QUANTIFYING AND RESPONDING TO THE ECONOMIC IMPACT OF AI IN INDIA, SINGAPORE, AND INDONESIA

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EXECUTIVE SUMMARY

This report analyses the existing regulatory environment and the economic impact of potential future regulatory scenarios governing artificial intelligence (AI) in India, Singapore, and Indonesia—three major digital economies in South and Southeast Asia. As AI rapidly transforms digital interactions, the need for adaptive governance is increasingly acute, particularly in emerging markets where institutional responses are still evolving.

The research presented here is structured around three interlinked themes: the maturity and direction of national AI regulation; the economic and distributive implications of AI diffusion across the three markets; and the role of AI in the smartphone ecosystem and adjacent digital infrastructure. These dimensions are examined as part of an evolving regulatory perspective in each country—one shaped by institutional capacity, market incentives, and global governance trends. The smartphone ecosystem, in particular, is highlighted as a most improtant interface where considerations of productivity, inclusion, privacy, and AI ethics converge in daily life.

The report draws on a structured expert survey carried out in March–April 2025 among 102 domain specialists from academia, civil society, regulatory bodies, and industry associations in the three countries. The survey captured perceptions of AI regulatory readiness, economic transformation, and the role of AI across infrastructure layers. Macroeconomic simulations that model the consequences of three regulatory scenarios—no regulation, self-certification, and licensing—on national economies complement the survey findings. These scenarios were selected because they span the fundamental choices facing regulators with respect to AI governance.

Key findings include:

- **Divergent Regulatory Trajectories**: Singapore is the most institutionally advanced in terms of governance frameworks for AI, featuring structured sandboxes, multistakeholder engagement, and internationally aligned frameworks. India favours a principle-based, decentralised approach, supporting global standards but facing coordination and implementation challenges. Indonesia is increasingly consultative and globally aware but remains constrained by limited regulatory capacity and institutional fragmentation.

- **Economic Impact of AI**: AI is expected to reduce production costs by 10-20 percent across all three countries; Indian experts anticipate the greatest savings, with many predicting reductions exceeding 20 percent. Firms are likely to reinvest AI-enabled savings primarily in innovation and capability development, implying substantial potential for productivity gains.

- **Preferred Regulatory Models**: Self-certification is the most favoured regulatory approach in India and Singapore, balancing innovation and oversight. Experts estimate that it preserves more than 90 percent of innovation potential, while imposing only moderate compliance costs and improving trust. Macroeconomic simulations indicate that self-certification yields consistent increases in total factor productivity (0.35-1.08 percent, compared with 0.05-0.96 percent under licensing), and in aggregate output (0.31-1.10 percent, compared with -0.05-0.97 percent under licensing), all with lower compliance burdens than licensing

- **Trade-offs in licensing:** Licensing offers the highest trust-building effects (0.75–1.19 percent under licensing, compared with 0.38–0.82 percent under self-certification) but at the cost of reduced innovation, efficiency, and capital quality. It is viable only in countries with advanced regulatory capacity, such as Singapore.

- **Relevance of smartphones:** Experts consistently identify smartphones as the most important layer for AI integration (3.05–3.20 on a scale of 4) because of their ubiquity and proximity to end-users. This underscores the strategic importance of mobile infrastructure in shaping regulatory outcomes and the need for flexible, context-aware models that promote equitable innovation without marginalising low-end users.

Our recommendations for the three countries to maximise the economic potential of AI are:

- **India** should, wherever possible, adopt a structured self-certification regime as its principal regulatory pathway and, simultaneously, enhance implementation capacity, institutionalise multistakeholder consultation, scale up AI testbeds, and operationalise ethical principles. The country should also deepen participation in international AI governance and adopt interoperability frameworks to support both domestic innovation and cross-border trust.

- **Singapore** should expand its AI sandbox and assurance initiatives into regional pilots, and deepen its co-regulatory model, consolidating its leadership in harmonised AI governance.

- **Indonesia** should prioritise foundational regulatory capacity-building, institutional design, cross-sectoral coordination, and mandate clarity before introducing formal AI governance frameworks. Piloting self-certification in low-risk sectors and leveraging voluntary standards can build regulatory learning, and stakeholder trust without imposing premature compliance burdens.

This report provides a granular, comparative understanding of how emerging digital economies can foster inclusive, innovation-friendly AI ecosystems. The report's novelty lies in a multiscalar approach that integrates institutional analysis, economic modelling, and infrastructure-level assessment, with a particular emphasis on the smartphone ecosystem. The findings and recommendations aim to inform ongoing debates on operationalising ethical AI governance in the Global South, bridging global norms with grounded national strategies.

INTRODUCTION

The rapid diffusion of AI is reshaping global economic structures, regulatory priorities, and technology governance. AI has become increasingly integrated across sectors—from finance to health—and the need for coherent, adaptive regulatory frameworks has grown. This governance challenge is particularly complex in the context of the Global South, as it requires balancing innovation and inclusion in the absence of mature regulatory institutions or coordinated governance mechanisms. This report examines these dynamics through the lens of three diverse economies in South and Southeast Asia: India, Singapore, and Indonesia. These countries are not only key digital markets in the region but also serve as important testbeds for the regulatory future of AI in emerging contexts, as they represent diverse developmental and market trajectories.

In this report, the policy focus is disaggregated into three reinforcing strands: the readiness and direction of national AI regulation; the economic and distributive implications of AI integration; and the role of AI in smartphones and adjacent digital-infrastructure layers. These dimensions are examined as part of an evolving regulatory ecosystem shaped by institutional constraints, market incentives, and global AI-governance trends. The smartphone ecosystem, in particular, provides a tangible context in which issues of productivity, inclusion, privacy, and AI ethics intersect most visibly in everyday use.

To support the analysis, we conducted a structured expert survey, administered during March–April 2025, that captured the views of 102 domain specialists—50 from India, 27 from Indonesia, and 25 from Singapore. The survey explored perceptions of AI regulatory readiness, AI-induced economic transformation, and the role of AI across digital layers, including smartphones, operating systems, browsers, and app stores. Respondents were drawn from industry, academia, think tanks, and government. The instrument employed a mixed-method design, combining Likert-scale assessments, ranking formats, numerical estimates, and open-ended responses, to ensure both quantitative rigour and qualitative depth. These survey findings are complemented by a growth-accounting simulation framework that models the macroeconomic consequences of alternative regulatory scenarios. Section 2 discusses the survey and simulation methodology in detail.

Section 3 analyses the regulatory environment for AI in India, Singapore, and Indonesia. It assesses the maturity of national frameworks, participation in global standard-setting, mechanisms for stakeholder input, and the availability of tools such as testing sandboxes and self-certification. The chapter also maps how these institutional features align with each country's broader regulatory traditions: India's principle-based and decentralised approach, Singapore's proactive and standards-led model, and Indonesia's evolving and consultative trajectory. Finally, it situates these national paths within global conversations on responsible AI, highlighting the importance of governance agility, transparency, and legitimacy (Gasser and Almeida, 2017; Jobin et al., 2019).

Section 4 focuses on the economic implications of AI, especially under three alternative regulatory scenarios—no regulation, self-certification, and licensing. It considers how these models influence key drivers of growth: labour quantity and quality, ICT and non-ICT capital, and total factor productivity. The chapter also examines how firms may allocate cost savings generated by AI—towards retained earnings, innovation, wages, or consumer benefits. These findings draw attention to the distributive impacts of regulatory choices and how innovation-friendly frameworks can still risk exacerbating inequality unless they are balanced with inclusive safeguards (Korinek and Stiglitz, 2021).

Section 5 extends this analysis through a detailed exploration of regulatory scenarios and their macroeconomic trade-offs. Using a simulation model, the section highlights the differential impact of each scenario on innovation, efficiency, trust, and compliance costs, while accounting for country-specific institutional capacity and administrative readiness. These differential impacts underscore the importance of tailoring regulatory models to national contexts.

Section 6 brings this analysis into sharper focus by examining AI integration in smartphones, the most ubiquitous and citizen-facing layer of digital infrastructure. The section explores how AI functionality is increasingly embedded in smartphones—often at the OS level—and how market structures and device heterogeneity shape AI deployment in the three countries. Singapore's premium market supports deep AI integration; India's fragmented device landscape presents challenges for uniform adoption; and Indonesia occupies an intermediate position, with rising use but limited institutional support. These differences highlight the need for regulatory models that are both flexible and context-aware. Given that smartphones are the primary interface for AI in much of the Global South, this chapter underscores the urgency of governance models that promote equitable innovation without overwhelming regulators or marginalising low-end users.

The key findings of this report are as follows:

- The regulatory trajectories of India, Singapore, and Indonesia reflect their broader institutional capacities. Singapore is the most institutionally advanced, characterised by structured sandboxes, multistakeholder engagement, and internationally aligned frameworks. India favours a principle-based and decentralised model, demonstrating strong normative support for global standards but facing coordination and implementation challenges. Indonesia, while increasingly consultative and globally aware, continues to operate within a capacity-constrained and fragmented regulatory environment.

- AI is expected to reduce production costs by 10–20 percent across all three countries, with the highest expectations for cost reductions above 20 percent reported by Indian experts. Firms are likely to reinvest AI-enabled cost savings primarily into innovation and capability development, suggesting considerable scope for productivity gains.

- Self-certification emerges as the most-preferred regulatory model across India and Singapore, balancing innovation with oversight and offering a pragmatic alternative to licensing in contexts with moderate institutional readiness. Experts view it as retaining more than 90 percent of innovation potential while delivering moderate compliance costs and public-trust gains.

- Macroeconomic simulations also support self-certification, as it yields the most consistent and positive gains in total-factor productivity and aggregate output across India and Singapore, while imposing comparatively lower compliance burdens than licensing. Indonesia's outcomes are more muted, reflecting structural limitations in regulatory implementation and enforcement.

- Licensing produces the highest trust-building effects in simulation results. However, these benefits come at the cost of significant reductions in innovation, efficiency, and capital quality, making licensing viable primarily in countries with advanced regulatory capacity, such as Singapore.

- Experts consistently identify smartphones as the most important layer for AI integration, owing to their ubiquity, proximity to end-users, and potential to support edge-computing applications. This prioritisation underscores the strategic importance of mobile infrastructure in shaping regulatory outcomes.

We have the following recommendations based on the research presented here:

- India should adopt a structured self-certification regime as the principal regulatory pathway for AI, while enhancing implementation capacity and regulatory coherence through institutionalisation of multistakeholder consultation, scaling up of AI testbeds, and operationalisation of ethical principles. In addition, the country should leverage global standards by deepening participation in international AI governance bodies, and adopting interoperability frameworks that support both domestic innovation and cross-border trust.

- Singapore should expand its AI sandbox and assurance initiatives into regional pilots, and deepen its co-regulatory model. These tools reflect Singapore's institutional maturity and reinforce its leadership role in shaping internationally harmonised AI governance.

- Indonesia should focus on foundational regulatory capacity-building, prioritising institutional design, cross-sectoral coordination, and clarity of objectives before introducing formal AI governance frameworks. The country can pilot self-certification approaches in low-risk sectors, using voluntary standards and consultative mechanisms to build regulatory learning and stakeholder trust, without prematurely imposing compliance burdens.

2

DATA AND METHODOLOGY

We conducted an expert survey to generate insights into the regulatory and economic implications of AI in India, Indonesia, and Singapore. In addition, we draw on secondary data sources—including the World Bank, the Conference Board Total Economy Database, and the Penn World Table—to obtain macroeconomic indicators related to labour markets, capital formation, and productivity growth. These sources ensure consistency, comparability, and replicability in the cross-country analysis.

The data are analysed using a combination of descriptive and comparative methods, including frequency distributions, measures of central tendency, sensitivity ratios, rank-based scoring, and stochastic dominance. To assess macroeconomic trade-offs under different regulatory models—no regulation, self-certification, and licensing—a growth accounting framework is simulated for each of the three countries.

2.1 Expert Survey Design

We conducted a structured survey of domain specialists across India, Indonesia, and Singapore to explore how the artificial intelligence (AI) landscape may evolve under three regulatory scenarios: no regulation, self-certification, and licensing. The survey gathered expert insights on the regulatory environment, economic implications, and governance readiness associated with AI integration within the mobile and digital-platform ecosystem. Particular attention was paid to four important components of digital infrastructure: smartphone devices, operating systems (OS), browsers, and app stores.

Administered during March–April 2025, the survey targeted professionals with demonstrated expertise in AI policy, digital markets, platform regulation, or mobile technologies. Respondents were drawn from academic institutions, think tanks, regulatory bodies, civil society, and industry associations. In total, 102 experts participated, including 50 from India, 27 from Indonesia, and 25 from Singapore.

The questionnaire focused on three key areas:

1. **The state of AI regulation in each country:** This section sought to establish a baseline understanding of how experts perceive their country's institutional readiness and global positioning within the AI policy landscape. Respondents reflected on the maturity of national AI regulatory frameworks and on the perceived importance of aligning with international standards and governance mechanisms.
2. **Economic dimensions of AI integration:** This section examined how AI may reshape value creation and growth under varying regulatory models, using a no-regulation scenario as the baseline. Experts assessed AI's expected impact on five production-related variables: labour quantity, labour quality, ICT capital, non-ICT capital, and total factor productivity. They also estimated potential cost savings from AI adoption and indicated how firms might allocate these gains—whether through retained earnings, innovation, increased wages, or consumer benefits—thus providing insight into anticipated distributional outcomes.
3. **AI's role across infrastructure layers:** This section enabled a comparative analysis of regulatory preferences and infrastructure-specific considerations. Experts ranked the relative importance of AI integration for smartphones, OS, browsers, and app stores, offering a perspective on where AI is viewed as most strategically significant. They also evaluated how self-certification and licensing might influence AI innovation within each layer, relative to the no-regulation scenario.

To ensure both rigour and flexibility, the survey employed a mix of question formats. Likert-based questions captured the direction and strength of expert sentiment regarding institutional readiness and macroeconomic impacts, using scales that ranged from highly negative to highly positive, or from no readiness to high readiness. Rank-based questions prioritised infrastructure components and regulatory preferences, enabling the calculation of composite scores through weighted-ranking techniques. Number-based questions asked respondents to estimate cost impacts and savings within predefined percentage ranges (e.g., up to 5 percent, 10-15 percent), thereby facilitating distributional comparisons across countries and policy models. Finally, open-ended questions followed each section, allowing experts to elaborate on their reasoning, highlight country-specific concerns, and raise additional issues not captured by the structured response options.

2.2 Methodology

The analysis of expert responses combined descriptive and comparative techniques to derive insights from quantitative and qualitative data. A range of methods was employed to assess variation across countries, regulatory models, and AI infrastructure layers.

Frequency graphs were used to visualise distributional patterns across survey responses, allowing the identification of skewness, concentration, or dispersion in expert views, particularly in relation to perceived costs, cost avoidance, and AI importance across infrastructure layers such as smartphones, operating systems, browsers, and app stores.

Measures of central tendency focused on the median, rather than the mean, when summarising expert responses. The median was preferred for representing central views because the mean is more susceptible to outliers.

Sensitivity ratio was used to evaluate responses captured through Likert-scale ratings. For selected variables, we adopted a neutral-augmented sentiment ratio (SR), calculated as:

$$R = \frac{Neutral + Positive + Highly\ Positive}{Highly\ Negative + Negative + Neutal}$$

This metric treats the neutral response as a shared middle ground and is intended to reflect the overall slant of opinion. An SR greater than 1 suggests a generally positive sentiment; a value less than 1 indicates a more negative sentiment; and an SR equal to 1 reflects a balanced view. While traditional sentiment analysis often excludes neutral responses, we retained them in this study because some survey questions elicited no negative responses, rendering conventional ratios undefined. In this context, SR functions as a moderated proxy for standard positive–negative sentiment ratios.

Rank-based scoring was used in questions in which experts prioritised infrastructure components or regulatory models. Each rank received a descending weight (rank 1, 4 points; rank 2, 3 points; rank 3, 2 points; rank 4, 1 point), and composite scores were computed from the frequency of each ranking. The approach draws on rank-aggregation techniques widely employed in decision theory and preference elicitation (Emerson, 2013; Saari, 2001; Georghiou et al., 2008). Although it assumes equal spacing between ranks—an acknowledged simplification—it offers a pragmatic, transparent means of summarising expert preferences in the absence of cardinal-utility values (Fishburn, 1974).

To assess the perceived trade-offs between regulatory costs and benefits—particularly when comparing self-certification and licensing with a no-regulation baseline—stochastic dominance techniques were applied. Stochastic dominance is a nonparametric method for comparing cumulative distributions without requiring a specific functional form. If the cumulative distribution curve of ‘A’ is at or below (i.e., lies entirely to the right of) that of ‘B’, then ‘A’ is said to first-order stochastically dominate (FSD) ‘B’.

However, when cumulative distribution curves intersect, FSD no longer applies. In such cases, we assess second-order stochastic dominance (SSD). SSD is relevant when one distribution exhibits lower dispersion (i.e., risk) while maintaining an equal or higher expected value (i.e., mean) than another. A practical way to infer SSD is to compare the area under the curve (AUC) of the two cumulative distributions. If distribution “A” has an AUC that is consistently smaller than or equal to that of “B,” distribution “A” is said to second-order stochastically dominate “B” (Levy, 1992; Barrett and Donald, 2003). To compute AUC, we used Simpson’s Rule, a standard method for numerical integration. For equally spaced intervals between x_i on the X-axis for i = 1, 2, 3 ..., Simpson’s Rule is given by:

$$AUC = \frac{\Delta x}{3}[f(x_0) + 4f(x_1) + 2f(x_2) + 4f(x_3) + \cdots + 2f(x_{n-2}) + 2f(x_{n-1}) + f(x_n)]$$

In the case where $\mathbf{x_i}$ represents intervals (e.g. 5–10 percent), the **midpoints** (e.g. 7.5 percent) are used, and Δx corresponds to the **interval width** (e.g. 5). For a detailed exposition of Simpson’s Rule, see Burden and Faires (2000) and Cartwright (2017).

Two cautions are worth noting when applying Simpson’s Rule to estimate the AUC. First, Simpson’s rule approximates the AUC by fitting quadratic polynomials between sets of three adjacent data points. While effective for smooth and continuous functions, this approach may introduce error when applied to functions with sharp inflections, discontinuities, or non-smooth characteristics—as is often the case with cumulative survey distributions featuring stepwise changes. Such deviations are particularly pronounced near the tails of the distribution, where data may shift abruptly or sparsely.

Second, in several instances, the data used to compute the AUC—as in this report—are censored at the upper end of the distribution. For example, a response category “over 25 percent” lacks an upper bound, preventing a precise midpoint estimate. This poses a challenge for numerical-integration techniques such as Simpson’s rule, which assume bounded and uniformly spaced intervals. A common workaround is to assign an arbitrary midpoint (e.g., 27.5 percent) to the final bin, but this practice introduces subjectivity and may under- or overestimate the true tail area, particularly when comparing distributions across groups.

