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AI-Driven Vocational Education and Lifelong Learning for Global Employability

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ABSTRACT

The development of AI technology alters the nature of the workforce and learning needs of workers within vocational systems. This paper evaluates how artificial intelligence technology is transforming vocational education and training (VET), as well as lifelong learning, for purposes of global employability. The synthesis incorporates the information obtained from the works of international organizations and scientific papers that appeared in 2024-2026, as well as one national case study of the digital skills program Future Skills PRIME for India. AI-powered instruments, namely adaptive learning solutions, intelligent tutoring solutions, simulators powered by VR/AR, and AI-driven assessments, have been proven to contribute positively to skills development and engagement in vocational settings. As far as the information available about the employer perspective goes, AI and big data skills are among the most rapidly growing core skills worldwide, while the application of generative AI has proved that there is a substantial number of current occupations at risk of being transformed owing to task automation; the effects vary from person to person, depending on their gender, income, and place of residence. The conceptual framework proposed consists of three layers, which are foundational AI literacy, AI-based pedagogies, and employability, all connected by governance and ethics considerations.

1. Introduction

Artificial intelligence is no longer just an external technology when it comes to the world of employment. The 2025 Future of Jobs Report, published by the World Economic Forum, shows that employers will require 39 percent of workers to acquire new skills by 2030, with the fastest-growing skill categories being artificial intelligence and big data skills, along with networks and cybersecurity, and technological literacy (World Economic Forum, 2025). Analytical thinking is the number one core skill required, according to seven out of ten employers; however, the most prominent trend revealed by the report is the growing importance of artificial intelligence and big data skills (World Economic Forum, 2025).

Even more changes are underway with the advent of Generative AI. The improved international index of occupational exposure developed by the International Labor Organization indicates that nearly one-quarter of all workers globally have an occupation that includes some level of exposure to generative AI, and 3.3% of global employment – amounting to approximately 115 million jobs – falls into the category of maximum exposure (Gmyrek et al., 2025). This is uneven exposure. Women are subject to a larger proportion of high-exposure occupations compared to men, and workers in high-income countries are much more exposed than those in low-income countries, owing to occupational structure and digital capacity and not any difference in aptitude (Gmyrek et al., 2025). A similar study by the International Monetary Fund concludes that AI skills have come into play in about five percent of all job ads in the United States, up from less than one percent prior to 2015, and that entry-level employees working in jobs with significant exposure to AI have already seen a discernible relative reduction in employment following the launch of widely used generative AI software tools (International Monetary Fund, 2026). This trend is compounded by demographic pressure. Population ageing is presented in the OECD's Employment Outlook 2025 as a crucial issue in the labor market, and digital skills are considered one of the key elements in retaining the activity of elderly workers (OECD, 2025a). In a follow-up OECD report, it was established that about one third of job openings across ten OECD member countries during 2021-2022 were in occupations highly exposed to AI, while a lack of employee skills was one of the most often mentioned obstacles to AI adoption by firms (OECD, 2026).

The organization of vocational education and training has been characterized by a fixed curriculum, physical workshops, and a one-off transition from training to work. The UNESCO strategy for technical and vocational education and training between 2022 and 2029 clearly defines TVET as a route where individuals can learn, work, and live throughout their life span, not as one preparatory phase for employment, and cites the use of AI technology as one of the issues to which TVET needs to be responsive (UNESCO, 2022). The recently published practical guide for the integration of AI in TVET from the UNESCO-UNEVOC takes the adoption of AI as an institutional issue covering eight areas of practice that include governance, curriculum design, pedagogy, assessment, and monitoring, among others, and is anchored on the principles of purpose, human agency, equity, and safety (Yang et al., 2026). Research in the field of lifelong learning is also experiencing its parallel reconceptualization. According to Palenski et al. (2024), three main conceptual positions can be found in the literature in question: AI as an instrument making the process of learning more efficient; AI as an equal that assists learners in their activities; and AI as a part of a larger process of restructuring of learning and working processes and even life itself. The UNESCO global education monitoring report on the use of technology in education highlights one caution that is central to many works in this field: technologies have entered the world of education under the conditions set by the producers themselves, rather than by users, thus not bringing their benefits to equity and quality automatically (UNESCO, 2023). The later UNESCO report on AI and the future of education extends this caution by claiming that AI implementation in education is a conscious decision, and there is a need to avoid hyper-personalisation, which might turn learning from a social process into an isolated and individualized activity (UNESCO, 2025).

