and resource management, and logistics businesses can optimise routes and supply chains.

The significance of AI entrepreneurship in Asia is also related to the region's rapidly expanding digital economy. Governments, universities, technology companies and investors are increasingly supporting AI research, digital infrastructure and startup development. This environment allows entrepreneurs to experiment with AI-based business models and introduce technology into sectors that previously depended heavily on manual processes.

However, entrepreneurial expansion also increases demand for computing resources. As startups move from experimentation to commercial deployment, their dependence on cloud platforms, specialised hardware and large-scale data processing may increase. Computational requirements can therefore become an important component of the cost and environmental profile of an AI business.

Sustainable AI entrepreneurship must consequently recognise that technological innovation and environmental responsibility cannot be considered separate objectives. The growth of AI-based businesses should be accompanied by greater attention to computational efficiency and resource consumption.

1.3 AI Startups and Digital Innovation Ecosystems in Asia

AI entrepreneurship develops within broader innovation ecosystems. Startups require access to finance, skilled professionals, research institutions, datasets, cloud infrastructure, technology providers and markets. Universities and research centres contribute knowledge and talent, investors provide capital, while governments establish policies and infrastructure that influence entrepreneurial activity.

Cloud computing has lowered some barriers to AI entrepreneurship by allowing smaller enterprises to obtain computing resources without constructing their own data centres. Pre-trained models and AI services also allow startups to integrate advanced capabilities without developing every component independently.

This development creates both opportunities and sustainability challenges. Shared cloud infrastructure can improve resource utilisation, but startups may have limited visibility into the environmental consequences of their computational workloads. A business may know how much it pays for computing but may not know precisely how much electricity, water or carbon emissions are associated with that usage.

This lack of environmental visibility can make sustainability difficult to integrate into entrepreneurial decision-making. If startups cannot measure the environmental implications of alternative models or infrastructure choices, environmental efficiency may remain secondary to speed, accuracy and cost.

Asian innovation ecosystems therefore have an opportunity to promote a broader model of AI entrepreneurship in which computational efficiency becomes part of innovation strategy. Sustainable infrastructure, access to efficient computing, environmental reporting and Green AI research can help align technological entrepreneurship with wider sustainability objectives.

1.4 Environmental Cost of AI Development and Deployment

The environmental footprint of AI extends across its lifecycle. It begins with the computational resources required for data processing and model development and continues through training, deployment, inference, updating and eventual replacement of hardware.

Training sophisticated AI models can require large datasets, powerful processors and repeated computational operations. Deployment introduces another source of consumption because every user interaction may require additional inference. A model that serves a small number of users may have relatively limited operational demand, while a widely deployed system can generate substantial cumulative computation.

AI hardware also contributes to environmental impact. Servers, GPUs, memory systems, storage equipment and networking components require raw materials and manufacturing processes. Their operation produces heat, requiring cooling infrastructure. At the end of their useful life, hardware replacement can contribute to electronic waste.

Energy consumption is another central issue. The electricity required by AI systems can contribute to carbon emissions depending on the source of electricity. Water can also become relevant because cooling systems and parts of the wider electricity and hardware supply chain may require water resources.

Therefore, an AI application should not automatically be considered sustainable merely because it provides an environmental benefit. The appropriate approach is to compare the environmental benefits generated by an AI solution with the environmental resources consumed by its development and operation.

This lifecycle perspective is essential for Green AI because it shifts attention from the visible application

to the complete technological system supporting it.

1.5 Energy Consumption, Computational Intensity and Data Centre Infrastructure

AI's environmental footprint is strongly influenced by computational intensity. Modern AI systems perform large numbers of mathematical operations, and computational requirements can increase with model complexity, dataset size, training duration, model parameters and frequency of use.

The infrastructure supporting this computation is equally important. GPUs, TPUs and other specialised processors are widely used to accelerate AI workloads. These processors require electricity and generate heat, creating additional requirements for cooling. Data centres therefore consume energy not only for computation but also for power management, cooling and other supporting functions.

The source of electricity influences the carbon consequences of AI. A workload powered by renewable or low-carbon electricity can have a lower operational carbon footprint than an equivalent workload powered primarily by fossil fuels. Consequently, energy consumption and carbon emissions should be treated as related but distinct indicators.

Data-centre infrastructure also creates questions concerning water consumption, land use and hardware lifecycle impacts. These factors demonstrate why a single metric cannot fully represent AI sustainability.

