



The Double-Edged Sword of Artificial Intelligence: Employee Productivity Gains and Capability Loss in the Indian Workforce

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Abstract

Artificial Intelligence (AI) is reshaping the global economy at unprecedented speed, and India — home to one of the world's largest and most dynamic workforces — stands at a defining crossroads. This paper examines the dual impact of AI on Indian employees: the measurable productivity gains it delivers, and the equally significant but less-discussed risk of human capability loss. Drawing on data from industry surveys (EY, McKinsey, NASSCOM, Microsoft), government policy documents (NITI Aayog, Economic Survey 2024-25 and 2025-26), and peer-reviewed research, the paper analyses how AI is transforming work patterns across India's IT, services, banking, and manufacturing sectors. It finds that while AI demonstrably boosts individual and organisational productivity — India leads globally with an 'AI Advantage' score of 53 points against a global average of 34 — the concentration of gains among skilled workers, the hollowing out of entry-level roles, and an accelerating deskilling dynamic pose serious structural risks. The paper argues that AI adoption in India is outpacing both human adaptation and institutional response, creating a paradox in which the country produces more AI-augmented output while simultaneously eroding the foundational human competencies that made its workforce competitive. Policy, managerial, and individual-level interventions are proposed to navigate this paradox toward inclusive, sustainable productivity growth.

Keywords: Artificial Intelligence, Employee Productivity, Skill Erosion, India IT Sector, Capability Loss, Digital Transformation, Workforce Disruption

1. Introduction

Artificial Intelligence has transitioned from a niche research domain to a pervasive operational reality. In board rooms, on factory floors, in software development studios, and even in agricultural fields, AI systems — encompassing machine learning, natural language processing, robotic process automation, and generative AI — are reordering the fundamental nature of work. No economy is immune to this transformation, but few face the simultaneous opportunities and vulnerabilities that India does.

India's workforce of over 560 million people is its single greatest economic asset. Its IT and business process management (BPM) sector — employing approximately 5.4 to 5.8 million workers directly and contributing US\$254 billion in revenues in FY2024 — has been the engine of India's middle-class expansion for three decades. Yet this sector is also among the most exposed to AI disruption globally. The IMF's 2024 report warned that unlike previous waves of automation, AI threatens not just routine manual tasks but cognitive functions previously thought to be the exclusive province of highly educated knowledge workers.

The academic and policy discourse on AI's workforce impact has largely focused on job displacement. While this is a critical concern, an equally consequential — and underexplored — dimension is capability loss: the erosion of

human cognitive skills, critical thinking, creative problem-solving, and domain expertise as individuals increasingly delegate tasks to AI tools. This paper addresses both dimensions, analysing productivity gains through empirical data while critically examining the mechanisms through which AI dependency may diminish the very human capabilities that underpin long-term economic value.

The paper is structured as follows: Section 2 reviews relevant literature. Section 3 maps the landscape of AI adoption across Indian industries. Section 4 presents evidence on productivity gains. Section 5 analyses the mechanisms and evidence for capability loss. Section 6 examines sectoral case studies. Section 7 discusses policy and managerial implications. Section 8 concludes.

2. Literature Review

2.1 AI and Productivity: Theoretical Foundations

The relationship between technology and productivity has been studied extensively since the Industrial Revolution. Bresnahan and Trajtenberg (1995) identified 'general purpose technologies' — innovations such as electricity, the steam engine, and information technology — as transformative forces that raise productivity across multiple sectors simultaneously. AI shares the hallmarks of a general purpose technology: it is pervasive, improvable, and innovation-spawning (Brynjolfsson & McAfee, 2014).

Empirical research has documented significant productivity effects. Agrawal et al. (2018) modelled AI as a reduction in the cost of 'prediction', enabling faster and cheaper decision-making across the economy. Brynjolfsson et al. (2019) found that AI adoption at the establishment level was associated with significant productivity improvements, though with a lag consistent with the 'intangible capital' required to reorganise work around new technology. More recently, Noy and Zhang (2023) conducted a randomised experiment with knowledge workers, finding that access to a generative AI tool increased productivity by 37% and improved output quality.

2.2 AI and the Risk of Skill Degradation

The risk that technology erodes human skill is not new. Cognitive scientists have long studied 'automation bias' — the tendency of humans to over-rely on automated systems and under-apply their own judgment (Parasuraman & Manzey, 2010). Bainbridge (1983) articulated the 'ironies of automation': the more reliable an automated system, the less practice humans get, and therefore the less capable they become at intervening when the system fails.