Most of the literature on AI and education can be categorized into one of two types. The first type explores specific classroom-level applications of AI, such as adaptive platforms and intelligent tutoring systems, typically focusing on a particular class or educational institution. In contrast, the second type explores macro-level labour market exposure to AI, but without relating it back to the ways in which vocational or lifelong learning systems can respond to it. There are very few cases where these two levels are combined, let alone where they explore how a large, diversified national skill system responds to the use of AI. However, such an analysis is important since the policy decisions regarding AI-powered vocational education are being made on both levels at once – while a ministry makes a decision to invest in the development of AI simulators for technical institutes, it needs both the evidence of their efficacy in classrooms and of how much different occupations are exposed to AI, and there is almost no research that combines these two pieces of evidence at once.

The study addressed four research questions given below:-

1. What AI-enabled pedagogical mechanisms are being used in vocational education and training, and what outcomes have they produced?

2. How is artificial intelligence changing the employability skills that employers demand, and how is this exposure distributed across gender, income level, and geography?

3. How is a large national skilling system, illustrated through India's Future Skills PRIME programme, responding in practice to AI-driven change in skill demand?

4. What conceptual model can integrate AI-enabled learning mechanisms with global employability outcomes, and what does this model imply for policy and institutional practice?

2. Review of Literature

This literature review is informed by three theoretical approaches. The first approach is human capital theory, where education and training are considered an investment that boosts individual productivity. This theory provides the core motivation behind public and private investment in the development of AI-enabled skills; under this approach, AI can be seen as a technology that modifies the rate of returns to investment in skill acquisition rather than a technology that eliminates any need for investing in such skills. Connectivism can also be used as another theoretical perspective for viewing learning in the context of AI, as connectivism considers knowledge to be distributed throughout people, tools, and technologies rather than residing within the person. Finally, the sociotechnical approach sees the application of AI in the field of education as something that happens at the institutional level because the outcome of using AI technology would be highly influenced by the governance and support systems that accompany its implementation. For instance, according to the institutional-level approach to the integration of AI in TVET by UNESCO-UNEVOC, AI is adopted in the form of governance, curriculum, pedagogy, and monitoring (Yang et al., 2026).

A growing body of literature exists on the application of AI technologies in vocational classrooms and workshops. For example, based on their review of eleven empirical papers, which have been published from 2021 till 2025, Zary & Zary (2025) find that AI-supported extended-reality simulators aid in the development of hands-on skills in vocational courses like welding; that AI-supported teaching factory in Indonesia improves proficiency and readiness for the profession of the learners; and that AI-supported robotics trainers in Malaysian polytechnics improve knowledge and confidence of the learners. Also, Yan et al. (2025) apply AI algorithms to classify students into competence groups in higher vocational education and reveal that AI-supported intensive training causes the formation of highly competent groups, while insufficient AI training causes the creation of low-performing groups, meaning that engagement, and not mere access, is the key factor in attaining competence through the use of AI. Finally, Hariyanto et al. (2025), in their systematic review of 142 peer-reviewed papers published between 2015 and 2025 notice that such AI technologies as supervised learning, deep learning, and multimodal analytics are increasingly used for classification and performance predictions in personalized learning environments.

