# Mapping the Scientific Production on Artificial Intelligence Training for Workers in the Industrial Sector

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**Abstract: The advent of Artificial Intelligence (AI), based technologies within the industrial sector has precipitated profound and disruptive transformations in operational routines and work dynamics, exerting a direct influence on the skill profile required of workers. These changes directly impact the set of skills required of professionals, who now need to transcend traditional technical expertise and develop new dimensions of knowledge. Given this context, the objective of this study is to map national and international scientific production about AI literacy for industrial workers. This is narrative research whose purpose is to identify, as evidenced in the literature, both the gaps and opportunities for improvement in professional training. The study revealed that, despite growing industry investments in intelligent systems, initiatives aimed at cultivating AI literacy among non-specialist professionals continue to be neglected. Furthermore, the available courses show a low alignment with industrial practice and fail to adequately consider the sociocultural profile of participants. Research indicates that AI training should go beyond the acquisition of technical knowledge, encompassing the development of reflective, adaptive, and interventional skills. Moreover, the literature highlights the importance of integrating inclusive strategies that address cultural, generational, and skills-level diversity in industrial environments, as these factors directly influence engagement, learning outcomes, and the equitable distribution of opportunities in an AI-driven economy. The expected results of this research are to identify the main challenges that can support more effective and sustainable educational strategies for professional qualification in the use of AI in the industrial sector.**

**Keywords: AI Training. AI Literacy. AI Literacy for Workers. AI Literacy in the Industrial Sector.**

## 1. INTRODUCTION

The integration of Artificial Intelligence (AI) within industrial contexts has precipitated profound transformations in the realm of work organization and the demand for novel professional competencies [1]. In addition to technical proficiency, it is essential to develop a critical, ethical, and practical understanding of the use of these technologies [2–3], considering not only mastery of the tools but also the ability to assess their impacts on the workplace, on society, and strategic decision-making.

AI by enhancing human capabilities, increases productivity, optimizes processes, and enables new business models, but also poses challenges related to professional responsibility and transparency in interactions with automated systems.

This ongoing advancement requires constant professional updating to ensure that skills remain relevant in the face of technological evolution and changing market

demands [4]. The reviewed literature indicates that technological advances only translate into tangible benefits when accompanied by adequate, continuous, and context-specific training programs [5]. Such programs should integrate technical content with reflective and adaptive practices, enabling workers to operate effectively in dynamic, collaborative, and ethically responsible contexts, thus ensuring a more efficient, inclusive, and sustainable technological transition.

In this context, the present research aims to map national and international scientific production related to AI literacy aimed at industrial sector workers. The recent European regulation and the Brazilian Artificial Intelligence Plan 2024–2028 (PBIA) emphasize the urgency of large-scale training [6–7].

AI literacy is defined by the capacity to engage in critical reflection and ethical application, extending beyond mere technical mastery [2-8]. This approach broadens the understanding and responsible use of technology, preparing individuals to interpret, evaluate, and apply AI in a contextualized manner [9-10]. Such a perspective fosters the development of professionals capable of responding to emerging challenges and generating sustainable value in diverse contexts.

With it, the worker moves from being a mere operator to becoming a critical agent of technology, [11] points out that mapping skills is essential to reducing the skills gap, and [12] highlights the need for workforce adaptation. Despite the economic advantages offered by AI, there are risks of job losses and increased inequality, as indicated by estimates of automation through 2030 and the potential social and economic disruptions that may follow [13–14].

Skilled workers can benefit more from AI, provided that adequate training is offered to them [11]. The absence of training exacerbates insecurities and resistance, making inclusive policies essential to ensure equity and reduce inequalities while fostering an environment of trust in technological adoption [15–16]. In this context, AI literacy can strengthen competitiveness and sustainable innovation [17].

In this regard, it becomes urgent to investigate academic publications focused on AI literacy in industry, identifying trends, challenges, and gaps that can optimize worker training and enhance the positive impact of this technology while aligning these efforts with the evolving demands of the industrial sector.

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## 2. METHODOLOGY

This research was conducted through a narrative literature review. A narrative literature review describes or discusses a given topic based on the author's interpretation and critical analysis, drawing on a broad search of bibliographic or electronic information, without necessarily detailing the criteria adopted for the selection and evaluation of works [18]. This is a qualitative approach, chosen for its ability to integrate conceptual studies, institutional reports, and empirical evidence, enabling the discussion of different perspectives from authors on workers' literacy in the context of the growing adoption of Artificial Intelligence (AI) in the industrial sector.

The searches were carried out between May and July 2025 in the following databases: Scielo, Scopus, Web of Science, IEEE Xplore, and Google Scholar. Descriptors in English and Portuguese were used, including: "AI workforce literacy industry," "industrial AI education," "artificial intelligence training," "AI in the industrial sector," "AI skills manufacturing," "alfabetização em inteligência artificial no setor industrial," and "letramento em IA."

Inclusion criteria: (i) studies published between 2000 and 2025; (ii) of a technical-scientific nature; and (iii) directly related to AI literacy, professional training, and impacts on work. Exclusion criteria: (i) duplicate works across databases; (ii) publications addressing exclusively technical aspects of AI without connection to training processes; and (iii) studies focused on non-industrial sectors, such as healthcare, basic education, commerce, and financial services.

