

Skill Gaps, Labour-Market Mismatch And Productivity Growth In India: A Review Of Evidence

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Abstract

Skill development is a route through which India can convert a working-age population into higher productivity, better jobs and regionally balanced growth. Yet training completion is not equivalent to skill acquisition, labour-market matching, firm adoption or productivity improvement. This review assesses past econometric and evaluation evidence on the relationships among vocational and technical training, workforce productivity, sectoral skill gaps and regional economic growth in India. It synthesizes peer-reviewed studies, official labour statistics, programme evaluations and skill-gap diagnostics published from 2000 to 2023. The review finds relatively consistent evidence that formal vocational training is associated with higher earnings, although returns differ sharply by sector, employment status, location, gender and training duration. Experimental evidence also shows that a targeted programme can improve women's employment and earnings, whereas broader programme evaluations report modest and uneven effects when training quality, local job demand, placement support and employer engagement are weak. State-level studies generally link human capital to productivity and growth, but service and manufacturing responses differ and causal attribution remains difficult. Recent Indian skill-gap work demonstrates why national training targets are insufficient: demand is occupational, sectoral and spatial, while supply is mediated by school quality, apprenticeships, digital access, migration and firm capability. The paper therefore develops a transparent econometric assessment framework using state–sector–year panels, outcome-specific measures and fixed effects, rather than claiming a new causal estimate. It concludes that India needs demand-led, regionally differentiated skills systems that pair training with workplace learning, technology diffusion, productive investment, inclusion and credible outcome measurement.

Keywords: skill development; workforce productivity; sectoral skill gaps; regional economic growth; vocational education and training; labour-market mismatch; India.

1. Introduction

1.1 Skills, productivity and India's development problem

India's skill-development debate is a productivity and structural-transformation debate. A larger labour force expands output only when workers have usable competencies, firms create productive tasks, and institutions match people to them. The National Policy links quality training, employability and productivity across sectors [1]. Labour-force data show expanded participation but persistent gender, location and employment differences. The question is therefore not how many people receive a certificate, but whether learning raises task capability, supports job progression, technology adoption and higher value added in lagging and leading regions. India's

labour market is heterogeneous. Workers move among agriculture, construction, manufacturing, trade, transport, services and self-employment, often in small or informal enterprises with limited time, finance and equipment for learning. A certificate can therefore have different returns by sector and place. Foundational literacy, numeracy, digital ability, communication, problem solving and workplace learning may matter as much as an occupation-specific module. “Skilled workforce” is not a homogeneous stock. Current policy is moving toward this granular view. Sectoral skill-gap diagnostics combine secondary data, forecasts, vacancy and occupational evidence, firm surveys, clusters and stakeholder interaction. Such diagnostics span crops, animal husbandry, textiles, auto, power, retail and programming. A gap may mean shortage, under-skilling, overqualification, weak practical exposure, poor soft skills, low retention, wage mismatch or missing demand. Each requires a different response; trainee counts cannot identify the binding problem.



Figure 1. Skills as a regional productivity system

Source: Author’s conceptual synthesis of the reviewed literature.

Figure 1 frames skills as a production and matching system rather than training alone. It shows how foundational, technical and transferable skills, workplace exposure and credentials interact with firm technology, capital, management and demand. These channels influence job matching, task quality, wages, output per worker. The moderator band: infrastructure, industry structure, gender norms, migration, labour-market institutions and local demand can strengthen or interrupt the conversion of learning into productivity. It does not assert a universal causal effect. Instead, it explains why an econometric assessment must include complementary conditions and distinguish individual training outcomes from regional productivity outcomes in every region.

1.2 Sectoral and regional asymmetry

Sectoral asymmetry makes national averages misleading. Formal vocational training is associated with an earnings premium in Indian data, but returns differ across primary, secondary and tertiary activities [4]. Manufacturing depends on firm scale, networks, standards, logistics and technology; services often depend on communication, credentials, digital access and urban markets. Agriculture and allied activities may need locally adapted advisory, equipment, post-harvest, business and climate skills rather than an urban course transplanted to a village. The relevant unit is the worker–occupation–firm–place match, not course seats filled.