In the context of AI specifically, researchers have begun documenting what might be called 'cognitive offloading'. When AI tools handle analysis, drafting, coding, and decision-support, humans may lose the opportunity to develop and maintain those competencies through practice. Deskilling — a process first analysed by Braverman (1974) in the context of industrial capitalism — may now be occurring in knowledge-intensive sectors previously considered immune (Autor, 2015).

2.3 The Indian Context: Unique Vulnerabilities

India's IT outsourcing model is structurally exposed to AI disruption in ways that distinguish it from advanced economies. The 'pyramid' model — large numbers of entry-level engineers billing hours for routine tasks, supported by a thinner layer of experienced managers — was built on the comparative advantage of low-cost skilled labour. AI erodes precisely this advantage by automating the repetitive, well-defined tasks that formed the base of the pyramid (Ganguly & Banerjee, 2023). Moreover, India's educational system — producing 1.5 million engineering graduates annually but with fewer than half immediately employable in emerging digital roles — is struggling to keep pace with the velocity of skill change.

3. AI Adoption Across Indian Industries

3.1 Scale and Speed of Adoption

The pace of AI adoption in India has been striking. The NASSCOM AI Adoption Index scores India at 2.45 out of 4, with 87% of enterprises actively deploying AI solutions as of late 2025. A 2025 McKinsey survey of 1,993 Indian firms found that 88% were using AI in at least one business function. India ranks among the world's leading AI adopters, with the EY 2025 Work Reimagined Survey placing India at the top of its 'AI Advantage' ranking with a score of 53 against a global average of 34. Approximately 62% of Indian workers are using generative AI tools regularly at work — a figure that climbs to 96% when broader AI or automation tools are included.

India's enterprise AI landscape is also maturing: 47% of enterprises now operate multiple generative AI use cases in full production, up sharply from the pilot-dominated landscape of just two years prior. Investment is concentrated in operations (63%), customer service (54%), and marketing and sales (33%). The Indian AI market itself has grown from US\$2.97 billion in 2020 to US\$7.63 billion in 2024 and is projected to reach US\$131.31 billion by 2032, at a compound annual growth rate of 42.2%.

3.2 Sectoral Distribution

IT and Software Services: The sector with the deepest and most consequential AI integration. AI tools handle code generation, testing, debugging, and documentation that previously required large teams of junior engineers. Major firms like TCS, Infosys, Wipro, HCL, and Cognizant are deploying AI at the platform level, reshaping the economics of project delivery.

Banking and Financial Services: Approximately 21% of Indian banks are currently implementing or developing AI solutions. Applications focus on fraud detection, credit scoring, algorithmic risk management, and customer-facing chatbots. Larger institutions are moving toward AI-driven underwriting and automated document processing.

Healthcare: AI-assisted diagnostics, patient data analytics, and drug discovery are transforming India's healthcare delivery, enabling medical professionals to serve more patients with greater accuracy. AI-driven crop monitoring and precision farming are increasing agricultural yields while reducing input costs.

Business Process Management (BPM): Generative AI-powered automation is handling customer support, data entry, and claims processing — sectors that have historically provided stable white-collar employment for large numbers of Indian workers without engineering degrees.

4. Productivity Gains: Evidence and Mechanisms

4.1 Quantitative Evidence

The evidence for AI-driven productivity gains in India is substantial. EY's forecasts suggest AI will contribute a 2.61% national productivity gain — equivalent to six years of average economic growth — by impacting 38 million jobs by 2030, with 24% of affected tasks fully automated and 42% experiencing significant time savings. Industry-level productivity growth in AI-exposed sectors in India has accelerated from 7% pre-2018 to a remarkable 27% between 2018 and 2024.

At the firm and individual level, the productivity effects are equally compelling. Globally, 91% of businesses deploying AI have reduced administrative workloads by over 3.5 hours per employee per week. In customer support, generative AI has improved issue resolution rates by 15% per employee per hour. Coders assisted by AI tools report productivity increases of up to 126%, while professionals using AI-enhanced document processing experience 59% faster completion times. Research from Stanford's AI Index 2025 confirms that generative AI tools boost overall productivity by 14%, with an outsized 34% gain among newer or lower-skilled workers.

