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Artificial Intelligence for Sustainable Growth and Social Welfare in Emerging Economies: Empirical Evidence from India and Policy Implications

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Abstract
Artificial intelligence (AI) is reshaping production, employment, financial services, and welfare, but its implications for inclusive growth in emerging economies remain uncertain. This study examines the emerging economic and social effects of AI adoption in India through a structured synthesis of recent academic, government, regulatory, and industry evidence. The analysis develops a conceptual framework linking AI inputs and diffusion mechanisms with productivity, distributional, and welfare outcomes, while considering institutional and governance capacity as a moderating factor. The evidence indicates substantial AI potential alongside uneven diffusion. India's AI policy architecture includes an IndiaAI Mission with an outlay exceeding ₹10,300 crore, while national estimates project a potential AI contribution of USD 500–600 billion to GDP by 2030. However, AI adoption remains considerably lower among MSMEs than among global enterprises, while routine and language-intensive tasks in sectors such as IT and business-process outsourcing face substantial automation exposure. AI-enabled financial infrastructure, including the Unified Lending Interface, shows emerging potential for improving access to formal credit among underserved groups, although its welfare effects remain preliminary. These patterns indicate a **second-order digital divide**, in which access to digital technologies has expanded but the capacity to convert AI into productive and inclusive outcomes remains uneven. The study concludes that inclusive AI-led growth requires complementary investment in skills, MSME capabilities, worker-transition support, and adaptive institutional governance alongside technological infrastructure.

Keywords: artificial intelligence; inclusive growth; social welfare; emerging economies; India; second-order digital divide; AI governance; MSMEs

1. Introduction

Artificial intelligence (AI) is increasingly regarded as a general-purpose technology with the potential to reshape production, employment, productivity, and economic organisation across sectors. Like earlier transformative technologies such as electricity and the internet, AI can alter how firms operate and how economic value is created (Filippucci et al., 2025). The potential gains are substantial. McKinsey & Company (2023), for example, estimated that generative AI could add USD 2.6–4.4 trillion annually to the global economy once widely adopted across business functions. However, these benefits are unlikely to be distributed uniformly. Recent evidence suggests that emerging economies may experience smaller short-run gains from AI than advanced economies because of differences in technological capabilities, digital readiness, human capital, and institutional capacity (Bank for International Settlements [BIS], 2025). This raises an important question for India: **can AI-driven technological change generate broad-based and inclusive economic gains, or could it create new disparities between firms, workers, and regions?**

India provides an important context for examining this question. The country has developed a substantial digital ecosystem and an increasingly ambitious national AI strategy, while significant sections of its economy continue to operate with limited access to formal finance, advanced skills, and institutional support. NITI Aayog (2025c) estimates that approximately 490 million workers are engaged in informal employment, highlighting the scale of the population that may remain outside the immediate benefits of AI-enabled formal economic activity. At the same time, the Indian government has accelerated AI-related investment. The IndiaAI Mission, approved in March 2024 with an outlay exceeding ₹10,300 crore, focuses on computing infrastructure, datasets, indigenous AI capabilities, applications, skilling, and responsible AI development (Press Information Bureau [PIB], 2025). NITI Aayog (2025a) estimates that AI could contribute approximately USD 500–600 billion to India's GDP by 2030, while its assessment of the AI economy also points to significant changes in employment and skill requirements (NITI Aayog, 2025b). Thus, India's AI trajectory combines substantial growth opportunities with potential labour-market and distributional challenges.

The implications extend beyond aggregate productivity. AI adoption may affect the distribution of economic gains across firms of different sizes, workers with different skill levels, and formal and informal sectors. Larger enterprises may be better positioned to adopt AI because they have greater access to computing resources, finance, data, and specialised talent, whereas MSMEs may face stronger constraints in acquiring and implementing these capabilities. Similarly, automation may disproportionately affect routine, repetitive, and language-intensive tasks, while simultaneously creating demand for new technology-related skills (Acemoglu & Restrepo, 2019; Agrawal et al., 2019; Gmyrek et al., 2023). In financial services, AI-enabled digital infrastructure may expand access to credit for underserved enterprises and individuals, but the ability to benefit from such infrastructure depends on complementary financial, digital, and organisational capabilities. These dynamics suggest that the economic consequences of AI cannot be assessed solely through aggregate investment or GDP projections. Against this background, this study develops the concept of a **second-order digital divide**. The first-order digital divide concerns access to basic digital infrastructure and technologies, whereas the second-order divide concerns differences in the capacity to use advanced digital technologies, particularly AI, to generate productive and welfare-enhancing outcomes. India's expanding digital infrastructure has reduced some barriers to basic digital participation, but differences in skills, firm-level capabilities, affordability, institutional readiness, and access to complementary resources may continue to determine who benefits from AI. This distinction provides a useful lens for examining whether AI-led growth can become broadly inclusive in an emerging economy.

The study has four main contributions. First, it synthesises recent academic, government, regulatory, and institutional evidence on the economic, labour-market, financial-inclusion, and governance implications of AI in India. Second, it develops a conceptual framework linking AI inputs and diffusion mechanisms to productivity, distributional, and welfare outcomes, with institutional and governance capacity treated as a moderating factor. Third, it systematically maps available evidence against four analytical propositions concerning differences in productivity potential across firms, AI-enabled financial inclusion, concentration of automation risk, and the role of institutional capacity. Finally, it derives policy implications for strengthening skills, MSME capabilities, worker-transition mechanisms, and adaptive governance so that AI adoption can contribute to more inclusive growth. The remainder of the paper is organised as follows. Section 2 reviews the relevant literature, while Section 3 identifies the research gap. Section 4 presents the research objectives, Section 5 develops the analytical propositions, and Section 6 presents the conceptual framework. Section 7 describes the research methodology, including the search strategy, inclusion and exclusion criteria, analytical framework, reliability procedures, and limitations. Section 8 presents the evidence and data analysis, followed by the results and discussion in Section 9. Section 10 outlines the policy implications, and Section 11 concludes the study.

