

India's Vocational Education Policy Response to Artificial Intelligence: Layering or Conversion?

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Research Article

Keywords: vocational education and training, artificial intelligence policy, institutional change, layering or conversion, informal economy, India

Posted Date: August 14th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10574518/v1>

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Additional Declarations: No competing interests reported.

Abstract

India has launched a wide range of AI-skilling initiatives such as the Skill India Programme, SOAR, SkillSaksham, and the IndiaAI Mission. While these initiatives have expanded rapidly, little is known about whether they represent incremental policy additions or a fundamental transformation of the VET system. Drawing on Streeck and Thelen's theory of gradual institutional change, this study asks whether India's AI policy response reflects institutional layering or institutional conversion. Using qualitative document analysis of national policies, government reports, and international guidance across six dimensions - curriculum, teacher capacity, governance, assessment and credentialing, lifelong learning, and equity/informal-economy reach - the study finds that India's response is predominantly additive. Five dimensions show institutional layering, while assessment and credentialing shows early movement towards structural change via NSQF-aligned, credit-linked AI courses. The paper offers a framework distinguishing layering from conversion and argues genuine transformation requires reforms extending beyond programme expansion.

Introduction

Artificial intelligence (AI) is rapidly reshaping labour markets by changing not only the demand for skills but also the nature of work itself. The World Economic Forum projects that 23 per cent of jobs worldwide will change by 2027 (World Economic Forum, 2023); the International Labour Organization's occupational exposure index finds that generative AI is likely to transform, rather than eliminate, most jobs, with the most pronounced effects concentrated in clerical and other routine, task-heavy occupations (Gmyrek, Berg and Bescond, 2023); and the OECD's parallel assessment finds that AI adoption is already reorganising the tasks within occupations and shifting the skills those occupations demand (OECD, 2023). Vocational education and training (VET) systems sit at the centre of this growing pressure by design. Their institutional purpose is to align training content directly with current labour-market requirements. A shift of this kind in what a trade actually involves is, for VET, a core mandate question rather than a peripheral one.

In response, TVET systems across the world have introduced a range of AI-related initiatives: new curricula, digital learning platforms, industry partnerships, and dedicated training programmes, with some systems going further to integrate AI directly into trade-specific instruction itself. Yet an important question remains largely unanswered. Do these initiatives fundamentally transform the institutions governing vocational education, or do they simply expand existing systems through additional programmes?

India provides a particularly revealing case for examining this question. It possesses one of the world's largest vocational education systems and has placed skill development at the centre of its development strategy through the vision of Viksit Bharat 2047. Since 2023, the Government of India has launched an extensive portfolio of AI-skilling initiatives spanning multiple ministries and agencies - including the Skilling for AI Readiness (SOAR) programme, SkillSaksham, AI-focused components within the Pradhan

Mantri Kaushal Vikas Yojana (PMKVY 4.0), the FutureSkills pillar of the IndiaAI Mission, and AI-related apprenticeship initiatives under the National Apprenticeship Promotion Scheme (NAPS) - representing one of the largest public investments in AI-related skills among developing economies. However, the scale of policy activity alone does not indicate institutional transformation. New programmes may coexist with unchanged governance arrangements, qualification structures, teacher preparation systems, and curriculum frameworks. Therefore, whether India's expanding AI-skilling agenda represents genuine institutional transformation or merely the layering of additional programmes onto an unchanged system remains an open empirical question.

Existing scholarship generally evaluates individual programmes or technological innovations rather than asking whether AI policies are reshaping the institutions that govern vocational education. See, for example, UNESCO-UNEVOC (2021, 2025, 2026a) reports. Each of these studies assessed the institutional readiness or the adoption of specific AI tools rather than institutional changes (Section 3.1 reviews this literature in full). The distinction between programme expansion and institutional transformation remains largely unexplored. This paper addresses that gap by applying the theory of gradual institutional change developed by Streeck and Thelen (2005) and Mahoney and Thelen (2010). It examines whether India's AI policy response to VET is characterised by layering or by conversion. Rather than assessing the effectiveness of individual AI-skilling programmes, the paper investigates whether the institutional architecture governing vocational education has itself been reconfigured. The paper examines this question across six interconnected dimensions of India's VET system: curriculum, teacher capacity, governance, assessment and credentialing, lifelong learning, and equity and informal-economy reach.

In doing so, the paper makes three contributions to the emerging literature on AI and vocational education. First, it extends theories of gradual institutional change into the study of AI-responsive VET reform through a transparent coding framework that operationalises the distinction between layering and conversion. Second, it shifts the analytical focus from programme-level evaluation towards system-level institutional analysis, showing that AI policy cannot be assessed solely by the number of initiatives introduced but also by the extent to which they reshape the institutions governing vocational education. Third, although the empirical analysis focuses on India, the analytical framework is designed to be transferable to other national contexts facing similar pressures to adapt vocational education to technological change.

Theoretical background

Streeck and Thelen (2005) and Mahoney and Thelen (2010) identify several modes of gradual institutional change, among which layering and conversion are particularly useful for analysing policy responses to technological change. Layering occurs when new rules, programmes, or organisational arrangements are added to existing institutions without altering their underlying logic. Existing institutions continue to operate as before, while new elements are introduced alongside them. Conversion, by contrast, occurs when existing institutions are redirected towards new purposes. The

organisational structures remain in place, but the rules, functions, and objectives that guide them are fundamentally redefined.

This distinction is well suited to examining how vocational education and training (VET) systems respond to artificial intelligence (AI). AI creates pressure for institutions to adapt, but adaptation can follow different paths. Governments may introduce new AI-related programmes while leaving existing institutional arrangements largely unchanged, or they may redefine the institutions themselves to respond to changing labour-market demands. Although AI-skilling initiatives have expanded rapidly across many countries, relatively little attention has been paid to whether these initiatives represent institutional transformation or simply the expansion of existing systems.

In this paper, the core institutional logic of the VET system refers to the rules governing curriculum, teacher preparation, governance, assessment and credentialing, lifelong learning, and the relationship between vocational qualifications and labour-market needs. Institutional change is therefore assessed not by the existence of AI-related initiatives, but by whether these underlying rules have been redefined.

