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The Transformative Impact of Emerging Technologies on Employment and Production Processes in Andhra Pradesh: A Review of Automation and AI Adoption in Manufacturing

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Abstract
Manufacturing in Andhra Pradesh is changing. Robots, machine-learning systems and connected sensors are now part of how cars are welded in Anantapur, how pharmaceutical batches are tested in Visakhapatnam, how garments leave Atchutapuram for export, and how mangoes from Chittoor are sorted before they reach a packed carton. The pace, however, is uneven. We review what published evidence says about this transition across four industries with strong AP presence — automotive (Kia India, Anantapur), pharmaceuticals (Visakhapatnam), textiles (Brandix, Atchutapuram) and food processing (Chittoor and Krishna) — anchored in ASI 2021-22 data, IFR robot-installation figures, the NASSCOM-EY AI Adoption Index 2.0 and WEF employment projections. India installed 5,353 industrial robots in 2022, the seventh-largest national figure that year. Kia's Anantapur plant alone, with more than 450 robots, accounts for roughly 8% of those installations — a striking concentration in one location. Indian manufacturing now sits at the 'Expert' stage of enterprise AI maturity. Throughput, quality and predictive-maintenance gains are real, but capital-intensive firms are reaching them first; routine manual roles are exposed to substitution, while demand is rising for robotics technicians, ML engineers and data analysts. The AP Industrial Development Policy 2023-27 and the IndiaAI mission set the policy floor; alongside, what is needed is workforce reskilling, MSME-focused technology support and credible state-level labour-market data.
Keywords: *automation, artificial intelligence, manufacturing, employment, Andhra Pradesh, industrial policy*

I. Introduction

Production is being reshaped by two related technologies. Automation — machinery and software performing tasks with limited human intervention — has been with manufacturing for decades. Artificial intelligence is newer in industrial use: algorithmic systems, including machine learning, computer vision and natural-language methods, that perform tasks once thought to need human cognition. Together they alter productivity, product quality and the mix of jobs on the factory floor (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2019).

Andhra Pradesh's manufacturing base is large and diverse. The Annual Survey of Industries 2019-20 (MoSPI, 2022) records a registered factory sector that employs several hundred thousand workers; food products, pharmaceuticals and non-metallic minerals lead manufacturing GVA. Industrial investment has been actively courted, most recently through the AP Industrial Development Policy 2023-27, approved in March 2023. On this base, automation and AI raise two questions at once: are they making existing operations more productive, and are they reshaping who works in them? The pull goes both ways. Efficiency gains are real, but so is the risk of routine roles being substituted out and skill gaps widening. India's manufacturing workforce is mixed — alongside the large factories sit thousands of MSMEs for whom the upfront cost of automation remains a real barrier. Published evidence on how these dynamics are unfolding inside AP is thin; we organise what is on the record and flag what is not.

1.1 Scope, research questions and methodology

Four manufacturing industries with documented AP presence anchor the review: automotive (Kia India, Anantapur / Sri Sathya Sai district), pharmaceuticals (Visakhapatnam, including JN Pharma City), textiles and apparel (Brandix India Apparel City, Atchutapuram), and food processing (Chittoor and Krishna districts). Three questions guide the work. What technologies are actually being deployed in these industries, and where? What can the available evidence tell us about effects on employment and production? Which policy levers are most directly relevant?

This is a structured review, not new primary fieldwork. The evidence comes from three places: official statistics (the Annual Survey of Industries, the AP State Economic Survey, the AP Industrial Development Policy 2023-27); industry and policy reports (IBEF, IFR, NASSCOM, NITI Aayog); and public firm-level disclosures. One important caveat runs through the analysis: state-disaggregated data on automation-related employment change in AP is simply not yet collected. Where this matters, we use national figures as proxies and say so.

II. Literature Review

The long-run shift toward digital production is well documented (Brynjolfsson & McAfee, 2014). Whether that shift is good or bad for workers is more contested. Acemoglu and Restrepo (2019) argue the answer depends on a single balance: how much labour displacement occurs versus how many new tasks are created. Frey and Osborne (2017), looking at US occupations, estimated a high share were technically susceptible to computerisation. Arntz, Gregory and Zierahn (2016) re-analysed the same problem at task level rather than occupation level, and arrived at considerably more conservative numbers. The IFR World Robotics Report (2023) confirms that industrial robot installations continue to climb, with India among the faster-growing Asian markets.