2. Literature Review and Theoretical Framework

2.1 AI as a General-Purpose Technology: Productivity and Economic Growth

Artificial intelligence (AI) is increasingly conceptualised as a general-purpose technology (GPT) because of its potential to diffuse across industries, transform production processes, and generate further innovation. Earlier GPTs, including electricity and information and communication technologies, contributed to sustained productivity improvements through widespread adoption and complementary organisational and technological changes (Filippucci et al., 2025). AI shares these characteristics, although the magnitude and timing of its economic effects depend substantially on the speed and breadth of adoption.

Estimates of AI's productivity effects vary considerably. The Penn Wharton Budget Model (2025) suggests that the near-term productivity effects of AI may initially be modest, with GDP gains potentially reaching approximately 1.5% by 2035 and approaching 3% by 2055. At the firm level, however, evidence indicates rapid growth in AI adoption and emerging productivity and innovation benefits. Global enterprise AI adoption has increased substantially in recent years, indicating that AI is moving from experimental use toward broader organisational implementation (Al Habtoor Research Centre, 2025). However, technological availability does not automatically translate into uniform productivity gains. Filippucci et al. (2024) emphasise that the effects of AI on productivity, distribution, and growth depend on complementary investments, organisational capabilities, skills, and the institutional environment. Similarly, BIS (2025), examining 56 countries and 16 industries, finds that the potential benefits of AI vary according to industrial composition, knowledge intensity, digital infrastructure, human capital, and broader AI readiness. These differences are particularly important for emerging economies, where limitations in infrastructure, skills, and institutional capacity may constrain the ability of firms and workers to convert AI investment into productivity gains.

The literature therefore suggests that AI should not be understood simply as an independent source of economic growth. Rather, productivity effects depend on the interaction between technological inputs, organisational adoption, complementary capabilities, and the wider economic environment. This provides the theoretical basis for examining differences in AI-related productivity potential between large enterprises and MSMEs in India.

2.2 AI, Task Transformation, and Labour-Market Inequality

A second strand of literature examines AI through the task-based approach to technological change. Rather than assuming that technology replaces entire occupations, this perspective considers how technological innovation changes the tasks performed within occupations. Acemoglu and Restrepo (2019) distinguish between displacement effects, where technology substitutes for tasks previously performed by workers, and reinstatement effects, where technological change creates new tasks and employment opportunities. The overall effect on employment and wages depends on the relative strength of these two processes.

Evidence from the United States suggests that automation can contribute to wage inequality when displacement effects outweigh the creation of new tasks, particularly for workers with lower levels of formal education (Acemoglu & Restrepo, 2022). Earlier research by Acemoglu (2002) similarly demonstrates how technological change can increase the relative demand for skilled labour and contribute to differences in wage outcomes. Agrawal et al. (2019) further argue that AI changes the economics of prediction and may alter the allocation of tasks between humans and machines.

Generative AI introduces an important extension to this literature because it can perform a wide range of language-intensive and cognitive tasks that were previously less exposed to automation. The International Labour Organization (Gmyrek et al., 2023) therefore highlights the importance of examining not only potential job displacement but also changes in job quality, task composition, and the possibility of human–AI complementarity.

The implications may be particularly significant for emerging economies with large service sectors. Cornelli et al. (2023) argue that AI-enabled automation of remotely deliverable service tasks could affect the comparative advantage of economies that have relied on labour-intensive service exports. For India, this issue is particularly relevant to information technology and business-process outsourcing, where routine and language-intensive tasks have historically supported employment and export growth. At the same time, AI may generate new occupations and complementary tasks, creating opportunities for workers with appropriate technical, analytical, and adaptive skills. The distributional outcome will therefore depend on the balance between task displacement, task creation, and the capacity of workers and institutions to manage the transition.

2.3 AI, Financial Inclusion, Welfare, and Institutional Capacity

The implications of AI extend beyond productivity and employment to financial inclusion and broader welfare outcomes. AI-enabled digital infrastructure can reduce information asymmetries, improve credit assessment, and potentially expand access to financial services among individuals and enterprises that lack conventional credit histories. In India, developments such as the Unified Lending Interface illustrate how digital public infrastructure can support the expansion of technology-enabled lending and potentially address persistent credit constraints among underserved groups.

However, greater technological access does not necessarily guarantee improved welfare outcomes. The ability to benefit from AI-enabled services depends on complementary factors including digital literacy, skills, affordability, data availability, institutional trust, and effective regulation. This is particularly relevant for MSMEs and informal workers, whose capacity to adopt advanced technologies may be constrained even where basic digital infrastructure is widely available.

The governance literature consequently emphasises the importance of institutional capacity in determining how the benefits and risks of AI are distributed. International evidence indicates significant differences between countries in their ability to design, implement, and enforce effective AI governance frameworks (International Telecommunication Union [ITU], 2025). Developing economies may face particular challenges because of limited regulatory resources, fragmented institutional structures, and gaps in technical expertise. Research on AI governance in developing-country contexts also highlights concerns relating to data protection, accountability, algorithmic risks, and the ability of existing regulatory systems to respond to rapidly changing technologies.

For India, this suggests that institutional capacity should not be treated as a final stage in the AI development process. Instead, governance, regulation, skills, and social-protection systems can shape the extent to which technological inputs translate into productive and inclusive outcomes throughout the adoption process.

2.4 The Second-Order Digital Divide

The literature reviewed above suggests that the contemporary digital divide increasingly extends beyond basic access to digital technologies. The first-order digital divide concerns differences in access to connectivity, devices, digital payments, and basic digital services. However, as digital infrastructure becomes more widespread, another form of inequality becomes increasingly important: differences in the ability to use advanced technologies such as AI productively.