Despite these limitations, Simpson’s Rule remains a useful and transparent technique for approximating AUC in applied policy contexts. While it may not yield strictly unbiased estimates, especially in the presence of nonuniform spacing or censored data, it provides a consistent and interpretable direction for comparing cumulative distributions—such as in second-order stochastic dominance analysis—when applied with appropriate caution.

Finally, to complement the expert survey and comparative indicators, we employ a **growth-accounting simulation framework** to quantify the macroeconomic effects of different AI regulatory scenarios across the three countries. The model estimates how each scenario influences key drivers of economic output, including innovation, efficiency, total factor productivity (TFP), and capital quality. Parameter values are calibrated using a combination of survey results and secondary data. Each regulatory regime is associated with a distinct value of regulatory stringency (R), which modulates compliance costs and trust effects in the simulation, thereby capturing real-world trade-offs between oversight and innovation potential.

The simulation adopts a counterfactual design in which baseline economic performance under a “no regulation” scenario is compared with the incremental changes observed under self-certification and licensing regimes. Trust-building benefits are modelled as a positive function of regulatory stringency, whereas innovation and efficiency decline when compliance costs become excessive. The framework allows country-specific parameter variation to capture differences in institutional capacity, sectoral composition, and readiness for AI integration. Output measures include percentage changes in innovation, efficiency, TFP, compliance costs, capital quality, and aggregate economic output. This approach provides a transparent, comparative assessment of the potential macroeconomic consequences of alternative regulatory pathways.

3

REGULATORY ENVIRONMENT ON AI IN INDIA, SINGAPORE AND INDONESIA, AND GLOBAL REGULATORY ALIGNMENT

SUMMARY

Dimension	India	Singapore	Indonesia
Stage of AI Regulation	Evolving, with frameworks like National Strategy for AI (2018) and IndiaAI Mission. Lacks binding laws.	Advanced voluntary frameworks such as Model AI Governance Framework (2024). No binding laws but robust guidelines.	Early stage. No binding AI law yet. Existing initiatives like Stranas KA and Circular No. 9/2023 provide ethical guidance but lack legal force.
Core Regulatory Approach	Principles-based (transparency, fairness, inclusivity). Reliance on ethics-oriented guidelines and sectoral laws (e.g., IT Act, Consumer Protection Act).	Industry-oriented, sandbox-based, with international alignment. Promotes AI innovation and accountability via voluntary self-regulation.	Contextual and fragmented. Drawing on international models (e.g., Singapore, Australia) but with little enforcement infrastructure.
Stakeholder Engagement	Emerging – open consultations in progress (e.g., Digital India Bill), but multistakeholder input is still formalistic.	Strong – emphasis on inclusive policymaking (e.g., SGTech, SBF) with private-public collaboration institutionalised.	Limited but growing – industry groups like idEA and CSOs like ELSAM pushing for human rights and inclusive governance models.
Testing Infrastructure (Sandboxes)	Limited – some initiatives in place but not institutionalised across sectors.	Well-developed – AI Verify, GenAI Sandbox, MAS regulatory initiatives promote structured testing environments.	Nascent – MOH sandbox for health tech; broader infrastructure underdeveloped.
AI Standards and Certification	BIS working with ISO/IEC standards. IS 17802 series under development.	TR 99:2021 and AI Verify incorporate global standards. Focus on ethics, robustness, transparency, and auditability.	No formal national standards yet. Early engagement with ISO/IEC; BSN not yet a key actor.
Industry Landscape	Fast-growing ecosystem; backed by IndiaAI Mission. Start-up surge and public-private partnerships (e.g., TCS, Microsoft).	Mature ecosystem; emphasis on open-source and high-tech skill development. Multinational presence and pilot programmes by Microsoft, Google, etc.	Fragmented sector-wise progress (finance, health, education); private sector leads innovation. High reliance on foreign tech firms and platforms.

Dimension	India	Singapore	Indonesia
Expert Perception of Regulatory Maturity	Minimal to moderately developed. Strongest support for global alignment.	Most advanced among the three. Perceived as institutionally robust.	Moderate but inconsistent. Regulatory frameworks seen as less mature and less responsive.
Expert Perception of Global Regulatory Alignment	Strong interest in global coordination despite nascent regulatory infrastructure.	Seen as capable but less urgently aligned with global norms due to confidence in domestic capacity.	Low sensitivity to global coordination, though aspirations remain.

Regulatory frameworks for AI in many emerging and developing economies remain in a formative stage and often struggle to keep pace with the rapid evolution of AI technologies. The cross-sectoral and transboundary nature of AI introduces complex governance challenges, particularly for countries with limited institutional capacity, fragmented oversight mechanisms, or evolving legal systems (Cath et al., 2018; Nemitz, 2018). These gaps have fuelled growing calls for global coordination to establish shared ethical norms, interoperability standards, and collective approaches to risk mitigation (Jobin et al., 2019).

At the same time, the literature suggests that more digitally advanced economies often feel less urgency to pursue international alignment, as robust domestic frameworks can serve as functional substitutes for multilateral governance (Wirtz et al., 2019). Furthermore, recent scholarship has emphasised the importance of inclusive governance models, particularly those that incorporate multistakeholder engagement, sandbox experimentation, and public consultation. Such approaches are viewed as essential to building legitimacy, adaptability, and accountability in AI regulation (Gasser and Almeida, 2017; Crootof et al., 2022). From this perspective, governance readiness depends not only on formal policy documents, but also on institutional responsiveness and the availability of infrastructure for testing, iteration, and global coordination.

Around the world, governments are actively developing regulatory frameworks to keep pace with AI's accelerating capabilities. These efforts are shaped by each country's economic priorities, societal norms, and strategic objectives, resulting in a diverse landscape of national approaches. Some jurisdictions have adopted comprehensive legislative models, while others rely on industry guidelines, voluntary standards, or sector-specific policies.

The European Union (EU), for example, enacted the world's first comprehensive AI law, the AI Act, in 2023. It adopts a risk-based approach, categorising AI systems from "unacceptable" to "minimal" risk and imposing obligations accordingly. In contrast, China has opted for a more targeted regulatory path, focusing on specific applications such as recommendation algorithms and generative AI through discrete policy instruments. Meanwhile, countries such as the United Kingdom and Japan have pursued innovation-centric strategies, aiming to balance regulatory oversight with technological leadership and economic competitiveness.

Against this global backdrop, this chapter turns to three key economies in South and Southeast Asia—India, Singapore, and Indonesia—to examine how each is navigating the governance of AI. While all three countries are shaping their AI regulatory ecosystems, they exhibit varied levels of institutional maturity, regulatory ambition, and global engagement. The following sections map their distinct trajectories, highlighting national strategies, institutional readiness, and alignment with emerging international norms.

3.1 Overview of AI Regulation in India

India's National Strategy for AI, published in 2018, aims to create a thriving AI ecosystem by promoting innovation, entrepreneurship, and international collaboration while leveraging AI to tackle social and economic challenges (NITI Aayog, 2018). The government acknowledges that, despite its benefits, AI systems also carry risks that could harm individuals, organisations, and society. To mitigate these risks, the national strategy emphasises stringent privacy safeguards and the protection of citizens. It also advocates AI development and deployment based on transparency, fairness, privacy, and security—principles highlighted in several government papers and reports. For instance, NITI Aayog's Responsible AI Approach Document (2021) outlines a framework centred on safety, reliability, inclusivity, nondiscrimination, transparency, accountability, and the reinforcement of positive human values (NITI Aayog, 2021).

More recently, the Ministry of Electronics and Information Technology (MeitY) published a detailed report setting out guidelines for AI governance and development for 2025 (MeitY, 2025). The MeitY report lays down eight key principles for AI governance in India, as listed in Figure 1.

Figure 1: Key principles for AI governance in India

Principles	Detail
Transparency	Development of AI systems should be interpretable and explainable for users to understand what they are dealing with
Accountability	Developers and deployers should take responsibility for the functioning and outcomes of AI systems
Safety, Reliability & Robustness	AI system should be resilient to risks, errors, or inconsistencies, the scope for misuse and inappropriate content should be reduced, and unintended or unexpected adverse outcomes should be identified and mitigated
Privacy & Security	AI systems must follow applicable data protection laws and protect user's privacy
Fairness & Non-discrimination	AI systems must not perpetuate biases or prejudices against or in favour of individuals, communities or groups
Human-centred values and "do not harm"	AI systems should be subject to human oversight, judgment, and intervention, as appropriate to reduce undue reliance on AI systems
Inclusive and sustainable innovation	Benefits of AI should be distributed equitably amongst all and should deliver on sustainable development goals
Digital by design governance	Governance of AI systems should leverage technologies to re-think and reengineer systems

Source: Ministry of Electronics and Information Technology (MeitY), Government of India

The government, while acknowledging the ethical and regulatory challenges, is also focused on fostering a supportive environment that promotes the development and adoption of AI solutions. Under the IndiaAI mission, it aims to create a vibrant ecosystem that spurs AI innovation through public–private partnerships. In the Union budget announcement of 2024, the government allocated ₹10,371 crore (≈ $1.24 billion) to the IndiaAI mission, with the objectives of democratising access to computing resources and chips, improving data quality, and helping developers build indigenous AI capabilities.

3.1.1. Regulatory Landscape of AI in India

India is revamping its technology laws—a process likely to affect millions of citizens online. One priority of these pieces of legislation is to ensure online safety and protect users from online fraud, cybercrime, phishing and other malicious activities. The government is assembling a broad regulatory framework that includes the Digital Personal Data Protection Act (DPDPA), 2023, the Telecommunications Act, 2023, the forthcoming Digital India Bill, and the draft digital competition bill to keep pace with rapidly evolving technologies. However, most of these pieces of legislation remain under consultation or are only at early stages of implementation. Nevertheless, several existing laws already provide a guiding framework for the development and deployment of AI:

- **Classification of AI systems based on risk:** Section 69A of the Information Technology Act 2000 empowers the Central Government to block information in the interests of national sovereignty, security, and public order. The Information Technology (Intermediary Guidelines and Digital Media Ethics Code) Rules 2021 (IT Rules 2021) further require intermediaries to prevent the hosting or dissemination of unlawful content, including AI-generated material, and impose a duty to remove false information, morphed images that infringe privacy, and content involving impersonation.

- **Algorithmic transparency:** Rule 4(4) of the IT Rules 2021 obliges significant social-media intermediaries to periodically review their automated tools. The review must proactively identify content relating to rape, child sexual abuse, or similar explicit acts, as well as content identical to information previously removed or disabled under Rule 3(1)(d). It must also assess the tools' accuracy, fairness, potential for bias and discrimination, and their impact on privacy and security.

- **Consumer protection:** The Consumer Protection Act 2019, together with the Consumer Protection (E-Commerce) Rules 2020, applies to any unfair trade practice or deficiency in a product or service offered by an AI platform.

- **Intellectual property rights (IPR):** Indian IPR statutes, notably the Copyright Act 1957 and the Patents Act 1970, encounter limitations when applied to AI-generated works. Under the Copyright Act, authorship is reserved for legal persons, thereby excluding AI systems. The Indian Copyright Office briefly recognised an AI tool as co-author, but later rescinded the entry. Similarly, the Patents Act defines "patentee" and "person interested" in terms that restrict patent recognition to humans, preventing AI systems from holding patents.

At the international level, India has actively participated in various international and intergovernmental forums, such as the G7 (Hiroshima AI Process) and the G20 (New Delhi Leaders Declaration 2023), to advance the vision of responsible AI aimed at achieving United Nations Sustainable Development Goals (UN SDGs). India also played an active role in the AI Safety Summit 2023, held in Buckinghamshire, UK, in November 2023. During this summit, India highlighted the significance of creating a secure, reliable, and accountable internet environment, including measures to protect users from harm.

The government acknowledges that enforcing AI governance frameworks and principles will require substantial collaboration between the government and industry, and that meaningful industry-led initiatives and demonstrable self-governance can enhance trust in the use of AI.

3.1.2. AI Standards in India

In India, the Bureau of Indian Standards (BIS) is developing AI standards through its technical committee LITD 30, which operates under the Electronics and IT Division Council (BIS, n.d.). BIS is actively aligning Indian AI standards with international efforts, particularly those of ISO/IEC JTC 1/SC 42, the global committee responsible for AI standardisation (ISO, n.d.). Its key focus areas include the trustworthiness of AI systems, data quality, the machine-learning lifecycle, and AI risk management. BIS is preparing to release standards in the IS 17802 series, which mirrors international documents such as ISO/IEC 22989 (AI concepts and terminology), 24028 (trustworthiness), and 23894 (risk management). Although currently voluntary, these standards are intended to form the foundation for future regulation and certification and will be adapted to local contexts such as language diversity and digital access.

3.1.3. Industry Landscape of AI in India

India's AI market has expanded rapidly in recent years, driven by enabling policy initiatives such as the IndiaAI mission, financing for DeepTech AI start-ups, and a 10,000-GPU compute capacity. A budding start-up ecosystem and the world's second-largest AI talent base are accelerating AI adoption within Indian companies (NASSCOM, 2024). India is also the second-largest contributor of AI-related patents and, according to Stanford's Global AI Index 2024, records one of the highest levels of AI skill penetration (Stanford, 2024). Industry estimates project that India's AI market will grow at a 25-35 percent compound annual growth rate (CAGR), from $ 7-9 billion (≈ ₹58,000-74,000 crore) in 2023 to $ 17-22 billion (≈ ₹1,41,000-1,83,000 crore) by 2027 (NASSCOM and BCG, 2024).

India's largest IT-services companies—including Tata Consultancy Services (TCS), Infosys, Wipro, HCL, and LTI Mindtree—have begun employing AI solutions for internal data and business-process management, collectively training more than seven lakh employees in generative AI (S&P Global, 2024). Big-tech firms such as Microsoft and Nvidia, together with the Indian Institute of Technology, Madras, have launched programmes to train the Indian workforce to integrate AI technologies into day-to-day tasks (S&P Global, 2024).

Industry bodies such as NASSCOM have introduced initiatives such as NASSCOM AI, which aims to foster collaboration on AI governance among government, start-ups, enterprises, academia, and investors by providing a common platform for discussion and consultation.

3.1.4. Challenges and Concerns

In March 2023, MeitY issued an advisory to intermediaries and other platforms that use generative AI—such as OpenAI and Google—as well as to entities whose AI systems are still in trial or testing phases. The advisory required every intermediary to submit an action-taken-cum-status report to the ministry within 15 days of its issuance.

The advisory directed intermediaries and platforms to:

- ensure that no AI system enables content prohibited under Rule 3(1)(b) of the IT Rules 2021;
- ensure that AI systems do not propagate bias or discrimination, or threaten the integrity of the electoral process;

- seek government approval before deploying AI systems that are under testing or otherwise unreliable, and provide such services to users only after clearly labelling the "possible and inherent fallibility, or unreliability, of the output generated". A consent pop-up mechanism may also be used to convey this message;
- inform users about prohibited content, and block or remove any material that is prohibited under Rule 3(1)(b); and
- ensure traceability by adding an identifiable marker to synthetically generated content that can be traced back to the person who instructed the service to create the misinformation or deepfake.

The advisory was later withdrawn after it was criticised by various industry stakeholders. It also caused significant distress within the Indian startup community, as the compliance costs of such measures would have been high, disrupting the development of AI tools and technologies. In addition, the advisory contained several legal gaps. For instance, it did not define key terms essential for its implementation, raising questions about its scope and compliance mechanism. The undefined terms include "inherent fallibility", "unreliability of output generated", "under-testing/unreliable", "Artificial Intelligence model(s)/LLM/Generative AI, software(s), or algorithm(s)", "misinformation", and "deepfake". Similarly, the advisory used the term "bias" without clarifying the standards or approaches that would be adopted to identify and understand it.

3.2. Overview of AI Regulation in Singapore

Singapore's regulatory approach to AI emphasises innovation alongside responsible use. To date, the country has neither enacted AI-specific legislation nor created a dedicated oversight agency; instead, it relies on voluntary, pro-business, and pragmatic frameworks. Most notably, the Model AI Governance Framework for Generative AI (2024) and the Model AI Governance Framework for Traditional AI (2019), authored by the Infocomm Media Development Authority (IMDA) and the Personal Data Protection Commission (PDPC), guide businesses operating in Singapore.

The government's strategy is to maximise innovation while maintaining accountability. It supports projects that contribute most to talent and resource development and that foster an open-source AI community. Accordingly, it collaborates with multinational companies to determine how best to monitor and govern AI applications. The Ministry of Digital Development and Information has issued several regulatory guidelines and sandboxes to help businesses self-regulate their AI products, including the AI Verify Foundation, the Spark Gen AI initiative, GenAI Sandbox 2.0, the Guidelines and Companion Guide on Securing AI Systems, and Project Moonshot. Agencies such as the Monetary Authority of Singapore (MAS) have also published deep-dive sectoral guidance on AI use for the financial sector.

3.2.1. Regulatory Landscape in Singapore

In May 2024, the IMDA and PDPC released their finalised Model AI Governance Framework for Generative AI (MGF for GenAI). This document builds upon the principles of the earlier Model AI Governance Framework for Traditional AI, released in 2019.

The new framework recognises the need for expanded and more detailed guidelines to achieve a balanced approach to AI governance. Its nine dimensions cover a broad range of AI topics, including accountability, data, trusted development and deployment, incident reporting, testing and assurance, security, content provenance, safety and alignment R&D, and AI for public good (Figure 2). While by no means exhaustive, the framework will shape discussions on AI regulation in Singapore in the years ahead.

It is important to note that some areas of the framework remain undefined. For example, accountability is defined as putting in place the right incentive structure for different players in the AI system development lifecycle to be responsive to end-users. Conversations on the appropriate incentive structure are under way and will likely materialise in subsequent editions of the governance framework.

Key players that will continue to lead this conversation include the IMDA—the agency that, since the early days, has set innovation and ethical guidance for the Smart Nation Initiative (2016) and the National AI Strategy (2019)—and the AI Verify Foundation, an open-source and government-led community of AI developers and users that has established a working AI governance testing framework and provides a software toolkit for industry players to self-regulate. At the sectoral level, the Monetary Authority of Singapore (MAS) and the Health Sciences Authority (HSA) will continue to make important contributions to self-regulation and risk mitigation. Industry associations such as SGTech, the Singapore Business Federation (SBF), and, of course, private-sector voices will remain important collaborators in shaping these discussions.