For Asian economies experiencing rapid digital infrastructure growth, the relationship between AI and data centres is particularly important. Expanding computing capacity without considering energy and resource constraints could create tensions between digital development and environmental objectives.

Computational efficiency can help address this problem. More efficient models and better hardware utilisation can potentially deliver comparable functionality with fewer computational resources.

1.6 Green AI and Sustainable Digital Entrepreneurship

Green AI provides a technological approach for reducing the environmental costs associated with artificial intelligence. Its central idea is that AI performance should not be assessed only through accuracy, capability or scale. The computational resources required to achieve that performance should also be considered.

Green AI can involve efficient model architectures, compression, pruning, quantisation, knowledge distillation, efficient hardware and edge computing. These approaches aim to reduce unnecessary computation while maintaining an acceptable level of performance.

For entrepreneurs, this creates an important connection between sustainability and business efficiency. A computationally efficient model can reduce cloud expenditure, infrastructure requirements and energy consumption. Consequently, environmental responsibility can sometimes strengthen rather than weaken business performance.

Sustainable digital entrepreneurship should therefore incorporate environmental considerations during product design. Instead of developing an AI product first and examining its environmental consequences later, entrepreneurs can consider model size, computational requirements, infrastructure and deployment methods from the beginning.

This approach may also create new entrepreneurial opportunities. Startups can develop lightweight AI systems, energy-efficient models, carbon-aware computing services, optimisation tools and technologies designed for resource-constrained environments.

Green AI should thus be viewed not merely as an environmental limitation but as a potential source of technical innovation and competitive advantage.

1.7 Limitations of Existing Frameworks, Research Gap, Objectives and Research Questions

Existing sustainability frameworks generally focus on areas such as carbon reduction, resource efficiency, environmental protection and corporate responsibility. These principles remain relevant to AI, but they do not always specify how the computational characteristics of an AI system should be measured or reported.

Entrepreneurship frameworks similarly emphasise innovation, investment, opportunity recognition and business growth, while conventional AI governance has concentrated strongly on issues such as privacy, fairness, transparency, safety and security. Environmental impacts have not always been integrated into these frameworks at a sufficiently operational level.

This creates a research gap at the intersection of AI entrepreneurship, computer science, environmental sustainability and law. Technical research can identify methods for reducing computational requirements, while sustainability research can identify environmental objectives. Entrepreneurship research can explain the role of AI in innovation, and legal research can determine how responsibilities should be structured. However, these dimensions require stronger integration.

The research therefore seeks to examine how AI entrepreneurship is developing in Asia, identify the environmental externalities associated with AI systems, analyse Green AI and computational-efficiency approaches, identify measurable sustainability indicators and explore how these indicators can support environmental accountability.

The research is guided by the following questions:

RQ1: How is AI-driven entrepreneurship developing across Asian economies?

RQ2: What environmental externalities arise from AI development and deployment?

RQ3: Which computational strategies can improve the environmental efficiency of AI entrepreneurship?

RQ4: What technical indicators can be used to measure AI sustainability?
RQ5: Why are existing sustainability and entrepreneurial governance frameworks insufficient for AI-related environmental impacts?
RQ6: How can environmental accountability be introduced without unnecessarily restricting AI startup innovation?
RQ7: What techno-legal framework can promote Green-by-Design AI entrepreneurship in Asia?

1.8 Methodology, Scope and Structure of the Paper

This research follows an interdisciplinary doctrinal and conceptual approach combining computer science, sustainable technology, entrepreneurship and legal analysis. The technological analysis examines computational intensity, AI infrastructure and efficiency techniques. The sustainability analysis considers energy, carbon, water and lifecycle impacts, while the legal analysis explores how measurable environmental impacts can potentially be connected with accountability mechanisms.

The geographical scope is Asia, understood as a diverse collection of economies rather than a uniform regulatory environment. Asian countries differ in technological capacity, energy systems, startup ecosystems and regulatory approaches. The proposed framework therefore seeks to establish common sustainability principles while allowing implementation to reflect national circumstances.

The research focuses primarily on the environmental dimensions of AI entrepreneurship. It does not attempt to provide a complete analysis of every issue associated with AI governance. Privacy, bias, cybersecurity and employment are relevant to responsible AI but fall outside the central focus unless they directly intersect with environmental accountability.

The paper is organised into four chapters. Chapter 1 establishes the research problem and explains why AI entrepreneurship must be examined through a sustainability lens. Chapter 2 examines the computer-science foundations of Green AI, focusing on computational intensity, energy consumption, algorithmic efficiency, infrastructure and technical measurement. Chapter 3 develops the legal and governance dimensions of sustainable AI entrepreneurship and considers how technical environmental indicators can be connected with accountability. Chapter 4 integrates the technical and legal analysis to propose a broader Green-by-Design approach for AI entrepreneurship in Asia.