This study refers to this phenomenon as the **second-order digital divide**. It describes the gap between having access to digital technologies and possessing the skills, organisational capabilities, financial resources, data, and institutional support required to convert AI access into measurable economic and welfare benefits. The concept is particularly relevant to India because digital inclusion has expanded rapidly, while AI adoption remains uneven across firms, sectors, and groups of workers.

The second-order digital divide therefore provides a bridge between the productivity, distribution, and institutional dimensions of AI. Large enterprises with greater financial, technological, and human-resource capabilities may adopt AI more rapidly than MSMEs. Similarly, workers performing routine cognitive tasks may face greater displacement risks, while workers with complementary technical and adaptive skills may benefit from emerging opportunities. Finally, institutional capacity can influence whether these differences translate into persistent inequality or are mitigated through skills development, social protection, financial inclusion, and adaptive governance.

2.5 Integrating the Theoretical Perspectives

Taken together, the literature provides a basis for understanding AI-led development through three interconnected channels.

First, the productivity channel concerns the extent to which AI inputs—including computing infrastructure, data, talent, and AI models—are converted into firm-level and aggregate productivity gains through adoption and complementary capabilities.

Second, the distribution channel concerns how AI changes the allocation of employment, wages, and economic opportunities through task displacement, task creation, and human–AI complementarity.

Third, the institutional and welfare channel concerns the extent to which financial infrastructure, skills systems, social protection, regulation, and governance capacity shape the distribution and inclusiveness of AI-related benefits.

These channels are interconnected rather than independent. Greater AI adoption may increase productivity while simultaneously increasing automation exposure for particular groups of workers. Similarly, AI-enabled financial infrastructure may expand access to credit, but its broader economic effects may remain limited if borrowers lack the capabilities required to use finance productively. Institutional capacity therefore acts as a moderating condition across the three channels. The theoretical synthesis provides the foundation for the conceptual framework presented in Section 6 and guides the evidence assessment undertaken in Sections 8 and 9.

3. Research Gap

Existing literature provides substantial evidence on the productivity, labour-market, welfare, and governance implications of AI, but these strands remain insufficiently integrated when examining emerging economies such as India. Macroeconomic studies focus primarily on AI's potential effects on productivity and economic growth (Filippucci et al., 2024, 2025; Penn Wharton Budget Model, 2025), while task-based research examines employment displacement, task creation, and wage inequality (Acemoglu & Restrepo, 2019, 2022). A separate body of research addresses AI readiness, institutional capacity, and governance challenges (BIS, 2025; ITU, 2025).

Cross-country research demonstrates that emerging economies may face greater constraints in converting AI into productivity gains because of differences in infrastructure, human capital, industrial structure, and institutional readiness. However, such studies generally operate at the country or sector level and provide limited insight into how AI-related opportunities and risks differ within a particular emerging economy across firm size, employment formality, and economic activity. India-specific reports provide valuable evidence on AI policy, MSMEs, employment, financial inclusion, and informal workers (NITI Aayog, 2025a, 2025b, 2025c; PwC India, 2026; PayNearby, 2026). Nevertheless, these sources are often examined separately and are rarely integrated within a common analytical framework linking AI adoption to productivity, distributional outcomes, welfare, and institutional capacity.

This study addresses this gap by integrating these dimensions within a single conceptual framework. In particular, it examines whether India's emerging AI landscape reflects a **second-order digital divide**, in which basic digital access has expanded but the capability to convert AI into productive and inclusive outcomes remains uneven. The study further maps available secondary evidence across productivity, distribution, and institutional channels and assesses whether the evidence is directionally consistent with four analytical propositions concerning firm-level productivity differences, AI-enabled financial inclusion, automation exposure, and institutional capacity.

4. Objectives of the Study

The study is guided by the following objectives:

RO1: To review and synthesise theoretical and empirical literature on the implications of artificial intelligence for economic growth, employment, financial inclusion, and social welfare, with particular emphasis on emerging economies.

RO2: To examine India's AI policy architecture and map major initiatives—including the IndiaAI Mission, Unified Lending Interface, and inclusion-oriented programmes—onto the productivity, distribution, and institutional dimensions of AI-led development.

RO3: To analyse available secondary evidence on AI adoption and its emerging effects across large enterprises, MSMEs, financial services, employment, and informal workers in India.

RO4: To assess whether the available evidence is directionally consistent with four analytical propositions concerning AI-related productivity differences, financial inclusion, labour-market automation exposure, and the moderating role of institutional capacity.

RO5: To derive policy implications for promoting inclusive and sustainable AI-led growth in India and, where relevant, other emerging economies.

5. Analytical Propositions

Based on the literature review and conceptual framework, four analytical propositions are formulated to guide the systematic assessment of available secondary evidence concerning AI adoption, productivity, financial inclusion, labour-market transformation, and institutional capacity in India.

Rather than treating these propositions as statistically testable hypotheses, the study evaluates them through **qualitative evidence mapping and cross-source comparison**. The propositions provide a structured basis for assessing whether the available evidence is consistent with the expected relationships identified in the theoretical literature.

Proposition 1: AI Adoption and Productivity Differences

P1: AI adoption is likely to generate greater productivity benefits for large enterprises than for MSMEs in India, owing to differences in technological infrastructure, financial resources, skilled human capital, and organisational capacity.

Proposition 2: AI-Enabled Financial Infrastructure and Credit Access

P2: AI-enabled digital financial infrastructure has the potential to improve access to credit among underserved MSMEs and informal-sector participants by reducing information asymmetries and facilitating data-driven credit assessment.

Proposition 3: AI Automation and Task-Based Labour-Market Risk

P3: AI-driven automation risk in India is likely to be concentrated in routine, rule-based, and language-intensive tasks rather than being distributed uniformly across different types of jobs.