Indeed, the evidence coming from the employer side indicates that employability-related skills are changing very rapidly. According to the 2025 report of the World Economic Forum, leadership and social influence, AI and Big Data, and talent management are the most notable areas which saw an increase in their importance as rated by employers when compared to the 2023 report, with the AI and Big Data gaining 17 percentage points of importance rating. This report also reveals that some traditional skills, including reliability, precision, and quality control are becoming less important. Aside from the insights mentioned above, one should pay attention to the additional perspective offered by the International Labour Organization's exposure index that states that the occupation most exposed to generative AI is that of clerical work, while digitized occupations of professionals and technicians are increasingly exposed to the development of generative AI despite the fact that most jobs being disrupted are transformed rather than replaced (Gmyrek et al., 2025). This conclusion is also supported by the results of the International Monetary Fund, based on the analysis of job postings that revealed that AI skills usage is not restricted to tech occupations but has spread across a number of occupations in developed countries (International Monetary Fund, 2026).

Disparities in exposure to AI and disparities in access to AI make up another critical area for discussion in this literature. According to the UNESCO global education monitoring report on technology in education, digital technologies have been included in educational institutions through a process during which the demands put forward by technology providers have not adequately addressed the problem of accessibility for disadvantaged learners (UNESCO, 2023). As for the data about AI exposure, provided by the ILO, it suggests that women account for more exposure to high-exposure occupations than men do, and that employees of high-income countries have significantly higher exposure to generative AI than employees of low-income countries (Gmyrek et al., 2025). Furthermore, the discovery by the International Monetary Fund about the relative reduction in job availability for early career workers in the AI-intensive industries denotes an additional aspect of equity, since early career workers are those who possess the least experience in dealing with such situations of technological change (International Monetary Fund, 2026). The report by UNESCO on Artificial Intelligence and the Future of Education brings everything together, indicating the probability of a division arising between those who can cope with the new work style and those who cannot, unless human capabilities are developed through education systems (UNESCO, 2025).

However, reactions to the impact of changes in the skills of employees due to the utilization of AI technology by policymakers vary from one country to another. As found out through the collaborative study between the OECD and Korea Labor Institute, the level of utilization of AI rises with the increase in firm size in Korea; half of all firms cite a deficiency in the skills of employees as the hindrance to the adoption of AI, and many employees doubt that AI has made their lives easier (OECD & Korea Labor Institute, 2025). In the OECD's research by the OECD on the case of Japan, the ageing and decreasing labor force creates an increased need for AI implementation, with most of the respondents stating a positive perception of the impact of AI on their performance, while companies face a shortage of AI developers and other related problems (OECD, 2025b). On an individual level of learning, the international youth survey conducted by UNESCO-UNEVOC with over 4,000 respondents from 128 countries reveals that even though 62 percent of youths are currently employing AI in practical scenarios, only 30 percent have had any form of training in the application of AI, which the survey states as being the major problem facing youth skills policy around the world (UNESCO-UNEVOC, 2025). The FutureSkills PRIME initiative of India is one of the examples explored in the findings of how an emerging economy is striving to fill such a gap.

3. Methodology

In this paper, an integrative narrative review methodology is employed where synthesis of recent international literature and policy documents is supplemented by an example from the national level. This paper is not a systematic review in accordance with PRISMA, as its aim is to make connections between evidence at different levels, namely classroom, labour market and national policy, and not to collect all the existing literature on one specific issue. Three types of sources were utilized in the research. The first type comprises international labour and education agencies reports from 2025-2026 and includes the following documents: the Future of Jobs Report 2025, prepared by the World Economic Forum; the updated version of the global index of generative AI exposure in occupations, developed by the International Labour Organization; OECD research into AI and the labour market in Korea and Japan and the OECD Employment Outlook 2025; the discussion paper by IMF staff on AI and job creation; publications by UNESCO and UNESCO-UNEVOC on AI in education and TVET. The second kind of source involves peer-reviewed literature on the use of AI in vocational and higher education published between the years 2024 and 2026, identified using keywords such as artificial intelligence, vocational education and training, lifelong learning, and employability. The third kind of source involves program-level data on the Future Skills PRIME program of India, based on government press releases on the issue.