Regional asymmetry reinforces this point. States differ in schooling, training density, industry, infrastructure, women’s participation, migration and labour absorption. Evidence points to lower training access in some poorer regions with demographic potential. State research links human capital with services performance but not an equivalent manufacturing effect, reflecting different skill intensity and complements [10]. Regional productivity

studies show divergence associated with infrastructure and production structure [12]. These indicators cannot be read as a common causal return to skills policy.

Automation and new services change tasks faster than curricula adapt. A region may have trained youth while employers offer low wages, temporary work or unrelated occupations. The result may be migration, overeducation, underutilization or labour-force exit rather than local productivity growth. Matching is two-sided: training shapes supply, while investment, firm practice, wages and local demand shape returns. This review therefore does not assume a one-way training-to-growth pathway.

1.3 Review question, econometric contribution and boundaries

This paper asks what past work shows about how skill development and sectoral skill gaps affect worker outcomes, workforce productivity and regional economic growth in India. It surveys outcomes, compares sectors and regions, evaluates econometric strength, and specifies a future state–sector–year panel using labour, enterprise, training and regional-output data. The contribution is a thematic econometric meta-synthesis, not a fresh estimation. Studies use different samples, outcomes, sector classifications, counterfactuals and time periods, so a pooled coefficient would create false precision. The review records sign, magnitude, identification strategy, horizon and conditions. Its prospective panel framework models labour productivity or value added per worker using skill-match indicators, training intensity, apprenticeship exposure, capital, infrastructure, demand and state, sector and year effects. It does not claim invented coefficients or causal results.

The boundary is essential. A positive wage association does not automatically measure productivity, and a state-growth association does not prove that training caused growth. Selection, reverse causality, migration, unobserved ability, firm sorting and simultaneous public investment can bias estimates. The paper separates individual returns, enterprise or sector productivity, allocative efficiency and regional growth. It also treats inclusion as substantive: if women, rural youth, marginalized groups or informal workers cannot access relevant learning and decent jobs, average capability may rise while social or regional gaps widen. The following sections synthesize evidence, methods and implications. Together, these boundaries keep the review clearly descriptive where evidence is observational and causal only where identification supports it.

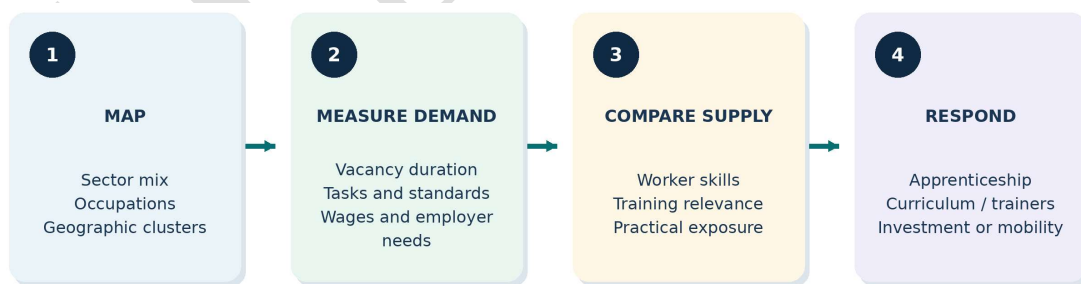


Figure 2. Sectoral skill-gap diagnostic sequence

Source: Author's interpretation of sectoral skills-demand methods.