Proposition 4: Institutional Capacity and Inclusive Welfare Outcomes

P4: Stronger institutional and governance capacity is likely to enhance the extent to which AI adoption contributes to inclusive welfare outcomes by strengthening regulatory adaptability, skill development, social protection, and responsible technology deployment.

6. Conceptual Framework

Building on the three interconnected channels identified in Section 2.4—productivity, distribution, and institutions—this study proposes a conceptual framework to explain how AI-related inputs may translate into economic growth and social welfare outcomes in India. The framework conceptualises AI inputs, including computing infrastructure, datasets, and skilled human capital, as foundational resources that operate through various diffusion mechanisms, such as firm-level adoption, AI-enabled financial inclusion, and task-level automation. These mechanisms are expected to influence productivity, employment and distributional outcomes, financial inclusion, and broader dimensions of social welfare.

Institutional and governance capacity is conceptualised as a moderating factor that may influence the extent to which AI inputs and diffusion mechanisms translate into inclusive outcomes. Rather than treating institutional capacity as a sequential stage, the framework recognises that regulatory adaptability, skill-development systems, social-protection mechanisms, and governance arrangements may shape the effectiveness and distributional consequences of AI adoption throughout the process. Table 1 summarises the proposed framework and provides the analytical basis for organising and interpreting the secondary evidence examined in Section 8.

Table 1
Conceptual Framework Linking AI Inputs to Growth and Welfare Outcomes

Stage	Components	Illustrative Indicators (India)
AI Inputs	Computing infrastructure; datasets; talent pipeline; indigenous foundation models	IndiaAI Mission outlay and GPU access; AIKosh datasets; FutureSkills fellowships
Diffusion Mechanisms	Firm-level AI adoption; AI-enabled financial inclusion; task-level automation in the labour market	MSME AI/ML adoption rate; Unified Lending Interface participation; IT/BPO task exposure
Growth and Welfare Outcomes	Aggregate productivity and GDP growth; distributional effects on wages and employment; financial and social inclusion	Projected AI contribution to GDP; IT workforce projections; potential credit-gap closure for MSMEs and informal workers
Moderating Factor	Institutional and governance capacity	AI governance guidelines; skilling and social-protection infrastructure; regulatory adaptability

Note. Author's own construction, informed by Acemoglu and Restrepo (2019, 2022), BIS (2025), and NITI Aayog (2025a, 2025b, 2025c). GDP = gross domestic product; MSME = micro, small, and medium enterprise; IT/BPO = information technology/business process outsourcing.

Institutional and governance capacity is conceptualised as a moderating factor rather than as a fourth sequential stage because, as discussed in Section 2.3, the quality of governance and institutional arrangements may influence how effectively AI inputs are converted into productive and inclusive outcomes at each stage of the process. This framing also provides the basis for assessing the fourth analytical proposition concerning the relationship between institutional capacity and inclusive welfare outcomes.

7. Research Methodology

7.1 Research Design

This study adopts a secondary-data-based research design that combines a structured review of existing literature with descriptive analysis of quantitative indicators reported in academic, institutional, governmental, regulatory, and industry sources. The design is appropriate to the objectives of the study because the principal AI-related policy initiatives examined in the Indian context—including the IndiaAI Mission, the Unified Lending Interface, and the proposed Digital ShramSetu Mission—were introduced primarily between March 2024 and late 2025. Consequently, sufficient longitudinal outcome data are not yet available to evaluate their long-term economic and welfare effects comprehensively.

Furthermore, at the time of the study, no nationally representative dataset providing sufficiently detailed firm- or worker-level information on AI adoption and its economic consequences in India was publicly available. Given these constraints, the study synthesises the best available secondary evidence within a clearly defined conceptual framework and evaluates its consistency with the four analytical propositions developed in Section 5. The approach therefore seeks to identify emerging patterns, relationships, and policy implications without making claims of statistical causality.

7.2 Search Strategy

Relevant sources were identified through a structured search conducted between December 2025 and July

2026. Academic articles and working papers were identified using Google Scholar, SSRN, the RePEc/IDEAS database, and working-paper repositories associated with the National Bureau of Economic Research, the Bank for International Settlements, and the International Telecommunication Union. Government and policy documents were obtained directly from the official sources of NITI Aayog, the Ministry of Electronics and Information Technology, the Press Information Bureau, the Reserve Bank of India, and the Small Industries Development Bank of India. Relevant industry evidence was obtained from the public research resources of McKinsey & Company, PwC India, and PayNearby.

The search strategy combined the term "artificial intelligence" with keywords representing three principal outcome dimensions. Economic and productivity-related terms included "economic growth," "productivity," and "GDP"; labour-market terms included "labour market," "employment," "automation," and "wage inequality"; and welfare-related terms included "financial inclusion," "informal workers," "MSME," "digital divide," "AI governance," and "India." The search was restricted to English-language sources published or updated between 2019 and 2026, with greater emphasis placed on literature published from 2023 onward, reflecting the accelerated diffusion of generative AI during this period.

7.3 Inclusion and Exclusion Criteria

Sources were included when they satisfied the following criteria: (a) they were peer-reviewed journal articles, working papers produced by recognised research institutions or central banks, or official government or regulatory publications; (b) they directly addressed the economic, labour-market, welfare, governance, or distributional implications of AI, either globally or in the Indian context; and (c) they were published or last updated between 2019 and 2026, with greater emphasis given to sources published from 2023 onward.

Sources were excluded when they consisted primarily of opinion-based writing, promotional material, or unverified media reporting without a clear institutional basis; when they merely reproduced statistics from another source without providing additional analytical value; or when specific quantitative claims could not be cross-checked against at least one independent source, consistent with the reliability and validation procedure described in Section 7.5.

Applying these criteria resulted in a final set of 24 sources used in the analysis, comprising peer-reviewed academic literature, institutional working papers, government and regulatory publications, and selected industry reports.