Sources were chosen based on their relevance to the four research questions mentioned above, with sources published after 2024 being preferred for providing up-to-date information about the adoption of generative AI. The India case was chosen due to its being among the largest publicly documented cases of a national programme of AI and digital skills training in a large emerging economy, and as district/state-level education data for the country have already been analyzed in previous studies. The India case is provided here as a case study for RQ3 and not as a representative sample of national skilling systems. The analysis starts with a synthesis of relevant evidence based on the literature review in order to answer RQ1 and RQ2, followed by the presentation of quantitative results from labour market and program-level sources to answer RQ2 and RQ3, and concludes with a synthesis of both to provide an answer to RQ4. This review is based solely on secondary sources that are in the public domain; hence, no new primary data has been collected involving humans, and no ethics approval was needed. As this review is not a systematic but a narrative review, the selection of sources will contain an element of subjectivity, and the review is not intended to be exhaustive. For the India case, the review uses data at the program level rather than the individual or district level.

4. Findings

Table 1 summarizes the main AI-enabled pedagogical mechanisms identified in the reviewed literature, addressing RQ1, together with illustrative reported effects.

Mechanism	Example application	Reported effect
Extended-reality (XR) simulators	AI-guided virtual welding trainer	Improved welding accuracy and faster skill acquisition than traditional VR instruction
AI teaching factory	Industry-linked simulated production line (Indonesia)	Higher technical proficiency, efficiency, and industry readiness
AI-powered robotics trainer	Polytechnic robotics training (Malaysia)	Increased student understanding and confidence
AI-based competency clustering	K-means clustering of student engagement and outcomes	Intensive AI-based training linked to highest-performing cluster
Adaptive/personalised learning systems	ML- and multimodal-analytics-based content adaptation	Improved personalisation and performance prediction across 142 reviewed studies (2015–2025)

Table 1. AI-enabled pedagogical mechanisms reported in vocational and technical education research.

The findings indicate that the use of AI in vocational education seems to be more effective when it is applied in a practical manner, involving simulators and vocational training programs linked with industry rather than being limited to just delivering content. The improvement has been reported mostly in terms of accuracy, efficiency, and confidence of the learners, but not necessarily in terms of employment opportunities.

Table 2 addresses the first half of RQ2 by summarising how employer-rated skill priorities have shifted.

Skill category	Direction of change (2023–2025)	Notable statistic
AI and big data	Sharp increase	+17 percentage points in employer-rated importance; fastest-growing skill category overall
Leadership and social influence	Sharp increase	+22 percentage points in employer-rated importance
Talent management	Increase	+17 percentage points in employer-rated importance
Analytical thinking	Stable, high priority	Cited as essential by 7 in 10 employers
Dependability, attention to detail, quality control	Decrease	Fell in relative importance compared with 2023

Table 2. Shifts in employer-rated core skill importance, 2023–2025. Source: World Economic Forum (2025).

The general impression from Table 2 is a trend towards analysis-based skills and technology-based skills, as well as towards interpersonal skills. Such trends put pressure on the structure of vocationally oriented curricula that are still built predominantly on technical skills only.

Table 3 addresses the second half of RQ2 by showing how exposure to generative AI is distributed globally.

Indicator	Value
Share of global workers in an occupation with some GenAI exposure	25% (about 1 in 4)
Share of global employment in the highest exposure category	3.3% (about 115 million jobs)
Women's employment exposed to GenAI	27.6%
Men's employment exposed to GenAI	21.1%
AI-related skills in U.S. job postings, pre-2015 vs. 2025	<1% → ~5%
Relative employment decline for early-career workers in highly exposed occupations	13%

Table 3. Global occupational exposure to generative AI and related labour-market indicators.

The gender gap and income level difference in Table 3 reveal that there exists a structural pattern, not just an incident. Generative AI adoption takes place primarily amongst those workers who are already engaged in digitised labour markets, including women in such digitised labour markets but not the entire global labour force in equal measure. In other words, this pattern strengthens the need to include equity concerns as part of vocational and lifelong learning policies that utilise AI.