Figure 2 turns a sectoral skill gap into a diagnostic sequence. Assessment begins with sector and occupation structure, comparing employer demand, vacancy duration and task requirements with worker skills, supply and practical exposure. The diagnosis should identify whether the binding problem is shortage, under-skilling, overqualification, curriculum lag, weak workplace learning, low wages or inadequate job demand. Each diagnosis implies a different response, such as apprenticeships, trainer upgrading, job information, equipment, mobility

support or investment policy. The figure therefore rejects an enrolment target as a complete measure of skill policy performance. It is a practical decision framework, not a numerical estimate.



Figure 3. Prospective econometric assessment blueprint

Source: Author; the model is proposed, not estimated in this review.

Figure 3 displays the review's econometric blueprint. Outcome is labour productivity or real GVA per worker by state-sector-year. The focal variable is a skill-match or gap indicator, plus training and apprenticeship measures. Capital, infrastructure, demand, worker composition and fixed effects address confounding, while interaction terms test whether effects vary across agriculture, manufacturing and services. The lower band presents identification upgrades lags, event studies, instruments and matched data that are needed before causal language is justified. No coefficient is reported because this paper synthesizes past evidence rather than estimating the model. It is a reproducible template for future work.

2. Survey of Past Work and Thematic Meta-Analytic Synthesis

Human-capital theory predicts that learning can raise productivity and earnings, while endogenous-growth models allow skills to support innovation, adoption and spillovers [18]–[20]. These mechanisms remain plausible for India, but they are not automatic. Skills may be underused in small firms, old technologies, segmented markets or immobile labour. The same course can raise earnings in a dynamic cluster and yield little where jobs, equipment or buyers are absent. This is why a review of skill development must include demand-side institutions and regional production conditions.

India's policy architecture has increasingly recognized this need for alignment. The 2015 national policy sought common standards, industry-linked training, lifelong learning, certification, entrepreneurship and outcome-based systems [1]. Sector Skill Councils and NSQF frameworks translate employer requirements into standards, while state missions, ITIs, apprenticeships, PMKVY and digital platforms deliver them [1]. The outcome is a match among worker capability, job, firm and local market, not a trained-person count.

Official data show why this transition remains unfinished. PLFS measures employment, wages and vocational training, but not task proficiency, course quality, employer demand or firm productivity. Evidence documents a coexistence of rising education, educated youth unemployment, overqualification, informality and uneven access to vocational learning. These patterns mean that a certificate can be both valuable and insufficient. A trained

worker may remain unemployed, work in an unrelated low-paid job or migrate. Enrolment, certification and placement counts need tracer, wage, firm and retention evidence.

The strongest Indian individual-level evidence supports positive but heterogeneous labour-market returns. Kumar, Mandava and Gopanapalli estimate that formal vocational training is associated with a 4.7 percent overall wage premium, with larger reported effects in primary and secondary sectors and an insignificant service-sector estimate in their specifications [4]. This sectoral variation is not a reason to downgrade service skills; rather, it suggests that certificates, worker selection and employer recognition differ across activities. Singh, Parida and Awasthi find employability and earning differentials among technically and vocationally trained youth, but also show the importance of social background and labour-market context [7]. Taken together, these results support the proposition that skills matter, while warning against a single national return.

Causal evidence provides a more specific lesson. Maitra and Mani's randomized evaluation of subsidized stitching and tailoring training for low-income women in New Delhi found sustained gains in employment, self-employment, hours and monthly earnings over the follow-up horizon [5]. Random assignment addresses important trained-untrained selection. It is not, however, a national estimate for all programmes, sectors or regions. The intervention targeted one population, trade and local market; success may reflect quality, completion, equipment and home-based work viability. Well-designed training can improve outcomes, but scaling requires testing whether its enabling conditions travel.

Evidence on self-employment further demonstrates heterogeneity. Bairagya uses instrumental-variable methods to examine formal training and earnings among rural self-employed workers, finding positive effects and stronger gains with longer-duration training [6]. This is relevant for regions where wage jobs are scarce and enterprises operate in agriculture, services or small manufacturing. Self-employment income also reflects assets, land, credit, demand, weather, labour and market access. A business-oriented course may improve capability without raising income if equipment finance or customers are unavailable. Salaried-wage measures miss self-employment survival, quality, diversification or resilience. An econometric assessment should therefore estimate separate outcome equations for regular employees, casual workers and self-employed workers rather than combine them into one undifferentiated average.