7.4 Analytical Framework and Evidence Assessment

The collected evidence was analysed through two complementary stages. First, each source was reviewed and classified according to one or more of the three analytical channels identified in the conceptual framework in Section 6: productivity, distribution, and institutions. This classification enabled evidence derived from diverse sources and methodological approaches to be organised within a common analytical structure.

Second, key quantitative indicators—including AI adoption rates, workforce projections, financial-inclusion indicators, and estimated credit gaps—were systematically extracted and organised in a comparative evidence table (Table 2). The evidence was subsequently assessed against the four analytical propositions presented in Section 5 using the structured evidence-mapping approach reported in Table 3.

Rather than conducting formal statistical hypothesis testing, each proposition was assessed according to the direction, consistency, relevance, and corroboration of the available secondary evidence. A proposition was considered to receive **broad support** when multiple relevant sources provided evidence that was directionally consistent with the proposition; **preliminary support** when the available evidence was suggestive but limited or emerging; and **insufficient evidence** when the available material did not permit a sufficiently reliable assessment. This approach is appropriate because the underlying evidence differs substantially in terms of data sources, samples, measurement approaches, and research designs and therefore cannot be statistically pooled into a common dataset.

7.5 Reliability and Trustworthiness

Several procedures were adopted to enhance the reliability and trustworthiness of the evidence synthesis. First, where discrepancies were identified across sources, greater weight was assigned to peer-reviewed academic research and official government or regulatory sources than to industry or media-based evidence. Second, wherever multiple independent sources reported information on the same issue, reported figures were cross-checked for consistency. For example, evidence concerning MSME AI adoption was compared across Kaur (2025) and PwC India (2026), while financial-inclusion indicators were assessed against PIB (2026) and available independent evidence concerning rural digital-payment adoption.

Third, quantitative indicators reported in Section 8 were linked to their respective original sources and publication dates wherever possible. This procedure allows readers to verify the evidence and helps distinguish time-sensitive estimates and projections from established empirical outcomes. Particular attention was given to the distinction between observed outcomes, projected outcomes, and policy targets to reduce the risk of interpreting projections or intended outcomes as established effects.

7.6 Limitations

The study has several limitations that should be considered when interpreting its findings. First, the analysis relies on secondary sources employing different research designs, samples, definitions, and measurement approaches. Consequently, the quantitative indicators presented in Section 8 should be interpreted as a structured synthesis of available evidence rather than as observations drawn from a single harmonised dataset.

Second, the absence of first-hand micro-level data prevents the study from conducting formal statistical significance tests or establishing causal relationships between AI adoption and the outcomes considered. The evidence-mapping procedure presented in Section 7.4 therefore assesses whether the available evidence is consistent with the analytical propositions rather than providing statistical confirmation or causal proof.

Third, several of the policy initiatives examined—particularly the Digital ShramSetu Mission and India's AI governance guidelines introduced in November 2025—are relatively recent. Consequently, evidence concerning their actual economic and welfare outcomes remains preliminary. The assessment of the fourth analytical proposition, concerning institutional and governance capacity, should therefore be regarded as an early-stage evaluation that requires reassessment as longitudinal evidence and outcome data become available.

7.5 Reliability and Trustworthiness

Three steps were taken to make the analysis as reliable as possible. First, when sources disagreed, peer-reviewed and official government sources were given more weight than industry or media reports. Second, wherever more than one independent source reported on the same topic, the figures were cross-checked against each other; for example, MSME AI-adoption figures were checked across both Kaur (2025) and PwC India (2026), and financial-inclusion figures were checked across PIB (2026) and independent reporting on rural digital payments. Third, every number reported in Section 8 is clearly linked to its original source and publication date, so readers can verify it independently and so that time-sensitive projections are not mistaken for settled facts.

8. Data Analysis

8.1 India's AI Policy Architecture

India's AI policy architecture has evolved from the National Strategy for Artificial Intelligence, launched by NITI Aayog in 2018 under the vision of "AI for All," toward a more comprehensive set of institutional initiatives and policy instruments. The IndiaAI Mission, approved by the Cabinet in March 2024, encompasses several interconnected pillars, including computing infrastructure, datasets, indigenous AI models, sectoral applications, skilling, and safety and governance (PIB, 2025). These components represent key elements of the AI-input dimension of the conceptual framework developed in Section 6.

Within the financial sector, the Unified Lending Interface (ULI) represents an important application of digital infrastructure to financial inclusion. The platform facilitates the integration of information such as land records, identity-related information, and other data through a common technical framework and is intended to support data-driven credit assessment for MSMEs and first-time borrowers with limited conventional credit histories. The available evidence estimates that AI-enabled lending mechanisms could potentially address a credit gap of approximately USD 130–170 billion among MSMEs and underserved borrowers (PIB, 2026). This initiative corresponds to the diffusion mechanism of AI-enabled financial inclusion identified in the conceptual framework.

The labour and welfare dimension of India's AI policy architecture is reflected in NITI Aayog's work on AI for inclusive development and the proposed Digital ShramSetu Mission. These initiatives envisage the application of AI, the Internet of Things, and blockchain-based technologies to support India's approximately 490 million informal workers through areas such as healthcare, skilling, and financial inclusion (NITI Aayog, 2025c). Collectively, these policy initiatives illustrate how AI-related inputs and diffusion mechanisms are being developed across infrastructure, finance, employment, and social-welfare domains. They therefore provide an important institutional context for assessing the analytical propositions developed in Section 5.

8.2 Uneven Adoption Across Different Parts of the Economy

Table 2 presents selected indicators identified through the structured search, source comparison, and cross-checking procedures described in Section 7. The evidence indicates three broad patterns in India's emerging AI landscape.

First, AI-related investment and policy attention remain substantially concentrated on enabling infrastructure, including computing capacity, AI models, digital public infrastructure, and AI-enabled financial systems. Although these investments provide important foundations for AI diffusion, their translation into firm-level and worker-level adoption remains uneven.