Moving to research question three, Future Skills PRIME is a programme for digital skills that is managed by a partnership between the National Association of Software and Service Companies (NASSCOM) in India and the Ministry of Electronics and Information Technology.

Table 4 summarises publicly reported programme statistics.

Indicator	Value
National registrations	About 3.4 million (34 lakh)
Candidates enrolled or trained	About 2.3 million (23 lakh)
Candidates completing training or certification	About 1.3 million (13 lakh)
Share of participants from Tier-2 and Tier-3 cities	86%
India's AI skill penetration index (relative to United States: 2.2; Germany: 1.9)	2.8
Growth in India's AI talent concentration since 2016	263%

Table 4. Future Skills PRIME programme statistics. Source: Press Information Bureau, Government of India, and related national reporting.

Two aspects of this particular case are notable in the wider context of the literature. Firstly, the focus of participation among Tier-2 and Tier-3 cities indicates that even a massive programme for digital skills development, funded by both government and industry, has the ability to extend AI training beyond the largest urban areas mentioned in Table 3, which have the highest incidence of AI contact. Secondly, the difference between the number of registrations (3.4 million) and completion of certification (1.3 million) indicates that a high volume of participation on its own is insufficient for successful completion of the programme. Evidence from OECD comparative studies shows that reactions of nations towards changes in the skills of their workforce due to AI differ according to market pressures. The application of AI is very much linked with the sizes of firms in Korea, where more than 40% of firms report a shortage of skilled employees to apply AI, and the workers feel that there is no reduction in their work due to AI technology (OECD & Korea Labor Institute, 2025). In the case of Japan, the issue of adoption of AI is linked with the demographic issue, whereby the aging workforce makes the use of AI technology a lucrative choice, and all workers surveyed in Japan feel positively about the performance effects of AI, although firms suffer from shortage of AI professionals in Japan (OECD, 2025b). Comparing this case study to that of India indicates that the driving force behind AI skilling varies and affects how a response is carried out nationally.

In the review of the available literature, it becomes evident that there is an inequality issue related to AI usage and AI training. According to the UNESCO-UNEVOC youth survey, 62 percent of youth are currently using AI in practice, while just 30 percent of those young people have been trained in the use of AI (UNESCO-UNEVOC, 2025). The mentioned inequality corresponds to the issues with completion of the course identified in the FutureSkills PRIME dataset as well as the gender and income gaps found in the ILO exposure index (Gmyrek et al., 2025). Overall, it can be stated that informal use of AI is ahead of its formal training almost everywhere.

5. Discussion

However, three themes emerge across the results above that address the research questions (RQ1 to RQ3). The first theme involves AI-enabled pedagogical tools, specifically simulators and adaptive systems, within hands-on skills training being beneficial, although in limited ways. Secondly, there is an evident shift in terms of skill demands on the part of employers towards the use of AI and analysis skills, along with interpersonal skills. This is accompanied by generative AI creating opportunities to transform tasks for a substantial proportion of jobs, especially for women and those from higher-income and more digitized economies. Finally, national approaches differ in terms of motivation and approach but have a common problem of informal use of AI and formal AI training.

The frameworks described above form the basis of an integrative framework which has three layers in linking AI-enabled vocational education and lifelong learning to employability worldwide so as to address the fourth research question. The first layer comprises the basic prerequisites for AI-enabled learning which include: reliable connectivity and access to devices; basic knowledge of AI and data among the learners; and AI-readiness of the instructors. The second layer involves the pedagogical tools listed in Table 1, such as adaptive learning platforms, extended reality and simulator-based learning, intelligent tutoring, and AI-enabled assessment and career guidance. The third layer is formed by the global employability outcomes to which the use of the mechanisms above is directed, including: accurate job-to-skill matching, portable and recognized credentials, labor market mobility, and inclusivity. Governance and ethical safeguarding measures for each of these layers include: data protection, minimizing the risk of bias, human oversight, and monitoring of equity considerations. Such a governance framework corresponds to the one outlined in UNESCO-UNEVOC's practical guide for using AI in TVET (Yang et al., 2026), and also takes into account the equity considerations raised by UNESCO in its recent works on AI and education (UNESCO, 2023, 2025).