Figure 2: Key principles for AI governance in Singapore

Principles	Detail
Accountability	Putting in place the right incentive structure for different players in the AI system development life cycle to be responsible to end-users
Data	Ensuring data quality and addressing potentially contentious training data in a pragmatic way, as data is core to model development
Trusted Development & Deployment	Enhancing transparency around baseline safety and hygiene measures based on industry best practices in development, evaluation and disclosure
Incident Reporting	Implementing an incident management system for timely notification, remediation and continuous improvements, as no AI system is foolproof
Testing and Assurance	Providing external validation and added trust through third-party testing, and developing common AI testing standards for consistency
Security	Addressing new threat vectors that arise through generative AI models
Content Provenance	Transparency about where content comes from as useful signals for end-users
Safety and Alignment R&D	Accelerating R&D through global cooperation among AI Safety Institutes to improve model alignment with human intention and values
AI for Public Good	Responsible AI includes harnessing AI to benefit the public by democratising access, improving public sector adoption, upskilling workers and developing AI systems sustainably

Source: Infocomm Media Development Authority (IMDA), Government of Singapore

3.2.2. AI Standards in Singapore

Singapore takes a proactive role in AI standardisation, led by Enterprise Singapore and the IMDA. Although it does not issue binding standards in the traditional sense, Singapore has developed internationally aligned frameworks and tools to assess and guide the ethical use of AI. A central component is AI Verify, launched in 2022, a testing framework and toolkit that helps organisations evaluate AI systems for fairness, transparency, robustness, and explainability (aiverifyfoundation, n.d.). This framework draws on standards such as ISO/IEC 24028 and 22989, along with IEEE and ETSI guidance. Additionally, Technical Reference TR 99:2021 serves as a national reference for AI governance. It offers practical implementation advice for responsible AI development across the early life cycle of an AI system (singaporestandardseshop, n.d.).

3.2.3. Industry landscape of AI in Singapore

According to the International Monetary Fund (IMF), women and younger workers in Singapore are more exposed to the effects of AI, which—if not accompanied by appropriate policies—could widen income inequality in the city-state (IMF 2024). Industry associations such as SGTech and the SBF are already examining labour-market impacts and other AI-related issues. They are shaping the national AI landscape by strengthening thought leadership, launching pilot programmes, and offering training programmes for the private sector.

For example, SGTech, working as a Skills Development Partner with SkillsFuture Singapore, has released a handbook on generative-AI skills development that outlines what an AI-enabled workforce looks like and sets out steps to up-skill or re-skill existing employees. SBF, by contrast, hopes to expand public-private partnerships to meet the demands of the accelerating digital economy through its trade and labour programmes. Industry associations such as SGTech and SBF therefore remain important channels of “soft” advocacy for a holistic AI ecosystem.

Multinational corporations, including Google and Microsoft, also play a pivotal role in driving AI innovation and adoption in Singapore by forming partnerships and mounting large-scale skilling initiatives. This year, Microsoft announced its Pinnacle Programme, which aims to spearhead business- and sector-level transformation and to scale the benefits of AI through systematic capability-building.

3.3. Overview of AI Regulation in Indonesia

The Government of Indonesia has underscored the importance of maximising the potential of digitalisation to boost Indonesia’s economic growth, improve public services, and enhance productivity. In early October 2024, Nezar Patria, Vice Minister for Communications and Digital Affairs (then Ministry of Communications and Informatics), stated that Indonesia is committed to monitoring and aligning its policies with global AI developments. Newly inaugurated President Prabowo Subianto has likewise echoed the previous administration’s enthusiasm for leveraging AI—Prabowo’s flagship strategy for achieving his ambitious eight percent economic-growth target is the expansion of Indonesia’s digital economy, which involves maximising technologies such as AI to raise productivity. Even so, there is little clarity on how Indonesian leaders envisage leveraging AI for economic development, whether at the individual, organisational, government, or policymaking level. Additionally, the absence of formal AI regulations has led to varied interpretations among government officials, many of whom equate AI with simple automation and robotics. While attitudes towards AI in government are generally optimistic, understanding of the technology and its practical implications remains thin.

3.3.1. Regulatory landscape of AI in Indonesia

As of December 2024, Indonesia had no legally binding AI regulations; the most recent directive was Ministry of Communications and Informatics (MOCI) Circular 9/2023 on the ethical use of AI—not, as sometimes misreported, a Ministry of Communications and Digital Affairs (MCDA) instrument.

Under President Jokowi, the absence of an umbrella AI law stemmed partly from lawmakers' focus on other technology-related statutes, leading the government to prioritise the Personal Data Protection (PDP) Law and amendments to the Electronic Information and Transactions (ITE) Law. The Prabowo administration has renewed its commitment to developing a comprehensive AI regulatory framework and has signalled that several detailed instruments will be issued in 2025. In November 2024, MCDA Vice-Minister Nezar confirmed that internal discussions are under way to identify the regulations needed to tackle urgent AI-related issues.

Indonesian lawmakers have been drawing on international models, notably Singapore's Model AI Governance Framework and Australia's AI Ethics Framework. Nevertheless, Vice-Minister Nezar Patria has stressed in the media that Indonesia's AI strategy will differ from those of the US, EU and China—all of which he recognises as technologically advanced—arguing that any new rules must reflect local conditions, national ideology and core values. This protective posture towards foreign businesses and investors has persisted across several administrations, despite increasingly welcoming messages for foreign investment.

In 2020, the Agency for the Assessment and Application of Technology (BPPT) issued the National AI Strategy (Stranas KA, n.d.). The document sets out a policy framework for using AI across sectors, with priorities that include ethics, talent development, infrastructure, data management, and industrial research and innovation. However, because it has neither legal force nor a detailed action plan, its effectiveness is limited, and many of its goals remain unimplemented. Consequently, AI development in Indonesia is fragmented: each industry pursues adoption independently and in the absence of a unified national standard.

The health, financial-services, and education sectors have made notable progress, largely because their respective regulators[1] have dedicated departments to advance technological innovation. Although these bodies have not issued binding AI regulations, they have taken a proactive approach by publishing directives and guidelines. For example, in November 2023 the Financial Services Authority (OJK) launched an AI code of ethics for the financial-services industry and banks. Similarly, the Ministry of Health (MOH) has created a regulatory and innovation sandbox for AI-driven health technologies, even though it has yet to issue operating licences for such applications. The sandbox encourages innovation while ensuring regulatory compliance and preventing new products from operating outside the legal framework. Other sectors, however, lack comparable structures, leading to uneven AI development.

3.3.2. AI Standards in Indonesia

In Indonesia, AI standard development remains at an early stage. The National Standardization Agency (BSN) has not yet issued formal AI standards; however, the government recognises the need for such frameworks in its National AI Strategy (Stranas KA, n.d.). Early priorities include establishing benchmarks for data quality, promoting transparency in algorithmic decision-making, and ensuring human oversight (Indonesia Center for Artificial Intelligence Innovation, n.d.; Digwatch, n.d.). Although BSN is not yet a major actor in international AI standard-setting, Indonesia participates in regional and global forums, including the ASEAN Committee on Science, Technology and Innovation (COSTI), and has begun engaging with ISO/IEC JTC 1/SC 42. Indonesia is also the first Southeast Asian country to implement UNESCO's

Readiness Assessment Methodology for AI—a macro-level instrument that helps countries gauge their preparedness to deploy AI ethically and responsibly, while highlighting the institutional and regulatory changes required (Global AI Ethics and Governance Observatory, UNESCO, n.d.).

3.3.3. Industry landscape of AI in Indonesia

The private sector has played a key role in shaping Indonesia's local AI development through business and advocacy activities. Among the most popular applications are personalised services, particularly on e-commerce platforms, and supply-chain optimisation. AI-powered chatbots, which leverage natural language processing (NLP), also handle customer queries efficiently and improve user experiences. Additionally, AI has gained recognition for its role in fraud detection and risk assessment, areas that have attracted significant government attention and support—users deploy AI algorithms to analyse and identify potentially fraudulent economic activities, thereby strengthening supervisory technology (suptech) and regulatory technology (regtech) efforts.

Local industry associations and civil-society organisations (CSOs), such as the Indonesian E-commerce Association (idEA) and Institute for Policy Research and Advocacy (ELSAM), are urging the government to introduce rules that ensure AI's innovative and safe development. For example, idEA has publicly called on the government to put forward AI regulations. idEA, a leading technology business association and strong advocate for a fair and innovative digital-business environment, is rebranding as a digital-economy association to broaden its scope and impact in line with its growing influence.

Meanwhile, ELSAM, a leading civil-society organisation working on democracy and civil-society empowerment in Indonesia, remains a prominent voice promoting the responsible use of artificial intelligence (AI). Its primary concerns involve AI-related violations of human rights. Accordingly, ELSAM has pushed for human-centred approaches to AI governance, prioritising human rights, inclusivity, and data protection when developing AI models. The organisation has also advocated extensively for the need to keep large language models in check.

Indonesians tend to trust the private sector more than the government when dealing with AI-related technologies. In a 2022 Jakpat survey on data privacy, 52.9 percent of respondents stated that they trusted private companies with their personal data, whereas only 37.2 percent trusted the government to do the same (Tirto-Jakpat, 2022). Additionally, a series of mass hacking incidents has heightened public concern about the cybersecurity risks of adopting new technologies, including AI. For example, a major hacking event in June 2024 disrupted national data centres for more than a week.

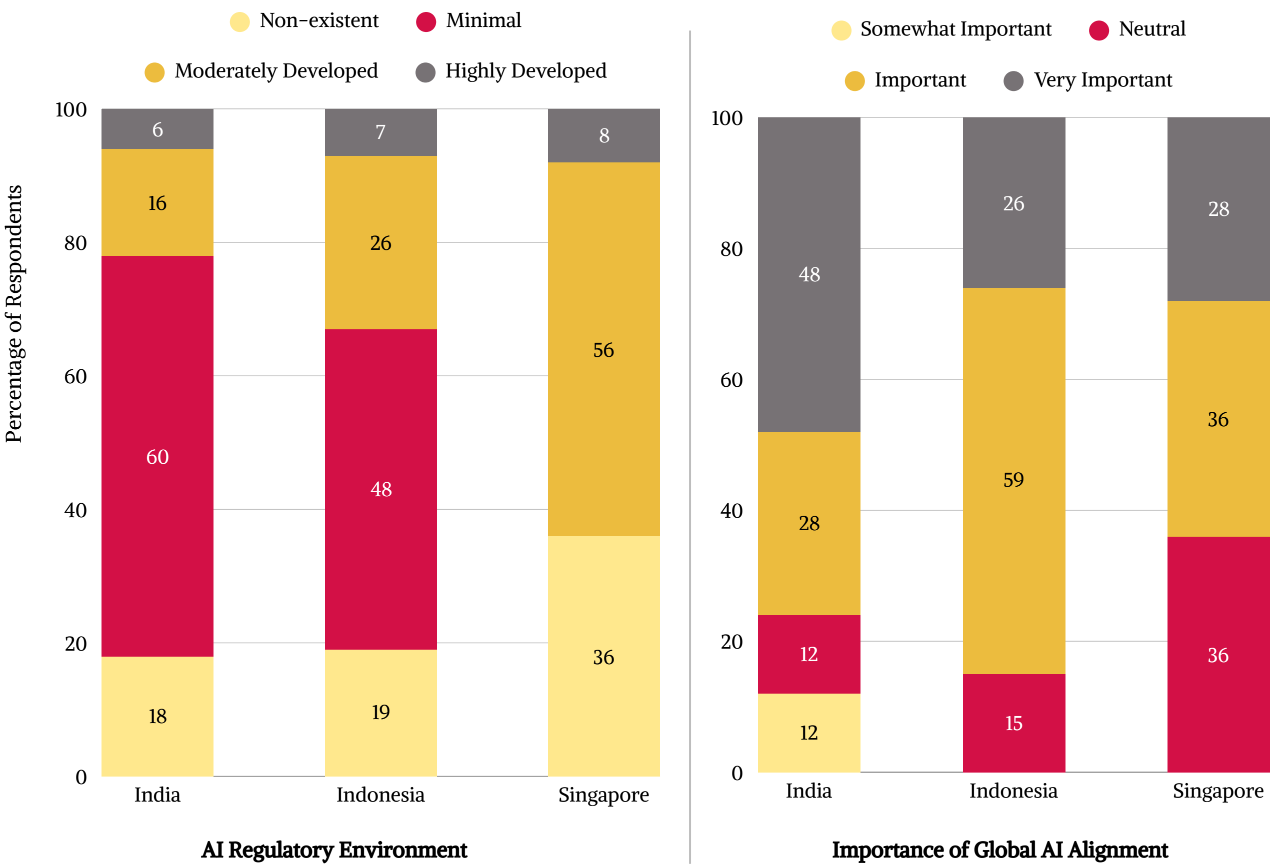
3.4. Expert Survey Results on Regulatory Environment on AI

Figure 3 presents the results of expert assessments of the regulatory environments in India, Indonesia, and Singapore. It suggests that all three countries are characterised by minimally to moderately developed regulatory systems, consistent with the literature's depiction of regulatory lag in emerging contexts. Despite these constraints, a majority of experts across the three countries view global AI alignment as important or very important. India demonstrates the strongest interest in international cooperation, even though its domestic framework remains nascent – reflecting a strategic awareness of AI's global externalities.

Indonesia also supports global alignment, albeit with slightly less urgency, likely reflecting competing developmental priorities and institutional limitations. In contrast, Singapore appears relatively less focused on global coordination, a stance that may be attributed to the maturity and coherence of its national AI policy framework – echoing literature that links institutional confidence with reduced dependence on international norms.

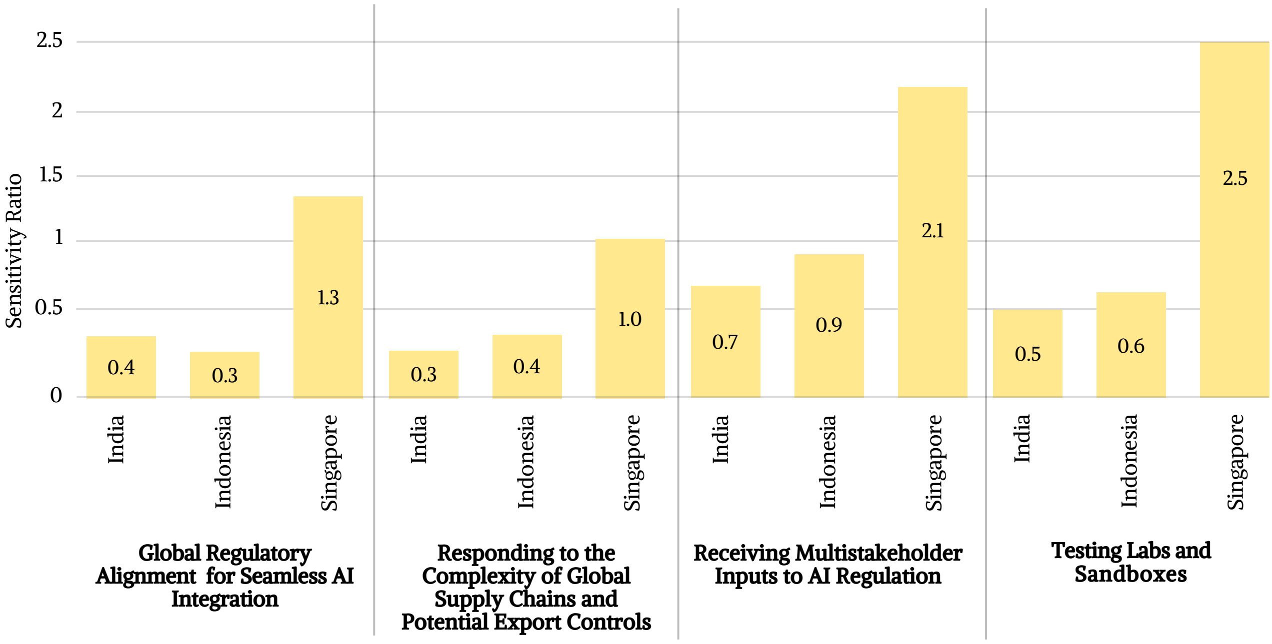
Figure 4 presents sensitivity ratios across four key domains of government readiness for AI: global regulatory alignment, responsiveness to export controls and supply-chain complexity, multistakeholder inputs to regulation, and testing infrastructure such as sandboxes and labs. It suggests that Singaporean stakeholders consider their country significantly more responsive and internationally oriented across all four dimensions. In particular, the country scores highest in testing labs and sandboxes (2.5), indicating strong institutional capacity to balance innovation with oversight through pilot-based governance approaches (Allhutter et al., 2020; IMDA, 2020). Singapore also leads in multistakeholder inputs (2.1)—an approach that the literature has linked to more adaptive and accountable regulation (Gasser and Almeida, 2017; Crootof et al., 2022). Its relatively high scores in global regulatory alignment (1.3) and export controls (1.0)—albeit proximate to "neutral" readiness—reflect a modest awareness of the importance of cross-border harmonisation and geopolitical considerations in AI development (Cath, 2018; World Economic Forum, 2021).

Figure 3: AI Regulatory Environment and Global Alignment



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of AI regulatory environment and importance of global AI alignment using a five-point Likert scale. For the former, ratings ranged from "non-existent" to "extremely developed," while for the latter, they ranged from "not important" to "very important."

Figure 4: Government Readiness for AI Integration and Development



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of government readiness across four dimensions using a five-point Likert scale, ranging from "least ready" to "extremely ready." These ordinal responses were converted into sensitivity ratios following the methodology outlined in Section 2.

By contrast, India and Indonesia display lower sensitivity across all four areas, with sensitivity ratios consistently below one. This suggests expert perceptions of more limited institutional responsiveness or prioritisation of these domains. In particular, both countries score low in export controls and supply chains (0.3–0.4), potentially reflecting a domestic-first development orientation that may overlook strategic vulnerabilities in global AI trade dynamics (Stix, 2021). Modestly higher ratios for multistakeholder inputs—0.7 in India and 0.9 in Indonesia—indicate that inclusive governance practices are emerging, though not yet fully institutionalised. The relatively low sensitivity for testing labs and sandboxes (0.5–0.6) in both countries points to underdeveloped infrastructure for safe and iterative AI deployment, a gap also highlighted in recent policy literature (Binns et al., 2018).

Together, Figures 3 and 4 illustrate that, while India and Indonesia remain in foundational phases of AI governance—focused on domestic capacity—Singapore's policy posture is more internationally integrated and operationally mature. These findings reinforce existing literature's distinction between developing and advanced digital economies in terms of regulatory agility, institutional experimentation, and strategic alignment with global governance trends (Kitchin, 2014).