Programme evaluations also temper optimistic narratives. The World Bank's multi-state assessment of five Indian skills-development programmes found positive average wage effects but modest and uneven employment results, with variation by programme and state [2]. Its qualitative component highlighted course relevance, provider quality, local demand, monitoring and post-placement support. A later World Bank results summary reports that market-relevant short-term training can connect disadvantaged youth with paid employment, but programme performance must be read against placement quality and the time horizon [3]. These sources show why a six-month placement rate is not enough. A meaningful productivity or regional-growth assessment should ask whether employment is retained, whether the task uses the training, whether wages rise net of mobility costs, whether firms value the skill and whether new jobs are additional rather than merely reallocated.

Skill mismatch studies illuminate the allocation channel. Gooptu, Bros and Roy Chowdhury document regional differences in overeducation and connect them to vocational-training incidence using PLFS data [8]. Bahl and Sharma find that informality and education-occupation mismatch shape wage outcomes, with mismatch operating differently across formal and informal work [9]. These studies matter because productivity is not only a function

of the average skill level. It also depends on whether skills are deployed in jobs that require them, whether firms can recruit needed workers, and whether productive enterprises expand relative to less productive ones. Overqualification may signal scarce suitable jobs; under-skilling may signal weak training, rapid technological change or poor in-work learning.

Regional-growth research gives a second, aggregate perspective. Amin and Mattoo use a panel of major Indian states and report that skilled-worker availability is positively associated with service output, while the manufacturing relationship is not comparable [10]. Bhat and Siddharthan find that human-capital variables help explain interstate differences in labour productivity and employment growth [11]. Babu and Natarajan show that manufacturing productivity growth diverged across regions and relate variation strongly to infrastructure [12]. Ghosh and Parab, alongside Naik and Bairagya, find a statistically significant long-run human-capital role in productivity or growth [13], [14]. Hussain and Das report a long-run relationship between human-capital investment and state income in panel cointegration analysis [15]. The common message is conditional complementarity: human capital tends to matter, but its effect is mediated by sectoral technology, capital, infrastructure, organization and market access.

The sectoral diagnostic literature supplies a practical bridge between individual and aggregate evidence. A sectoral skill shortage is best assessed using job roles, vacancy duration, employer reports, wage and employment indicators, worker characteristics, occupational standards, geographic clusters and demand forecasts, rather than a single national training target. A gap may reflect weak foundations, outdated curricula, poor practice, wage mismatch, low female participation, retention or training–industry misalignment. District-level job diagnostics that align local training with local economic opportunities are similarly preferable to extrapolating a national supply target, because they identify where training should be redesigned, where apprenticeships or information may help, and where the binding constraint is investment or job creation rather than skills.

Firm and workplace learning remain a comparative blind spot. Many Indian studies observe workers but not their employers' technology, management, training intensity, vacancy duration or output. Yet productivity improves when skills are complemented by equipment, processes, quality systems and supervisory capability. The ILO's framework for anticipating future skill needs recommends combining household data with employer surveys, vacancy analysis, graduate tracer studies and stakeholder intelligence [17]. OECD evidence links mismatch with lower labour productivity and weaker allocation of skills to productive firms, though international estimates should not be imported mechanically into India [16]. For India, this implies that a valid regional model should combine PLFS-type measures with ASI or enterprise data, state accounts, training and apprenticeship data, and indicators of infrastructure and industrial demand.