The overall argument is that sustainable AI entrepreneurship requires environmental considerations to be integrated into the technology-development process itself. AI should be evaluated not only according to the social or economic benefits produced by its applications but also according to the computational resources required to produce those benefits.

Green-by-Design AI Entrepreneurship therefore represents a shift from treating sustainability as a later-stage compliance concern to treating it as a component of technological design, entrepreneurial strategy and governance. Such an approach can support AI innovation while encouraging computational efficiency, environmental transparency and proportionate accountability across Asian startup ecosystems.

2. THE COMPUTER SCIENCE OF GREEN AI: COMPUTATIONAL EFFICIENCY AND SUSTAINABLE AI ENTREPRENEURSHIP

2.1 Computational Foundations of Modern AI Systems

The environmental impact of Artificial Intelligence (AI) is closely connected with the computational processes required to develop, train and operate AI systems. Although AI is generally experienced as a software-based technology, its functioning depends on physical computing resources such as processors, memory, storage, networking equipment and data-centre infrastructure. Green AI therefore requires an understanding of how AI systems perform computation and why increasing model capability can lead to increasing resource requirements.

Machine learning enables computer systems to identify patterns from data and use those patterns to make predictions or decisions. During training, a model processes data, calculates errors and adjusts its parameters through optimisation techniques. Deep learning extends this approach through multi-layer neural networks capable of learning complex representations from large datasets. The computational requirements of these systems depend upon factors such as dataset size, model architecture, number of parameters and training duration.

Foundation models represent a further development in AI because they are trained on broad datasets and can support multiple downstream applications. Generative AI systems, including large language models, generate new outputs such as text, images, audio or code. Their environmental significance arises not only from the computational resources required during initial training but also from repeated inference when users interact with deployed systems.

The Green AI perspective therefore introduces an additional question into conventional AI development: how much computational effort is necessary to obtain a useful level of performance? AI development cannot be evaluated only through accuracy or capability. Computational efficiency should also become an important technical criterion.

2.2 Computational Intensity of AI

Computational intensity refers to the quantity of processing required by an AI workload. One of the most important distinctions is between training and inference. Training involves repeatedly processing data and updating model parameters. Large models may require extensive computation over long training periods. Inference, by contrast, occurs when a trained

model processes new input and produces an output.

Although inference is usually less demanding than training on an individual operation, its cumulative impact can become significant when a system serves a large number of users. A startup may train a model once or periodically, but its commercial service may perform millions of inference operations during deployment. Consequently, sustainability analysis should consider the complete operational life of an AI system.

GPUs are widely used for AI because they can perform many mathematical operations in parallel. TPUs and other specialised accelerators are designed to support machine-learning workloads more directly. The efficiency of such hardware depends not only on its theoretical performance but also on utilisation, workload characteristics, software optimisation and cooling requirements.

Model size is another important factor. Increasing the number of parameters can improve capability in some circumstances but can also increase memory and computational requirements. However, parameter count alone cannot determine environmental performance. Two models with similar parameter counts may have different energy requirements because of differences in architecture, numerical precision, hardware and inference methods.

Computational complexity must therefore be considered at the system level. Green AI seeks to improve the amount of useful performance obtained from a given quantity of computation. This approach makes computational efficiency relevant to both environmental sustainability and technical performance.

2.3 Energy Consumption and Carbon Footprint

Computational activity ultimately requires electricity. AI-related energy consumption occurs at different levels, including processors, memory, storage, networking and supporting data-centre systems. High-performance processors also produce heat, which creates additional energy requirements for cooling.

Data centres are therefore an important component of AI's environmental footprint. Their total electricity consumption is not limited to the computing equipment itself. Cooling systems, power-management equipment and other supporting infrastructure also consume resources. Metrics such as Power Usage Effectiveness (PUE) are used to evaluate the efficiency of data-centre infrastructure.

The carbon footprint of AI depends on both the amount of electricity consumed and the carbon intensity of the electricity supply. A simplified relationship can be represented as:

Carbon Emissions = Energy Consumption × Electricity Carbon Intensity

Consequently, identical AI workloads can produce different carbon emissions depending on where and when they are operated. Computing powered by low-carbon or renewable electricity may have a lower operational carbon footprint than equivalent computing supplied by carbon-intensive electricity.