Applied to India, layering refers to the addition of AI-literacy modules, laboratories, apprenticeship targets, and training programmes to the existing VET system without fundamentally changing how institutions operate. Conversion, in contrast, would involve existing institutions - including Industrial Training Institutes (ITIs), the National Council for Vocational Education and Training (NCVET), and the National Skills Qualification Framework (NSQF) - being redirected to incorporate AI into their core functions, including curriculum design, teacher development, governance, assessment, and lifelong learning.

This distinction offers two analytical advantages. First, it makes the distinction between additive and structural reform empirically observable rather than a matter of interpretation. The question is not whether AI-related initiatives exist, but whether they alter the institutional rules governing the VET system. Second, it recognises that layering and conversion are distinct trajectories of institutional change rather than different stages of the same process. This theoretical distinction provides the basis for the analytical framework developed in the following section.

2.1 Analytical framework

To operationalise the distinction between layering and conversion, this paper examines six dimensions of India's VET system: curriculum, teacher capacity, governance, assessment and credentialing, lifelong learning, and equity and informal-economy reach. The first five dimensions are widely recognised as central components of vocational education systems. The sixth - equity and informal-economy reach - is included because of the distinctive structure of India's labour market. According to the Economic Survey (Government of India, Economic Survey Division, 2024), only 4.4 per cent of young people aged 15–29 possess a formal vocational qualification, while a further 16.6 per cent acquire skills informally. A policy response that reaches only formal institutions cannot be considered structurally transformative if most

vocational learning takes place outside them. Equity and informal-economy reach are therefore treated as a separate analytical dimension rather than being subsumed within the others.

Each dimension is assessed using the theoretical distinction between layering and conversion developed in Section 2. A dimension is coded as layering when AI-related initiatives are added without changing the institutional rules that govern it. It is coded as a conversion when those rules are redefined in response to AI. Together, these six dimensions provide a systematic framework for assessing whether India's AI policy response represents institutional layering or institutional conversion.

Literature review

3.1 The global TVET-AI literature

UNESCO-UNEVOC's *Understanding the Impact of Artificial Intelligence on Skills Development* (2021) provides the most comprehensive overview of AI in TVET. It argues that AI is already influencing legislation, governance, and skills systems in many countries, although the pace of adaptation varies considerably. While some TVET systems have integrated AI into vocational training, others remain at an early stage of policy development. More recent evidence reinforces this challenge. UNESCO-UNEVOC's global youth survey found that although 62 per cent of young people already use AI in everyday life, only 30 per cent have received formal AI training (UNESCO-UNEVOC, 2025). Similarly, UNESCO's AI Competency Framework for Teachers (2026b) argues that effective AI integration requires continuous professional development rather than one-off training programmes.

International experience also demonstrates that institutional responses to AI differ across countries. Germany has integrated AI and virtual reality directly into trade-specific competencies within its dual VET system. Poland has embedded AI literacy within existing vocational curricula at a national scale. Malta has focused on coordinated institutional leadership, while Switzerland has prioritised educator confidence and trust as conditions for successful AI adoption (UNESCO-UNEVOC, 2026a). Although these approaches differ, they share an important feature: AI is treated as part of the core vocational system rather than as an isolated training initiative.

These international experiences demonstrate that institutional responses to AI can follow different pathways depending on national context. At the same time, they show that structural adaptation is achievable across different governance arrangements and system sizes. However, existing studies largely describe institutional readiness, programme design, or implementation experiences. They pay much less attention to whether AI policies are transforming the institutions that govern vocational education. This institutional question remains largely unexplored.

3.2 The Indian VET-AI literature

Research on AI and education in India has expanded rapidly in recent years, but most of it focuses on schools and higher education. Rehman, Dar, and Rasool (2025) review AI literacy in Indian higher

education, while Patro (2026) examines AI-driven reforms in education policy and governance. Both studies discuss curriculum, governance, and institutional preparedness in detail. Comparable work on India's vocational education and training system, however, remains limited.

The literature that does address Indian VET focuses on specific issues rather than the institutional effects of AI. Albertz and Pilz (2025), for example, examine how ITI teachers understand green skills, another emerging competency introduced into existing vocational programmes. They show considerable variation in teachers' understanding and conclude that brief training interventions alone are unlikely to produce meaningful pedagogical change. Although their study is not about AI, it provides useful insights into the challenges of introducing new competency areas through short-term teacher training.

Other studies identify broader structural challenges within India's VET system. Pilz and Regel (2021) discuss persistent issues such as limited employer recognition of vocational qualifications and institutional fragmentation. Regel and Pilz (2019) examine informal skill formation in India's tailoring sector, highlighting the importance of learning outside formal institutions. Similarly, NCAER's review of VET reform priorities points to low seat utilisation in Industrial Training Institutes and comparatively modest employment outcomes, suggesting that institutional weaknesses continue to shape the effectiveness of vocational policy (Afridi & Chandna, 2025).

Taken together, the existing literature provides valuable insights into AI adoption, teacher preparedness, and structural challenges within India's vocational education system. However, it does not examine whether India's expanding AI-skilling agenda is changing the institutional architecture of VET itself. Existing studies evaluate individual programmes or specific dimensions of reform in isolation. An integrated analysis of curriculum, governance, teacher capacity, assessment, lifelong learning, and equity from an institutional perspective is still missing. This paper addresses that gap by examining whether India's AI policy response represents institutional layering or institutional conversion.

Research Methodology

This paper uses a qualitative, document-based policy analysis, grounded in the theory of gradual institutional change set out in Section 2, to ask whether India's AI-skilling response has altered the core rules of its VET institutions or simply added to them. The question is treated as a question about the documented policy record and is answerable, in the first instance, from that record rather than from fieldwork. This section proceeds in four parts: it sets out the evidence base and search protocol (Section 4.1), the coding procedure that operationalises the layering-conversion distinction across the six dimensions set out in Section 2.3 (Section 4.2), the rationale for comparator case selection (Section 4.3), and the scope and limitations inherent to a document-based design (Section 4.4).