4

ECONOMIC IMPACT OF AI AND PREFERENCE FOR REGULATORY SCENARIO

SUMMARY

Dimension	No Regulation	Self-Certification	Licensing
Growth (Literature)	High short-term growth; 1.5–2× faster than under regulation, but risk of systemic instability (5–10% GDP loss during crises).	90% of innovation levels retained; 30% lower systemic risk; balanced trade-off between innovation and oversight.	Growth reduction of up to 15% initially; long-term stability through safety and reliability, especially in high-risk sectors.
Labour Quantity (Literature)	Significant risk of displacement (up to 47% of jobs); lower-income groups may lose 20–30% income.	25% reduction in job loss; firms increase upskilling by 15% compared to unregulated environments.	Reduces displacement but also limits job creation (by 15–25%); slows hiring among smaller firms.
Labour Quality (Literature)	Limited improvements; focus remains on automation rather than skills.	Encourages training investments and human-AI complementarity.	15–20% higher investment in training due to compliance needs.
ICT Capital (Literature)	Prioritised heavily (ICT exceeds 60% of capex); neglect of other infrastructure.	Maintains ICT investment at ~90% of unregulated levels.	Slower due to compliance costs (10–15% drop in short term); encourages thoughtful, integrated planning.
Non-ICT Capital (Literature)	Declines up to 20%; imbalance in capital development.	Increases 15–20% over unregulated scenario due to strategic AI integration.	Encourages deliberate alignment with capital infrastructure but initial capex slows down.
Total Factor Productivity (Literature)	Initial gains up to 20% but drop 10% in long-term due to ethical and quality-related risks.	Maintains 90–95% of productivity gains; reduces operational inefficiencies by 25%.	Short-term slowdown (~10–15%); long-term stability and ethical safeguards ensure sustainable improvements.
Cost Efficiency (Literature)	Cost reductions up to 30%, but high risk of externalities (e.g., labour, environment).	Sustains 20–25% efficiency gains; aligns with ethical and responsible deployment.	Initial costs increase by 10–15%, but long-term risk-related savings (20–30%) support sustainability.
Innovation (Literature)	Highest (20–30% higher than under regulation); but risks ethical lapses, bias, and loss of trust.	Retains ~90% innovation; reduces ethical lapses by 25%; supports public trust.	Reduces innovation output by 10–15% in short term; ensures high safety, especially for critical applications.

Dimension	No Regulation	Self-Certification	Licensing
Consumer Prices (Literature)	Sharp price reductions (20–30%) but risk of quality and safety compromise.	Up to 15% price decline; balances affordability with quality assurance.	Prices may increase by 10–20%; justified by consumer safety, reliability, and long-term trust.
Expert Perception of Cost Allocation	Higher allocation to profits and price reduction; less on innovation or reskilling.	Balanced allocation to innovation (India: 17%, Singapore: 37%) and retained earnings (India: 33%, Singapore: 23%).	Costlier implementation, but supports long-term resilience; innovation benefits more visible in high-stakes sectors like health and finance.
Expert Perception of Regulatory Preference	Indonesia: No regulation > Self-certification > Licensing	India: Self-certification > No regulation > Licensing	Singapore: Self-certification > No regulation > Licensing (except for certain infrastructure domains where licensing is preferred).

AI has the potential to reshape economies fundamentally by transforming key productive factors—labour, capital, and total factor productivity—and by enabling new pathways for value creation. The integration of AI with ICT capital is widely viewed as a critical enabler of economic growth, particularly in countries with robust digital infrastructure that supports large-scale data processing and intelligent automation (Brynjolfsson and McAfee, 2014; OECD, 2023). By contrast, non-ICT capital offers more limited opportunities for AI-driven transformation, owing to its lower adaptability and diminishing marginal returns (Acemoglu and Restrepo, 2019). Empirical studies have linked AI adoption to improvements in total factor productivity, especially through enhanced operational efficiency, automation, and data-informed decision-making (Agrawal et al., 2019).

The impact of AI on labour is more nuanced. While concerns about job displacement are widespread—particularly in routine and low-skill occupations—there is also optimism about AI's potential to improve labour quality through upskilling, educational alignment, and greater complementarity between human and machine intelligence (Frank et al., 2019; Chiacchio et al., 2018). Thus, the net economic effect of AI hinges not only on technological deployment but also on the regulatory and institutional ecosystems in which it is embedded.

AI also contributes to value creation primarily through cost efficiencies. However, these gains tend to accrue incrementally rather than through rapid or disruptive transformation (Brynjolfsson and McAfee, 2017; Agrawal et al., 2018). While some high-impact applications may deliver significant returns in isolated sectors, broader economic benefits usually unfold gradually—through steady improvements in productivity, process optimisation, and resource allocation.

How organisations allocate the cost savings enabled by AI is a crucial determinant of whether the technology promotes inclusive growth or exacerbates inequality. Evidence suggests that firms frequently prioritise internal reinvestment—such as product innovation, capability development, and capital formation—over immediate distributional outcomes, including wage increases or reductions in consumer prices (Brynjolfsson and McElheran, 2016; Bughin et al., 2018). Retained earnings may also serve as a strategic buffer during periods of technological uncertainty or evolving regulation (Autor et al., 2022). However, without adequate policy safeguards, such reinvestment-heavy approaches risk reinforcing inequality, especially if the gains from AI are not broadly shared (Korinek and Stiglitz, 2021).

The economic impact of AI is likewise shaped by the regulatory environment, particularly in three scenarios: no regulation, self-certification, and licensing. These frameworks influence not only the pace and direction of innovation, but also the distribution of associated costs and benefits across sectors and societal groups.

Self-certification offers firms regulatory flexibility and lower transaction costs, making it especially attractive in settings with mature institutions and well-established compliance cultures. It supports innovation, accelerates time-to-market, and reduces administrative burdens, provided that appropriate governance safeguards—such as testing infrastructure and clear accountability mechanisms—are in place (Black, 2008; Baldwin et al., 2012; Lodge and Wegrich, 2012). In well-functioning institutional contexts, decentralised regulatory models can alleviate pressure on regulators and incentivise proactive industry engagement (Glaeser and Shleifer, 2003). However, in countries with limited regulatory capacity, self-certification may lead to increased operational risks, compliance ambiguity, and inconsistent enforcement (Ghosh, 2021; Korinek and Stiglitz, 2021).

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Against this backdrop, the following section explores how these regulatory models shape AI's macro- and microeconomic outcomes. It assesses how each scenario influences growth dynamics, cost-efficiency, innovation, and labour-market transitions—both within firms and across economies.

4.1 Existing Evidence on the Macroeconomic Impacts of AI and Its Regulation

Growth: An unregulated environment facilitates the rapid integration of AI, potentially accelerating economic growth through swift adoption and the absence of compliance costs. This scenario allows firms to focus entirely on innovation and market expansion, often resulting in short-term growth rates 1.5 to 2 times higher than those in regulated environments (Brynjolfsson et al., 2018). However, a lack of oversight can lead to societal risks, such as data misuse, bias amplification, and reduced public trust in AI systems. For example, studies show that unregulated AI deployments increase the risk of systemic instability, with potential economic losses estimated at 5-10 percent of GDP during crises caused by poorly governed AI advancements (Veale and Brass, 2019; Chen et al., 2021).

Self-certification of products and services offers a pragmatic middle ground between innovation and accountability, allowing industries to devise and follow their own compliance mechanisms. This approach encourages sustainable growth by fostering industry standards while avoiding the high costs associated with stringent external oversight. Empirical evidence suggests that well-designed self-certification frameworks can sustain innovation at approximately 90 percent of the level observed in unregulated settings, while simultaneously reducing systemic risks by about 30 percent (Blind, 2012; Hahn and Tetlock, 2008). However, the effectiveness of this model depends on each industry's commitment to ethical AI practices; inconsistently enforced standards can quickly erode its efficacy.

Licensing is the most stringent regulatory approach; it requires firms to meet comprehensive external standards before deploying AI technologies. Although compliance costs may reduce short-term growth by as much as 15 percent (Floridi et al., 2018), licensing ensures safety, reliability, and public trust, particularly in high-stakes sectors such as healthcare and autonomous vehicles. For instance, in the pharmaceutical industry, licensing frameworks have yielded long-term benefits, including a 40 percent reduction in safety-related incidents (Cockburn and Henderson, 2001). By prioritising trust and reliability, licensing promotes economic stability, albeit at the expense of immediate innovation and growth.

Labour Quantity and Quality: Rapid AI adoption in an unregulated environment can lead to significant labour displacement, as automation replaces human tasks without sufficient reskilling initiatives. Estimates suggest that up to 47 percent of jobs in advanced economies are at risk of automation in the coming decades, disproportionately affecting low-skill and routine occupations (Acemoglu and Restrepo, 2020; IMF, 2024). This dynamic exacerbates unemployment and income inequality, with lower-income households potentially losing 20–30 percent of their total income due to AI-induced job-market shifts (Chen et al., 2021). An absence of regulatory safeguards further amplifies these challenges, as firms prioritise cost-efficiency over workforce adaptation.

Self-certification provides firms with regulatory flexibility by allowing them to develop and implement internal compliance mechanisms tailored to their specific risk profiles and operational contexts. This autonomy enables faster adoption of AI technologies without the procedural delays often associated with licensing regimes. At the same time, the responsibility placed on firms to self-govern incentivises investment in workforce upskilling and reskilling, which is vital for mitigating labour-displacement effects, as firms seek to avert reputational and operational risks associated with job displacement. Studies show that self-certification frameworks can reduce automation-induced job losses by 25 percent, with participating industries reporting a 15 percent increase in training and upskilling investments compared with unregulated environments (Blind 2012; Veale and Brass 2019). However, the success of self-certification depends heavily on industries' commitment to enforce robust standards for reskilling and worker protection.

Licensing regimes can have mixed effects on labour outcomes. In terms of labour quantity, stringent licensing may slow the pace of automation, thereby reducing the risk of immediate job displacement and preserving existing employment levels—particularly in low- and middle-skill occupations. However, this regulatory burden may also dampen innovation and expansion, especially for smaller firms, and may result in a 15–25 percent reduction in job creation compared with firms operating under more flexible regimes (Zhang and Dafoe, 2020).

On the labour-quality front, licensing often compels firms to hire or upskill specialised staff to meet compliance and audit requirements. Empirical estimates suggest that firms subject to higher regulatory scrutiny are 15–20 percent more likely to invest in AI-related training, and workforce-development initiatives (Frank et al., 2019).

ICT and Non-ICT Capital Services: In an unregulated environment, firms tend to prioritise rapid investment in ICT to maximise AI capabilities. This focus often comes at the expense of non-ICT capital—such as physical infrastructure and traditional machinery—leading to imbalanced capital development. Empirical studies indicate that, in unregulated scenarios, ICT investment as a share of total capital expenditure can exceed 60 percent, whereas non-ICT capital investment may decline by up to 20 percent over the same period (Chen et al., 2021; Popp, 2002). This imbalance creates vulnerabilities in sectors that rely on non-ICT capital, thereby reducing overall productivity and economic resilience.

Self-certification enables context-specific integration, allowing firms to optimise AI adoption across both ICT capital—such as cloud infrastructure and data systems—and non-ICT capital, including manufacturing equipment and logistics networks. By fostering responsible AI adoption through industry standards, the framework ensures that technological advancements align with existing infrastructure. Research suggests that self-certification can increase non-ICT capital investment by 15–20 percent compared with unregulated environments, while maintaining ICT growth rates at approximately 90 percent of their unregulated potential (Blind 2012; Floridi et al. 2018). This balance supports sustainable capital development, enhancing the overall productivity of firms without disproportionately favouring ICT assets.

Licensing—the most stringent regulatory framework—may initially slow ICT and non-ICT investments because of compliance hurdles and higher operational costs. Firms operating under licensing frameworks report a 10–15 percent reduction in capital expenditure during the early stages of implementation (Cockburn and Henderson, 2001; Popp, 2002). However, by requiring firms to meet predefined regulatory standards, the licensing process may foster a more deliberate and strategic integration of AI technologies within existing capital infrastructure. Before deployment, firms are compelled to assess compatibility, long-term impacts, and compliance risks, thereby creating a more coherent alignment between AI systems and both ICT and non-ICT assets.

TFP: In an unregulated environment, TFP often experiences a rapid initial rise owing to the swift adoption of AI technologies. Firms leveraging AI without compliance burdens can achieve productivity gains of up to 20 percent in the short term (Brynjolfsson et al., 2018). However, the absence of oversight introduces risks to the quality and sustainability of these gains. Without frameworks to mitigate issues such as bias, interoperability, and ethical lapses, long-term productivity can suffer. Studies indicate that unregulated AI adoption may lead to inefficiencies, reducing long-term TFP growth by up to 10 percent, as firms face reputational damage, interoperability failures, and increased operational risks (Chen et al., 2021).

Self-certification fosters continuous productivity improvements within a framework of industry standards. This model allows firms to innovate while adhering to ethical guidelines and operational norms. Empirical evidence shows that self-certification frameworks maintain TFP growth at approximately 90-95 percent of the rate observed in unregulated environments while reducing systemic risks and operational inefficiencies by 25 percent (Blind, 2012; Hahn and Tetlock, 2008). This approach ensures that AI applications remain effective and ethical, providing sustainable productivity improvements aligned with market and societal expectations.

Licensing often results in an initial slowdown in productivity, as resources are diverted to meeting compliance standards. Firms operating under licensing frameworks report a 10-15 percent reduction in TFP growth during the early stages of regulatory adoption (Cockburn and Henderson, 2001). However, the emphasis on safety, reliability, and ethical compliance may foster long-term stability and sustainable productivity enhancements (Veale and Brass, 2019).

4.2 Existing Evidence on the Microeconomic Impacts of AI and Its Regulation

Prices (Consumption Side): In an unregulated environment, AI-driven efficiencies often result in significantly lower consumer prices, as firms capitalise on cost reductions achieved through automation and optimised processes. Studies suggest that prices for AI-enhanced services can decline by as much as 20-30 percent in such scenarios (Brynjolfsson et al., 2018). However, the lack of quality control poses substantial risks to consumer welfare. Without oversight, firms may prioritise cost-cutting over product integrity, leading to subpar products or services that fail to meet safety or ethical standards. For example, unregulated AI algorithms deployed on consumer platforms have been linked to bias, inaccuracies, and privacy violations, undermining trust and long-term consumer satisfaction (Blind, 2012).

Self-certification provides a balanced framework, promoting cost reductions alongside quality assurance. By adhering to industry standards, firms can ensure that their AI-enabled products and services maintain high quality while passing efficiency savings on to consumers. Research indicates that self-certification can reduce consumer prices by up to 15 percent, while maintaining trust and product reliability (Hahn and Tetlock, 2008). Moreover, this approach fosters transparency and accountability, as firms voluntarily commit to ethical and operational benchmarks. The effectiveness of self-certification, however, depends on the robustness of the industry standards and their enforcement.

Licensing often increases compliance costs, which may be passed on to consumers in the form of higher prices. Studies show that consumer prices can rise by 10-20 percent under licensing frameworks, especially in sectors with complex regulatory requirements (Floridi et al., 2018). However, this price premium is frequently justified by the assurance of quality, safety, and reliability. Licensing minimises risks associated with AI technologies, such as algorithmic errors or security breaches, thereby fostering consumer confidence and long-term market stability (Veale and Brass, 2019). While initial costs are higher, the benefits of robust oversight often outweigh the drawbacks in critical applications such as healthcare and autonomous systems.

Innovation (Production Side): In an unregulated environment, AI innovation is rapid and often disruptive because firms are free to experiment without constraints or compliance costs. This freedom fosters high levels of creativity and technological advancement, with studies indicating that firms in unregulated settings can achieve innovation growth rates 20–30 percent higher than those operating under strict regulations (Brynjolfsson et al., 2018). However, this approach is not without risks. The absence of oversight frequently leads to ethical dilemmas and societal risks, such as biased algorithms, privacy breaches, and unequal access to technology. These issues can erode public trust, potentially offsetting the benefits of rapid innovation in the long-term (Chen et al., 2021).

Self-certification offers a middle ground, encouraging responsible innovation within a framework of industry standards. This approach enables firms to maintain high levels of creativity while ensuring that their advancements align with ethical and societal expectations. Research shows that self-certification frameworks sustain innovation at approximately 90 percent of the level observed in unregulated scenarios, while reducing the incidence of ethical violations by 25 percent (Blind, 2012; Popp, 2002). By fostering trust and accountability, self-certification also enhances consumer confidence, which is critical for the adoption of AI technologies.

Licensing often slows the pace of innovation. Firms operating under licensing frameworks report a 10–15 percent reduction in innovation output during the initial phases of compliance implementation (Cockburn and Henderson, 2001). However, this approach ensures that new technologies meet rigorous safety and ethical standards, leading to more socially acceptable and sustainable innovations. Licensing reduces the likelihood of negative externalities, such as harm caused by faulty AI applications, making it particularly valuable in high-stakes sectors like healthcare and finance (Veale and Brass, 2019). While the pace of innovation may be tempered, the emphasis on quality and safety ensures long-term benefits for both society and the market.

Cost Efficiency (Production Side): In an unregulated environment, firms can achieve high levels of cost efficiency by fully integrating AI technologies without compliance constraints. Estimates suggest that unregulated firms may reduce operational costs by up to 30 percent, driven by automation, streamlined processes, and reduced administrative burdens (Brynjolfsson et al., 2018). However, this pursuit of efficiency often entails significant externalities. Common risks in unregulated scenarios include environmental impacts, such as increased energy consumption from AI-driven systems, and labour exploitation, including workforce displacement and inadequate protections (Popp, 2002). These externalities can erode societal trust and lead to long-term economic and reputational costs, offsetting the initial gains in efficiency.

Self-certification provides a balanced approach, enabling firms to maintain cost efficiency while adhering to industry standards that promote ethical practices and social responsibility. Research indicates that firms operating under self-certification frameworks sustain cost reductions of 20–25 percent, comparable to unregulated environments, while mitigating externalities such as environmental degradation and poor labour conditions (Floridi et al., 2018). Additionally, self-certification fosters transparency and accountability, which enhance consumer trust and long-term profitability. By voluntarily committing to industry standards, firms can balance profitability with the broader societal expectations of ethical AI deployment (Veale and Brass, 2019).

Licensing, characterised by stringent compliance requirements, often increases operational costs in the short term. Firms operating under licensing frameworks report a 10–15 percent rise in costs due to documentation, audits, and regulatory approvals (Cockburn and Henderson, 2001). However, these upfront costs can lead to long-term savings by reducing risks associated with system failures, legal liabilities, and reputational damage. For instance, licensing frameworks within high-stakes industries have reduced risk-related expenses by 20–30 percent over time, ensuring sustainable business practices and operational resilience (Hahn and Tetlock, 2008). While short-term cost efficiency may be compromised, licensing prioritises sustainability and societal trust, making it an essential framework for critical AI applications.