Choi and Lee (2019) survey AI applications in manufacturing — condition monitoring, quality control, process optimisation. Kusiak's (2018) framing of smart manufacturing puts data-driven decision-making across the production lifecycle at the centre. Since 2022, generative AI has added another layer to this picture, with applications in design support, technical documentation and engineering knowledge work, and early enterprise adoption now documented in industrial settings (NASSCOM, 2022; WEF, 2023).

On employment, the global picture is mixed. The WEF Future of Jobs Report (2023) projects displacement of about 83 million job roles globally over a five-year horizon, against creation of about 69 million new ones. For India, McKinsey Global Institute (2017) estimates that 51-64% of activities in Indian manufacturing are technically automatable; what actually happens to jobs depends heavily on how much reskilling investment moves alongside the technology. India's own policy stack is now substantial — NITI Aayog's National Strategy for AI (2018) and the IndiaAI mission (MeitY, 2024) — and Hira and Richards (2017) caution that displacement can hit harder in emerging economies. What remains thin is sub-national evidence: at the state level, including AP, the empirical record is sparse. We organise that record rather than close it.

III. Manufacturing Landscape And Quantitative Anchors

AP's manufacturing base is broad. Food products, pharmaceuticals, non-metallic minerals, textiles, automobiles and chemicals are all present at scale, and the state's long coastline with its major ports supports export-oriented activity in each. The Andhra Pradesh Industrial Development Policy 2023-27 sets the overall direction. Industrial infrastructure is delivered through the Andhra Pradesh Industrial Infrastructure Corporation (APIIC) and through SEZs at Visakhapatnam and Sri City. Two sector-specific policies — the AP Food Processing Policy and the AP MSME and Entrepreneur Development Policy — add targeted support.

3.1 Indian manufacturing performance: ASI 2021-22 baseline

The headline numbers for Indian manufacturing in 2021-22 (MoSPI, 2024) tell a story of recovery. GVA grew 26.6% in current prices over 2020-21, riding on industrial output growth above 35%. Total employment grew 7.0% year-on-year, and persons engaged exceeded the pre-pandemic 2018-19 level by more than 9.35 lakh. Six industries — Basic metals, Coke and refined petroleum, Pharmaceuticals, Motor vehicles, Food products and Chemicals — accounted for around 56% of manufacturing GVA between them. Average emoluments per employee climbed 8.3%. The point that matters for AP is in the detail: three of those six leading drivers (pharmaceuticals, motor vehicles, food products) are the focal industries of this paper, and the state has visible operations in each. AP's own numbers fit the picture. Pharmaceutical exports from the state were reported at about Rs. 24,298 crore (~USD 2.74 billion) in FY24 (IBEF, 2024), and state GSDP at current prices for FY24 was Rs. 15.4 lakh crore (Government of Andhra Pradesh, 2024). Automation, in other words, is being layered onto a manufacturing economy that is itself growing.

3.2 Industrial robotics in India: scale and trajectory

India sits seventh worldwide by annual industrial-robot installations, with 5,353 units installed in 2022 (IFR, 2023). The operational stock has been growing at about 14% per year since 2017, and automotive remains the single largest customer. Compared to China, which installed 290,258 robots in the same year, India's number is small — less than one-fiftieth. But the curve is steepening, not flattening. AP's state-level share of national installations is not reported separately. What is on the record is that one of India's largest single robotics deployments — the 450+ robots at Kia Anantapur — sits inside the state. Whatever AP's exact share is, it is not negligible in automotive.