Equity and geography cut across all findings. Formal training participation and returns can differ by gender, caste, household resources, rural–urban location and migration opportunity. Evidence shows that training capacity and access are spatially uneven, while many young women face constrained transitions from education to work. Apprenticeship and workplace exposure are especially important because they reveal employer needs and convert classroom learning into productive routines; their availability, however, is concentrated unevenly across establishments and states. A regional strategy must not treat migration only as a failure. Migration can improve matching, but it can also drain talent from low-demand regions and impose high costs on women and poorer

households. Place-based skills policy must consequently link local training to a realistic mix of local work, mobility support and nationally portable credentials.

Overall, the past work supports a calibrated synthesis. Formal, relevant training can improve earnings and employment; education and skills can support productivity and regional growth; and mismatch can depress wages and productive allocation. However, effect size and direction vary by design, sector, worker group, firm capability, region and outcome horizon. The best evidence does not say “train more” in the abstract. It says to diagnose the occupational and sectoral bottleneck, match the intervention to the bottleneck, measure employment quality and productivity rather than certificates alone, and evaluate effects against credible counterfactuals. That synthesis directly informs the proposed methodology and policy.

OUTCOME / MECHANISM	CONVERGENCE	INTERPRETATION
Formal training and individual earnings	CONSISTENT	Positive returns appear repeatedly, but sector, selection and measurement matter.
Targeted programme employment effects	MODERATE	Credible local evidence exists; external validity and scaling conditions remain limited.
Human capital, productivity and regional growth	MODERATE / CONDITIONAL	Effects depend on technology, capital, infrastructure, demand and sector mix.
Mismatch and allocative efficiency	EMERGING	Indian and international work supports the mechanism; measures remain unharmonized.
Firm-level productivity and workplace learning	LIMITED	Linked worker-firm evidence remains scarce despite strong conceptual relevance.

Figure 4. Evidence-convergence matrix from past work on skills and productivity

Source: Author’s thematic synthesis of the evidence base in references [1]–[20].

Figure 4 summarizes evidence convergence. Formal training and individual earnings receive support, although causal designs and sectoral coverage vary. Targeted programmes are moderate: randomized evidence is compelling but local. Human capital, productivity and regional growth are moderate and conditional: complementary technology, capital, and infrastructure and demand matter. Skill mismatch and allocative efficiency are supported by emerging Indian and international evidence, but measures are not yet harmonized. Firm-level productivity effects remain especially limited because linked worker–firm data are scarce. The matrix is qualitative. It does not transform different regressions, samples and outcomes into a misleading universal effect size or programme ranking.

3. Methodology

This review applied a structured evidence protocol to past work on skill development, productivity, mismatch and regional growth in India. Searches covered English-language academic articles, working papers, programme evaluations, official reports and policy documents released from 2000 to 2023. Search terms combined “India” with “skill development,” “vocational training,” “technical education,” “workforce productivity,” “skill mismatch,” “overeducation,” “regional growth,” “state panel,” “sectoral,” “apprenticeship,” “earnings,” and “employment.” Sources were drawn from government and multilateral repositories, journal databases, World Bank, ILO, OECD, NITI Aayog, MSDE and MoSPI records. Inclusion required an explicit Indian setting or a

clearly identified transferable method, plus an outcome related to training participation, wages, employment, productivity, mismatch, technology adoption, sectoral performance or regional growth. Descriptive policy documents were used to define institutions and data systems, but causal claims were anchored in experimental, quasi-experimental, panel, econometric or systematically appraised evidence. Promotional completion stories without a stated method were not treated as impact evidence. Search results were deduplicated by title and source, and the reference list balanced household, programme, enterprise and regional evidence.