The environmental footprint also extends beyond operational energy. AI hardware requires raw materials, semiconductor manufacturing, transportation and eventual disposal. Water can be associated with cooling and with parts of the electricity and hardware supply chain. Therefore, carbon emissions alone do not provide a complete measure of AI sustainability.

For Green AI, the relevant assessment should consider energy, carbon, water and hardware lifecycle impacts wherever reliable data are available. This broader approach prevents an AI system from being labelled sustainable solely because its direct electricity consumption appears relatively low.

2.4 Green AI and Algorithmic Efficiency

Green AI focuses on improving AI performance while reducing unnecessary computational requirements. Several computer-science techniques can contribute to this objective.

Model compression reduces the size or computational requirements of a trained model. Pruning removes parameters or structures that contribute relatively little to model performance. When effectively supported by hardware and software, pruning can reduce computation and memory requirements.

Quantisation reduces the numerical precision used by a model. Lower-precision representations can decrease memory requirements and may improve computational efficiency when supported by appropriate hardware. Knowledge distillation provides another approach in which a smaller student model learns useful behaviour from a larger teacher model. The resulting model can require fewer resources during deployment.

Efficient architectures are designed to achieve useful performance without relying entirely on increasing model size. Such approaches are particularly valuable for mobile devices, embedded systems and applications where computational resources are limited.

Edge AI moves some processing from centralised cloud infrastructure to local devices. Smartphones, sensors, cameras and industrial systems can perform selected AI tasks locally. This may reduce data transmission and cloud dependence, although local hardware also has energy and performance constraints.

The important principle is that technical optimisation should be measured through actual resource savings rather than theoretical model reduction alone. A smaller model does not automatically guarantee lower energy consumption if the underlying hardware cannot effectively exploit the optimisation. Green AI therefore requires coordination among algorithms, software and hardware.

2.5 Sustainable AI Infrastructure

Efficient algorithms require efficient infrastructure to

achieve meaningful environmental benefits. Sustainable AI infrastructure includes computing hardware, data centres, cooling systems, cloud platforms and electricity management.

Energy-efficient processors can reduce the electricity required for particular computational workloads. Data centres can improve sustainability through efficient cooling, better server utilisation and improved power management. Renewable-energy-powered computing can further reduce operational carbon emissions, although renewable electricity does not eliminate other environmental impacts such as hardware production or water consumption.

Cloud computing provides startups with access to computing resources without requiring them to establish their own physical data centres. Shared infrastructure can improve utilisation, but it can also make environmental impacts less visible to individual users. A startup may know how many computing hours it purchased without knowing the precise electricity or water consumption associated with its workload.

Carbon-aware computing offers another possibility. Where workloads are flexible, computational tasks can potentially be scheduled when electricity has a lower carbon intensity. Such systems require information about energy availability, workload requirements and data-centre conditions.

Sustainable infrastructure should therefore be understood as a combination of efficient hardware, responsible data-centre operation, renewable energy, intelligent workload management and transparent environmental information.

2.6 Green AI for Startups

Green AI has direct economic relevance for startups. Early-stage enterprises frequently operate under constraints involving capital, computing capacity and technical personnel. Large computational workloads can therefore create both environmental and financial pressures.

An inefficient AI model may increase cloud expenditure, energy consumption and infrastructure dependence as the number of users grows. Efficient models can reduce these costs while maintaining adequate performance. Startups can therefore consider computational efficiency as part of product design rather than treating sustainability as a separate compliance activity.

A startup does not necessarily need the largest available model for every application. A smaller specialised model may be sufficient for a narrowly defined task. Quantisation, model compression, caching, batching and efficient inference can further reduce unnecessary computation.

Edge AI may also be appropriate for applications involving sensors, industrial monitoring, agriculture or other environments where continuous cloud connectivity is expensive or impractical.

Green AI can consequently create a competitive advantage. Lower computational requirements may improve scalability, reduce operating expenditure and make AI services accessible in resource-constrained environments. Sustainability and economic efficiency can therefore reinforce rather than contradict each other.

For Asian startup ecosystems, this approach is particularly relevant because enterprises operate across economies with substantially different levels of computing infrastructure and energy availability. Computationally efficient innovation can enable startups to develop useful AI products without depending entirely on extremely large-scale infrastructure.

2.7 The Technical Problem of Measuring AI Sustainability

The final technical challenge is measurement. Green AI cannot become an effective design principle unless the environmental performance of AI systems can be assessed through meaningful indicators.

