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AI and Economic Divergence in India: Navigating the Viksit Bharat 2047 Ambition in an Age of Uneven Technological Transition

A Policy-Oriented Commentary on the IMF Framework for AI-Driven Cross-Country and Within-Country Divergence

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Abstract:
India has set itself the dual ambition of becoming the world's third-largest economy in the near term and an advanced, high-income economy by 2047 under the Viksit Bharat 2047 vision. Artificial intelligence (AI) is widely presented, as a decisive lever for accelerating this transition all over the world and also in India. A recent International Monetary Fund working paper, Natasha X. Che, Weining Xin, and Taichi Yoshida (2026), develops a small open economy overlapping generations model of endogenous AI adoption for fifteen Asia-Pacific economies. It shows that AI could simultaneously widen growth gaps across countries and inequality within them. Capital-deepening, skill-biased technological change, and global interest-rate spillovers are the main drivers for growth gaps. This article applies the framework to India's situation. India has a large and young workforce that is still developing. It also has less capital-intensive and skill-based production. Its growth depends mainly on its large workforce and the benefits of its demographic dividend, rather than on capital income . It argues that, absent an acceleration of structural reform along the lines the IMF paper's simulations suggest, India risks a transition period in which rising global capital costs generated by early AI adopters elsewhere in Asia constrain investment and growth at precisely the moment India needs both to be rising, while domestic AI diffusion could widen wage and generational disparities that cut against the inclusive-growth premise of Viksit Bharat 2047. The article closes with policy priorities specific to India's institutional endowments, including its digital public infrastructure, skilling architecture, and fiscal constraints.

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1. Introduction

India's official development narrative has, since 2023, coalesced around a single benchmark: Viksit Bharat 2047, the goal of becoming a fully developed, high-income economy by the hundredth anniversary of independence. Embedded within this longer horizon is a nearer-term marker of national pride, the ambition to overtake Germany and Japan to become the world's third-largest economy within the next few years, and a longer-run aspiration, voiced with increasing frequency in public discourse, of India eventually standing as the world's largest or foremost economy. Artificial intelligence occupies an unusually prominent place in the policy conversation around how this transition is to be achieved. It is invoked as a productivity multiplier for a labour force that is still, on average, young and expanding; as a shortcut around some of the capital-intensive stages of industrialisation that earlier developers had to traverse; and as a domain in which India's software and digital-public-infrastructure strengths could translate into genuine competitive advantage.

Yet the macroeconomic literature on AI and growth has increasingly emphasised that the technology's aggregate promise does not translate uniformly across countries, nor evenly within them. Che, Xin, and Yoshida (2026), in an International Monetary Fund working paper prepared for the Asia and Pacific Department, provide the most detailed quantitative treatment to date of this question for the Asia-Pacific region specifically. Using a calibrated small open economy overlapping generations model spanning fifteen economies, the authors show that AI adoption at scale is best understood as an act of capital deepening, and that the timing of adoption is endogenous to each country's capital intensity, skill composition, total factor productivity, and demographic structure. Because early adopters draw on the same global pool of savings, their surging investment demand raises the global cost of capital for everyone else, creating a self-reinforcing cycle in which structurally prepared, typically ageing advanced economies adopt early and gain immediately, while structurally unprepared, typically younger emerging markets and developing economies (EMDEs) face both delayed adoption and an interim growth penalty.

India appears throughout the IMF's fifteen-economy sample as an illustrative case of precisely this second category: a large, young, labour-abundant EMDE whose very demographic strengths, in this framework, translate into a lower capital-to-labour ratio and therefore a later crossing of the profitability threshold for economy-wide AI adoption. This is a striking tension for Viksit Bharat 2047, a vision explicitly built on the premise that India's demographic dividend is a growth asset. This article asks what the IMF's divergence mechanisms imply, more specifically, for India's own AI transition, and what they suggest about the policy priorities required if India is to convert its stated ambition into a materially different, more favourable, position in the model's cross-country ranking.

2. The IMF Framework: How AI Generates Divergence

The analytical core of Che, Xin, and Yoshida (2026) is a technology-choice problem facing firms in each economy. Firms compare output under a traditional, calibrated production technology against output under an alternative, more capital-intensive and skill-biased frontier technology that represents AI deployed at scale, encompassing not only generative AI and large language models but also robotics and the physical and digital infrastructure needed to support them. Adoption occurs when an economy's effective capital-to-labour ratio, weighted by productivity, crosses a threshold at which the AI-intensive technology becomes more profitable than the incumbent one. Because the capital share embedded in the AI technology rises over time along a common global path, while each country begins from its own calibrated baseline, the model generates a common technological frontier whose adoption timing nonetheless diverges sharply across countries.