Each source was coded for geography, sector, population, training or skill measure, outcome, identification strategy, data period, comparator, principal result, limitations and relevance to a state-sector assessment. The synthesis separated four levels of inference: individual labour-market returns; enterprise or sector productivity; allocative effects of mismatch; and regional output or growth. It also separated formal VET, informal learning, apprenticeship, education, occupational skill requirements and actual skill use because these are not interchangeable constructs. Evidence strength was classified narratively as consistent, moderate, mixed or limited according to design credibility, replication, outcome validity and contextual transferability. This coding prevents an average wage coefficient from being interpreted as a productivity effect, and a state-level correlation from being read as an individual treatment effect. It also records whether the analysis addresses selection into training, reverse causality, migration, informality, labour-force selection and sector composition. This prevented conflation of measured skill possession, formal credentials, employer demand, task use and training exposure.

The proposed econometric assessment is a prospective state-sector-year panel, not an analysis estimated in this paper. A baseline specification would model log labour productivity or real gross value added per worker as a function of a sector-specific skill-match or skill-gap index, formal-training intensity, apprenticeship exposure, capital intensity, infrastructure, industrial demand and state, sector and year fixed effects. Interaction terms would test whether training returns vary between agriculture, manufacturing and services, or between high- and low-demand regions. Where data permit, lagged training variables, event-study designs around programme roll-outs, instrumental variables based on historical training access, and matched worker-firm or tracer data could strengthen identification. The review does not pool reported coefficients because outcome definitions, samples and estimators are incompatible. It uses cautious language and treats the framework as a blueprint for transparent future measurement rather than evidence of an unobserved causal effect. Robustness should also examine alternative mismatch definitions, sector aggregation, migration-sensitive samples and placebo outcomes unlikely to respond immediately to training. These choices make null results interpretable to policy.

4. Critical Analysis of Past Work

The literature distinguishes education, training and productivity. Stronger studies distinguish training type, employment status, earnings, productivity and skills supplied from skills used. The randomized evaluation by Maitra and Mani offers unusually credible evidence on a defined programme and population [5]; formal-training wage studies separate sectoral outcomes [4]; and state-panel work considers regional heterogeneity [10], [11], [15]. Skill-gap diagnostics add employer, occupational and spatial information [8]. This is more useful than trainee totals. They show why a sectoral skill-gap assessment must ask what capability is missing, in which occupation, for which firm type, in which place and with what consequence.

The largest empirical weakness is selection. Participants differ from non-participants in education, resources, ability, networks, urban residence and employer access. OLS wage premiums may capture selection as well as training. Matching addresses observed differences; IV needs credible exclusions; one-city randomized evidence has limited external validity. Programme evaluations can also compare trainees with applicants or registrants who are not equivalent counterfactuals. A rigorous Indian assessment needs baseline measures, transparent eligibility rules, pre-training earnings or employment history where possible, and longer follow-up. It should report balance, attrition, completion and control-group alternatives.

Measurement creates a second problem. “Skill” is proxied by schooling, certificates, duration, occupation, employer assessment, self-report or mismatch. Each captures something different. Completion may not measure competence; occupational levels may miss digital or social tasks; earnings do not measure output per worker. Self-employment income is difficult to observe and informal firms lack reliable records. The proposed framework should therefore use a dashboard: formal and informal VET participation, assessed competence where available, training relevance, occupation–qualification match, wages, work intensity, enterprise sales or value added, retention, vacancy duration and real GVA per worker. No single indicator establishes a sectoral gap.

There is also a unit-of-analysis problem. Individual regressions concern wages or employment regional regressions aggregate people, firms, capital and institutions. A higher individual wage implies state productivity only if tasks are productive, firms expand, labour is additional and gains stay local. Moving from a state GSDP association to a training effect makes the reverse leap. State economies with high productivity may invest more in training precisely because they already have strong firms, revenues and labour demand. Fixed effects, lags and IV reduce but cannot eliminate endogeneity. Results should state causal scope, not equate correlation with impact. Sector definitions are another source of overclaiming. Agriculture, manufacturing and services contain occupations with different skills, capital, scale and markets. Repair, retail, textiles, programming, solar and agriculture cannot share one training response. Within a sector, gender, contract status, firm size and location may matter more than the sector average. A diagnostic focus on occupation, job role and geographic cluster is therefore a methodological advance. Future panels should, wherever data allow, distinguish NCO occupations, NIC industries, firm size and formal status; otherwise, a statistically significant sector coefficient can conceal precisely the mismatch that policy needs to solve.