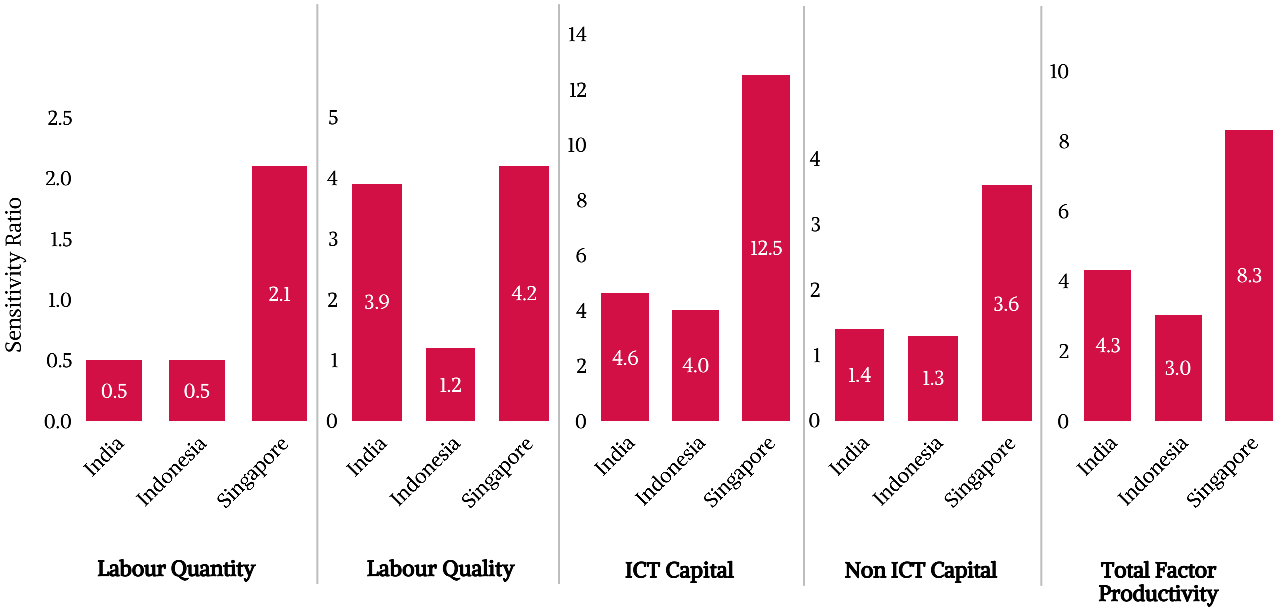
4.3 Expert Survey Results on Economic Impact of AI Regulation Scenarios

This section presents expert survey results on the economic impact of different regulatory scenarios in India, Singapore, and Indonesia.

When asked about AI's effect on productive factors (Figure 5), experts identified AI integration with ICT capital as a key growth driver, with particularly high confidence in Singapore (sentiment ratio 12.5), followed by India (4.6) and Indonesia (4.0). These differences reflect variation in digital readiness and institutional capacity to leverage ICT for AI-led transformation. Conversely, non-ICT capital is viewed as a less significant growth channel, with low sentiment ratios across all three countries—India (1.4), Indonesia (1.3), and even Singapore (3.6).

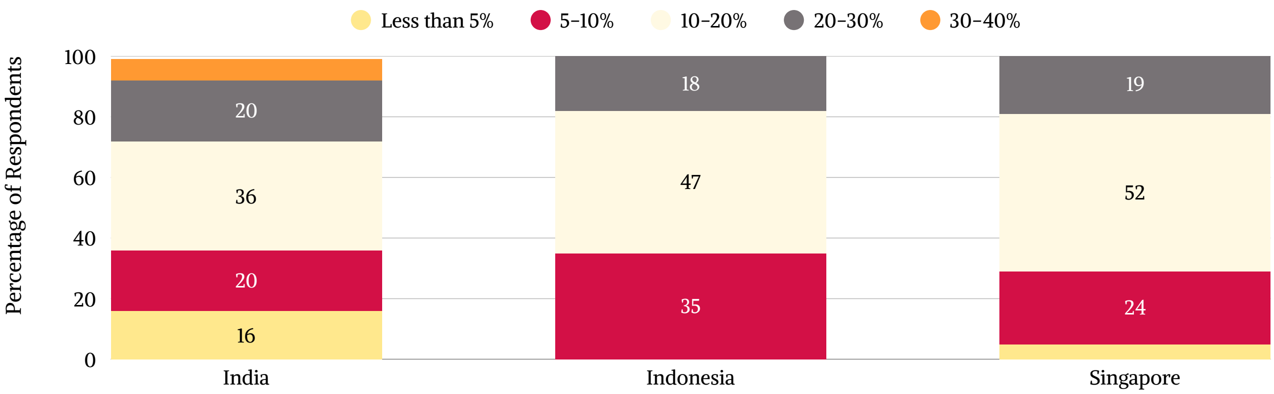
There is widespread belief in AI's potential to enhance total factor productivity, especially in Singapore (8.3) and India (4.3), consistent with the literature. Experts also express confidence in AI's positive effects on labour quality, underscoring the importance of education and skills as complements to AI adoption. However, concerns persist about its effect on labour quantity, particularly in India (0.5) and Indonesia (0.5), echoing global anxieties about workforce displacement.

Figure 5: Impact of AI on Factors of Production



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the impact of AI across five dimensions using a five-point Likert scale, ranging from "extremely" to "extremely positive." These ordinal responses were converted into sensitivity ratios following the methodology outlined in Section 2.

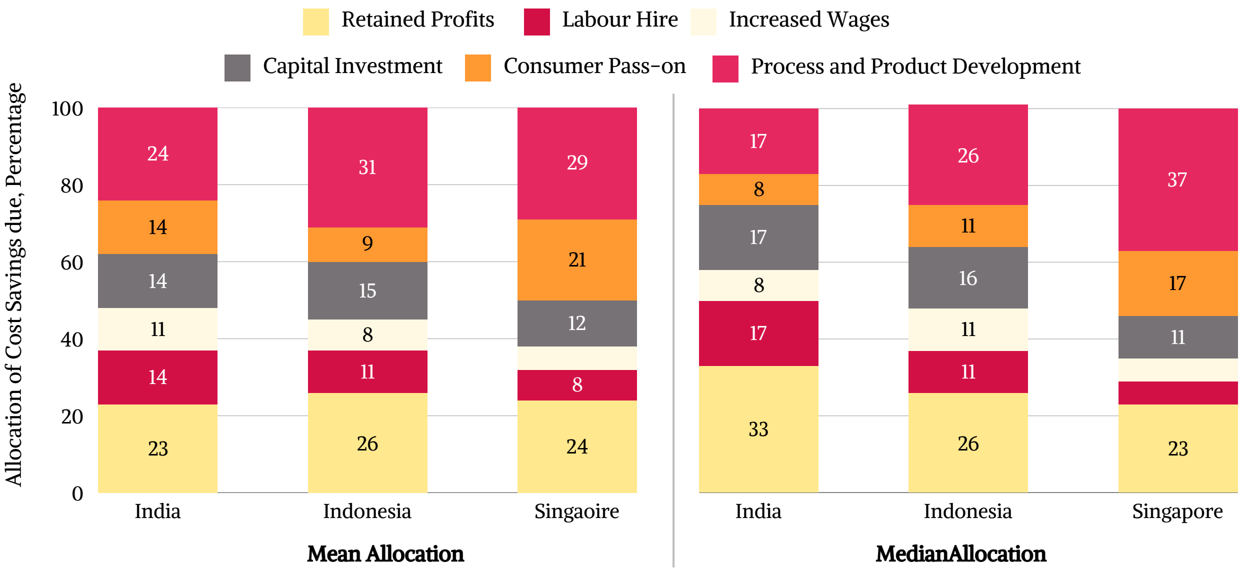
Figure 6: Impact of AI in Reducing the Cost of Production



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the impact of AI on reducing production cost in a five-percentage point range.

Figure 6 presents findings on experts' perceptions of AI's potential to reduce production costs. The most common expectation across all three countries is a reduction of 10–20 percent, reported by 36 percent of respondents in India, 47 percent in Indonesia, and 52 percent in Singapore. India also shows a larger share of experts (27 percent) who expect greater savings of 20–40 percent, indicating a stronger belief in AI's transformative potential. An even smaller subgroup (seven percent) in India anticipates savings of 30–40 percent, suggesting that expectations of dramatic cost reductions remain uncommon. Overall, the distribution points to a measured and realistic outlook, consistent with the literature's emphasis on incremental gains driven by operational efficiency, and enhanced data use.

Figure 7: Allocation of Cost Savings due to AI



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to state their perception of how firms may allocate a cost savings of $100 due to AI deployment across six parameters.

Figure 7 presents results regarding how experts believe cost savings from AI will be allocated. It suggests a clear prioritisation of innovation and capability development, with Singapore allocating the highest median share (37 percent), followed by Indonesia (26 percent), and India (17 percent). This supports the idea that firms view AI not only as a cost-saving tool but also as a strategic lever for product and process enhancement. Retained profits receive significant allocations—33 percent in India, 26 percent in Indonesia, and 23 percent in Singapore—indicating their role as a mechanism for financial resilience. Capital investment is particularly prominent: median allocations reach 17 percent in India and 16 percent in Indonesia, both higher than Singapore (11 percent). This pattern reinforces India's emphasis on scaling and modernising its production base.

Allocations toward labour-related outcomes (such as labour hire and wage increases) and consumer pass-through remain modest in comparison. However, Singapore stands out with a relatively high allocation to consumer benefits (17 percent), while labour-related allocations are slightly higher in both India and Indonesia (22–25 percent). These patterns suggest that countries at earlier stages of industrial AI adoption may prioritise foundational capabilities over direct distributive gains. Nonetheless, the relatively lower emphasis on labour- and consumer-related allocations lends weight to concerns raised in the literature about the risk of widening inequalities if policy frameworks do not explicitly support inclusive outcomes (Korinek and Stiglitz, 2021).

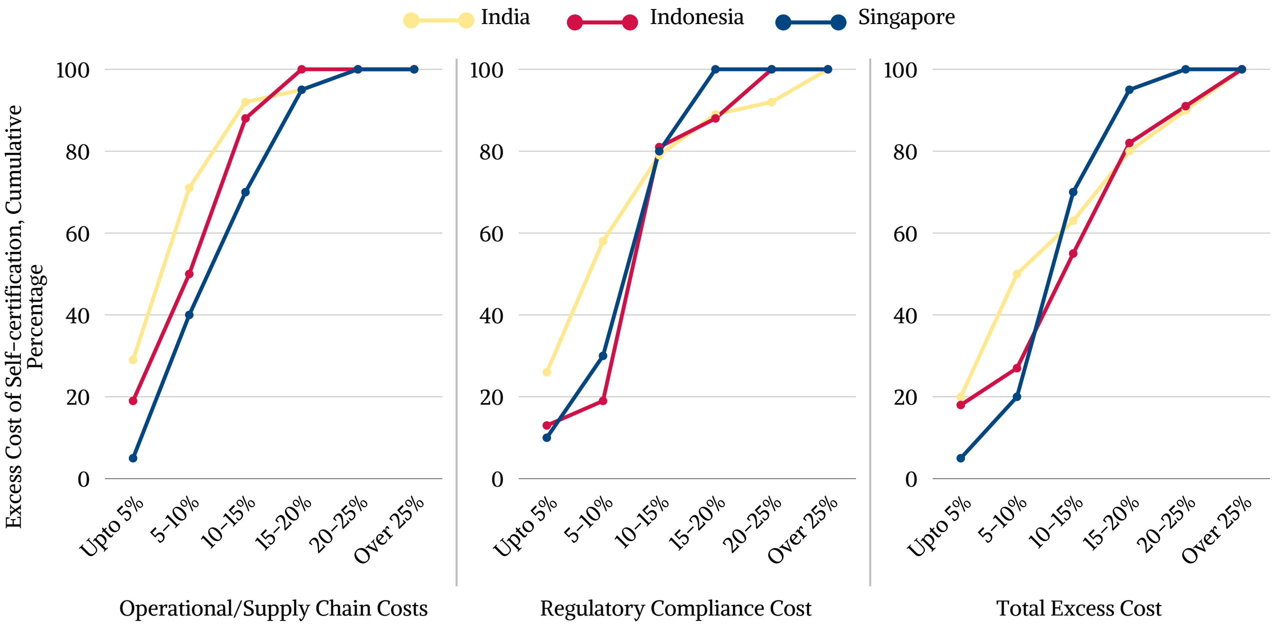
4.4 Expert Survey Results on Preference for Regulatory Scenarios

4.4.1 Preference for Self-Certification, Relative to No Regulation

We asked experts to assess the excess costs and cost avoidance associated with self-certification, relative to a no-regulation baseline. Three dimensions of excess cost were considered: operational and supply-chain costs, regulatory-compliance costs, and total excess cost. Cost avoidance captures reductions in the expenses required to ensure user trust and safety, ease the burden on state institutions (for example, regulators and courts), and facilitate ethical AI deployment.

Figure 8 presents the excess-cost results. The cumulative distributions indicate that Singapore is perceived as bearing the highest operational and supply-chain burden, with 60 percent of experts expecting these costs to exceed 10 percent, compared with 50 percent in Indonesia, and just 29 percent in India. For regulatory-compliance costs, Indonesia is viewed most negatively: 81 percent of experts expect compliance costs above 10 percent, versus 70 percent in Singapore, and 42 percent in India.

Figure 8: Excess Cost of Self-Certification



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the excess cost of self-certification on three parameters, on a progressive five-percentage point range.

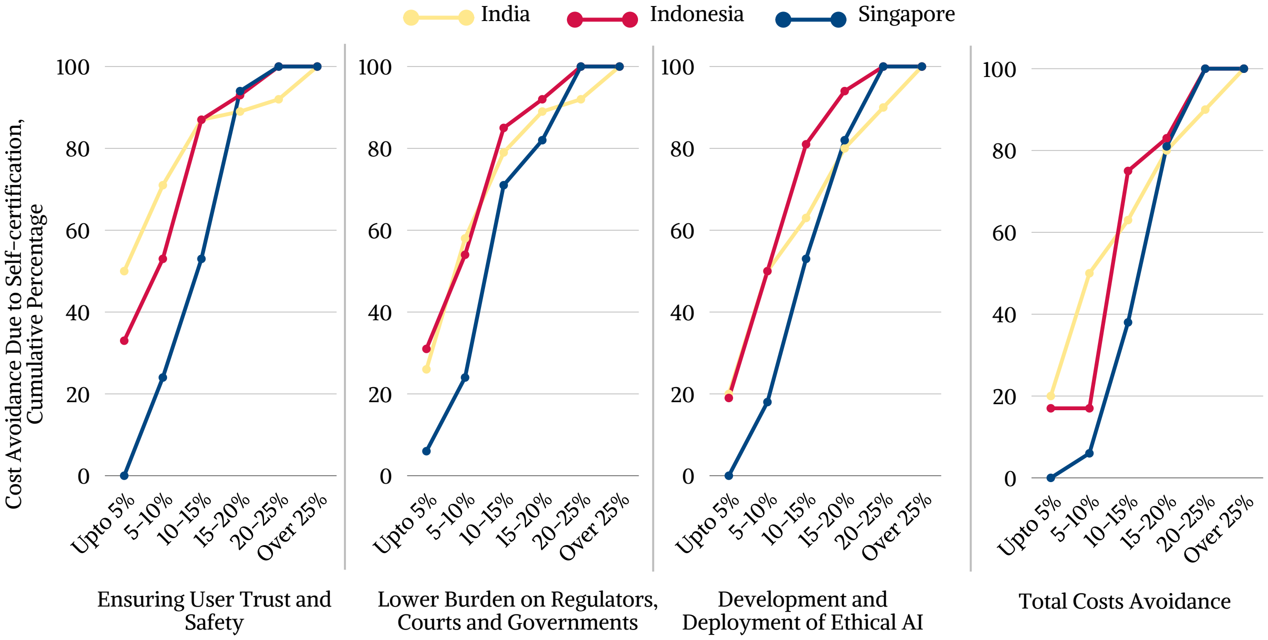
When considering the overall picture of total excess cost, expert assessments show that the median expert in India estimates an impact of between five and 10 percent, whereas Indonesia and Singapore register higher medians of 10-15 percent. This pattern is corroborated by the area-under-the-curve (AUC) values, which are used to assess second-order stochastic dominance (Table 1). The results suggest that India is perceived to have the most favourable cost profile under self-certification, followed by Singapore, while Indonesia bears the greatest burden.

Table 1: Excess Cost under Self-certification, AUC

Parameters	Area Under Curve			Inference
	India	Indonesia	Singapore	
Operational/supply chain cost	1908	1823	1642	Singapore most regressive costs; India least
Regulatory compliance cost	1763	1500	1650	Indonesia most regressive costs; India least
Total excess cost	1578	1409	1508	Indonesia most regressive costs; India least

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

Figure 9: Cost Avoidance Due to Self-Certification



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the cost avoidance/savings due to self-certification on four parameters, on a progressive five-percentage point range.

Figure 9 presents the results on cost avoidance. Singapore leads across all dimensions: 47 percent of its experts expect cost savings above 15 percent in both trust-and-safety and ethical-AI deployment, and 29 percent anticipate similar benefits from reduced institutional burden. By contrast, only 13 percent of Indian and Indonesian experts expect savings above 15 percent in trust-and-safety.

For total cost avoidance, the median expert in India anticipates savings in the 5–10 percent range, whereas both Singapore and Indonesia expect 10–15 percent. These patterns are mirrored in the AUC values (Table 2). Singapore is perceived as gaining the most in cost avoidance under self-certification, followed by Indonesia and India.

Table 2: Cost Avoidance under Self-Certification, AUC

Parameters	Area Under Curve			Inference
	India	Indonesia	Singapore	
Ensuring user trust and safety	1917	1822	1461	Cost avoidance highest for Singapore; India least
Reduced burden on regulators, courts and governments	1530	1808	1451	Cost avoidance highest for Singapore; Indonesia least
Development and deployment of ethical AI	1610	1760	1343	Cost avoidance highest for Singapore; Indonesia least
Total cost avoidance	1542	1444	1208	Cost avoidance highest for Singapore; India least

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

Table 3 synthesises these insights by comparing total excess cost with total cost avoidance to determine the net regulatory impact. The results suggest that India and Singapore record net gains under self-certification. In contrast, Indonesia incurs a small net loss, as cost avoidance does not fully offset the higher perceived burden of self-certification.