Three structural features determine how quickly a country crosses this threshold: its initial capital intensity, its skill composition, and its total factor productivity, with population ageing providing a further, largely mechanical, push toward earlier adoption in countries where labour supply growth is slowing. Advanced, capital-rich, skill-intensive, and ageing economies in the sample, including Singapore, Japan, Korea, Australia, and New Zealand, adopt immediately across all simulated scenarios. Younger, labour-abundant EMDEs, by contrast, adopt only after a delay that can extend from roughly a decade under the mildest scenario to several decades under faster, more capital-intensive paths of AI progress, and considerably longer still for low-income countries.

Crucially, the model does not treat the pre-adoption period for late adopters as a neutral waiting phase in which such economies simply forgo AI's benefits while continuing along an otherwise unaffected baseline path. Instead, because early adopters' investment surge pushes up the global interest rate against which all economies in the model borrow, late adopters face an active headwind: higher financing costs slow their own capital accumulation, reducing investment and growth relative to a counterfactual without AI, and in doing so push their own eventual adoption date out even further. Only once late adopters cross the threshold does the relationship invert, with catch-up capital accumulation delivering a growth rate that, for a period, exceeds the early adopters' pace.

Beyond this cross-country channel, the paper documents two within-country distributional mechanisms that operate even in early-adopting economies. First, because the AI technology is skill-biased, the labour-income share of low-skilled workers contracts fastest as capital deepening proceeds, so that, depending on the pace of AI progress, low-skilled wages can fall in absolute terms for an extended transition period before eventually recovering, while high-skilled wages rise from the outset. Second, because a rising capital share raises the return on existing wealth, older cohorts, who hold accumulated savings, capture AI's income gains earlier and more fully through capital income, while younger and mid-career workers must wait for wage gains to build gradually and, in the fastest-progress scenario, can see measured income fall as they borrow against a higher expected lifetime income. The authors show that both structural reforms, targeting skills, labour productivity, and capital-allocation efficiency, and redistributive transfers can mitigate these pressures, though the two policy levers involve distinct fiscal and efficiency trade-offs that are country specific.

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3. India's Structural Position in the Asia-Pacific Sample

India is included among the fifteen Asia-Pacific economies calibrated in the IMF model, and the paper's qualitative discussion places it, alongside Bangladesh and the Philippines, among the region's young, growing-population economies for which "the challenge lies in ensuring that AI adoption creates rather than displaces employment opportunities for growing labour forces" rather than the ageing, capital-rich economies for which AI substitutes for a shrinking workforce. In the model's adoption-timing simulations, India appears in the middle of the emerging-market cluster, adopting later than China and Malaysia but generally earlier than the region's low-income economies, with the precise ranking shifting across the mild, moderate, and accelerated AI-progress scenarios as interest-rate dynamics interact with each country's demographic trajectory.

The paper's calibration section indicates that the underlying skill composition varies enormously across the sample, with the model-implied high-skilled labour share ranging from roughly ten to fourteen percent in Singapore, Korea, Australia, and Japan down to two to five percent in the lowest-income economies in the sample. While the paper does not report a country-specific figure for India in its published text, India's classification alongside the region's labour-abundant EMDEs, together with its large workforce still concentrated in agriculture and low-productivity informal services, suggests a high-skilled share considerably below the frontier economies' ten-to-fourteen percent range, even as India's absolute pool of tertiary-educated and technically skilled workers is, in raw numbers, among the largest in the world. This distinction between a low share and a large absolute stock is analytically important: it implies that pockets of India's economy, particularly in information-technology services, financial technology, and global capability centres, could plausibly cross an AI-adoption threshold well ahead of the aggregate, calibrated, economy-wide date the model produces.

India's capital intensity, similarly, sits below that of the region's advanced economies, where the model calibrates capital shares of roughly forty to fifty percent of output, against a broader Asia-Pacific range of thirty to forty-eight percent. Combined with continued labour-force growth, driven by a working-age population that, unlike Japan's or Korea's, is not yet contracting, India's effective capital-to-labour ratio in the model's terms rises only gradually, reinforcing a later economy-wide adoption date relative to the region's ageing, capital-rich advanced economies.

4. Applying the Divergence Mechanism to India's Growth Trajectory

The practical significance of these calibration facts for Viksit Bharat 2047 lies less in the precise simulated adoption year for India, which the IMF paper itself cautions should be read as ordinal and illustrative rather than as a calendar forecast, and more in the shape of the transition path the model predicts. During the years before India's own economy-wide adoption threshold is crossed, the model implies that India would nonetheless be affected by AI progress elsewhere in the region and the world: as Japan, Korea, Singapore, Australia, and other early adopters increase investment to deploy AI at scale, global demand for capital rises and, in an environment of close integration with global capital markets, pushes up the cost of capital that India itself faces. Higher financing costs would be expected to slow India's own capital accumulation, weighing on investment and growth during precisely the period in which Viksit Bharat

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2047's nearer-term milestones, including the ambition to become the world's third-largest economy, are meant to be achieved.