4.2 Mechanisms of Productivity Enhancement

AI enhances employee productivity through three primary mechanisms. The first is task automation: AI systems handle repetitive, well-defined tasks — data entry, basic coding, report generation, appointment scheduling — freeing human workers to focus on higher-order activities. The second is decision augmentation: AI provides real-time analytics, predictive recommendations, and pattern recognition that improve the quality and speed of human decision-making. The third is knowledge amplification: large language models and generative AI act as on-demand knowledge repositories, enabling employees to access information, best practices, and expertise previously requiring specialist consultations.

In the Indian context, a fourth mechanism is also significant: AI as an equaliser. The 34% productivity gain among lower-skilled workers — substantially higher than the 14% average — suggests that AI tools can compress skill gaps, enabling less experienced employees to perform at levels previously requiring years of training. This democratisation of expertise is particularly important in a country where structured mentorship and training programmes have historically been inadequate.

4.3 The Inequality of Productivity Gains

However, the distribution of productivity gains is sharply unequal. The 56% wage increase for skilled workers in AI-exposed sectors stands in stark contrast to the stagnation of entry-level wages, which at India's major IT firms have barely moved from their late-2000s levels of ₹2.5–3.5 lakh per year. Chief Economic Adviser V. Anantha Nageswaran warned explicitly in 2026 that India risks widening inequality at precisely the moment of greatest transformation. The concentration of productivity gains — and the associated wage premium — among the highly skilled further stratifies an already unequal labour market.

5. Capability Loss: Mechanisms, Evidence, and the Indian Context

5.1 Defining Capability Loss

Capability loss, as used in this paper, encompasses three related phenomena: (a) deskilling, the erosion of existing technical and cognitive competencies through non-use; (b) skill obsolescence, the rendering of previously valuable skills irrelevant by AI automation; and (c) skill gap widening, the growing mismatch between the skills workers possess and those the AI-transformed economy demands. All three are occurring simultaneously in India's workforce, though they affect different occupational categories differently.

5.2 Deskilling Through AI Dependence

As AI tools automate cognitive tasks, employees who rely on them may progressively lose their capacity to perform those tasks independently. This is the contemporary manifestation of Bainbridge's ironies of automation: the better AI becomes, the less humans practise, and the less capable they become without AI assistance. In the Indian IT sector, this dynamic is particularly acute because the traditional 'on the job' training model — in which freshers developed expertise through years of repetitive project work — has been disrupted precisely at the moment that entry-level roles are being automated away.

An IIM-Ahmedabad study of white-collar workers found that while 55% have adopted AI tools and 48% have received some training, 68% fear their roles could be fully automated within five years. This anxiety reflects an implicit recognition: employees sense that their human capabilities are not keeping pace with the AI systems they are meant to supervise and collaborate with.

5.3 The Hollowing of the Entry-Level Pathway

Perhaps the most structurally damaging form of capability loss in India is the disappearance of the entry-level career pathway. For three decades, the Indian IT pyramid worked by channelling large numbers of engineering graduates into structured, if repetitive, entry-level roles that served as the foundation for skill development. Freshers learned debugging, testing, client communication, and project management through years of hands-on practice before rising to more complex responsibilities.

This pathway is collapsing. From 600,000 freshers hired by India's major IT firms in FY 2022-23, the number plunged by approximately 75% to around 150,000 in the following hiring cycle. TCS announced 12,000 layoffs in July 2025 — its first mass layoff in history — explicitly citing AI-driven 'skill mismatches'. The CFO of TeamLease Services confirmed that at entry and early mid-level positions, there is virtually no net hiring occurring because AI tools have made those tasks redundant. Demand for entry-level roles now stands at approximately 30% of available supply.

The implications are generational. Without the entry-level learning environment, a cohort of India's engineering graduates is being deprived of the experiential development that builds genuine expertise. They enter the workforce without the foundational skills to progress, while the AI tools that replaced their training-ground roles are themselves unable to build the judgment, contextual knowledge, and adaptive capability that come from years of practice.

5.4 Skill Obsolescence at Scale

Skill obsolescence is occurring at a pace that institutional systems are ill-equipped to handle. The World Economic Forum's Future of Jobs 2025 report projects that 44-46% of core job skills in India will change by 2030. PwC research finds that skills required for AI-exposed roles are already changing 66% faster than those in less-exposed occupations. Degrees — once a near-permanent credential — are losing their signalling power in a labour market where relevance has a shelf life of just two to three years.

India's educational response has been inadequate to this pace of change. Despite producing 1.5 million engineering graduates annually, fewer than half are immediately employable in emerging digital roles. The talent shortage in AI-specific skills, reported by 59% of enterprises surveyed by NASSCOM, coexists with rising graduate unemployment — a paradox of simultaneous surplus and scarcity that reflects the depth of the skills mismatch.