IV. Review Of Automation And AI Adoption In Focal Industries

4.1 Technologies adopted

Where adoption has happened, it has happened in capital-intensive, export-oriented operations. Kia India's Anantapur facility opened in December 2019 after a USD 1.1 billion investment and now runs more than 450 robots across its press, body, paint and assembly shops, with installed capacity of 300,000 units per year (Kia Motors, 2019; Business Standard, 2019). In Visakhapatnam, pharmaceutical units have invested in process-control automation, IoT environmental monitoring and AI-assisted quality assurance — partly because their export markets demand it (IBEF Pharmaceuticals, 2023). Brandix India Apparel City at Atchutapuram operates as an integrated apparel zone with computer-controlled cutting, vision-based defect inspection and ERP-linked planning (IBEF Textiles, 2023). In Chittoor and Krishna districts, food-processing units have moved to automated sorting and grading, IoT cold-chain monitoring and analytics-led demand forecasting (MoFPI, 2023).

Table 1. Technologies adopted in focal industries

Industry	Technologies in use	Reported outcome	Source
Automotive (Kia India, Anantapur)	Industrial robotics in press, body, paint and assembly shops; smart-tag tracking; AI-monitored paint shop	450+ robots; capacity 300,000 units/year; USD 1.1 bn greenfield plant opened Dec 2019	Kia Motors (2019); Business Standard (2019)
Pharmaceuticals (Visakhapatnam cluster)	Process-control automation, AI-assisted QA, IoT environmental monitoring, ML in formulation R&D	Improved batch consistency; reduced rejection rates at Visakhapatnam-area facilities	IBEF Pharmaceuticals (2023)
Textiles (Brandix, Atchutapuram)	Computer-controlled cutting and stitching, vision-based defect inspection, ERP-linked planning	Integrated apparel park compressing supply-chain lead times for export	IBEF Textiles (2023); APIIC
Food processing (Chittoor & Krishna)	Automated sorting/grading, IoT cold-chain monitoring, demand-forecasting analytics	Higher throughput in pulp and packaged-food units; reduced cold-chain spoilage	MoFPI Annual Report (2022-23)

4.2 Implications for employment

There is no published state-level series tracking automation-related employment change in AP, so this section uses national and global indicators as proxies. The proxies, however, point in consistent directions. Routine manual roles — welding, sorting, packaging, basic quality inspection — are the ones most exposed to substitution by robotic and vision-based systems. At the same time, demand for technical roles is rising: industrial-robotics technicians, ML engineers, data analysts, computer-vision QA engineers (NASSCOM, 2022; WEF, 2023). And MSMEs sit awkwardly in the middle of this. The transition costs they face are higher, their internal capacity to absorb new technology is lower, and the gains tend to flow to larger firms first (NITI Aayog, 2018; McKinsey, 2017).

Table 2. Indicators relevant to employment effects of automation and AI

Indicator	Magnitude reported	Scope	Source
Industrial robot installations, India (annual)	5,353 units installed in 2022; operational stock ~39,000 units, growing ~14% per year since 2017; India ranked 7th globally	National (proxy for state-level pressure)	IFR, World Robotics Report (2023)
Jobs displaced vs. created (5-yr projection)	83 million displaced and 69 million created over five years — net decline of 14 million (~2% of current employment), concentrated in routine roles	Global, all sectors	World Economic Forum, Future of Jobs (2023)
Indian enterprise AI maturity index	AI Adoption Index moved from 2.45 (2022) to 2.47 (2024) on a 5-point scale; 87% of enterprises in	National enterprise survey, 500 firms across 7 sectors	NASSCOM-EY, AI Adoption Index 2.0 (2024)

Indicator	Magnitude reported	Scope	Source
	middle stages, 45% at Expert; manufacturing classified Expert-stage		
Manufacturing-sector AI strategy	39% of surveyed manufacturing firms report transformation-focused AI strategy; >50% maintain dedicated AI budget	Manufacturing sub-sample of national survey	NASSCOM-EY (2024)
Indian workforce automation exposure	51–64% of activities in Indian manufacturing technically automatable using current technology; net impact depends on reskilling	National manufacturing	McKinsey Global Institute (2017)

4.3 Implications for production processes

What firms report on the production side maps closely onto what the literature predicts: shorter cycle times and high welding-automation rates in automotive (Business Standard, 2019; IBEF, 2023); predictive maintenance and AI-supported QA in pharmaceuticals (Choi & Lee, 2019; IBEF, 2023); vision-based inspection and integrated planning in apparel (IBEF, 2023); automated sorting and analytics-led forecasting in food processing (MoFPI, 2023).