Table 3: Cost-Benefit under Self-Certification, AUC

Parameters	Area Under Curve		
	India	Indonesia	Singapore
Total excess cost	1578	1409	1508
Total cost avoidance	1542	1444	1208
Inference, Preference	Benefits dominate costs;Self-certification > No regulation	Costs dominate benefits; No regulation > Self-certification	Benefits dominate costs; Self-certification > No regulation

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

This finding reflects broader regulatory theory. In institutional environments with stronger governance frameworks—such as Singapore—self-regulation can function as a flexible, cost-effective mechanism, offering advantages in innovation and trust-building without heavy compliance costs (Black, 2008; Baldwin et al., 2012). In India, the preference for self-certification may reflect optimism about digital infrastructure, and a desire for lighter-touch regulation as AI policy evolves (Narula, 2022). Conversely, in Indonesia, the perceived burden of self-certification—combined with lower expectations of trust or compliance benefits—suggests scepticism regarding its effectiveness.

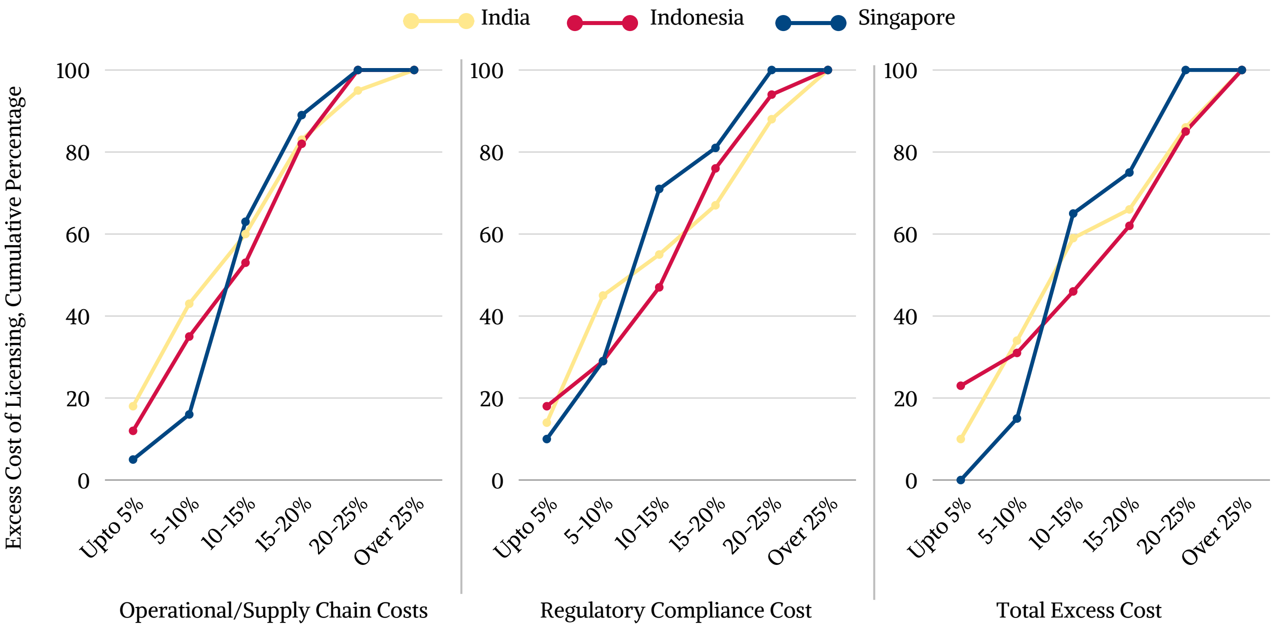
4.4.2 Preference for Licensing, Relative to No Regulation

We asked experts to assess the excess costs and cost avoidance associated with licensing, relative to a no-regulation baseline. Figure 10 presents the results for excess costs. Singapore is perceived to face the most prohibitive operational and supply chain costs, with 84 percent of experts estimating these to exceed 10 percent, followed by Indonesia (65 percent) and India (57 percent). This finding aligns with concerns in the literature about the administrative rigidity, and high overheads, often associated with licensing regimes.

On regulatory compliance costs, Indonesia ranks as the most burdened; 71 percent of experts expect these to exceed 10 percent, compared with 70 percent in Singapore, and 55 percent in India. These figures reflect the additional institutional costs that licensing imposes in settings where procedural clarity and enforcement infrastructure are still evolving.

In terms of total excess cost, perceptions are again most severe in Indonesia, where 15 percent of experts expect costs to exceed 25 percent, compared to 14 percent in India, and none in Singapore. This pattern is reinforced by the AUC scores in Table 4, where Indonesia records the lowest AUC, followed by Singapore and India. These findings underscore that licensing is viewed most unfavourably in Indonesia, while India emerges as the least burdened—though still more costly than no regulation.

Figure 10: Excess Cost of Licensing



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the excess cost of licensing on three parameters, on a progressive five-percentage point range.

Table 4: Excess Cost under Licensing, AUC

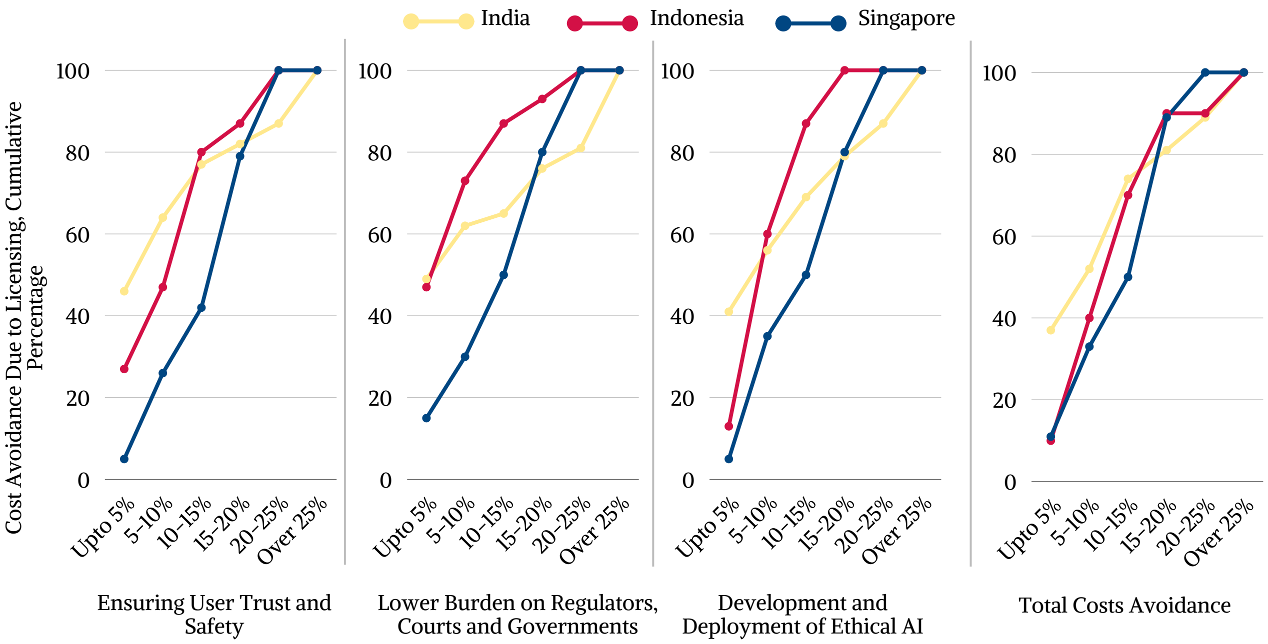
Parameters	Area Under Curve			Inference
	India	Indonesia	Singapore	
Operational/supply chain cost	1546	1480	1421	Singapore most regressive costs; India least
Regulatory compliance cost	1413	1373	1484	Indonesia most regressive costs; Singapore least
Total excess cost	1333	1256	1317	Indonesia most regressive costs; India least

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

Figure 11 presents the results for cost avoidance under licensing. Singapore is consistently seen as the greatest beneficiary across all categories. Notably, 58 percent of its experts believe savings from improved user trust and safety will exceed 15 percent, compared with 23 percent in India and just 20 percent in Indonesia. In terms of reduced burden on regulators and courts, 50 percent of Singaporean experts anticipate savings beyond 15 percent, as opposed to 35 percent in India and 13 percent in Indonesia.

This trend continues with the development of ethical AI, where 50 percent of Singaporean experts expect cost savings over 15 percent, versus 31 percent in India and only 13 percent in Indonesia. These perceptions reflect Singapore's advanced regulatory and ethical frameworks for AI, which may enable more efficient, lower-risk deployment (Floridi et al., 2018).

Figure 11: Cost Avoidance Due to Licensing



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the cost avoidance/savings due to licensing on four parameters, on a progressive five-percentage point range.

Table 5: Cost Avoidance under Licensing, AUC

Parameters	Area Under Curve			Inference
	India	Indonesia	Singapore	
Ensuring user trust and safety	1765	1700	1351	Cost avoidance highest for Singapore; India least
Reduced burden on regulators, courts and governments	1653	1978	1425	Cost avoidance highest for Singapore; Indonesia least
Development and deployment of ethical AI	1662	1878	1442	Cost avoidance highest for Singapore; Indonesia least
Total cost avoidance	1660	1583	1500	Cost avoidance highest for Singapore; India least

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

Finally, for total cost avoidance, Singapore again leads, with 50 percent of experts expecting gains above 15 percent, followed by Indonesia (30 percent), and India (24 percent). This pattern is reinforced by the AUC scores in Table 5, where Singapore records the lowest value, followed by Indonesia, and India. These findings suggest that licensing benefits are viewed as most favourable in Singapore, whereas India fares last.

Table 6: Cost-Benefit under Licensing, AUC

Parameters	Area Under Curve		
	India	Indonesia	Singapore
Total excess cost	1333	1256	1317
Total cost avoidance	1660	1583	1500
Inference, Preference	Costs dominate benefits; No regulation > Licensing	Costs dominate benefits; No regulation > Licensing	Costs dominate benefits; No regulation > Licensing

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

Table 6 synthesises these insights by comparing total excess costs with total cost avoidance under licensing. It reveals that, for all three countries, costs exceed benefits. Although the gap is narrowest in Singapore, the negative net balance across the board points to a clear expert preference for no regulation over licensing.

These results reinforce concerns raised in the literature that traditional licensing regimes may not be proportionate to the governance needs of emerging technologies. The modest perceived benefits—even in high-capacity contexts such as Singapore—suggest that licensing, in its current form, may not justify its administrative and compliance costs. In India and Indonesia in particular, the data indicate doubts over the practicality and cost-efficiency of licensing, given institutional constraints. Overall, the findings support broader calls for risk-based, adaptive regulation that aligns oversight intensity with the degree of risk, technological maturity, and local capacity (Black and Baldwin, 2010; Brownsword and Goodwin, 2012).

4.4.3 Preferences Between No Regulation, Self-Certification and Licensing

The preceding discussion provides a foundation for interpreting expert perceptions of the relative advantages and limitations of no regulation, self-certification, and licensing. Building on these insights, Table 7 synthesises, for India, Indonesia, and Singapore, the total excess costs and total cost avoidance associated with self-certification and licensing regimes, relative to no regulation. This comparative analysis delineates the ordering of regulatory preferences within each country and highlights where lighter or more structured approaches are considered most conducive.

Clear country-level preferences emerge. In India, experts perceive self-certification as offering the most favourable trade-off, followed by no regulation, with licensing seen as the most regressive in terms of excess costs relative to benefits. This perception reflects the country's growing institutional interest in regulatory frameworks that support innovation while containing compliance burdens (Mehta and Kapoor, 2023).

In contrast, experts in Indonesia express a stronger preference for no regulation, rank self-certification second, and place licensing last. This order likely reflects concerns about regulatory capacity and enforcement challenges, which may diminish the perceived effectiveness of structured regulatory regimes (Kenny et al., 2022). It also aligns with evidence that, in lower-capacity contexts, premature regulatory imposition can hinder innovation without generating proportional social benefits (Acemoglu et al., 2022).

Table 7: Cost-Benefit under Self-Certification and Licensing, AUC

Parameters	**Area Under Curve**		
	India	Indonesia	Singapore
Self-certification			
Total excess cost	1578	1409	1508
Total cost avoidance	1542	1444	1208
Net AUC (Cost-benefit)	36	-35	300
Licensing			
Total excess cost	1333	1256	1317
Total cost avoidance	1660	1583	1500
Net AUC (Cost-benefit)	-327	-327	-183
Net AUC $_{\text{self-certification}}$ – Net AUC $_{\text{licensing}}$	**363**	**292**	**483**
Inference, preference	**Self-certification > No regulation > Licensing**	**No regulation > Self-certification > Licensing**	**Self-certification > No regulation > Licensing**

Notes: Area under curve is derived using the Simpson's Rule to draw interferences on the second-order stochastic dominance, as discussed in Section 2. Second-order stochastic dominance is a non-parametric technique used to compare cumulative distributions without assuming a specific functional form, when the cumulative distribution curves intersect.

Singapore exhibits a preference similar to that of India: self-certification ranks highest, no regulation follows, and licensing is viewed least favourably. This supports findings in the literature that advanced regulatory ecosystems often value flexible, industry-led approaches such as self-certification, which allow for rapid iteration while maintaining public trust (Brynjolfsson and McElheran, 2016; OECD, 2021). Singapore's preference aligns with its strategic focus on maintaining competitiveness through agile governance mechanisms.

REGULATORY SCENARIOS AND ECONOMY-LEVEL TRADE-OFFS

SUMMARY

Dimension	No Regulation	Self-Certification	Licensing
Innovation	Maximised due to zero compliance burden, but risks ethical lapses and fragmentation.	Slight reduction (~0.1–0.42%); promotes trust through voluntary compliance.	Declines more notably (~0.12–0.59%); burdened by formal procedures and delays.
Efficiency	Uncoordinated gains; may lead to duplicated efforts.	Gains in India and Singapore (+0.15%, +0.51%); minor loss in Indonesia (-0.05%).	Mostly negative in India and Indonesia (-0.41%, -0.32%); modest gain in Singapore (+0.36%).
Trust	Low; institutions and consumers may be sceptical of unregulated actors.	Moderate increases across countries (0.44–0.52%) as firms self-declare adherence to norms.	Highest trust-building gains (up to 1.19%) due to robust third-party validation and oversight.
Total Factor Productivity	Strong short-term; volatile long-term due to weak coordination.	Balanced and strongest in Singapore (+1.08%); moderate in India (+0.44%) and Indonesia (+0.35%).	Lower and capped gains due to compliance frictions.
Compliance Costs	Negligible.	Moderate: 10–15% rise from baseline	High: 28–35% increase; heaviest in Indonesia.
Capital Quality	May degrade over time due to absence of reinvestment pressure.	Stable or modestly positive (Singapore +0.03%); minor decline in others.	Decline in India and Indonesia due to compliance cost drag (-0.27%, -0.36%).
Aggregate Output	Strongest in early phases; risks long-term inefficiencies and inequality.	Consistent and highest output gains across all countries (0.31–1.10%).	Mixed: only Singapore sees meaningful output gain (+0.97%); contraction in India (-0.05%).
Policy Implication	Suitable only in contexts with high innovation urgency and minimal governance capacity.	Optimal balance of growth and oversight for all countries.	Useful for Singapore as second-best option; not optimal for economies with lower institutional readiness like Indonesia.

We employ a growth-accounting framework to model the trade-off between economic growth—through its components of capital, labour, and productivity—and AI regulation. In this framework, AI regulation enters via its effects on innovation, efficiency, consumer trust, and compliance costs. The resulting model balances the benefits and drawbacks of regulation to identify an optimal policy level.

5.1 Growth Accounting Framework

The growth accounting framework has long been central to understanding the drivers of economic growth, first formalised by Solow (1956) and later extended by Mankiw et al. (1992). This section proposes a model that extends the traditional output decomposition into total factor productivity (TFP), capital, and labour. The model incorporates dynamic feedback loops, non-monotonic regulatory effects, endogenous quality dynamics, and global interdependencies to address the complexities of AI regulation.

Output Equation

Economic output (Y) is expressed as:

$$Y = A.\left(K_q.K_l\right)^{\alpha}.\left(L_q.L_l\right)^{\beta} \tag{1}$$

where A represents TFP, K_q and K_l represent quantity (e.g. machinery, infrastructure) and quality (e.g., technological sophistication) of capital, L_q and L_l represent quantity (e.g., workforce size) and quality (e.g., skill levels) of labour, and and are output elasticities of capital and labour respectively, satisfying $\alpha+\beta=1$ under constant returns to scale. This formulation aligns with empirical studies emphasising the role of both quantity and quality in growth (Fernald and Jones, 2014; Katz and Murphy, 1992).

Total Factor Productivity (TFP)

TFP (A) represents the component of output growth not explained by capital or labour. In an AI-driven context, TFP is influenced by innovation, efficiency gains, trust dynamics, and global coordination. To incorporate these effects, TFP is modelled as:

$$A = A_0.(1-\rho R).(1+\eta R).(1+\lambda C_t - \mu C_t^2).I^t \tag{2}$$

where A_0 represents baseline TFP without regulation, R is regulation stringency, Ct represents global coordination in regulation, ρR is negative effect of regulation on innovation because of compliance burdens (Bloom et al., 2021), ηR is positive effect of regulation on efficiency through standardisation (Hahn and Tetlock, 2008), $C_t - \mu C_t^2$ is the net effect of regulation on trust with diminishing returns at higher levels (Floridi et al., 2018) and I^t is cumulative innovation that represents the feedback loop between regulation and technological progress.

Innovation Dynamics

Innovation (I^t) follows a logistic growth path to account for saturation effects as regulatory complexity increases:

$$I^t = \frac{\kappa}{1+e^{-\rho(1-R)}} \tag{3}$$

where denotes the baseline innovation–rate of innovation under minimal regulation. This reflects how early regulatory interventions stimulate innovation, but excessive constraints lead to diminishing returns (Griliches, 1980; Schumpeter, 1939).

Global Interdependencies

Domestic regulation interacts with global coordination (C_t):

$$C_t = \omega R_{global} + (1 - \omega)R \tag{4}$$

where represents the weight of global alignment. For regulation misalignment, where ω→0 (low global coordination), TFP evolves as:

$$A = A_0.(1 - \rho R).(1 + \eta R).(1 + \lambda R - \mu R^2) \tag{5}$$

For regulation alignment, where ω→1 (high global coordination), this evolves as:

$$A = A_0.(1 - \rho R).\left(1 + \eta R_{global}\right).\left(1 + \lambda R - \mu R_{global}^2\right) \tag{6}$$

This specification reflects the importance of regulatory harmonisation in reducing misalignment costs and promoting cross-border innovation (Agrawal et al., 2019; Chen et al., 2021).

Capital Dynamics

Capital is decomposed into quantity (K_q) and quality (K_l). Capital quantity (K_q) is fixed (i.e. capital quantity has constant baseline value), while capital quality (K_l) depends on reinvestment and compliance costs:

$$K_q = K_q^0 \tag{7}$$

$$K_l = K_l^{t-1} + \gamma(Y^{t-1} - C) \tag{8}$$

$$C = C_0.R^2 \tag{9}$$

where represents sensitivity of capital quality to reinvestment and C represents compliance costs that is increasing quadratically with R (Feinstein, 1989) with C_0 as the baseline compliance cost scaling factor. This dynamic captures the trade-off between regulatory compliance and technological sophistication (Dechezleprêtre et al., 2020).