Regional comparison compounds the issue. States vary in reporting, training density, education, urbanization, infrastructure, credit, policy and migration. They jointly influence supply, demand and productivity. State fixed effects do not control changing infrastructure, investment, migration or implementation. Spatial spillovers are also plausible: training in one state may supply workers to a nearby industrial cluster, while a national employer may hire across borders. Researchers should test spatial dependence, include region-specific trends where defensible, and treat inter-state migration as a matching mechanism rather than missing data. District-level work is valuable but needs enough observations and consistent data to avoid noisy inference.

Policy evaluations frequently privilege outputs over sustained outcomes. Enrolment and certification are visible; relevance, wage progression, job quality, productivity and retention are harder. Yet a policy can achieve high certification while producing weak employment if courses are detached from employers or local demand. Low immediate placement can still yield entrepreneurship or mobility. The World Bank’s five-state evaluation emphasizes relevance, quality assurance, employer engagement and post-placement support [2]. Evaluation

designs should therefore pre-specify outcome horizons, distinguish employment from decent and productive employment, and link trainee records to follow-up and, where feasible, establishment data.

Equity is not an add-on. If formal VET is more available to urban men with stronger schooling and employer networks, observed average returns may coexist with wider opportunity gaps. Women face mobility, safety, care and norm constraints; rural and informal workers may lack access, devices, transport, credit or time. Estimating separate effects and access constraints by gender, social group, rurality, income and migration status is essential. A nationally successful skills system should not merely raise average employability among already advantaged candidates. It should expand the capability of workers and regions to convert learning into productive, safe and fairly rewarded work. This is both an equity requirement and a condition for broad-based regional growth, monitored with transparent uncertainty, sensitivity and cost checks.

5. Discussion

The evidence supports a change in policy question. Instead of asking how many people a scheme can train, planners should ask which regional industries and occupations are constrained by which missing capabilities, and whether training is the binding response. A district with high vacancies for technicians may need apprenticeship partnerships, modern equipment and instructor upgrading. A rural area with constrained non-farm demand may need entrepreneurship, market access, producer services and credit alongside skills. A region with qualified but underemployed youth may need job information, mobility support and employer investment more than another generic certificate. This diagnostic approach prevents skills policy from being used as a substitute for industrial, infrastructure or labour-demand policy.

The proposed state–sector–year framework is useful as a public accountability device. It can report training intensity, occupation–qualification mismatch, apprentice availability, vacancy duration, real wages, employment quality, enterprise productivity, gender inclusion and GVA per worker for comparable sectors. Results should be disaggregated by formal status and firm size and released with data definitions, uncertainty and limitations. Combining PLFS with enterprise surveys, administrative training data, state accounts and tracer studies would allow policy makers to distinguish a shortage of skilled labour from a shortage of decent jobs. It would also reveal whether regional skill strategies are improving matching, productivity or simply moving workers across locations. Workplace learning deserves greater priority. Employers know task change, quality requirements and technology adoption, but small firms may underinvest because of cost, turnover and limited training capacity. Shared apprenticeship models, cluster-based training centres, portable credentials, trainer exchanges and incentives tied to completion and retention can reduce these constraints. Sector Skill Councils should update standards using employer evidence while guarding against narrow occupational lock-in; foundational, digital, green and transferable skills need to travel across occupations. Training providers should be rewarded not only for certification but for independently verified placement, retention, earnings progression, employer satisfaction and inclusion.