Several measurements may be relevant. Energy per training run can indicate the electricity required to develop a model, while energy per inference can help assess deployment efficiency. For commercial applications, energy per user, transaction or completed task may provide a more practical measure. Computational indicators such as GPU-hours, TPU-hours or floating-point operations can describe workload intensity, but they do not directly equal electricity consumption. Carbon emissions require information about electricity use and the carbon intensity of the relevant energy supply. Water consumption may also need to be considered where cooling systems or energy production create significant water impacts.

A broader assessment can include lifecycle emissions, covering hardware manufacturing, transportation, operation, replacement and disposal. However, obtaining complete lifecycle data remains difficult. Environmental measurement is further complicated by cloud infrastructure, where multiple workloads operate simultaneously and precise attribution may not always be available.

A useful Green AI measurement framework should therefore distinguish between direct measurements, calculated estimates and lifecycle assumptions. Transparency about the methodology is as important as the numerical result.

This technical measurement problem provides the foundation for the legal analysis that follows. Once energy use, computational resources, carbon emissions, water consumption and lifecycle impacts can be expressed through defined indicators, policymakers can consider whether such information should be disclosed or reported.

The fundamental question consequently moves from “How much computation does AI require?” to “Which computational impacts should become measurable, reportable and legally accountable?” The answer requires a connection between computer science and law. Technical research identifies the sources of

environmental impact and possible efficiency solutions, while legal governance can determine which impacts require disclosure, who should bear responsibility and how obligations can remain proportionate to the size and capacity of AI enterprises.

Green AI therefore provides more than an engineering strategy. It offers the technical foundation for developing a system in which computational efficiency, environmental measurement and entrepreneurial accountability can be connected within a broader techno-legal framework.

3. The Legal Governance of Sustainable AI Entrepreneurship in Asia

3.1 Introduction

Artificial Intelligence (AI) is increasingly becoming a central component of entrepreneurship and digital innovation in Asia. Startups are using AI for financial services, healthcare, education, logistics, manufacturing, agriculture and consumer services. At the same time, the development and deployment of AI systems require substantial computational resources, including specialised hardware, data centres and electricity. AI therefore presents a dual sustainability question. It can contribute to sustainable development by improving efficiency and reducing resource use, but the technology itself can also generate significant environmental costs.[]

This creates an important legal question. Existing AI regulation largely focuses on privacy, discrimination, transparency, safety, cybersecurity and accountability. Environmental sustainability has received comparatively less attention. The emerging regulatory challenge is therefore not merely whether AI entrepreneurship should be regulated, but whether the environmental consequences of AI development should form part of the legal responsibilities of AI developers, providers and deployers.

The issue is particularly relevant to Asia because the region is experiencing rapid growth in both digital entrepreneurship and AI infrastructure. India, Singapore and the ASEAN Member States are developing different approaches to AI governance while attempting to preserve technological innovation. A sustainable regulatory framework must therefore protect environmental interests without creating disproportionate compliance burdens for emerging enterprises.

3.2 AI Governance and Environmental Sustainability

The European Union provides one of the most developed examples of an attempt to connect AI governance with environmental protection. Regulation (EU) 2024/1689, commonly known as the Artificial Intelligence Act, expressly identifies environmental protection among the interests that must be protected against harmful effects of AI.[] More importantly, Article 95 encourages providers and deployers to adopt voluntary codes of conduct that include the assessment and reduction of environmental impacts, energy efficient programming and efficient design, training and use of AI systems.[]

The EU framework is significant because it begins to convert sustainability from a general ethical principle into a governance consideration. The AI Act also requires providers of general purpose AI models to document known or estimated energy consumption. Where actual consumption is unavailable, providers may use estimates based on computational resources.[] The European Commission is currently working towards more consistent methodologies for measuring energy consumption and emissions associated with AI models and systems.[]

This development has particular significance for AI entrepreneurship. Once environmental performance becomes measurable, it can potentially become part of regulatory compliance, corporate disclosure, procurement decisions and investment assessment. The law can therefore influence the design choices made by technology entrepreneurs rather than intervening only after environmental harm has occurred.

3.3 The Asian Regulatory Approach

The Asian regulatory environment remains more fragmented. ASEAN has adopted a principles based approach through the ASEAN Guide on AI Governance and Ethics 2024. The Guide seeks greater regional alignment and interoperability while recognising that AI governance must operate alongside national laws relating to data governance, cybersecurity, software development and other areas.[] Its voluntary nature allows flexibility and may be particularly useful for developing AI markets where rigid regulation could impose substantial costs on smaller enterprises.