Second, the available projections indicate potentially significant labour-market effects in India's formal IT and business-process-outsourcing (IT/BPO) sector. NITI Aayog projects that India's IT services workforce could decline from approximately 7.5–8 million workers in 2023 to around 6 million by 2031, representing a projected reduction of approximately 20–25%, even as new AI-related occupational opportunities emerge elsewhere in the economy (NITI Aayog, 2025b). These figures should be interpreted as projections rather than observed employment outcomes. Nevertheless, they indicate the potential concentration of AI-related disruption in particular categories of cognitive and service-sector tasks.

Third, and particularly relevant to the inclusive-growth dimension of the study, AI adoption among Indian

MSMEs remains comparatively limited. A 2022 survey reported that fewer than 15% of Indian MSMEs had adopted an AI or machine-learning application, despite the sector's substantial contribution to national economic activity and employment (Kaur, 2025). In comparison, the global enterprise AI-adoption rate was reported at approximately 78% in 2025, compared with approximately 20% in 2017 (Al Habtoor Research Centre, 2025). While these figures are derived from different surveys and contexts and should therefore not be interpreted as a direct like-for-like comparison, they indicate a substantial disparity in the diffusion of AI capabilities between Indian MSMEs and global enterprise adoption.

More recent evidence further suggests that digital access does not necessarily translate into effective AI utilisation. The PayNearby MSME Digital Index Report 2026 indicates that digital payments and Aadhaar-enabled banking are well established across surveyed rural and semi-urban retail outlets, accounting for approximately 61% of transactions. However, awareness of AI-enabled tools has not necessarily translated into effective adoption, with limitations relating to training, affordability, and uncertainty regarding the commercial benefits of such technologies (PayNearby, 2026, as reported in Devdiscourse, 2026). Similarly, PwC India's (2026) assessment of MSME competitiveness identifies capital availability, skills, and infrastructure as significant barriers to AI adoption among smaller enterprises. These findings reinforce the distinction developed earlier in this study between basic digital access and the organisational and human capabilities required to convert technological access into productive outcomes.

Table 2
Selected Indicators of AI Diffusion and Policy Response in India

Indicator	Value or Finding	Source
Projected AI contribution to India's GDP by 2030	USD 500–600 billion	NITI Aayog (2025a)
IndiaAI Mission outlay (approved March 2024)	Over ₹10,300 crore; approximately 38,000 GPUs onboarded at subsidised rates	PIB (2025)
AI-exposed formal IT/BPO workforce	IT services workforce projected to decline from 7.5–8 million (2023) to approximately 6 million by 2031, representing a projected decline of 20–25%; approximately 60% of formal jobs classified as automation-exposed by 2030	NITI Aayog (2025b)
Informal workers targeted by inclusion-oriented AI initiatives	Approximately 490 million informal workers; proposed Digital ShramSetu Mission with phased rollout from 2025–2035	NITI Aayog (2025c); PIB (2026)
MSME AI/ML adoption rate (2022 survey)	Fewer than 15% of Indian MSMEs had adopted an AI/ML application	Kaur (2025), citing AIMO survey data
Global enterprise AI adoption rate (2025)	Approximately 78%, compared with approximately 20% in 2017	Al Habtoor Research Centre (2025)
Rural and semi-urban digital-payment penetration	UPI and Aadhaar-enabled banking account for 61% of transactions at surveyed rural/semi-urban retail outlets	PayNearby (2026), as reported in Devdiscourse (2026)

Indicator	Value or Finding	Source
AI-driven credit-gap potential for MSMEs and first-time borrowers	Estimated USD 130–170 billion credit gap potentially addressable through AI-enabled lending	PIB (2026)
Unified Lending Interface participation (December 2025)	64 lenders (41 banks and 23 NBFCs) using more than 136 data services across 12 loan journeys	PIB (2026)
AI-skilled talent pipeline (IndiaAI FutureSkills)	500 PhD fellowships, 5,000 postgraduate scholarships, and 8,000 undergraduate scholarships supported	PIB (2025)

Note. PIB = Press Information Bureau, Government of India; GPU = graphics processing unit; MSME = micro, small, and medium enterprise; NBFC = non-banking financial company; AIMO = All-India Manufacturers' Organisation. Compiled by the author from the sources indicated; see the reference list for full citations.

8.3 Evidence Assessment of the Analytical Propositions

Table 3 assesses the evidence presented in Table 2 against the four analytical propositions developed in Section 5, following the evidence-mapping procedure described in Section 7.4. Because the study relies on heterogeneous secondary evidence rather than a harmonised micro-level dataset, the propositions are not subjected to formal statistical hypothesis testing. Instead, each proposition is assessed according to the direction, consistency, relevance, and corroboration of the available evidence.

The evidence provides **broad support for Proposition 1**, which suggests that AI adoption is likely to generate greater productivity benefits for large enterprises than for MSMEs. The substantially higher global enterprise adoption rate compared with the reported adoption rate among Indian MSMEs, together with evidence concerning capital, skills, and infrastructure constraints, indicates an uneven capacity to translate AI access into productive applications. However, the available evidence does not directly estimate or statistically compare productivity gains between large Indian enterprises and MSMEs. Therefore, the proposition should be interpreted as receiving broad evidence-based support rather than as being statistically confirmed.

Proposition 2 receives preliminary support. The participation of 64 lenders in the Unified Lending Interface and the estimated credit-gap potential associated with AI-enabled lending indicate growing institutional capacity to expand data-driven financial access for underserved borrowers (PIB, 2026). However, these indicators primarily demonstrate the development and reach of the financial infrastructure rather than a statistically established causal effect on credit access. Accordingly, the evidence is suggestive but remains insufficient to establish the magnitude or causal effect of AI-enabled financial infrastructure on credit outcomes.