Labour Dynamics

Labour inputs are also divided into quantity (L_q) and quality (L_l). Labour quantity (L_q) is fixed with constant baseline value reflecting demographic constraints, while labour quality (L_l) evolves dynamically based on reinvestment:

$$L_q = L_q^0 \tag{10}$$

$$L_l = L_l^{t-1} + \phi Y^{t-1}.(1 + vR - \sigma R^2) \tag{11}$$

where is the fraction of output reinvested in skill development, vR represents the positive impact of moderate regulation on skill enhancement, and -R2 represents the negative impact of excessive regulation having diminishing returns (Autor et al., 2020). This specification aligns with findings that labour quality improves with AI adoption and targeted regulatory incentives (Arntz et al., 2019; OECD, 2019).

The extended growth-accounting equation can be obtained by substituting equations (2)–(11) into equation (1).

In the current framework, incorporating cumulative innovation aligns with empirical evidence showing that regulation's impact on innovation evolves dynamically (Brundage et al., 2020). Adding diminishing returns captures real-world observations of over-regulation that limit consumer welfare (Veale and Brass, 2019). The dynamic evolution of labour and capital quality reflects the reinvestment-driven growth seen in AI-intensive industries (Brynjolfsson and McAfee, 2014). Accounting for global alignment addresses the role of international regulatory frameworks in shaping domestic outcomes (Fjeld et al., 2020).

This analytical framework provides the theoretical foundation for the numerical simulations in the following section, where the model is calibrated for three regulatory scenarios: no regulation, self-certification, and licensing. By applying real-world data to the parameters, the simulations quantify the trade-offs between economic output, and innovation across these scenarios, illustrating the practical implications of regulatory decisions on AI-intensive economies.

5.2 Numerical Simulation

This section presents numerical simulations that evaluate how regulatory stringency affects economic output and innovation within the analytical framework introduced earlier. The simulations are calibrated for three regulatory scenarios—no regulation, self-certification, and licensing. Baseline parameter values, derived from the expert survey and corroborated by empirical studies, are listed in the annexure (Table A1).Regulatory stringency (R) serves as the principal differentiator across the three scenarios, described as follows:

- **No-Regulation Scenario:** The model assumes an unregulated environment in which innovation is driven solely by market mechanisms and private R&D investment. Compliance costs are negligible, and firms operate without external regulatory constraints, enabling them to allocate resources entirely to strategic priorities. This pattern accords with *laissez-faire* ("let do") approaches historically prevalent in emergent technology domains, particularly when regulatory institutions lag behind (Blind, 2012). Although such settings can accelerate innovation by removing bureaucratic hurdles, they also risk ethical lapses and a loss of public trust (Brynjolfsson et al., 2018; Veale and Brass, 2019). For simulation purposes, **the regulatory-stringency parameter is held constant at R = 0.1 for all three countries.**

- **Self-Certification Scenario**: This scenario depicts a moderately regulated regime where firms develop and maintain internal compliance systems, typically informed by industry standards. Regulatory oversight is minimal, and enforcement is largely decentralised, yielding relatively low compliance costs. This framework mirrors real-world precedents such as industry-led data-privacy regimes (Hahn and Tetlock, 2008). Self-certification enhances flexibility and reduces bureaucratic inertia, thereby supporting innovation. Moreover, the model acknowledges the rising significance of trust-building effects (λR), as firms' voluntary adherence to recognised standards can bolster stakeholder confidence. Nevertheless, in the absence of third-party enforcement, there exists the risk of fragmented compliance, potentially undermining uniform trust outcomes (Chen et al., 2021). Based on the expert-survey results, **the regulatory-stringency parameter increases by 5 percent for India, 7.1 percent for Indonesia, and 6.5 percent for Singapore, relative to the no-regulation scenario.**[2]

- **Licensing Scenario**: This represents a highly regulated environment where firms must obtain external authorisations—such as certifications or approvals—to operate. Regulatory burdens are considerable, encompassing extensive documentation, third-party audits, and ongoing compliance monitoring. Such frameworks are commonplace in sectors necessitating high safety or ethical standards, such as pharmaceuticals and aviation (Cockburn and Henderson, 2001). While licensing delivers substantial trust-building dividends by signalling adherence to rigorous standards, it also imposes significant compliance costs and procedural delays, potentially inhibiting innovation in general-purpose technologies (Popp, 2002; Veale and Brass, 2019). According to expert survey data, **regulatory stringency under this scenario increases by 13.2 percent for India, 16.3 percent for Indonesia, and 13.5 percent for Singapore relative to the no-regulation baseline.**

Table 8: Simulation Results

Outcome, percentage change	Self-certification, relative to no regulation			Licensing, relative to no regulation		
	India	Indonesia	Singapore	India	Indonesia	Singapore
Innovation	-0.10	-0.15	-0.42	-0.12	-0.30	-0.59
Efficiency	0.15	-0.05	0.51	-0.41	-0.32	0.36
Trust-building	0.38	0.63	0.82	0.75	1.06	1.19
TFP	0.44	0.35	1.08	0.05	0.21	0.96
Compliance cost	10.25	14.67	13.42	28.17	35.14	28.82
Quality of labour	0.02	0.02	0.02	0.02	0.03	0.03
Quality of capital	-0.01	-0.13	0.03	-0.27	-0.36	-0.02
Economic Output	0.45	0.31	1.10	-0.05	0.11	0.97

Notes: The theoretical framework for the simulation is in Section 5.1. Baseline parameters are in the Annexure (Table A1).

Innovation and Efficiency

Under the self-certification regime, innovation declines marginally across all three countries—0.10 percent in India, 0.15 percent in Indonesia, and 0.42 percent in Singapore. These findings accord with theoretical predictions that moderate regulatory stringency introduces slight bureaucratic frictions while preserving overall flexibility (Hahn and Tetlock, 2008). The negative effect is more pronounced under licensing: innovation falls by 0.12 percent in India, 0.30 percent in Indonesia, and a sizeable 0.59 percent in Singapore, supporting concerns that heavy compliance burdens inhibit dynamic R&D processes (Popp, 2002; Veale and Brass, 2019).

Efficiency gains under self-certification are observable in India (0.15 percent) and Singapore (0.51 percent), whereas Indonesia records a modest decline (0.05 percent). By contrast, licensing produces substantial efficiency losses in India (0.41 percent) and Indonesia (0.32 percent); Singapore, however, again records an increase (0.36 percent). This pattern resonates with the institutional-readiness differentials discussed in Section 4, where Singapore's mature administrative capacity and digital infrastructure enable more effective utilisation of structured regulatory frameworks (Floridi et al., 2018).

Trust-Building and TFP

Trust-building effects scale with regulatory intensity, reflecting model assumptions around the λR parameter. Trust improvements are highest under licensing: +0.75 percent in India, +1.06 percent in Indonesia, and +1.19 percent in Singapore, compared with more modest gains under self-certification.

These results echo earlier findings in section 4 that light-touch regulation may better foster AI-driven growth, particularly in emerging digital economies (Brynjolfsson and McAfee, 2014; Fjeld et al., 2020).

Compliance Costs and Capital Quality

Unsurprisingly, compliance costs rise significantly with regulatory stringency. Under self-certification, the increase is moderate: 10.25 percent for India, 14.67 percent for Indonesia, and 13.42 percent for Singapore. However, licensing leads to a much steeper rise—28.17 percent for India, 35.14 percent for Indonesia, and 28.82 percent for Singapore. This pattern aligns with earlier empirical work showing that, in resource-constrained settings, regulatory burden can be disproportionate to the corresponding benefit (Feinstein, 1989; Black and Baldwin, 2010).

The resultant drag on capital quality is most evident in Indonesia (-0.36 percent) and India (-0.27 percent) under licensing. Even under self-certification, Indonesia records a minor decline (-0.13 percent), whereas Singapore remains marginally positive (+0.03 percent). These results reaffirm the model's premise that resources are diverted from reinvestment to compliance (Dechezleprêtre et al., 2020).

Aggregate Economic Output

Most importantly, the net impact on economic output underscores the trade-offs embedded within each regime. Under self-certification, economic output grows by 0.45 percent in India, 0.31 percent in Indonesia, and 1.10 percent in Singapore. Licensing, by contrast, yields a contraction in India (-0.05 percent) and modest growth in Indonesia (0.11 percent) and Singapore (0.97 percent).

These trends closely mirror the regulatory preferences established in the previous section, where expert assessments favoured self-certification in India and Singapore, attributing higher net benefits than both no regulation and licensing. Indonesia, however, preferred no regulation, reflecting scepticism about the net utility of formal regulatory regimes, given its administrative capacity constraints.

These findings reaffirm expert perceptions that AI's economic benefits are closely tied to institutional contexts. Singapore, with advanced regulatory infrastructure, consistently achieves higher gains across multiple indicators, supporting a nuanced application of both self-certification and licensing. India, while less structurally prepared, benefits substantially from self-certification, suggesting that flexible but standards-informed regulation can yield economic dividends without stifling innovation. Conversely, Indonesia's negative efficiency and capital-quality metrics, even under the relatively advantageous position conferred by self-certification, suggest that the country may require foundational improvements in regulatory design before it can derive value from more formal governance mechanisms.

AI AND SMARTPHONE ECOSYSTEM

SUMMARY

Dimension	Key Insights	Country-Level Highlights	Regulatory Implications
AI-driven Productivity	On-device AI, enabled by NPUs and optimised chipsets, boosts responsiveness, personalisation, and productivity.	Singapore leads in seamless AI integration. India and Indonesia have uneven access due to varied device quality.	Self-certification allows rapid rollout; licensing may slow adoption, especially in less mature markets.
Market Landscape & Device Diversity	India has the largest market but with significant hardware fragmentation. Singapore is compact but AI-ready. Indonesia is mid-range in scale and capability.	India: Large base, mostly Android, fragmented specs. Indonesia: Mobile-first, rising fintech AI. Singapore: High-end market, strong digital policy.	Tiered or adaptive regulations are needed to reflect diverse device capabilities and infrastructure readiness.
Perceived Importance of Layers	Experts consistently rank smartphones as the most important AI layer, followed by browsers and then app stores inIndia	India: Smartphone > OS > Browser > App Store. Indonesia: Same as India. Singapore: Smartphone > App Store > OS > Browser.	Policy should prioritise enabling AI innovation in smartphones and OS
Layer-Specific Regulatory Preference	Smartphone innovation seen as more resilient to regulation. Licensing is favoured in high-trust ecosystems (e.g. Singapore).	India/Indonesia prefer self-certification or no regulation for most layers. Singapore shows more support for licensing, especially in app governance.	Use flexible, layer-specific regulatory models. Overregulation of smartphones may constrain inclusive AI adoption.

AI integration across digital layers—including smartphone devices, the operating system (OS), browsers, and app stores—has diverse implications for innovation, user experience, and platform governance. Among these, the smartphone ecosystem occupies a uniquely central position. As the primary interface through which billions of users interact with digital services, smartphones are critical enablers of AI-driven functionalities such as personalisation, privacy-preserving computation, and on-device processing. Their widespread adoption and deep integration into daily life make them the most immediate and high-impact layer for AI deployment (Georghiou et al., 2008; Lu et al., 2020).

The OS, as a system-level layer, facilitates cross-application learning, device-level security, and real-time updates. It serves as the backbone that connects hardware and software, ensuring that AI tools can be scaled seamlessly across devices. In contrast, browsers and app stores operate closer to the application layer and play a different, yet fundamental, role in shaping digital interactions. Browsers enable access to web-based AI services and data, while app stores govern the distribution of AI-integrated applications. These layers are especially important for ensuring algorithmic transparency, content moderation, and compliance with ethical standards, particularly in mature digital ecosystems (Calo, 2017; Veale and Edwards, 2018).

Given the differing roles and governance functions of each layer, regulatory strategies for AI must be tailored accordingly. A one-size-fits-all approach may fail to address the operational realities and risk profiles unique to each component. While smartphone devices demand safeguards that prioritise security, privacy, and hardware compatibility, operating systems (OS), browsers, and app stores require oversight mechanisms focused on platform accountability, data governance, and developer compliance (Gasser and Almeida, 2017; IMDA, 2020).

The following section explores how AI impacts innovation across these layers, with particular emphasis on the smartphone ecosystem. It examines how different regulatory models—no regulation, self-certification, and licensing—shape the opportunities and constraints for AI development and deployment across these key digital infrastructure components.

6.1 AI integration in Smartphones and Productivity

Smartphones constitute a most transformative layer of digital infrastructure for AI integration. Their ubiquity and functionality—as the direct interface between users and AI technologies—make them the central medium for delivering personalised, context-aware, and real-time AI applications. On-device AI supports key use cases, such as voice assistants, image recognition, adaptive user interfaces, and privacy-preserving computation through edge AI (Georghiou et al., 2008; Lu et al., 2020). This direct and continuous interaction with users places smartphones at the heart of AI-driven productivity gains and user engagement.

By contrast, operating systems (OSs) enable back-end AI functionalities, such as system-wide security and inter-application data sharing, while browsers and app stores govern user access and content curation. Though important in their own right—especially for ethical AI governance (Veale and Edwards, 2018)—these components are secondary enablers rather than primary sites of AI value creation. The distinct edge of smartphones lies in their capacity to unify computing, sensing, and communication within a single, AI-enabled device—an advantage that other infrastructure layers cannot replicate.

AI integration in smartphones has rapidly become a key differentiator in the mobile technology landscape, with major players such as Apple, Google, and Samsung embedding generative AI at the core of their innovation strategies. Apple's "Apple Intelligence," launched in 2024, integrates generative AI across iPhones, iPads, and MacBooks, while Google's Gemini assistant is now embedded within the Android ecosystem (Apple, 2024; Gemini, n.d.). Samsung's Galaxy AI has likewise become a hallmark feature across its flagship devices (Samsung, n.d.). Together, these developments reflect a broader shift toward AI-enabled mobile ecosystems, supported by advanced operating systems as well as specialised hardware, such as neural processing units (NPUs) and AI-optimised mobile processors (Google, 2024; Qualcomm, n.d.; Counterpoint Research, 2023).

However, a major concern surrounding AI integration in smartphones is its potential energy intensity. Traditional AI models—particularly those based on deep learning and complex neural networks—typically require significant computational power and frequent reliance on cloud infrastructure to function effectively. Yet, recent advancements in on-device processing have begun to address these limitations. The emergence of AI-specific hardware, including NPUs and graphics processing units (GPUs), has dramatically improved energy efficiency and reduced dependence on remote servers. These chips enable local processing of AI tasks directly on smartphones, minimising latency, improving user privacy, and substantially lowering overall energy demands (Chang, 2024).

As a result, smartphones are now capable of delivering a wider range of real-time AI functionalities—from intelligent personal assistants, adaptive user interfaces, and accessibility features to task automation. These capabilities not only enhance user experience but also contribute to meaningful productivity gains at both individual and organisational levels. The ability to process AI workloads on-device—faster, privately, and with greater energy efficiency—positions smartphones as a uniquely powerful layer of AI deployment within the broader digital infrastructure.

Companies such as Samsung, NVIDIA, Google, Qualcomm, and MediaTek have been at the forefront of integrating AI into consumer-electronic devices, including smartphones, tablets, and laptops (Counterpoint Research, 2023). NVIDIA, one of the highest-valued companies in the world, has gained a dominant position in AI thanks to its early investments in, and research on, GPUs. Although these chips were initially developed to render graphics in online games, NVIDIA later modified them—through specialised software—to perform AI tasks (NVIDIA, 2012).

Google also made early strides with its Tensor Processing Units (TPUs), which have been deployed in data centres since 2015. These chips are specially designed for neural networks and parallel processing, allowing trillions of operations to be executed per second. They enable "on-device processing" of AI tasks, a feature relevant not only to smartphones but also to smartwatches and security cameras (Google, 2024).
Samsung began integrating AI features into its devices as early as 2021 (Bernard Marr & Co, n.d.; Samsung, n.d.). In 2019, the company launched an AI-enabled mobile application processor (AP) that offers seven times the computational power of traditional processing units.

These technology firms have invested not only in R&D for AI hardware, but also in AI software. Estimates suggest that tech giants such as Microsoft, Google, Apple, Amazon, and NVIDIA have ramped up their AI investments, particularly since the advent of generative AI (Financial Times, 2023), with many positioning AI integration as the defining feature of the next generation of personal devices. The technology now simplifies tasks that once required a PC or laptop—such as real-time translation, or virtual assistants that summarise documents and messages—thereby transforming a smartphone into a versatile productivity tool (Qualcomm, n.d.).

Empirical studies suggest that such integrations significantly boost productivity. Brynjolfsson et al. (2023) found that access to generative AI tools improved customer-support productivity by 15 percent, particularly benefiting less-experienced workers. Because many generative-AI tasks—writing emails, summarising messages, scheduling—are performed on mobile devices, smartphones are key enablers of these gains. Noy and Zhang (2023) similarly reported that generative AI reduced task-completion time and improved output quality in professional-writing tasks, reinforcing the relevance of AI in mobile productivity. Conversely, Simkute et al. (2024) caution that AI integration can increase complexity by making easy tasks easier but difficult ones more complex, potentially leading to cognitive overload or workflow disruptions. For example, tasks such as data entry or summarisation become easier with AI, whereas those that require creative thinking and problem-solving may become harder; in addition, AI can introduce bias and inconsistencies. Such outcomes underscore the need for thoughtful interface design and robust user-support systems within smartphones.