The ASEAN approach, however, also demonstrates a limitation. Voluntary governance can encourage responsible innovation, but it does not necessarily create enforceable environmental obligations. The ASEAN framework therefore provides an important foundation for sustainable AI governance, but further national measures may be required to translate sustainability principles into concrete duties.

Singapore represents another important Asian model. Its regulatory approach generally attempts to combine technological innovation with practical governance safeguards. The 2026 Model AI Governance Framework for Agentic AI recommends technical and non technical safeguards, risk assessment, human accountability and controls throughout the AI lifecycle.[] Although the framework is primarily concerned with responsible deployment and autonomous AI risks, its lifecycle approach is relevant to sustainability because environmental considerations can similarly be incorporated into the assessment and design stages.

India is also moving towards a more structured AI governance framework. The Government of India has emphasised that AI systems should be safe, resilient and sustainable, and that AI development should be

environmentally responsible and resource efficient. The use of smaller and resource efficient models has specifically been encouraged.[] The IndiaAI Mission also seeks to strengthen access to computational infrastructure while supporting AI startups and responsible AI development.[]

These developments suggest that Asian jurisdictions are moving towards governance models that seek to preserve innovation while introducing safeguards. However, environmental sustainability has not yet emerged as a uniform and enforceable regulatory requirement across the region.

3.4 Data Governance and Algorithmic Accountability

Sustainable AI governance cannot be separated from data governance. AI systems depend upon large volumes of data and computational infrastructure. Consequently, responsible AI entrepreneurship must comply with legal requirements relating to privacy, data protection, cybersecurity and responsible data management.

The ASEAN Guide recognises this interconnectedness by requiring AI developers and deployers to consider applicable national laws and related governance frameworks.[] Similarly, India's emerging AI governance approach emphasises accountability, transparency and due diligence as important components of trustworthy AI.[]

This provides an opportunity to develop a broader concept of AI impact assessment. At present, assessments may focus primarily on risks such as discrimination, privacy violations or cybersecurity. A sustainable approach could require organisations to consider environmental consequences as well. For computationally intensive AI systems, this could include assessing energy consumption, computational requirements and resource efficiency.

Such an approach would move sustainability from the sphere of voluntary corporate responsibility into the broader framework of responsible technological design.

3.5 Environmental Accountability of AI Entrepreneurs

The question of legal responsibility becomes more complicated because environmental impacts arise at several stages of the AI lifecycle. These include data processing, model training, inference, hardware use, cooling requirements and data centre operations. Responsibility may consequently be distributed among AI developers, cloud service providers, infrastructure operators and deployers

A uniform legal obligation imposed on every AI startup would be inappropriate. A small enterprise developing a limited AI application does not create the same environmental impact as a company developing a large general purpose AI model. Regulation should therefore adopt a principle of proportionality.

Large AI developers could be required to disclose energy consumption and environmental performance, while smaller startups could be subject to simplified reporting mechanisms. Governments could also use regulatory sandboxes, financial incentives, public procurement and sustainability certifications to encourage green AI innovation.

Such an approach is consistent with the broader innovation sensitive character of contemporary AI regulation. The EU AI Act itself places particular emphasis on supporting SMEs and startups while implementing AI governance.[]

3.6 Towards a Techno Legal Framework

The principal regulatory gap is therefore the absence of a strong connection between legal standards and technical measurements. Environmental sustainability cannot be effectively regulated through broad principles alone. The law requires measurable indicators, while computer science provides the technical methods necessary to identify and measure them.

A techno legal framework for sustainable AI entrepreneurship should contain five interconnected elements.

First, computational transparency should require relevant AI enterprises to identify and, where feasible, disclose energy and resource consumption.

Second, sustainability by design should encourage efficient algorithms, model optimisation and resource efficient AI architectures.

Third, lifecycle assessment should examine environmental effects from development and training to deployment and continued operation.

Fourth, proportionate accountability should differentiate obligations according to the size, computational intensity and risk profile of the AI enterprise.

Finally, innovation incentives should complement legal obligations. Governments can encourage sustainable entrepreneurship through grants, tax benefits, green AI certification, public procurement preferences and access to sustainable computing infrastructure.

3.7 Conclusion

The emerging Asian approach to AI governance demonstrates a preference for flexible and innovation oriented regulation. This is important for entrepreneurship, but environmental sustainability remains insufficiently integrated into enforceable AI governance. The future regulatory challenge is therefore to move from the broad idea of responsible AI towards sustainable by design AI.