Proposition 3 receives broad support from the available evidence. The projected decline in India's IT/BPO workforce and the reported exposure of formal jobs to automation indicate that AI-related labour-market risks may be concentrated in particular categories of routine, rule-based, and language-intensive tasks (NITI Aayog, 2025b). This interpretation is consistent with the task-based perspective developed in the literature review. Nevertheless, the available figures are largely projections and should not be interpreted as observed employment displacement attributable solely to AI.

Proposition 4 remains inconclusive. The available evidence indicates that institutional and governance capacity is potentially important in determining whether AI adoption generates inclusive outcomes. However, several relevant policy instruments, including the Digital ShramSetu Mission and India's AI governance guidelines introduced in November 2025, are relatively recent. Consequently, sufficient outcome data are not yet available to assess their moderating effects empirically. The proposition therefore remains theoretically plausible but requires further longitudinal and empirical investigation.

Overall, the evidence-mapping exercise suggests that the available secondary evidence is broadly consistent with the study's conceptual framework, while also demonstrating important differences in the strength of evidence across the four propositions. The findings provide comparatively stronger support for the propositions concerning uneven AI diffusion and task-level labour-market exposure, preliminary evidence regarding AI-enabled financial inclusion, and insufficient evidence for drawing firm conclusions about the moderating role of institutional capacity.

Table 3
Evidence Mapping for Analytical Propositions 1–4

Analytical Proposition	Supporting Evidence	Evidence Assessment
P1 — AI adoption is likely to generate greater productivity benefits for large enterprises than for MSMEs in India.	Global enterprise AI adoption was approximately 78% in 2025, compared with fewer than 15% of Indian MSMEs reporting AI/ML adoption in the cited 2022 survey. PwC (2026) identifies capital, skills, and infrastructure constraints as important barriers to MSME AI adoption.	**Broadly supported by available evidence.** However, the evidence does not directly estimate or statistically compare productivity gains between large enterprises and MSMEs.
P2 — AI-enabled digital financial infrastructure has the potential to improve access to credit among underserved MSMEs and informal-sector participants.	By December 2025, 64 lenders were participating in the Unified Lending Interface, while an estimated USD 130–170 billion credit gap was identified as potentially addressable through AI-enabled lending. Digital payments and Aadhaar-enabled banking accounted for 61% of transactions at surveyed rural and semi-urban retail outlets.	**Preliminary support.** The evidence demonstrates expanding infrastructure and potential for improved access, but does not establish a causal or statistically measurable effect on credit outcomes.
P3 — AI-driven automation risk in India is likely to be concentrated in routine, rule-based, and language-intensive tasks.	India's IT/BPO workforce is projected to decline by approximately 20–25% by 2031, while approximately 60% of formal jobs are classified as automation-exposed by 2030.	**Broadly supported by available evidence.** The available figures are primarily projections and do not establish observed employment displacement attributable solely to AI.
P4 — Stronger institutional and governance capacity is likely to enhance the extent	India's AI governance guidelines were introduced in November 2025, while the proposed Digital ShramSetu Mission is planned for phased implementation during	**Evidence insufficient for a conclusive assessment.** The proposition remains theoretically plausible, but its

Analytical Proposition	Supporting Evidence	Evidence Assessment
to which AI adoption contributes to inclusive welfare outcomes.	2025–2035. However, outcome data for these initiatives were not yet available at the time of analysis.	moderating effect requires further longitudinal and empirical investigation.

Note. Evidence assessments follow the evidence-mapping procedure described in Section 7.4. "Broadly supported" indicates that multiple relevant sources provide directionally consistent evidence; "preliminary support" indicates that the available evidence is suggestive but limited or emerging; and "evidence insufficient" indicates that the available material does not yet permit a reliable assessment. These classifications represent qualitative assessments of the available secondary evidence and should not be interpreted as formal inferential statistical tests.

8.4 A Second-Order Digital Divide

Taken together, the findings suggest that India is not confronting a conventional digital divide defined solely by differences in access to digital technologies. Earlier phases of digital-inclusion policy have substantially expanded access through platforms and infrastructures such as UPI, Aadhaar, and mobile connectivity. The evidence examined in this study instead points toward a **second-order digital divide**: a gap not merely in access to digital technologies, but in the capacity of individuals and firms to convert AI-enabled technologies into meaningful economic and welfare gains.

This distinction has important policy implications. Closing the first-order gap in basic digital access does not necessarily eliminate differences in AI-related skills, organisational readiness, financial capacity, and firm-level absorptive capability. Consequently, the second-order digital divide requires policy interventions that extend beyond connectivity and infrastructure toward human capital, organisational capability, affordable technology access, and institutional support. These implications are considered further in Section 10.

9. Results and Discussion

9.1 The Productivity Channel (Proposition 1)

India's ambitions for AI are substantial. NITI Aayog's projection of a USD 500–600 billion contribution to GDP by 2030 indicates that AI could become a significant contributor to India's economic growth during the remainder of the decade (NITI Aayog, 2025a). This estimate is broadly consistent with international assessments of AI's productivity potential, although it lies toward the more optimistic end of the range, given evidence suggesting that emerging economies may realise smaller short-term gains from AI than advanced economies (BIS, 2025).

The substantial difference between the reported global enterprise AI-adoption rate of approximately 78% and the below-15% adoption rate among Indian MSMEs, discussed in Section 8.2, provides broad support for Proposition 1. The evidence suggests that the capacity to adopt and utilise AI remains concentrated among firms with greater access to financial resources, technological infrastructure, skilled human capital, and organisational capabilities. As a result, potential productivity gains may initially accrue disproportionately to larger and more technologically capable enterprises rather than being distributed evenly across the enterprise sector.