5.5 The Psychological Dimensions of Capability Loss

A peer-reviewed study published in 2025 in a Taylor and Francis journal, drawing on Delphi-validated thematic analysis of Indian IT professionals, identified six core psychological themes arising from AI-driven role disruption: emotional shock, erosion of professional identity, chronic anxiety and anticipatory rumination, social withdrawal, adaptive and maladaptive coping strategies, and perceived organisational betrayal.

The study found that AI-induced role redundancy in the Indian IT sector is not merely a labour market shift but 'a deep psychological disruption', with gendered and role-based distinctions showing that female professionals and support staff experienced deeper identity threats and reduced coping efficacy. This psychological dimension of capability loss — the erosion not just of skills but of professional identity, confidence, and sense of future — has significant implications for workforce wellbeing and, ultimately, for economic performance.

EY's 2025 workforce survey also found that while AI has enabled efficiency gains, it has contributed to rising workloads for many, with AI often layered onto existing roles rather than prompting genuine role redesign. This

intensification — doing more with the same headcount — may compound both cognitive fatigue and the risk of deskilling, as employees have less time for the deliberate practice and reflection that build genuine capability.

6. Sectoral Case Studies

6.1 IT Services: The Crumbling Pyramid

India's IT services sector offers the most vivid example of the dual impact described in this paper. The sector has simultaneously experienced substantial productivity gains and fundamental structural disruption. In 2025 alone, the top five IT firms — TCS, Infosys, Wipro, HCL, and Cognizant — lost over US\$150 billion in combined market capitalisation, reflecting investor reassessment of a business model built on labour arbitrage that AI is rapidly undermining.

Employee cost growth in the Indian IT industry has fallen sharply from 19% year-on-year in 2022-23 to just 5% in 2024-25 (CareEdge Ratings). This wage stagnation, combined with the collapse of entry-level hiring, represents a structural compression that has both productivity and capability implications. Workers remaining in the sector are increasingly required to supervise AI outputs, manage AI-augmented teams, and handle the exceptions and edge cases that AI cannot resolve — demanding a qualitative upgrade in human capability at precisely the moment when the pathways to developing that capability are being removed.

NITI Aayog's October 2025 report projected that in a business-as-usual scenario, the tech services sector headcount could decline from 7.5-8 million in 2023 to 6 million by 2031. The customer experience (BPM) sector could shrink from 2-2.5 million to 1.8 million over the same period. In the worst case, up to 2.7 million jobs could be eliminated by 2031 if no significant policy intervention occurs.

6.2 Banking and Financial Services: Efficiency vs. Judgement

In India's financial sector, AI is being deployed primarily in areas of pattern recognition and rule-following — fraud detection, customer segmentation, loan processing automation, and algorithmic trading support. The efficiency gains are real: AI-driven document processing has reduced turnaround times significantly, and customer-facing chatbots have reduced the demand for call-centre agents. However, the delegation of credit decisions and risk assessments to AI systems raises concerns about the erosion of the experienced human judgement that is critical when AI models encounter conditions outside their training distribution.

India's Economic Survey 2025-26 itself cited concerns about AI-driven herding behaviour in financial markets, where AI models adopted by large numbers of investors simultaneously recommend similar actions, amplifying systemic risk. This is precisely the capability-loss risk applied to institutional level: as financial institutions rely increasingly on shared AI models, the diversity of human analytical perspectives — and the associated systemic resilience — diminishes.

6.3 Healthcare: Diagnostic Support vs. Clinical Expertise

In healthcare, AI-assisted diagnostics and patient analytics have meaningfully improved the speed and accuracy of service delivery. India's severe shortage of specialist physicians means that AI diagnostic tools can extend the reach of specialist expertise to underserved populations — a genuine capability amplifier. However, medical educators have begun to raise concerns that if physicians come to rely on AI diagnostic support early in their training, they may not develop the clinical pattern recognition and differential diagnosis skills that come from years of independent diagnostic practice. This is the healthcare instantiation of the broader deskilling paradox.

7. Policy and Managerial Implications

7.1 Government Policy Directions

India's policy response to AI-driven workforce disruption has been active but insufficient in scale. The IndiaAI Mission (2024), NITI Aayog's AI Roadmap for Job Creation (2025), the National Strategy for Artificial Intelligence, and programmes under Digital India collectively represent a framework of intent. The government has enrolled 8.65 lakh candidates in emerging technology courses through NITI Aayog programmes as of August 2025, and is supporting 500 PhD scholars, 5,000 postgraduates, and 8,000 undergraduates in AI-related work under the IndiaAI FutureSkills initiative.