4.1 Evidence base and search protocol

The evidence base comprises three categories of source, identified through a structured search conducted between January and May 2026 and covering documents published between January 2023 and April 2026, the period since India’s AI-skilling initiatives began in earnest.

The first category is primary government documentation: ministry notifications, budget documents, the Economic Survey, NCVET and NSQF materials, and programme-level reporting from MSDE, the Ministry of Education, and the Ministry of Electronics and Information Technology (MeitY). These were located through the official websites and press-release archives of each body, and through the Press Information Bureau (PIB), using the search terms “AI skilling India”, “SOAR NCVET”, “PMKVY AI”, “IndiaAI Mission”, and “NSQF artificial intelligence”, cross-checked against each ministry’s own publication list to confirm completeness. Forty-one primary government documents were identified; thirty-one were retained as directly relevant to at least one of the six coding dimensions, and ten were excluded as duplicative or out of scope (for example, state-level press coverage of a national announcement already captured through the originating ministry document).

The second category is international and comparative documentation, principally UNESCO-UNEVOC’s institutional surveys and regional briefs, used to establish how comparable TVET systems elsewhere have responded to the same disruption, and identified through UNESCO-UNEVOC’s own publication archive.

The third category is peer-reviewed and grey literature, identified through Google Scholar and ScienceDirect using the terms “vocational education India AI”, “TVET artificial intelligence”, and “ITI teacher capacity”, supplemented by citation-tracking from the sources located. This literature is used both to identify the gap the paper addresses and, in the findings below, to situate India’s documented response against existing scholarship on related dimensions, such as teacher capacity and informal-sector skill formation.

4.2 Coding procedure

For each of the six system dimensions, the layering-conversion distinction was operationalised into an indicator of structural change (conversion) and an indicator of additive change (layering), summarised in Table 1. A dimension is coded structurally only where a core-rule change of the kind indicated is documented in the evidence base. Where the evidence shows AI-related activity without a documented core-rule change, the dimension is coded additive. Where the evidence is not enough to code either way confidently, it is coded indeterminate rather than assumed. This coding was applied to the policy inventory in the findings section, and the basis for each coding decision is stated alongside the finding it supports, so the paper’s central claim is a reported outcome of the procedure, not an impression formed before it.

Table 1
Coding indicators for structural versus additive change, by system dimension

Dimension	Indicator of structural change (conversion)	Indicator of additive change (layering)
Curriculum	Revision of existing trade-specific job-role descriptors or syllabi to reflect AI-augmented task content	A separate AI-literacy course or module added alongside an unrevised trade curriculum
Teacher capacity	A recurring, credentialed AI-pedagogy requirement built into pre-service or in-service VET-teacher education	A one-off onboarding or orientation module with no standing curricular status
Governance	A single authority, existing or newly created, with end-to-end coordinating responsibility for AI-specific VET policy	AI-specific initiatives are distributed across the same ministries and bodies that already divide non-AI VET governance
Assessment and credentialing	Documented revision of NSQF job-role or competency descriptors for AI-augmented content	Assessment and credentialing instruments unchanged; new training delivered outside the certification structure
Lifelong learning	A reskilling pathway, credit-bearing or otherwise, explicitly extended to workers already in the labour market	Programmes confined to new entrants, students, or apprentices
Equity and the informal economy reach	A deliberate extension mechanism, such as vernacular delivery, mobile units, or association partnerships, reaching informally trained workers	Delivery is confined to formal institutions such as ITIs, National Skill Training Institutes (NSTIs), and polytechnics
<i>Source: Author's framework, adapting Mahoney and Thelen's (2010) layering-conversion distinction</i>		

4.3 Comparator case selection

Germany, Poland, Malta, and Switzerland were selected as international comparators because they represent different institutional contexts. They vary in both system scale and governance arrangements. Malta has a small, unitary system, whereas Germany operates a large federal system. Their coordination models also differ, ranging from dual apprenticeship to centrally administered and trust-based approaches. This variation allows the paper to examine whether structural responses to AI are feasible across different institutional settings. The purpose is not to identify a single best-practice model or to compare India's performance with these countries. Instead, the cases illustrate that institutional adaptation can occur under different governance arrangements. The cases were selected purposively rather than to provide a comprehensive or statistically representative international comparison. The paper therefore uses them to establish institutional feasibility, not to rank national performance. A fifth case, Fiji, is considered separately. Unlike the four European systems, Fiji is included because of its AI-supported outreach to informal and geographically isolated learners. It is discussed only in relation to the equity and informal-economy dimension, rather than institutional scale.

4.4 Scope and limitations of the design

A document-based design can establish what the Government of India and its partner institutions have proposed and implemented through official policies and programmes. Using the analytical framework developed in this paper, it can also assess whether these documented initiatives amount to institutional layering or conversion. However, documentary evidence cannot capture how policies are implemented in classrooms, workshops, or informal apprenticeships. Nor can it assess implementation fidelity, state-level variation, resource availability, or teachers' day-to-day practices. The findings should therefore be interpreted as an assessment of the documented policy record as of mid-2026, rather than of implementation outcomes on the ground.

Findings

5.1 The policy landscape: administering bodies and initiatives

India's AI-skilling response is spread across at least four central government bodies. The Ministry of Education provides the curriculum foundation through the National Education Policy (NEP) 2020 and the National Curriculum Framework for School Education (NCF-SE) 2023, which underpin AI's introduction into formal education, including pre-vocational tracks. The Central Board of Secondary Education introduced AI as an elective subject from Class IX in 2019-20 and Class XI in 2020-21, and a proposed Centre of Excellence in Artificial Intelligence for Education has been allocated ₹500 crore (roughly USD 57 million at an indicative rate of ₹87 to the dollar) under the Union Budget 2025-26, as a national hub for AI-integrated pedagogy and faculty development in higher education. NCVET, notified in December 2018 to consolidate previously fragmented regulatory mechanisms, oversees the NSQF and is working to integrate vocational education with the National Credit Framework (NCrF) introduced under NEP 2020. NCVET has itself acknowledged a pre-existing, non-AI-specific challenge of limited employer confidence in NSQF-aligned qualifications, a challenge distinct from, and not resolved by, the AI-specific initiatives reviewed in this paper.