Law should not attempt to determine the technical architecture of every AI system. Instead, it should establish clear sustainability expectations and require technology enterprises to demonstrate compliance through reliable technical measurements and appropriate standards. Computer science can determine what can be measured and improved, while law can determine when such measurements become relevant to accountability.

For Asian economies, this approach can create a regulatory environment in which sustainability is not treated as an obstacle to AI entrepreneurship. Instead, computational efficiency, environmental responsibility and technological innovation can become mutually reinforcing elements of the emerging AI economy.

4. CONCLUSION: TOWARDS A TECHNO LEGAL FRAMEWORK FOR GREEN AI ENTREPRENEURSHIP IN ASIA

Artificial Intelligence is increasingly becoming an important driver of entrepreneurship, innovation and economic transformation across Asia. The growth of AI based enterprises has created new opportunities in sectors such as healthcare, education, agriculture, financial services, manufacturing, transportation and public administration. AI can improve productivity, reduce wastage, optimise the use of resources and support solutions to several sustainability challenges. However, the sustainability of AI itself cannot be assumed merely because AI is being used to solve environmental or social problems. The development and operation of AI systems require substantial computational resources, energy, data infrastructure and specialised hardware. The central concern of this paper has therefore been the need to examine AI entrepreneurship not only as a source of technological and economic innovation, but also as an activity carrying environmental and regulatory consequences.

The analysis demonstrates that AI has a fundamentally dual relationship with sustainability. On one side, AI can support sustainable entrepreneurship by enabling better prediction, resource management, energy optimisation, intelligent transportation, precision agriculture and more efficient industrial processes. On the other side, increasingly complex AI systems can require significant computational power during training and deployment. Large models may require extensive computing infrastructure, repeated training processes and continuous inference. These requirements create environmental costs through electricity consumption, cooling requirements, hardware production and associated resource use. Sustainability therefore cannot be evaluated only by examining what an AI system does. It must also consider how the system is developed, trained, deployed and maintained.

The technological analysis in this paper establishes why this problem cannot be addressed through law alone. Concepts such as model size, computational intensity, energy consumption, model optimisation, quantisation, pruning, knowledge distillation and efficient computing are not merely technical considerations. They have direct implications for environmental sustainability and, consequently, for regulatory policy. Computer science provides the means through which the environmental performance of AI systems can be identified and improved. More efficient models can reduce computational requirements without necessarily compromising their practical usefulness. Similarly, energy efficient hardware, carbon aware computing and renewable energy powered infrastructure can reduce the environmental burden associated with AI deployment. The technical capacity to measure environmental impact is therefore an essential precondition for meaningful legal regulation.

At the same time, technological solutions alone cannot resolve the problem. Market incentives do not always ensure that environmental costs are internalised by AI enterprises. An entrepreneur may have a commercial incentive to develop a larger and more computationally intensive model if doing so provides a competitive advantage. The environmental cost may, however, be distributed across electricity systems, data centres, water resources and the wider environment. This creates a classic regulatory problem in which private economic benefits may coexist with broader social and environmental costs. Law therefore has an important role in determining how responsibility is allocated and how sustainability expectations are incorporated into AI development.

The legal analysis reveals that AI governance is rapidly evolving, but environmental sustainability has not yet achieved the same degree of regulatory attention as privacy, safety, discrimination, transparency or cybersecurity. Existing legal and policy frameworks increasingly recognise responsible and sustainable AI as an important objective. However, recognition at the level of principle does not necessarily create clear and enforceable obligations. There remains a gap between the aspiration that AI should be environmentally responsible and the practical question of what an AI entrepreneur must actually measure, disclose or change.

This gap is particularly significant in Asia. Asian economies do not possess a single regulatory model for AI. Different jurisdictions are adopting different combinations of legislation, policy guidelines, voluntary frameworks, technical standards and regulatory experimentation. This diversity reflects differences in economic development, technological capacity and institutional structures. It also provides an opportunity. Instead of simply reproducing regulatory approaches developed elsewhere, Asian jurisdictions can develop frameworks that respond to their own entrepreneurial ecosystems and sustainability priorities.

A sustainable regulatory framework should nevertheless avoid treating all AI enterprises in the same manner. The environmental impact of a small startup developing a specialised AI application cannot reasonably be equated with that of an enterprise developing and operating a large general purpose model. Excessive regulation could increase compliance costs, discourage innovation and create barriers for precisely those startups that policymakers seek to encourage. A proportionate approach is therefore essential. Regulatory obligations should correspond to factors such as computational scale, environmental impact,

technological capacity and the risk associated with the particular AI system.