However, the scale of intervention is not yet proportionate to the challenge. When 60% of formal sector jobs may be susceptible to automation by 2030, and when 2.7 million IT and BPM jobs could disappear in eight years, programmes reaching hundreds of thousands of learners are necessary but not sufficient. The following policy directions are recommended based on the evidence reviewed in this paper:

1. Mandatory AI literacy frameworks integrated into undergraduate and postgraduate curricula across disciplines, not merely engineering programmes, to ensure broad workforce readiness.
2. A national skills recognition system that validates micro-credentials and continuous learning, reducing dependence on degrees as sole proxies for employability and enabling the latent AI talent already in the workforce to be identified and deployed.
3. Skilling investment redirected from enrolment numbers to employment outcomes, with accountability mechanisms ensuring that training programmes result in genuine capability development, not merely certification.
4. Social protection frameworks updated for an AI-disrupted labour market, including portable benefits, income support during reskilling transitions, and expanded active labour market programmes.
5. Tax incentives for employers who invest in structured, role-based AI learning pathways — as opposed to ad hoc tool adoption — to internalise the positive externalities of workforce capability development.

7.2 Organisational Strategies

For organisations, the evidence in this paper suggests that the dominant pattern of AI adoption — layering tools onto existing roles without redesigning work — is both inefficient and capability-destroying. Three strategic shifts are recommended:

- Human-AI task design: Deliberate design of work so that AI handles automation-appropriate tasks while humans retain responsibility for judgment-intensive, relationship-intensive, and novel problem-solving activities — preserving the experiential learning that builds genuine capability.
- Structured AI learning pathways: Moving beyond ad hoc AI tool adoption to invest in structured, role-specific AI training. The EY data shows clearly that employees who invest more time in AI capability development report significant time savings and demonstrate lower intent to leave — a powerful business case for structured investment.
- Psychological safety and wellbeing: Given the evidence of deep psychological disruption from AI-driven role change, organisations should invest in proactive wellbeing support, transparent communication about AI's role in organisational strategy, and career transition support for workers whose roles are being restructured.

7.3 Individual Strategies

For individual workers, the imperative is continuous, intentional learning. The evidence that 94% of Indian professionals perceive AI mastery as essential for career progression reflects an accurate reading of the labour market.

Workers who invest in AI capability development not only protect their employability but actively enhance it — the EY data shows a clear link between AI learning investment and both productivity gains and organisational loyalty. Critically, however, individuals should pursue AI fluency not as a substitute for deep domain expertise, but as a complement to it. The human capabilities most resistant to AI displacement — contextual judgment, ethical reasoning, interpersonal trust-building, creative synthesis, and adaptive problem-solving — are developed through deliberate practice and cannot be acquired from an AI tool itself.

8. Conclusion

This paper has examined the dual impact of artificial intelligence on India's workforce: the measurable and significant productivity gains that AI adoption delivers, and the less visible but structurally consequential erosion of human capability that follows in its wake. The evidence is clear that both are real, simultaneous, and intersecting. India's AI Advantage score of 53 — the highest globally — reflects genuine productivity transformation. The simultaneous collapse of entry-level hiring, stagnation of real wages, deepening skills mismatches, and psychological distress among displaced workers reflect a capability crisis unfolding beneath the headline numbers.

The central paradox this paper identifies is this: India is deploying AI to generate more output with fewer workers, while simultaneously losing the experiential pathways through which workers develop the capabilities to generate value independently of AI. If left unaddressed, this paradox risks creating an economy that is highly productive in the short term but increasingly brittle over time — one that has optimised human labour out of its knowledge base and finds itself without the adaptive human capacity to respond when AI models fail, change, or encounter unprecedented conditions.

The path forward requires policy foresight, organisational courage, and individual intentionality. The AI-enabled productivity boom is real and should be embraced. But it must be paired with deliberate investment in human capability development: redesigning AI-augmented work to preserve experiential learning, scaling structured reskilling programmes to match the velocity of skill change, updating social protection systems for a labour market in transition, and building the deep expertise — contextual, ethical, adaptive, relational — that AI cannot replicate and organisations cannot survive without.

India's AI story is being written now. Whether it becomes a story of inclusive, sustainable transformation or one of concentrated gains and diffuse capability loss will depend on choices made — by government, by organisations, and by individual workers — in the next five years.

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