MSDE administers the largest cluster of AI-specific vocational initiatives. In 2025, the Union Cabinet restructured three of its flagship schemes, namely PMKVY 4.0, NAPS-2 and the Jan Shikshan Sansthan scheme, into a single Central Sector Scheme, the Skill India Programme, with a combined outlay of ₹8,800 crore (approximately USD 1.01 billion) through 2025-26 (Prime Minister's Office, 2025). This consolidation streamlines scheme administration within MSDE, but does not itself create an AI-specific coordinating authority. Within this structure, PMKVY 4.0 had trained 36,584 individuals in AI-related skills as of 30 June 2025, forty-five per cent of them women. NAPS-2 had placed 1,480 apprentices in AI-related roles between 2022-23 and 2025-26. SOAR, launched on 22 July 2025, targets Classes VI-XII and their educators with three fifteen-hour student modules and a forty-five-hour teacher module, delivered in partnership with Microsoft, HCL Technologies, and NASSCOM (Press Information Bureau, 2025a). By

early 2026, ministry reporting placed enrolment above 1.74 lakh students and teachers. SkillSaksham, an MSDE-Microsoft partnership targeting two hundred ITIs, offers 1,200 hours of foundational and 400 hours of advanced AI training and has trained 8,500 of a targeted 10,000 candidates by late 2025. A one-year AI Programming Assistant micro-degree, delivered with the Directorate General of Training across thirty-three National Skill Training Institutes, had enrolled more than 350 students. The pre-existing Craftsmen Training Scheme, delivered through more than fifteen thousand public and private ITIs, remains the institutional base into which these AI-specific additions are introduced.

MeitY’s IndiaAI Mission, approved in March 2024 with an outlay of ₹10,371.92 crore (approximately USD 1.19 billion) over five years, includes a FutureSkills pillar supporting five hundred PhD scholars, five thousand postgraduate students, and eight thousand undergraduate students, alongside twenty-seven IndiaAI Data and AI Labs in Tier-2 and Tier-3 cities delivered through the National Institute of Electronics and Information Technology (NIELIT). By late 2025, one hundred and seventy-four ITIs and polytechnics across twenty-seven states had been approved to establish additional AI laboratories, the clearest direct contact point between IndiaAI’s research-oriented architecture and the vocational ITI system. MeitY’s YUVAi programme targets Classes VIII-XII, and the YUVA AI for All course aims to reach one crore (ten million) citizens with a four-to-four-and-a-half-hour foundational programme.

Table 2 maps each initiative against its administering body, making the fragmentation described above visible as evidence rather than assertion.

Table 2
AI-related VET initiatives in India

Initiative	Administering body	Primary VET touchpoint
NEP 2020 / NCF-SE 2023 / CBSE AI elective	Ministry of Education	School-level pre-vocational curriculum
Centre of Excellence in AI for Education	Ministry of Education	Higher education pedagogy, not ITIs directly
NSQF / NCrF	NCVET (statutory body)	Qualification levels and credit transfer
Skill India Programme (PMKVY 4.0 / NAPS-2 / JSS) / SOAR / SkillSaksham / Craftsmen Training Scheme	MSDE	Direct ITI and apprenticeship delivery
IndiaAI Mission FutureSkills / AI Labs in ITIs / YUVAi / YUVA AI for All	MeitY / IndiaAI	Research-oriented skilling and 174 ITI AI labs

Source: Author’s compilation from government sources cited above.

No single body in Table 2 holds end-to-end ownership of AI’s implications for vocational education. Curriculum sits mainly with the Ministry of Education, delivery and apprenticeship with MSDE, qualifications and credit with NCVET, and the most AI-specific technical training with MeitY and IndiaAI.

This fragmentation is treated below both as a coding outcome for the governance dimension and, in the discussion, as part of the explanation for the pattern observed across all six dimensions.

5.2 Curriculum (Coding: Additive)

SOAR's modules and SkillSaksham's training programmes are delivered as stand-alone courses alongside existing ITI curricula. They are not integrated into the trade-specific programmes already taught in Industrial Training Institutes. None of the initiatives reviewed here document revisions to the core curricula for NSQF-aligned trades, such as electrician, fitter, welder, and more than one hundred other trades, to reflect the growing use of AI-enabled diagnostics, monitoring, and automation. According to the coding framework in Table 1, this represents layering. AI has been introduced as an additional learning stream, while the underlying trade curricula remain unchanged. UNESCO-UNEVOC (2026b) distinguishes between providing general AI literacy and integrating AI into existing trade curricula. The latter involves redesigning vocational programmes because AI is changing how occupations are practised. It cites automotive technicians using AI-assisted diagnostics as one example. The initiatives reviewed here resemble the first approach rather than the second. This is notable because trades such as electricians and fitters are already beginning to use AI-enabled technologies and could therefore justify curriculum redesign rather than stand-alone AI courses. Germany provides a useful point of comparison. Its dual VET system has integrated AI- and virtual reality-enhanced learning directly into trade-specific competency development. This demonstrates that curriculum-level conversion is institutionally feasible. As discussed in Section 4.3, Germany differs substantially from India in both system scale and governance. The comparison, therefore, illustrates institutional feasibility rather than a model that can be directly transferred to the Indian context.