The paper accordingly proposes a shift from the conventional idea of responsible AI towards the concept of sustainable by design AI. Under this approach, sustainability should not be considered an external obligation imposed after an AI system has been developed. It should become a consideration incorporated into the technological design and entrepreneurial decision making process from the beginning. Developers should consider whether a task requires a highly complex model, whether an existing smaller model could achieve the same objective, whether computational processes can be optimised and whether infrastructure can be operated more efficiently. Sustainability would consequently become part of innovation itself.

Such a transition also requires a closer relationship between legal standards and technical standards. A law requiring AI enterprises to reduce their environmental impact is of limited practical value if environmental impact cannot be reliably measured. Conversely, technical measurements have limited regulatory significance unless the legal system determines when those measurements matter. A techno legal framework can bridge this divide. Computer science can establish appropriate methods for measuring computational efficiency, energy consumption and resource use, while law can establish disclosure requirements, accountability mechanisms and incentives based on those measurements.

The role of government should therefore extend beyond traditional command and control regulation. Sustainable AI entrepreneurship can be encouraged through a combination of regulatory requirements and positive incentives. Governments can support green AI research, provide access to energy efficient computing infrastructure, introduce sustainability criteria into public procurement and develop regulatory sandboxes for environmentally responsible AI solutions. Financial incentives and certification mechanisms can further encourage startups to treat computational efficiency as an element of technological quality. Such measures would be particularly valuable in emerging entrepreneurial ecosystems where startups may lack the financial resources available to large technology companies.

Another important conclusion is that sustainability should be understood across the entire AI lifecycle. Focusing exclusively on model training provides an incomplete assessment. Environmental consequences can arise from data processing, repeated training, inference, cloud infrastructure, cooling, hardware production and eventual disposal. Regulation should therefore move towards lifecycle based assessment rather than isolated measurement of a single stage of AI development. This approach would also make it possible to identify where environmental improvements can have the greatest practical effect.

The Asian context makes proportionality and accessibility even more important. Many Asian economies are attempting to expand digital infrastructure while simultaneously pursuing sustainable development. AI regulation should not create a situation in which only large corporations can afford to comply with environmental requirements. Instead, regulation should encourage innovation among startups while ensuring that enterprises with greater computational and environmental footprints assume greater responsibility. This would create a regulatory structure in which compliance is scaled according to actual impact rather than simply organisational identity.

The broader implication of this study is that sustainability should increasingly be regarded as a component of technological accountability. An AI system cannot be described as fully responsible merely because it is accurate, transparent or non discriminatory if its development and operation generate significant and avoidable environmental costs. Similarly, an AI startup cannot be regarded as sustainable merely because its products are marketed as supporting the Sustainable Development Goals. Sustainability must extend to the technological foundations of the enterprise itself.

The future of AI entrepreneurship in Asia will therefore depend not only on the ability to develop more powerful systems, but also on the ability to develop more efficient and responsible systems. The objective should not be to discourage computationally intensive innovation. Rather, it should be to ensure that computational intensity is justified, measurable and progressively reduced where technological alternatives are available. This would allow environmental responsibility to coexist with entrepreneurial freedom.

Ultimately, the relationship between law, computer science and entrepreneurship should not be viewed as one of restriction and resistance. It can instead become a relationship of mutual reinforcement. Computer science can make AI systems more efficient. Entrepreneurship can convert those technological improvements into scalable solutions. Law can create the institutional conditions necessary to ensure that such innovation remains accountable and sustainable. When these three dimensions operate together, sustainability ceases to be a separate policy objective and becomes part of the architecture of technological innovation itself.

The central proposition of this paper is therefore that Asia requires a regulatory transition from AI that is merely responsible in its outcomes to AI that is sustainable in its design. Green AI entrepreneurship should be encouraged not by treating environmental considerations as an additional compliance burden, but by recognising computational efficiency and environmental responsibility as characteristics of better technological innovation. A future oriented techno legal framework can provide the necessary bridge between these objectives. Such a framework can allow Asian economies to remain competitive in

the global AI economy while ensuring that technological progress does not externalise its environmental costs onto society and future generations.

The success of AI entrepreneurship should ultimately not be measured only by the number of startups created, models developed or investments attracted. It should also be assessed by whether technological innovation contributes to a more efficient, accountable and sustainable economy. The real challenge for Asian policymakers is therefore not to choose between AI innovation and sustainability. It is to design a regulatory and technological environment in which the two can advance together.

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