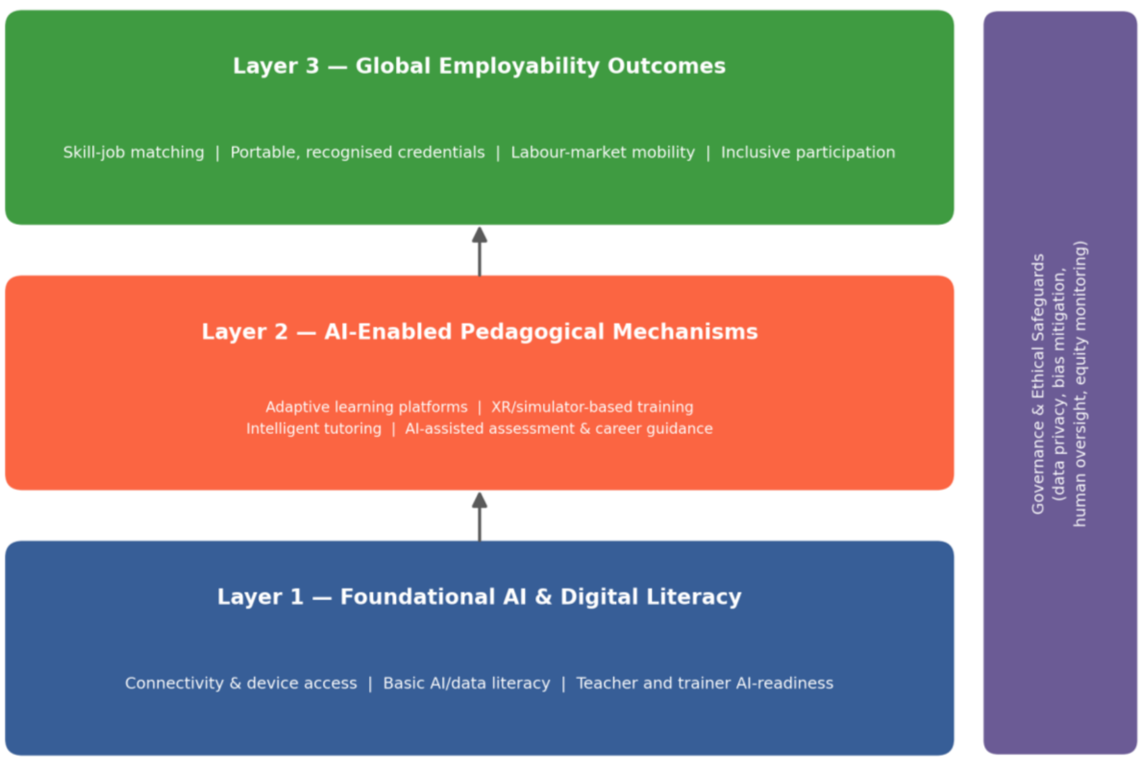

Figure 1. A three-layer conceptual model of AI-driven vocational education and lifelong learning for global employability.

The model is deliberately multilayered, not flat, because it is clear from the analysis of the evidence above that neglecting the foundational layer will jeopardize the upper layers. That is why the fact that a majority of AI users among youth have had no formal training (as per the UNESCO-UNEVOC youth survey) is, in this context, a gap in the foundational layer which constrains the benefits that can be gained from AI-powered pedagogical mechanisms at the employability layer. In terms of global employability, what comes out of the model is that it is not possible to reduce AI-powered vocational education to adopting certain tools. Nations and institutions that spend huge amounts of resources in developing AI-powered pedagogical mechanisms without addressing the issue of digital literacy and preparedness of teachers are likely to reproduce the exposure gaps presented in Table 3 rather than address them.