5.3 Teacher capacity (Coding: Additive)

SOAR's 45-hour teacher module is the only AI-specific teacher training programme operating at a national scale identified in this review. Its significance is best understood alongside Albertz and Pilz's (2025) study of ITI teachers and green skills. They found that teachers' understanding of an unfamiliar competency varied widely, from limited awareness to a sophisticated, values-based understanding. Their findings suggest that short training programmes alone are unlikely to produce consistent pedagogical change. No evidence was found of AI-related revisions to pre-service training at the National Skill Training Institutes, changes in recruitment criteria for AI competencies, or a structured programme of continuous professional development. Instead, SOAR and SkillSaksham provide one-time training modules. UNESCO's AI Competency Framework for Teachers distinguishes between acquiring AI literacy and developing the ability to integrate AI into teaching and curriculum design (UNESCO-UNEVOC, 2026b). The available evidence suggests that the current teacher training initiatives focus primarily on basic AI awareness. No documented pathway was identified to support progression towards more advanced levels of professional competence. According to the coding framework in Table 1, this represents layering rather than conversion. AI-specific training has been added to the existing system, but the institutional arrangements governing teacher preparation and professional development remain unchanged.

5.4 Governance (Coding: additive)

Table 2 shows that responsibility for AI-related vocational education is distributed across multiple central government bodies. The Ministry of Education leads curriculum policy, MSDE oversees major skilling programmes, NCVET regulates qualifications and credit, and MeitY supports advanced AI training and digital infrastructure. State governments remain responsible for administering Industrial Training Institutes. This distribution of responsibilities creates a fragmented governance structure. The 2025 restructuring of PMKVY 4.0 and NAPS-2 into the unified Skill India Programme simplified programme administration within MSDE. However, it did not resolve the broader coordination challenge. Curriculum, qualifications, and advanced AI training continue to be managed by different institutions.

A further governance challenge predates the current AI initiatives. NCVET has acknowledged limited employer recognition of NSQF qualifications (Pilz & Regel, 2021; NCAER, 2025). None of the AI-specific initiatives reviewed in this paper directly addresses this long-standing institutional issue. Instead, new AI programmes have been introduced within the existing governance architecture. This finding is also consistent with UNESCO-UNEVOC's (2026b) international policy inventory. It identifies India's National Strategy for Artificial Intelligence (2018), coordinated by NITI Aayog, as a national AI strategy that includes education and skills. However, this is a broad digital policy rather than a VET-specific governance framework. Unlike countries such as China and Tanzania, no dedicated AI policy or coordinating authority for the vocational education sector was identified. NCVET's decision to establish a Skill Development Research Division in January 2026 is an important institutional development. The division is intended to strengthen research on labour-market trends and system performance. However, the available evidence does not suggest that it functions as a central coordinating authority for AI across the VET system. According to the coding framework in Table 1, this dimension is classified as layering. AI initiatives have been added across existing institutions, but the governance arrangements that coordinate the VET system remain largely unchanged.

5.5 Assessment and credentialing (Coding: Additive, with an emerging exception)

The National Skills Qualification Framework (NSQF) and the National Credit Framework (NCrF) were largely designed before the recent expansion of generative AI. No evidence was identified that the competency standards for established ITI trades have been systematically revised to reflect AI-enabled work practices. For example, the formal job-role descriptors for trades such as electrician or fitter do not yet specify competencies related to AI-assisted diagnostics, monitoring, or automation. This is the dimension in which institutional conversion would be most clearly observable if such revisions were introduced. It is therefore identified as a priority for future research.

The available evidence also suggests that this is the least settled dimension in the analysis. According to the Ministry of Skill Development and Entrepreneurship (Press Information Bureau, 2026), Phase I of SOAR introduced four NSQF-aligned AI courses approved by the National Skills Qualification Committee,

three of which were offered as NCrF micro-credentials. By early 2026, Phase II had expanded this to 50 NSQF-aligned AI and AI-application courses across multiple sectors. Thirty-five of these were developed as micro-credentials with defined credit values, learning hours, and progression pathways. The courses were developed with NCVET-recognised Awarding Bodies and industry partners, including the Confederation of Indian Industry (CII), NASSCOM, Microsoft, and several Sector Skill Councils. These developments indicate that AI content is increasingly being incorporated into India's credentialing architecture rather than being delivered entirely outside it. However, the new courses remain separate AI qualifications. They do not yet involve systematic revisions to the competency standards of existing ITI trades. Nor has their implementation been evaluated independently. According to the coding framework in Table 1, this dimension is therefore classified as layering. At the same time, it represents the strongest evidence of movement towards conversion identified in this study. If future reforms revise the competency standards of established vocational qualifications, rather than creating parallel AI credentials, the coding of this dimension may change. This development is therefore highlighted as an important priority for future monitoring.

5.6 Lifelong learning (Coding: Additive)

Most AI initiatives reviewed in this study, including SOAR, YUVAi, and the AI Programming Assistant micro-degree, are designed for school students, new entrants, or learners in formal education. They do not provide recurring learning pathways for the existing workforce, including ITI graduates and informally trained workers whose occupations may be affected by AI. The National Credit Framework (NCrF) has the potential to support lifelong learning because it allows learners to accumulate and transfer credits across programmes over time. However, the available evidence does not indicate that this mechanism has been used to deliver AI-related reskilling for workers already in the labour market. Its current application remains largely focused on learners entering or progressing through the formal education system. This contrasts with UNESCO-UNEVOC's (2026b) guidance, which identifies incumbent workers as a distinct group requiring flexible and modular AI-reskilling opportunities. Such pathways enable workers to update their skills throughout their careers rather than relying solely on pre-employment training. According to the coding framework in Table 1, this dimension is classified as layering. AI-related learning opportunities have been added for new entrants, but they have not yet been extended into a systematic lifelong-learning strategy for the existing workforce.

5.7 Equity and informal-economy reach (Coding: Additive; the clearest case among the six dimensions)

All AI-skilling initiatives reviewed in this study are delivered through formal institutions, including Industrial Training Institutes (ITIs), National Skill Training Institutes (NSTIs), schools, and polytechnics. According to the *Economic Survey 2023-24*, however, only 4.4 per cent of young people hold a formal vocational qualification. Another 16.6 per cent acquire vocational skills informally. Existing AI initiatives do not specifically target this group or the much larger population of informally trained adult workers. Access within the formal system also remains uneven. UDISE 2022 data show that private ITIs (11,568) now substantially outnumber government ITIs (3,180). This growing reliance on private provision may

create financial barriers for many learners. As a result, even formal AI-skilling programmes may not reach those workers who are most vulnerable to AI-driven labour-market change.