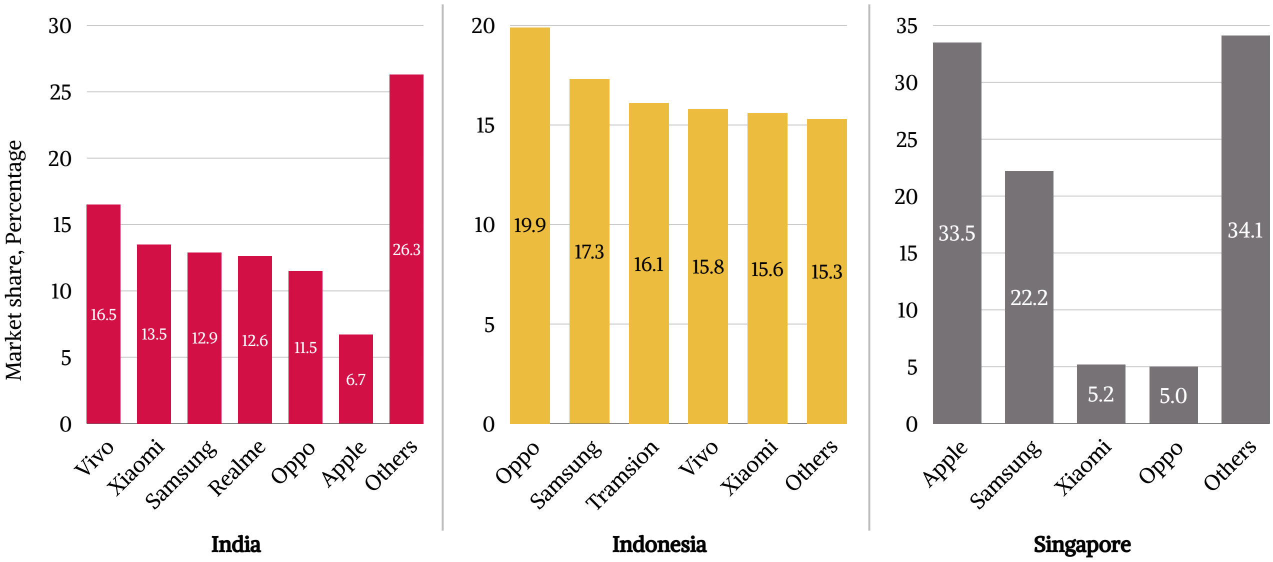
The implications of regulatory frameworks—such as no regulation, self-certification, and licensing—are particularly significant in this context. Self-certification offers flexibility for device manufacturers and OS providers to deploy iterative updates and respond quickly to emerging needs, while also promoting voluntary compliance with industry standards. Licensing, by contrast, may encourage more thorough safeguards and greater accountability in privacy, data management, and algorithmic fairness, but potentially at the cost of slower AI rollout and innovation cycles (Floridi et al., 2018; Black and Baldwin, 2010).

6.2 Overview of the Smartphone Market in India, Indonesia and Singapore

This section examines how advances in AI integration shape the structure and dynamics of the smartphone markets in India, Indonesia, and Singapore. Understanding these markets is essential to assess the potential reach and effectiveness of AI technologies, particularly with respect to innovation, user experience, and regulatory strategy.

According to the Stanford AI Index (2024), all three countries—India, Indonesia, and Singapore—rank among the fastest adopters of AI-powered smartphone technologies globally. This rapid uptake is underpinned by a surge in generative AI capabilities, embedded hardware such as NPUs, and software services including voice assistants, summarisation tools, and translation applications, many of which now run directly on smartphones (Brynjolfsson et al., 2023; Noy and Zhang, 2023). However, local ecosystem characteristics significantly shape the degree and quality of AI integration, affecting the realisation of productivity gains at scale.

Figure 12: Smartphone Market in India, Indonesia and Singapore, 2024



Source: IDC (2024), Statista (2024)

India's smartphone ecosystem, with over 750 million users, constitutes one of the world's largest by volume (Statista, 2024). Android OS represents over 90 percent of the operating-system market, compared with 6–7 percent for Apple iOS (Figure 12). This ubiquity is driven by the affordability and variety of Android devices, produced by brands such as Vivo, Xiaomi, Realme, and OnePlus, which collectively account for the majority of India's market share (IDC, 2024). However, despite its size, India's smartphone landscape is highly fragmented in terms of hardware capabilities and software optimisation. Devices range from low-cost models with limited processing power to premium phones equipped with dedicated AI chips. While this hardware heterogeneity may constrain the uniform adoption of advanced AI features and lead to uneven productivity outcomes, it also highlights a bidirectional synergy between AI innovation and patterns of end use. In this context, India's regulatory regime must recognise and accommodate the need for differentiated AI functionalities tailored to a diverse user base. Such an approach would maximise productivity gains by ensuring that AI applications are both accessible and contextually relevant across the full spectrum of devices.

In Indonesia, smartphone penetration is high and growing, with Android brands such as Vivo, Xiaomi, Oppo, and Samsung accounting for nearly the entire market (Figure 12). Apple maintains only a marginal presence, primarily within the premium segment because of high import duties and localisation rules, such as the requirement for 40 percent local content in devices (Reuters, 2024). This market structure mirrors India's in terms of brand diversity and Android dominance, but AI integration remains uneven. Device capabilities and network infrastructure continue to shape how AI features are adopted and used. Nevertheless, Indonesia's openness to platform-level AI innovation—evidenced by the growing use of voice assistants and financial-technology apps—points to increasing awareness of AI's productivity potential. That said, its regulatory readiness remains nascent, suggesting that a hybrid model of self-certification with stronger safeguards may be more effective than licensing at this stage.

Singapore presents a stark contrast. With a smaller but more mature smartphone market, it is the only country in this group where Apple and Samsung hold the largest share of the device market (Table 12). The prevalence of premium devices ensures greater uniformity in hardware quality and AI-feature availability. Singapore's advanced regulatory ecosystem—including initiatives such as AI Verify and the IMDA Governance Framework—also enables effective oversight of AI integration. The preferred AI regulatory model, in this context, should reflect institutional confidence in formalised governance mechanisms and user protections.

6. 3 Expert Survey Results on AI Integration and Impact of Regulatory Scenarios

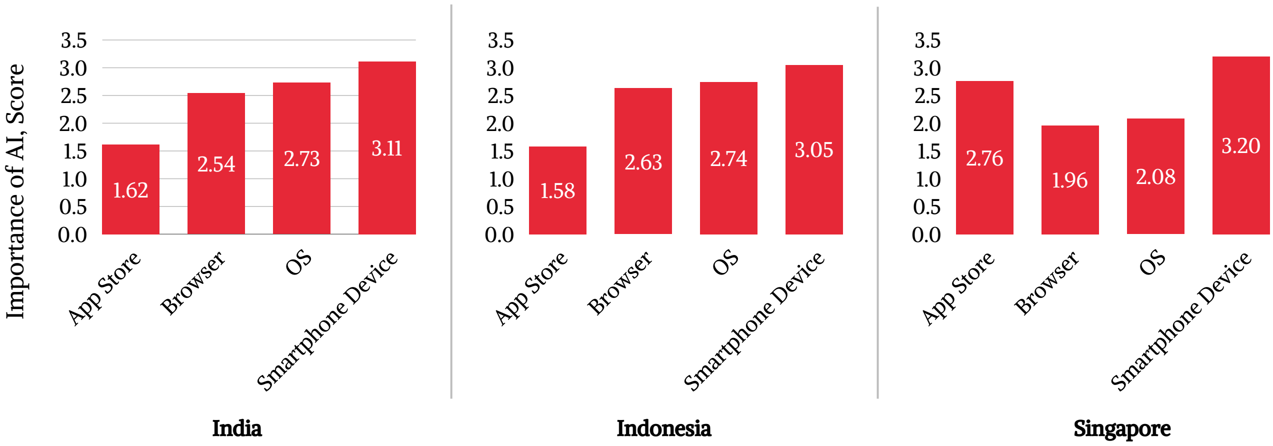
To gain deeper insight into the four key digital-infrastructure layers—smartphone devices, operating systems (OS), browsers, and app stores—experts were asked to rank the importance of AI integration across each. Figure 13 presents the results, derived from the weighted-composite scoring method outlined in Section 2.

The findings show that smartphone devices are regarded as the most important layer for AI integration across India, Indonesia, and Singapore. Experts from all three countries consistently assign the highest scores to this layer, reflecting a strong consensus on the foundational role of embedded AI, edge computing, and personalisation in shaping user experience, and driving innovation.

In India and Indonesia, the OS layer ranks second, with composite scores of 2.73–2.74, underscoring a widespread belief in the system-level role of AI in enabling cross-platform intelligence and user-interface adaptability. In contrast, Singapore places greater emphasis on app stores, with a composite score of 2.76, positioning them ahead of both OS (2.08) and browsers (1.96). This suggests a stronger institutional focus on platform governance in Singapore, where app stores are viewed not only as commercial distribution hubs but also as levers for transparency, privacy, and trust-building—an approach consistent with Singapore's Model AI Governance Framework (IMDA, 2020).

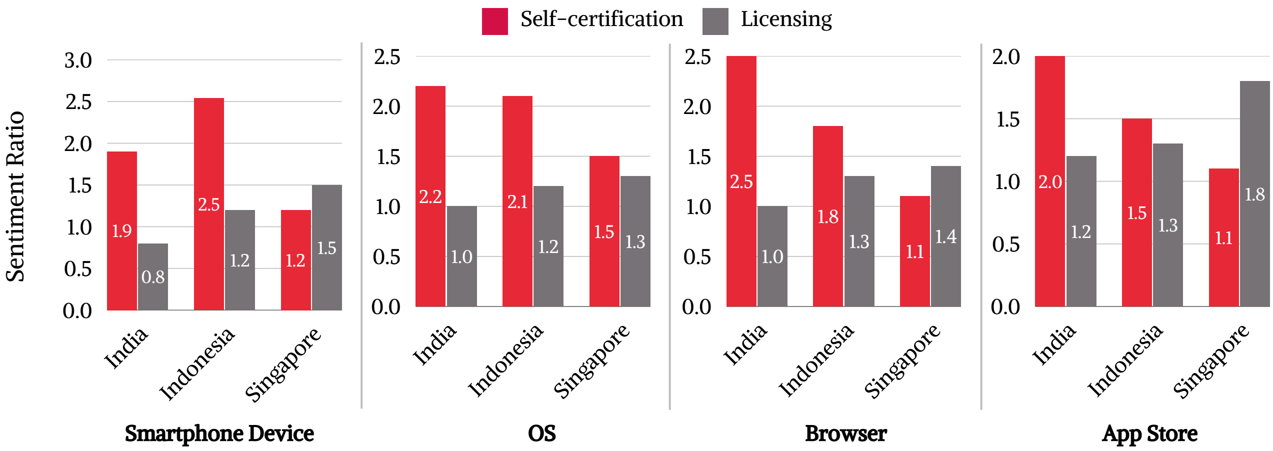
Meanwhile, app stores score lowest in both India (1.62) and Indonesia (1.58), indicating that these countries attach relatively less importance to AI within digital marketplaces. This pattern may reflect a more limited institutional focus on marketplace regulation in the context of digital services.

Figure 13: Importance of AI for Smartphone Device, OS, Browser and App Store



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rank their perception of the importance of AI across the four infrastructure layers. These rankings were converted into a composite following the methodology outlined in Section 2.

Figure 14: Impact of Regulatory Models on AI Innovations in Infrastructure Layers



Notes: The data presented are based on a survey of 102 domain experts—50 from India, 27 from Indonesia, and 25 from Singapore. Respondents were asked to rate their perception of the impact of AI innovations across the four infrastructure layers using a five-point Likert scale, ranging from "highly negative" to "highly positive." These ordinal responses were converted into sensitivity ratios following the methodology outlined in Section 2.

Figure 14 presents the results on expert perceptions of how regulatory models—self-certification and licensing—affect AI innovation across these infrastructure layers. It suggests that self-certification is generally perceived as more conducive to AI innovation, particularly in India and Indonesia, where it is favoured across all four layers. This finding supports the broader preference for agile, principle-based governance frameworks that avoid excessive bureaucratic overhead and foster iterative innovation (Gasser and Almeida, 2017; Crootof et al., 2022). However, Singapore deviates from this trend in all cases except OS, where licensing is viewed more positively than self-certification.

Across all three countries, the OS layer is considered the layer that benefits most from self-certification, owing to its need for seamless integration and agile updates—qualities that can be constrained by traditional licensing models (Cath, 2018; Binns et al., 2018). Likewise, smartphone devices also benefit from self-certification. Experts view this as essential for enabling rapid, low-friction innovation in areas such as on-device AI, personalisation, and privacy-centric computation.

7 GOVERNMENT READINESS AND INSTRUMENTS FOR ACTION

The analysis presented in the report reveals that pathways to responsible and inclusive AI governance in India, Singapore, and Indonesia must be contextually grounded yet globally informed. Each country is navigating a distinct trajectory shaped by its regulatory maturity, market structure, and technological infrastructure—particularly within the rapidly evolving smartphone ecosystem, which serves as the primary interface for AI adoption. Singapore's approach is marked by advanced governance and institutional experimentation; India balances scale with regulatory flexibility; and Indonesia is building foundational capacity amid rapid digitisation.

The recommendations below are tailored to each country's current state of AI readiness and are organised around four priority pillars: global alignment, public–private collaboration, support for innovation and experimentation, and consumer centricity. These pillars reflect not only international best practices but also the first principles of digital governance embraced by each country—namely, openness, inclusion, innovation, and trust.

7.1 India

Advance regulatory coherence through global alignment

India has consistently voiced support for global AI governance—including during its G20 presidency and its participation in the Paris AI Safety Summit. However, this normative alignment must be translated into operational regulatory coherence through institutional mechanisms.

Institutionalise structured multistakeholder engagement

India's Digital India Act consultations marked progress towards collaborative regulation, but wider adoption of formalised public–private mechanisms is needed. Building sector-specific AI councils—modelled on the UK's AI Regulation Forum—can ensure inclusive input from civil society, start-ups, academia, and consumers (UK DCMS, 2023).

Develop distributed AI sandboxes across digital geographies

India's digital divide and smartphone heterogeneity necessitate decentralised sandboxes across tier-two and tier-three cities. These environments should support context-specific testing—for instance, evaluating voice-based AI in low-bandwidth regions or deploying AI tutors for vernacular learners.

Adopt flexible AI standards for heterogeneous devices

Given India's fragmented smartphone market, AI regulation should not enforce a uniform standard. Instead, tiered or use-case-based compliance can allow basic AI features to proliferate on budget devices while encouraging advanced integration in premium models. Such differentiated design ensures both inclusivity and innovation, preventing regulation from becoming a barrier to access.

7.2 Singapore

Consolidate leadership in global AI interoperability: Singapore's AI Verify initiative, and its participation in GPAI, position the country as a global reference point for responsible AI. Building on this foundation, Singapore should champion convergence in international standards through the pilot adoption of cross-border assurance tools. Participating in joint AI-testing protocols with like-minded partners—for example, Japan and the UK—would not only reinforce trust, but also enable local firms to access AI-sensitive global markets. The EU–Japan mutual-recognition framework for digital services is a replicable model (OECD, 2022).

Deepen public–private co-regulation in emerging sectors: Singapore's strength lies in agile governance and trusted institutions. It should now evolve towards co-regulatory models, especially in high-risk AI sectors such as health and finance. Empowering sectoral councils to co-develop binding codes of practice—akin to the Australian eSafety Commissioner's regime for online content—can bring sector expertise into rule-making, improve adaptability, and reduce regulatory overhead (eSafety Commissioner, 2023).

Expand AI experimentation into regional and cross-border pilots: Singapore's GenAI Sandbox and AI Verify are cutting-edge, but should now be scaled. Establishing joint sandboxes with ASEAN neighbours—for instance, on AI in cross-border logistics, or digital trade—would allow Singapore to export regulatory influence, while enabling regional alignment. Such shared experimentation has a precedent in the Bank of England and the Monetary Authority of Singapore's collaboration on financial AI models (MAS and BoE, 2021).

7.3 Indonesia

Build institutional capacity for global AI engagement: Indonesia supports global AI norms in principle but lacks the institutional structures required for effective engagement. Establishing a national AI task force—with representation from BSSN (Cyber and Crypto Agency), civil society, and academia—would help translate high-level alignment into technical contributions to Asean, Unesco, and OECD initiatives. The Philippines' AI roadmap task force provides a regional blueprint (Philippines DTI, 2021).

Formalise stakeholder involvement in AI policy: Current public-private consultation remains informal or ad hoc. Indonesia should institutionalise stakeholder inputs—especially from entities such as idEA, ELSAM, and digital start-ups—through formal advisory panels.

Protect vulnerable users through minimum AI safety baselines: Indonesia's mobile-first digital ecosystem relies heavily on mid- and low-tier smartphones. AI regulation should therefore focus on minimum ethical design and safety guardrails, rather than on advanced compliance frameworks.

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Endnotes

1 Ministry of Health (MOH), the Financial Services Authority (OJK), and the Ministry of Education, Culture, Research, and Technology (MECRT) - which has since been split into the Ministry of Primary and Secondary Education (MPSE), the Ministry of Higher Education and Technology (MHERT), and the Ministry of Culture (MOC)

2 Regulatory stringency under self-certification and licensing, relative to no regulation, is estimated from the perceived total excess costs reported by the median expert. The position of the median respondent is approximated by assuming that the distribution of responses within the bracket that contains the median is uniform. For example, if the middle 20 percent of respondents—that is, those between the 40th and 60th percentiles—report excess costs in the range of 5 to 10 percent, the excess cost attributed to the median respondent is imputed as 7.5 percent. See Manski and Tamer (2002) and Hurd and McGarry (1995) for precedents.

Annexure

Table A1: Baseline Parameter Values for Numerical Simulation

Description	Range	Initial value			Source
		India	Indonesia	Singapore	
Sensitivity of innovation to regulation	$0<\rho<1$	0.17	0.26	0.37	Expert survey
Efficiency gain from regulation	$0<\eta<0.5$	0.14	0.13	0.14	Expert survey
Trust-building parameter	$0.1<\lambda<0.5$	0.4	0.4	0.4	Expert survey
Trust diminishing returns parameter	$0.01<\mu<0.2$	0.1	0.1	0.1	Floridi et al. (2018)
Compliance cost scaling factor	$1<C_0<100$	10	10	10	Feinstein (1989)
Labour quality improvement rate	$0.1<v<0.5$	0.08	0.11	0.06	Expert survey, Arntz et al. (2019)
Labour quality diminishing returns	$0.01<\sigma<0.2$	0.03	0.04	0.02	
Capital quality reinvestment sensitivity	$0.1<\gamma<0.5$	0.17	0.16	0.11	Expert survey
Weight, global alignment in regulation	$0<\omega<1$	0.08	0.12	0.22	Expert survey
Baseline TFP	$A_0>0$	3.00	3.03	4.80	Conference Board, Penn World Table
Quantity of labour, mn	$L^q_0>0$	607.69	143.14	3.67	World Bank
Quantity of capital, USD bn	$K^q_0>0$	1086.26	385.56	78.09	World Bank
Quality of labour	$L_t^{l-1}>0$	0.2	0.3	0.3	Conference Board
Quality of capital	$K_t^{l-1}>0$	4.5	3.1	7.5	Conference Board
Elasticities of capital	$\alpha+\beta=1$	0.418	0.337	0.316	Computed
Elasticities of labour	$\alpha+\beta=1$	0.582	0.663	0.684	
Baseline innovation rate	$0.01<\kappa<0.5$	1.00	1.00	1.00	Brynjolfsson et al. (2018)
Fraction of output reinvested in skilling	$0.01<\phi<0.1$	0.17	0.14	0.17	Expert survey
Lagged output, USD bn	$Y^{t-1}>0$	3126	1179	387	World Bank

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