However, India proves that geographically distributed national programs can provide access to the foundational layer beyond major metropolitan regions. While the governance and ethics band of the model could be thought of as a mere add-on, it needs to precede the third layer of the model because it is not desirable for employability outcomes to be unfairly distributed by gender and geography. The model can also serve to elucidate the difference between the Korea and Japan findings by the OECD, as well as the Future Skills PRIME findings, because in the former case the problem is found in the second layer (lack of AI skills in companies), while in the latter case it is located at the first layer (demographic pressure pushing for adoption in spite of remaining safety and transparency issues). As for India, it demonstrates achievements at the first layer (wide geographical coverage) and weakness at the second (incomplete transformation of enrollment into certification). Analyzing the national responses through the prism of the model's layers allows one to determine the layer to address with the particular intervention policy.

6. Conclusion

The four research questions on which this paper focused were those about the effect of AI on vocational education, training and lifelong learning, and on how that reshaping links with global employability outcomes. With regard to RQ1, AI-assisted pedagogical mechanisms, such as simulators and adaptive learning systems integrated into practical training, demonstrate clear advantages in acquiring vocational skills. In answer to RQ2, employer-side data prove a fast increase in demand for AI-related, analytical, and interpersonal skills, along with the exposure of a great many jobs to transformation through the use of generative AI, and, especially, with that exposure affecting more women and higher-income, more digitally advanced countries. With respect to RQ3, the Indian Future Skills PRIME project provides a good example of a nationwide digital-skilling initiative, which reaches beyond urban areas but also encounters similar difficulties with completion and equality, found in other studies. Finally, with regard to RQ4, the paper’s most important contribution consists in developing a three-layer model including governance and ethical safeguards, foundational AI and digital literacy, AI-assisted pedagogical mechanisms, and global employability outcomes.

These three sets of actions are informed by this analysis. First, invest in the foundational layer prior to upscaling pedagogical tools: connectivity, basic AI literacy, and readiness for teachers and trainers in relation to AI should precede any large-scale use of adaptive platforms and simulators, as such tools would be hard to develop without a strong foundation and would not help to bridge the existing exposure gaps. Second, develop vocational courses with AI through a focus on completion rather than mere registration: the difference between the number of registrations and certifications in the Future Skills PRIME example shows that further attention should be paid to assessing, mentoring, and linking to employers throughout the learning process and not just at the registration stage. Third, integrate the elements of governance and monitoring of inequities into AI-based skilling from the beginning, taking into account the institutional governance framework recommended by UNESCO-UNEVOC (Yang et al., 2026).

This literature review is confined by its narrative style as opposed to a more systematic approach, as well as by the use of secondary sources reporting publicly available data regarding the India case, rather than primary individual data. Future research may profit from conducting longitudinal studies following vocational learners equipped with AI skills and their transition into work, to see whether their reported acquired skills lead to lasting employment advantages; comparative research involving other national AI skills training programs beyond the three national programs reviewed in this paper; and primary research on how global gender, income, and geographical divides reveal themselves at the institutional level.

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Author Contributions:
Ashok Kumar Yadav conceived and designed the study, conducted the literature synthesis and thematic analysis of international policy and academic sources, and drafted the original manuscript.
Dr. Abhishek Kumar Mishra provided supervision, validated the overall findings against the cited sources, and undertook critical revision of the manuscript's conceptual framework.
Prof. Sandeep Kumar Singh performed data curation and software-assisted analysis of the international policy and academic literature, and designed the study's methodology and review protocol.
Tejaswi Sharma performed data curation of the global labour-market and national programme-level statistics, and contributed to the formal analysis of these datasets.
Mousumi Baskey contributed to the development of the conceptual-model visualization and assisted with the formatting and compilation of the manuscript.
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