Regional strategy should embrace both place and mobility. Skill hubs in manufacturing, renewable energy, logistics, health, tourism, agriculture and digital services need local labour-market intelligence. At the same time, portable credentials, housing or travel support, safe migration information and recognition of prior learning can improve matching where local demand is thin. Women's participation requires more than course seats: safe

transport, childcare, flexible schedules, employer commitments and non-discriminatory job design matter. For informal and self-employed workers, modular learning must be combined with tools, finance, market linkages and advisory support. Otherwise, training can raise aspiration without creating a viable productivity pathway.

Finally, evaluation should be built into programme design. Baseline data, transparent comparison groups, employer surveys and longer follow-up should be funded as core components, not as post hoc audits. Researchers should report heterogeneous effects, non-completion, displacement and cost-effectiveness. A negative or null result can be policy useful if it identifies whether the issue is course relevance, local demand, selection, technology, finance or institutional capacity. Such learning would shift India's skills system from an enrolment-and-certification apparatus toward an adaptive evidence-led regional productivity system capable of responding to sectoral transformation.

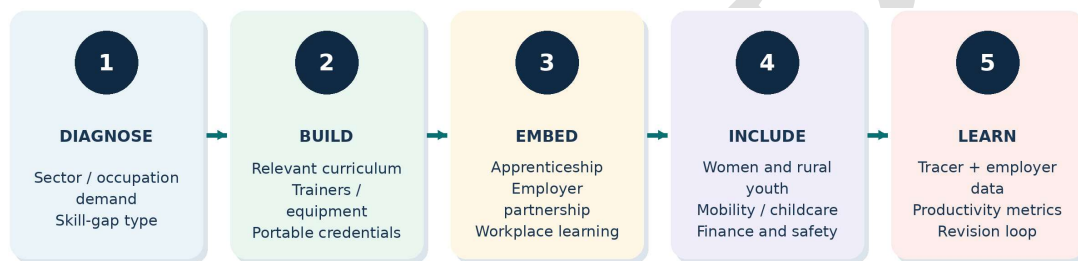


Figure 5. Adaptive regional skills strategy for India

Source: Author's policy synthesis based on the reviewed evidence.

Figure 5 translates evidence into a regional-skills strategy. It begins with labour-demand diagnostics, then layers relevant curricula, workplace learning, employer partnerships and inclusion supports. It connects these inputs to three measurable outcomes: skill match and job quality, firm productivity and regional value added. A learning loop uses tracer, employer and enterprise data to revise diagnosis. Regions may require different mixes of jobs, mobility, entrepreneurship, technology and training. It does not prescribe one sector for every district. It makes policy accountable to labour-market and productivity outcomes.

6. Conclusion

This review finds that skill development can contribute to better earnings, employment, productivity and regional growth in India, but only through conditional pathways. The most credible past work supports positive labour-market returns to relevant formal training and shows that targeted vocational programmes can improve women's work outcomes. State-level and national studies also associate human capital with productivity and growth. Yet these gains are uneven across sectors, employment arrangements, gender, regions, training duration and local demand. A certificate does not by itself guarantee competence, job matching, technology adoption or an increase in value added.

Sectoral skill gaps should therefore be understood as worker–occupation–firm–place mismatches. They may reflect shortages of technical, cognitive or social skills; weak foundational learning; outdated equipment; limited apprenticeships; low wages; poor job information; or insufficient productive investment. India's regional diversity makes a single national return to training analytically misleading. Econometric analysis must separate individual, enterprise, sector and regional outcomes, address selection and reverse causality, and combine labour data with firm, training and state-output information.

The proposed state–sector–year framework offers a practical next step. It would measure skills, match quality, workplace learning, labour-market outcomes, productivity and inclusion with fixed effects and transparent limitations. Policy should then sequence demand diagnostics, modern training, apprenticeship, technology and investment support, mobility options and rigorous follow-up. The goal is not maximal certification; it is an inclusive capability to convert learning into productive, secure and fairly rewarded work across India’s regions and sectors. It should make policy failure visible early.

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