This gap reflects more than an incomplete policy rollout. Current MSDE and NCVET initiatives are designed to operate through registered training institutions. Reaching workers outside the formal system would therefore require new delivery mechanisms rather than simply expanding existing programmes. International experience illustrates what such an approach could look like. Fiji National University, working with the Asian Development Bank, has used AI-supported virtual reality training delivered through short, language-light sessions to reach women and young people in rural and maritime communities (UNESCO-UNEVOC, 2026b). The emphasis is on adapting delivery to learners who cannot easily access conventional institutions. No comparable outreach mechanism was identified in the Indian evidence reviewed in this study. There is no evidence of AI-skilling being delivered through mobile training units, vernacular-language programmes, community-based learning centres, or partnerships with informal-sector trade associations. According to the coding framework in Table 1, this is the clearest example of layering. AI initiatives have been added to the existing formal VET system, but the institutional boundaries of that system remain unchanged.

5.8 Summary of coding

Table 3 summarizes the coding outcome across all six dimensions. The coding is additive on five of six dimensions without qualification, and additive with a documented, still-developing exception on the sixth. This near-uniformity is itself a finding: it suggests the additive pattern is systemic, not confined to one weak link in an otherwise structural response. The exception on assessment and credentialing indicates the pattern is not static, a distinction the discussion draws on directly.

Table 3
Summary of coding outcomes across the six system dimensions

Dimension	Coding	Basis	Primary evidence
Curriculum	Additive	No documented revision of trade syllabi or job-role content	Absence of revision across NSQF trade documentation
Teacher capacity	Additive	One-off modules, no standing curricular status	SOAR teacher module design; Albertz and Pilz (2025) on comparable green-skills modules
Governance	Additive	Fragmented across four central bodies, no single coordinating authority	Table 2 mapping: Prime Minister's Office (2025) on Skill India Programme restructuring
Assessment and credentialing	Additive, with an emerging exception	NSQF descriptors for established trades not revised; SOAR's own NSQF-aligned, credit-linked expansion is a recent, still-developing signal of movement	Press Information Bureau (2026) official SOAR press release
Lifelong learning	Additive	Programmes confined to new entrants, not incumbent workers	Absence of NCrF application to incumbent-worker reskilling
Equity and the informal economy reach	Additive	Delivery is confined to formal institutions; no extension mechanism is identified	Economic Survey 2023-24 (Government of India, Economic Survey Division, 2024); UDISE 2022 ITI counts

Source: Author's coding, applying the Table 1 framework to the evidence presented above.

Discussion

6.1 The strongest counter-argument: NEP 2020 and the NCrF

A reasonable objection to this paper's central claim is that NEP 2020 and the NCrF already constitute the structural response the paper finds largely absent. Both are explicitly designed around multidisciplinary learning, modular credit accumulation, and movement between vocational and academic pathways, rather than around a single fixed curriculum. This objection has real force. NEP 2020 and the NCrF are structural in intent and architecture. They provide the institutional scaffolding, credit mobility, and multidisciplinary design that a genuine AI-responsive redesign of vocational education would need. In Mahoney and Thelen's (2010) terms, they created the conditions under which conversion becomes institutionally possible. The evidence reviewed above, however, indicates that this scaffolding has not yet been operationalised specifically for AI's disruptive effects on vocational trade content, with the partial

exception of SOAR's credentialing expansion noted in Section 5.5. NEP 2020 and the NCrF are therefore better understood as structural potential that India's AI-skilling response has begun, in one instance, to draw on, not as evidence that conversion has already occurred across the system.

6.2 Explaining the pattern

Diagnosis is not an explanation. Four factors, each grounded in the evidence above, plausibly combine to produce a predominantly additive response.

Governance fragmentation is a structural incentive toward layering. Table 2 shows curriculum, delivery, credentialing, and the most advanced AI-specific training held by four separate central bodies. Layering is, almost by construction, the lower-coordination-cost form of institutional change available to a fragmented governance system. Any single body can add a module, a laboratory, or a training target within its own remit, without needing agreement from the other three. Conversion, revising NSQF job-role descriptors, for instance, would require MSDE, NCVET, and the Ministry of Education to coordinate a shared redefinition of what a trade certifies. Fragmentation does not merely coexist with the additive pattern; it makes layering the path of least institutional resistance.

Mission-mode incentives reward visible scale. The initiatives above are consistently reported, in government communication and in this paper's own compilation, in enrolment and placement numbers: 36,584 PMKVY trainees, more than 1.74 lakh SOAR enrolments, 174 ITI AI laboratories. These are metrics that can be generated quickly and reported easily against a mission-mode target. Redesigning NSQF job-role descriptors or overhauling teacher-education curricula would generate no comparably quick or visible metric, and the reward structure evident in this paper's own evidence base favours the former.

Rapid-implementation pressure follows from India's AI-talent targets. Pressure to scale training quickly makes layering onto existing institutions faster to implement than redesigning them. A new module can be delivered within an existing ITI immediately, while a systematic, trade-by-trade NSQF revision is a multi-year regulatory undertaking. Under time pressure, the faster option is the one a system under a numerical target is likely to choose, independent of which option is structurally preferable.

International policy diffusion also plays a role. India's AI-skilling programmes resemble initiatives adopted in many other countries. Common features include short AI-literacy modules, partnerships with global technology firms, and national AI-talent targets. This pattern is consistent with what organisational institutionalism describes as isomorphism. Organisations facing uncertainty often adopt models that are already regarded as legitimate internationally (DiMaggio & Powell, 1983). Andrews, Pritchett, and Woolcock (2017) offer a related but distinct explanation. They describe isomorphic mimicry as the adoption of the visible form of a credible reform without developing the institutional capability that the reform is intended to create. The two perspectives, therefore, explain different aspects of policy change. DiMaggio and Powell explain why similar policy models spread across countries facing comparable uncertainty. Andrews and colleagues explain why those models may persist without

producing deeper institutional transformation. Taken together, these perspectives do not imply that India's AI initiatives are merely performative or insincere. They suggest something more limited. Governments confronting a new technological challenge often converge on similar policy responses, such as AI-literacy modules, industry partnerships, and enrolment targets. These measures may expand participation and build awareness, but they do not by themselves demonstrate the curriculum- or credential-level conversion identified in this paper.