This headwind is not a minor technical footnote. In the IMF paper's regional aggregation of emerging market and developing economies, growth during the pre-adoption phase is roughly half a percentage point lower annually under the mild and moderate AI scenarios than in a no-AI counterfactual, with the investment-to-GDP ratio five to six percentage points lower, before recovering and eventually exceeding baseline levels once adoption occurs. For an economy of India's scale, aiming for sustained growth rates well above the regional emerging-market average in order to compress a multi-decade development timeline into the roughly two decades remaining before 2047, even a temporary half-point drag compounds meaningfully over time. The corollary, however, is that the model also implies a subsequent catch-up phase, in which India's eventual adoption of AI-intensive production, once its capital-to-labour ratio crosses the threshold, delivers growth rates above baseline as capital accumulation accelerates toward the new equilibrium. Whether Viksit Bharat 2047 benefits more from the pre-adoption drag or the post-adoption boost depends critically on when, within the 2025-to-2047 window, India's own crossing occurs, which is itself a function of policy choices rather than a fixed exogenous date.

It is this last point that gives the IMF framework its clearest policy relevance for India. The paper's structural-reform simulations show that a sustained, decade-long programme raising the high-skilled labour share, labour productivity across all skill groups, and capital-specific productivity can advance an EMDE's simulated adoption date by one to two decades and materially amplify the growth dividend once adoption occurs, with the gains scaling with the ambition of the reform programme. The magnitudes used in the paper's most ambitious reform scenario are explicitly benchmarked to historical episodes of rapid structural transformation, comparable to Korea's in the 1970s or China's in the 2000s. For India, this suggests that the country's own structural reform agenda, spanning skilling, labour productivity, and capital-market efficiency, is not merely a general good-governance objective but a direct determinant of whether the AI transition helps or hinders the Viksit Bharat 2047 timeline specifically.

5. Within-Country Distributional Risks for India

The IMF model's within-country findings raise a second, distinct set of concerns for India, concerns that bear directly on the inclusive-growth language that accompanies the Viksit Bharat 2047 vision. The paper shows that, even where AI adoption delivers clear aggregate gains, those gains are distributed unevenly across skill groups and generations, and that the direction and magnitude of this unevenness depends on the pace of AI progress. Under slower AI progress, low-skilled workers' wages can fall below a no-AI baseline for an extended transition period before eventually recovering, as the direct effect of a shrinking labour-output elasticity temporarily outweighs the indirect benefit of working alongside more capital. For India, where a very large share of the workforce remains low-skilled by the model's education-based definition and where labour-market flexibility to move workers into higher-skilled, AI-complementary roles is constrained by the pace of human-capital formation, this transitional wage compression is a material risk rather than a purely theoretical one.

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The generational dimension is, if anything, more directly in tension with India's own growth narrative. The IMF model finds that older cohorts, who have accumulated savings over their working lives, capture AI-driven income gains earlier and more fully than younger cohorts, because a rising capital share raises the return on existing wealth while wage gains for the young and mid-career build only gradually as capital deepens. India's growth strategy, and much of the rationale for treating its demographic profile as an asset, rests on the opposite premise: that a large, young, working-age population, then entering its prime earning years over the coming two decades, will be the primary engine of both consumption and production. A technology whose income gains accrue disproportionately to older, asset-holding households, rather than to the young workers on whom the demographic-dividend narrative depends, would work against, rather than reinforce, one of Viksit Bharat 2047's central structural bets. This tension is a modelling implication that Indian policymakers would be well advised to treat as a live risk rather than a distant hypothetical, given how central the demographic dividend is to the plan's own logic.

The IMF paper's own caveats are relevant in tempering, without dismissing, this concern. The authors are explicit that their three-way, education-based skill classification is a stylised proxy for task-level exposure to AI rather than a literal ranking, and that some low-skilled, in-person service and manual roles may in practice be less exposed to current AI capabilities than certain information-intensive, medium- or high-skilled occupations. For India, where a large share of low-skilled employment remains in agriculture and manual services relatively distant from current-generation AI, this caveat may be more consequential than for economies where low-skilled work is more concentrated in routine clerical tasks. At the same time, India's large and rapidly growing white-collar, clerical, and business-process-outsourcing workforce, which is precisely the kind of information-intensive, medium-skilled employment that recent evidence on generative-AI exposure identifies as disproportionately affected, suggests that the distributional risk may fall differently across India's occupational structure than the model's education-based categories alone would indicate.