Table 3. Documented production-process gains in focal industries

Industry	Documented gain	Underlying mechanism	Source
Automotive	Reduced cycle time per vehicle; high welding-automation rates; AI-assisted defect tracking	Robotic press, body and paint shops; smart-tag tracking	Kia Motors (2019); IBEF Automobile (2023)
Pharmaceuticals	Reduced unplanned downtime; improved batch consistency; tighter regulatory compliance	Predictive maintenance; AI-supported QA and process optimisation	Choi and Lee (2019); IBEF Pharma (2023)
Textiles & apparel	Lower defect rates; improved on-time delivery for export contracts	Vision-based defect inspection; ERP-linked production planning	IBEF Textiles (2023); APIIC
Food processing	Higher throughput; reduced waste and stockouts; lower cold-chain spoilage	Automated grading; analytics-led demand forecasting; IoT cold-chain monitoring	MoFPI (2023); Kusiak (2018)

4.4 Synthesis and quantitative analysis

Pulling these strands together, four points stand out. The headline trajectory is real but the absolute scale is still small. India's robot installations have grown at roughly 14% per year over 2017-2022 to 5,353 units in 2022 (IFR, 2023), and operational stock at the end of that year (about 39,000 units) was still around one-fortieth of China's. AP has policy time to prepare its workforce, not catch-up time. The concentration effect of anchor investors is striking. Kia's 450+ robots at Anantapur are equivalent to roughly 8% of India's full-year 2022 installations — from a single facility. Comparable concentration is likely in Visakhapatnam pharmaceuticals and at Brandix Atchutapuram, but the public data does not let us quantify it at facility level. AI adoption is uneven, but Indian manufacturing is no longer at the bottom of the curve. The NASSCOM-EY AI Adoption Index 2.0 (2024) places Indian manufacturing at the 'Expert' stage, with 39% of manufacturing firms reporting a transformation-focused AI strategy; the all-India composite index, however, moved only marginally from 2.45 in 2022 to 2.47 in 2024. The labour exposure is large, but how much of it lands on workers depends on us. The WEF (2023) projects roughly 14 million net displacement over five years globally; McKinsey (2017) estimates that 51-64% of Indian manufacturing activities are technically automatable. The binding question for AP is whether reskilling moves at the same speed as substitution. APSSDC's co-located training facility at Kia Anantapur (Kia Motors, 2019) is one template for what an answer might look like.

V. Discussion, Policy Implications And Conclusion

Three implications come out of this. First, automation and AI are diffusing in AP's manufacturing sector, but the diffusion is uneven — most visible in capital-intensive, export-oriented operations and least in MSMEs. Second, employment effects cannot yet be quantified at state level with any confidence. Periodic firm-level surveys on technology adoption and workforce composition, conducted at AP level, would directly improve the design of policy responses. Third, the policy framework is already in place: APIDP 2023-27 and the AP MSME and Entrepreneur Development Policy give the state instruments for incentives and infrastructure. Whether those instruments succeed in managing the automation transition will depend on what is layered on top — skilling investment and active partnership with national missions like IndiaAI.

On the available evidence, three policy directions are warranted. The first is targeted reskilling. Workers in roles most exposed to substitution need pathways out, delivered through ITIs and sector skill councils, with curricula that actually reflect generative-AI applications rather than ten-year-old tooling. The second is calibrated MSME support — credit-linked subsidies for entry-level automation, shared-infrastructure models for AI tools, technology that fits a smaller balance sheet. The third is state-level monitoring. Building state-specific ASI modules would create the data on which everything else depends.

What the available evidence shows is this: adoption in AP is concentrated in large, capital-intensive operations across automotive, pharmaceutical, textile and food-processing industries, and it is delivering reported gains in throughput, quality and predictive maintenance. What the available evidence does not yet show — and this is the priority for future empirical work — is the net employment effect at state level. With a stronger state-level evidence base, the policy framework already in place can be calibrated so that productivity gains are accompanied by broad-based employment outcomes.

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