However, the available secondary evidence does not directly measure productivity gains among large Indian enterprises and MSMEs using a common dataset. The finding should therefore be interpreted as evidence of **uneven AI diffusion and productivity potential**, rather than as statistical confirmation of a productivity differential. This distinction is important because differences in adoption rates alone cannot establish the magnitude or causal direction of productivity effects.

9.2 The Distribution Channel (Proposition 3)

The labour-market evidence presented in Section 8 reflects the task-displacement and task-creation dynamics highlighted by Acemoglu and Restrepo (2019, 2022). India's IT and business-process-outsourcing sector is projected to experience a decline in formal employment of approximately one-fifth to one-quarter, even as new AI-related occupational opportunities emerge elsewhere in the economy. This evidence provides broad support for Proposition 3, which suggests that AI-related automation risks are concentrated in particular categories of tasks rather than being distributed uniformly across occupations.

Routine, repetitive, rule-based, and language-intensive cognitive tasks—many of which have historically contributed to India's comparative advantage in IT-enabled services—may be particularly exposed to generative AI. This development is consistent with the wider concern raised by Cornelli et al. (2023) that AI-driven technological change may weaken some of the labour-cost advantages that have supported services-led growth in emerging economies.

At the same time, the emergence of new AI-related occupations indicates that technological change may involve both task displacement and task creation. India's large and relatively young workforce, together with increasing demand for AI-related capabilities, provides opportunities for new forms of employment and productivity enhancement. The key constraint may therefore lie less in the absence of potential demand for AI-related skills and more in the capacity of India's education and skilling systems to supply workers with the capabilities required for emerging tasks. NITI Aayog's estimates indicating that demand for AI talent is increasing faster than domestic supply further reinforce the importance of addressing this skills gap (NITI Aayog, 2025b).

9.3 The Welfare and Inclusion Channel (Proposition 2)

The welfare and inclusion implications of AI in India are particularly visible in two areas targeted by current policy: AI-enabled financial inclusion and the proposed application of digital technologies to the welfare of informal workers. The Unified Lending Interface addresses a longstanding constraint in developing economies, namely the limited access to formal and affordable credit among individuals and small enterprises without conventional credit histories. The participation of 64 lenders by December 2025 and the estimated USD 130–170 billion credit-gap potential provide **preliminary support** for Proposition 2 (PIB, 2026).

Nevertheless, the available evidence primarily demonstrates the expansion of financial infrastructure and its potential to improve credit assessment rather than establishing a causal relationship between AI-enabled lending and actual improvements in credit access. The growing use of digital payments among rural and semi-urban MSMEs also illustrates that digital access does not automatically translate into effective AI adoption. Evidence indicates that awareness of AI tools has expanded faster than the training, affordability, and business capabilities required to use these technologies effectively (PayNearby, 2026, as reported in Devdiscourse, 2026).

This suggests that improvements in access to AI-enabled financial services may occur more rapidly than corresponding improvements in firms' capacity to use financial resources productively. For India's informal workforce, the proposed Digital ShramSetu Mission remains a multi-phase policy initiative rather than a fully operational programme at the time of writing. Its welfare effects therefore cannot yet be evaluated empirically. The effectiveness of the proposed 2025–2035 rollout is likely to depend substantially on implementation capacity, accessibility, skilling, and integration with existing social-protection and financial-inclusion systems (NITI Aayog, 2025c).

9.4 Institutional Readiness and Governance Gaps (Proposition 4)

The governance literature reviewed in Section 2.3 indicates that institutional capacity may play an important role in determining whether AI-related technological change translates into inclusive development outcomes. India's AI governance guidelines introduced in November 2025 adopt a relatively light-touch and risk-based approach, emphasising voluntary measures, coordination through an AI Governance Group, and technical oversight through an AI Safety Institute rather than the more prescriptive risk-tiered regulatory approach associated with frameworks such as the European Union's AI Act (Principal Scientific Adviser, Government of India, 2025).

This approach presents an important policy trade-off. A flexible regulatory environment may support innovation and reduce barriers to experimentation, but it simultaneously places greater responsibility on existing institutions—including skilling systems, financial regulators, labour institutions, and social-protection mechanisms—to manage emerging risks associated with AI adoption. These risks may include unequal access to AI-enabled opportunities, biased automated decision-making, labour displacement, and potential exclusion from digital financial systems.

As indicated in Table 3, the evidence currently remains insufficient to assess Proposition 4 conclusively. The principal institutional mechanisms relevant to the proposition are relatively recent, and outcome data are not yet available to determine whether stronger institutional capacity has moderated the distributional or welfare effects of AI adoption. Evidence from other developing-country contexts nevertheless suggests that limited governance capacity can increase the likelihood of reactive regulation and delayed responses to emerging technological harms (Governance and Regulation of Artificial Intelligence in Developing Countries, 2026; ITU, 2025). India's institutional response therefore represents an important area for continued monitoring and future empirical research.

10. Conclusion

This study examined the implications of AI adoption for economic growth and social welfare in India. The findings indicate that India has developed an ambitious AI policy ecosystem, with substantial potential for productivity growth and financial inclusion. However, AI adoption remains uneven, with larger and technologically capable firms benefiting more readily than MSMEs, while informal workers continue to face significant capability and skills constraints.

The evidence broadly supports the propositions concerning uneven AI diffusion and concentration of automation risks in routine and language-intensive tasks. Evidence regarding AI-enabled financial inclusion remains preliminary, while the role of institutional and governance capacity cannot yet be assessed conclusively because several relevant initiatives are still at an early stage.

The study highlights that AI-led inclusive growth requires more than investment in technology and infrastructure. Closing the **second-order digital divide** requires sustained investment in AI skills, MSME capabilities, worker transition support, and adaptive governance. Future research should use firm- and worker-level data and comparative evidence from other emerging economies to test these relationships more rigorously. The findings should be interpreted as an evidence-based assessment rather than causal estimates because of the study's reliance on heterogeneous secondary data..

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