6. Policy Priorities for Viksit Bharat 2047

Read through the IMF's mechanism-based lens, India's AI-related policy agenda for Viksit Bharat 2047 should be organised around three priorities that map directly onto the paper's own reform and redistribution levers, adapted to India's specific fiscal, demographic, and institutional circumstances.

First, on the adoption-timing channel, the priority is to accelerate the structural fundamentals that determine when, within the 2025-to-2047 window, India's economy-wide capital-to-labour ratio crosses the AI-adoption threshold, and to do so quickly enough that the eventual catch-up growth boost, rather than the interim financing-cost headwind, dominates the period that matters most for the Viksit Bharat milestones. This points toward sustained investment in human capital formation, through the National Education Policy's skilling architecture and large-scale vocational and technical training programmes, alongside continued deepening of capital markets and infrastructure to raise capital-specific productivity, and continued improvements in the ease of doing business and capital allocation to raise total factor productivity more broadly. The IMF paper's own simulations suggest that reforms of this kind, sustained over a decade and comparable in ambition to earlier East Asian structural transformations, are what separate an EMDE that merely absorbs the interim headwind from one that converts the AI transition into an accelerant for its broader development goals.

Second, on the within-country distributional channel, India's redistributive and labour-market policy design should draw on the IMF paper's finding that targeted transfers, while more effective at narrowing measured inequality, tend to impose larger output costs than universal transfers of equivalent fiscal size, because they concentrate work disincentives on both the taxed and the recipient population, with these costs rising in the baseline tax rate. Given India's still-developing fiscal capacity and the administrative demands of fine-grained means-testing at national scale, this suggests a premium on broad-based, low-distortion instruments, potentially built on India's existing direct-benefit-transfer infrastructure, complemented by active labour-market policies, including retraining and job-matching support, that the IMF model does not itself simulate but flags as a likely complement to transfer-based redistribution.

Third, the IMF paper's own caveats point to a specifically Indian research and policy priority: because the model treats each economy as a single aggregate sector and assumes a uniform, economy-wide adoption date, it necessarily abstracts from the sectoral staggering that is likely to characterise India's actual AI transition, in which capital-intensive, information-intensive sectors such as information technology services, financial technology, and global capability centres may cross an effective adoption threshold well ahead of agriculture, construction, and much of manual services. A sector-differentiated extension of the IMF's framework, calibrated specifically to India's sectoral structure, would sharpen the policy guidance considerably, and would allow Indian policymakers to identify where within the economy AI-driven capital deepening is likely to arrive soonest, and therefore where transition-support policies are most urgently needed.

Finally, the IMF paper's discussion of large economies is directly relevant to how India should interpret the model's cross-country mechanism. The authors note that their small-open-economy assumption, under which each country takes the global interest rate as given, is more defensible for genuinely price-taking economies than for large economies such as Japan or China, which can themselves influence global savings, investment, and technology development. As India's economy continues to grow toward the scale implied by the world's third-largest-economy ambition, it will increasingly resemble these systemically important economies rather than a small price-taking EMDE, meaning that India's own AI-related investment decisions may, over the Viksit Bharat 2047 horizon, begin to shape the global capital-market conditions the IMF model treats as external to India, rather than being simply imposed upon it by others.

7. Conclusion

Che, Xin, and Yoshida (2026) offer a disciplined, mechanism-focused account of how artificial intelligence could reshape growth and inequality across the Asia-Pacific region, built on the central insight that AI adoption at scale is best understood as an episode of capital deepening whose timing is endogenous to each country's structural fundamentals, and whose cross-country spillovers run through the global cost of capital rather than through trade or technology diffusion alone. Applied to India, this framework yields a cautionary complement to the optimism embedded in the Viksit Bharat 2047 vision. India's demographic profile, precisely the feature most often cited as its central growth advantage, places it, in the IMF's

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calibration logic, among the region's later AI adopters, exposed to a transition period in which early adopters elsewhere in Asia could raise the global cost of capital that India itself depends on. Within India, the same technology that promises substantial aggregate gains could, absent deliberate policy design, widen wage gaps across skill groups and income gaps across generations in ways that sit uneasily against the demographic dividend on which India's growth strategy is built.

None of this implies that AI is inimical to Viksit Bharat 2047. The IMF paper is explicit, and this article follows it, in treating AI as neither an automatic panacea nor an inevitable source of harm, but as a technology whose distributional and cross-country consequences are substantially shaped by the pace and comprehensiveness of structural reform and the design of redistributive policy. For India, the practical implication is that the AI-related components of the Viksit Bharat 2047 agenda, spanning skilling, digital infrastructure, capital-market deepening, and social protection, are not peripheral to the technology's macroeconomic promise but are the principal levers determining whether India experiences the transition as a temporary financing headwind on the way to an accelerated, catch-up-driven leap toward developed-economy status, or as a prolonged period in which the aspiration to global economic leadership remains persistently out of reach.

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