These four factors are not mutually exclusive. Nor does this paper claim to have tested them against competing explanations using the kind of implementation evidence that such an analysis would require. Instead, they are presented as the most plausible interpretation of the documentary evidence assembled here. They also point to an important agenda for future state-level governance research (Section 7). A more charitable interpretation is also possible. UNESCO-UNEVOC's (2026b) phased model of institutional AI integration views layering-type activities as an expected and often appropriate starting point. The model describes a gradual progression from diagnosis and low-risk early applications to deeper pedagogical integration and, eventually, ecosystem-wide governance. From this perspective, the concern is not that India's response began with additive measures. Rather, the concern is that, three years into implementation, the available evidence shows only limited documented movement beyond this initial phase across five of the six dimensions examined in this study.

The international cases considered above also help interpret India's trajectory. Germany, Poland, Malta, and Switzerland differ substantially in institutional scale, governance arrangements, and economic context, yet each shows some degree of integration between AI policy and the core architecture of vocational education. India's response differs less in its ambition than in the institutional mechanisms through which that ambition is pursued. Rather than redesigning existing institutional arrangements, the documented response has largely expanded AI provision through additional programmes, partnerships, and training initiatives operating alongside the existing VET architecture. This comparison reinforces the paper's central analytical argument: the key distinction lies not in the presence or absence of AI initiatives, but in the extent to which those initiatives redefine the core institutions governing vocational education.

6.3 Implications for reform

The findings point to five reform priorities. Together, they would move the relevant institutional dimensions from layering towards conversion, as defined in Table 1. They also align closely with UNESCO-UNEVOC's (2026b) recommendations for national policy-makers. These include regularly updating occupational standards and qualification frameworks, strengthening labour-market intelligence, and extending governance beyond formal institutions to work-based and enterprise-based learning. This convergence suggests that the priorities identified here are not unique to India. Rather, they reflect a broader international reform agenda that India has only partially adopted.

First, NSQF job-role descriptors should be reviewed systematically on a trade-by-trade basis to reflect AI-augmented work practices, rather than relying primarily on new stand-alone AI qualifications. This

addresses the curriculum findings presented in Section 5.2.

Second, AI pedagogy should become a recurring requirement in both pre-service and in-service teacher education. This would replace the current reliance on one-time training modules and address the teacher-capacity findings in Section 5.3.

Third, India requires a single coordinating authority for AI-specific vocational policy. One possible approach would be to build on NCVET's newly established Skill Development Research Division and its planned transition to full statutory status. This would address the governance fragmentation identified in Section 5.4.

Fourth, AI-skilling initiatives should incorporate deliberate outreach mechanisms for workers outside the formal VET system. These could include vernacular-language delivery, mobile training units, and partnerships with informal-sector trade associations. Such measures would address the equity gap identified in Section 5.7.

Fifth, NCeF-enabled modular reskilling pathways should be extended to existing ITI graduates and informally trained workers, rather than focusing primarily on new entrants. This addresses the lifelong-learning findings in Section 5.6 and complements the fourth priority. Both require extending AI-skilling opportunities beyond the institutions through which policy is currently delivered.

These priorities reinforce the demographic and labour-market challenge outlined at the beginning of the paper. A VET system that continues to certify trade competencies without recognising AI-enabled work practices, trains teachers only once rather than throughout their careers, and reaches only a minority of the vocationally active population risks preparing young people for occupations that are already changing. The reforms proposed here should therefore be understood not as an additional policy wish list, but as practical conditions for ensuring that India's demographic advantage translates into the skilled workforce envisioned in *Viksit Bharat 2047*, rather than into a widening mismatch between training and labour-market demand.

Conclusion

This paper examined whether India's vocational education and training (VET) policy response to artificial intelligence represents institutional layering or institutional conversion. Applying a coding framework grounded in theories of gradual institutional change, the analysis finds that India's response remains predominantly additive. Five of the six institutional dimensions are coded as layering, while assessment and credentialing show early signs of movement towards structural change. Official government confirmation of SOAR's expansion into 50 NSQF-aligned, credit-linked AI courses (Press Information Bureau, 2026) indicates that credentialing reform has begun, although it has not yet extended to established ITI trades. The paper's principal methodological contribution is to provide a theory-driven framework for distinguishing institutional layering from institutional conversion in AI-related VET reforms. The analysis further suggests that governance fragmentation, mission-mode implementation,

pressure for rapid delivery, and international policy diffusion help explain why AI initiatives have expanded without fundamentally transforming the institutional architecture of India's VET system. Among the six dimensions examined, equity and informal-economy reach show the widest gap between additive reform and structural change, as every initiative identified in this study operates through formal institutions that reach only a minority of India's vocationally relevant population.

This study has several limitations. First, the policy landscape is evolving rapidly. Several initiatives discussed in this paper were launched within the twelve months preceding its completion, and their scale, design, or continued implementation may have changed by the time of publication. The expansion of SOAR's credentialing framework discussed in Section 5.5, in particular, should be regarded as an emerging development that warrants continued monitoring. Second, the analysis relies primarily on official government documents and grey literature because independent academic evaluations of India's AI-skilling initiatives remain limited. This reflects the broader gap in the literature identified in Section 3. Most importantly, the study is based on documentary evidence rather than primary fieldwork in Industrial Training Institutes (ITIs), National Skill Training Institutes (NSTIs), or informal-sector training settings. Consequently, the findings should be interpreted as an assessment of the documented policy record rather than of implementation outcomes. Documentary evidence can establish what governments have introduced and whether those initiatives meet the institutional criteria specified in the analytical framework. It cannot determine how policies are implemented in classrooms, workshops, or informal apprenticeships. Finally, the coding was undertaken by a single researcher using the indicators presented in Table 1. Future studies would benefit from independent coding to assess inter-coder agreement, particularly for borderline cases such as the assessment and credentialing dimension. This was beyond the scope of the present study but should be considered in future applications of the framework.

Three directions for future research follow directly from these limitations. None can be addressed through a document-based design alone. First, field-based research is needed to examine how AI is reshaping skill formation in India's informal economy. Building on studies such as Regel and Pilz's (2019) work on the informal tailoring sector, future research could test the equity gap identified in Section 5.7 using primary evidence. Second, comparative state-level studies are needed because, although ITIs operate within the national framework of NCVET and the NSQF, they are administered by state governments. Differences in AI readiness, institutional capacity, and resource availability may therefore shape implementation in ways that this national-level analysis could not capture. Third, future research should track whether NSQF job-role descriptors are revised to incorporate AI-augmented competencies and whether SOAR's credentialing model is extended beyond its own courses. These developments would provide the clearest empirical test of whether India's AI-skilling response is beginning to move from institutional layering towards institutional conversion.

Declarations

Availability of data and materials: All documents analysed in this study are publicly available government, institutional, and grey-literature sources, cited in full in the reference list. No new datasets were generated during this study.

Author contribution: Single-authored. The author was solely responsible for conceptualisation, evidence collection, coding, analysis, and writing.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Competing interests: The author declares no competing interests.

Ethics Declaration: This study is based solely on publicly available policy documents and reports and did not involve human participants, personal data, or primary data collection. Therefore, ethical approval and informed consent were not required. The study was conducted in accordance with the principles of good research practice, including academic integrity, transparency, and the responsible use and citation of publicly available sources.

Use of AI tools: The author used ChatGPT (OpenAI) to assist with language editing. The author reviewed, revised, and takes full responsibility for the final content of the manuscript.

References

1. Afridi, F., & Chandna, S. (2025). *India's vocational training system needs to reinvent itself to boost employability*. National Council of Applied Economic Research.
2. Albertz, A., & Pilz, M. (2025). Green skills at Industrial Training Institutes in India: An exploratory study of VET teachers' subjective theories. *International Journal of Educational Development*, 118, Article 103406.
3. Andrews, M., Pritchett, L., & Woolcock, M. (2017). *Building state capability: Evidence, analysis, action*. Oxford University Press.
4. DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147–160.
5. Gmyrek, P., Berg, J., & Bescond, D. (2023). *Generative AI and jobs: A global analysis of potential effects on job quantity and quality* (ILO Working Paper No. 96). International Labour Organization.
6. Government of India, Economic Survey Division. (2024). *Economic Survey 2023–24*. Ministry of Finance.
7. Government of India, Ministry of Education. (2020). *National Education Policy 2020*. Ministry of Education.
8. Government of India, Ministry of Education. (2023). *National Curriculum Framework for School Education*. Ministry of Education.

9. Government of India, Ministry of Education. (2025). *Centre of Excellence in Artificial Intelligence for Education: Proposal note*. Ministry of Education.
10. Mahoney, J., & Thelen, K. (2010). A theory of gradual institutional change. In J. Mahoney & K. Thelen (Eds.), *Explaining institutional change: Ambiguity, agency, and power* (pp. 1–37). Cambridge University Press.
11. Ministry of Electronics and Information Technology. (2024). *IndiaAI Mission*. Government of India.
12. Ministry of Skill Development and Entrepreneurship. (2025). *Skilling for AI Readiness (SOAR) programme*. Government of India.
13. National Council for Vocational Education and Training. (2023). *Overview and mandate*.
14. OECD. (2023). *OECD Employment Outlook 2023: Artificial intelligence and the labour market*. OECD Publishing.
15. Patro, S. (2026). *AI-driven reforms in Indian education policy and governance (2016–2026): A review* [Preprint].
16. Pilz, M., & Regel, J. (2021). Vocational education and training in India: Prospects and challenges from an outside perspective. *International Journal of Training Research*, 19(1), 1–20.
17. Press Information Bureau. (2025a). *SOAR – Skilling for AI Readiness: Pioneering initiative launched by MSDE and NCVET*. Government of India. <https://www.pib.gov.in/PressReleasePage.aspx?PRID=2204136>
18. Press Information Bureau. (2026). *SOAR (Skilling for AI Readiness) programme*. Government of India. <https://www.pib.gov.in/PressReleasePage.aspx?PRID=2236967>
19. Prime Minister's Office. (2025). *Cabinet approves continuation and restructuring of Skill India Programme*. Government of India. https://www.pmindia.gov.in/en/news_updates/cabinet-approves-continuation-and-restructuring-of-skill-india-programme
20. Regel, J., & Pilz, M. (2019). Informal learning and skill formation within the Indian informal tailoring sector. *International Journal of Training Research*, 17(2), 140–156.
21. Rehman, M., Dar, M. A., & Rasool, I. (2025). AI literacy at higher education and India's vision Viksit Bharat 2047: A systematic review. *Discover Artificial Intelligence*, 5, Article 294.
22. Streeck, W., & Thelen, K. (2005). Introduction: Institutional change in advanced political economies. In W. Streeck & K. Thelen (Eds.), *Beyond continuity: Institutional change in advanced political economies* (pp. 1–39). Oxford University Press.
23. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training. (2021). *Understanding the impact of artificial intelligence on skills development*. UNESCO-UNEVOC.
24. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training. (2022). *Transforming technical and vocational education and training for successful and just transitions: UNESCO strategy for TVET 2022–2029*. UNESCO-UNEVOC.
25. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training. (2025). *World Youth Skills Day 2025: Youth survey report on AI and digital skills*. UNESCO-UNEVOC.

26. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training. (2026a). *European insights: Adoption of AI in TVET institutions—Challenges, opportunities and recommendations*. UNESCO-UNEVOC.
27. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training. (2026b). *Integrating AI in TVET: A practical guide for institutions*. UNESCO-UNEVOC.
28. World Economic Forum. (2023). *The future of jobs report 2023*. World Economic Forum.