As inclusion criteria, articles of any study design, book chapters, theses, dissertations, and institutional documents available online in full were considered, published between 2000 and 2025, in Portuguese, English, or Spanish, of a technical-scientific nature and directly related to AI literacy, professional training, and impacts on work. Excluded were duplicate works across databases, publications that addressed exclusively technical aspects of AI without connection to training processes, and studies focused on non-industrial sectors such as healthcare, basic education, and financial services.

Given the exploratory nature of the narrative review, the total number of documents identified in each database was not quantified. The selected texts were critically reviewed and organized into thematic axes: (1) definition of AI competencies for the industrial sector; (2) structural and cultural barriers to training; (3) reskilling and upskilling strategies; and (4) inclusion and ethics in AI literacy. The analysis

sought to highlight consensus, divergences, and gaps, supporting a critical discussion on the topic.

## 3. RESULTS AND DISCUSSION

Recognizing AI literacy in the industrial sector continues to face significant barriers. The reviewed literature highlights central gaps that hinder the broad, inclusive, and sustainable adoption of AI and reduce the effectiveness of training programs [1,6,11,21]. Most of the empirical evidence is concentrated in the manufacturing sector, which appears as the primary locus of analysis in the studies reviewed. These gaps manifest in the absence of evaluation metrics [1,3,21], the disconnection between training courses and industrial practices [1,11,22], workers' cultural resistance and insecurity [10,23], the neglect of ethical, social, and generational dimensions [6,7,10,22], and the weak articulation between workforce training and national reskilling policies [11,16,20].

The absence of reliable tools for diagnosing and measuring competencies is identified as one of the most recurrent obstacles [1,3,12,19,21,22]. The lack of reliable tools makes it difficult to monitor the development of competencies and limits the ability to continuously improve training programs. Evidence from the United States reinforces this problem, showing that the fragmentation of AI training initiatives makes it difficult to compare results and weakens integration with productive demands [26,28].

Another critical challenge lies in the disconnection between the training content offered and actual industrial practices. Programs that are overly generic or excessively technical tend to generate low engagement and limited results [1,11,22]. In manufacturing sectors in Pakistan, for instance, short-term training programs that were poorly aligned with shop floor activities resulted in low initial adherence. Conversely, when training was contextualized and integrated into operational routines, greater acceptance and organizational performance gains were observed [30]. International studies corroborate this finding, showing that training tailored to factory operations increases engagement and reduces resistance, particularly in emerging economies [25].

Cultural resistance and worker insecurity also represent recurring barriers. Research in manufacturing industries in Gujarat, India, revealed ambivalent perceptions: while some workers acknowledged efficiency gains, many associated AI with the risk of job displacement, which reduced their willingness to participate in training programs [23]. By contrast, experiences in factories in the Philippines showed that when training programs were adapted to local conditions and implemented gradually, workers demonstrated greater acceptance and incorporated AI into daily routines [31]. The

cases analyzed show that the success of literacy programs depends on their adaptation to local cultural and organizational conditions.

Comparative analyses allow the observation of a trajectory of transformation: disjointed initiatives, characterized by low alignment with shop floor practices and worker insecurity, tend to generate rejection, whereas more contextualized programs promote greater integration of AI into industrial dynamics. The effectiveness of training is closely tied to how well educational content reflects the realities of industrial practice.

Another critical issue relates to the neglect of ethical, social, and generational dimensions. A significant portion of training programs continues to privilege technical content, while relegating to the background competencies associated with critical thinking, social responsibility, and adaptation to generational differences [6,7,10,22]. This limitation exacerbates inequalities and particularly affects non-specialist workers, who should be among the main beneficiaries of reskilling initiatives [11,21]. The literature converges in indicating that the most effective training programs are those that balance technical and human competencies, creating conditions for a more critical and responsible application of technologies.

Weaknesses are also evident in the sphere of public policies, where the absence of consistent national plans limits the effectiveness of AI literacy initiatives. In developing countries, large companies often advance with internal programs, while small and medium-sized industries remain on the margins of digital transformation [16,20]. In contrast, international experiences highlight possible solutions: in the United States, the creation of a federal coordination office and targeted funding for AI training have sought to reduce the fragmentation of initiatives, although regional inequalities in workforce preparation persist [26,28,29]; in Germany, long-term industrial policies associated with Industry 4.0 ensured that automation was accompanied by training programs, generating productivity gains and positive impacts in partner countries integrated into supply chains [27].

This heterogeneity reveals that the consolidation of AI literacy depends not only on technological diffusion but also on the ability to align public policies, business practices, and inclusive strategies.

In summary, the evidence indicates that the lack of adequate AI literacy undermines not only the qualification of workers but also the ability of industries to incorporate technologies strategically. Disjointed programs weaken innovation, intensify cultural resistance, and exacerbate inequalities, especially among small

and medium-sized enterprises. On the other hand, experiences that integrate consistent evaluation, contextualized content, and long-term policies demonstrate that it is possible to align productivity gains with socioeconomic inclusion. The key challenge is to make AI literacy a structural axis of industrial development, combining competitiveness with the human dimension of work. Table 1 was created using data from the analyzed studies to present the research comprising this review more clearly.

**Table 1. Study Data**

| | Summary of the studies used | | | |
|---|---|---|---|---|
| | **Author(s) and year of publication** | **Country** | **Study Design** | **Objective** |
| 1 | Zahoor, Ahmed. (2025) | Pakistan | Quantitative | Investigate the influence of AI on business performance and HR management |
| 3 | Laupichler et al. (2023) | Germany | Quantitative | Validation of self-assessment tools for AI training courses |
| 6 | UNESCO, **United nations Educatiponal, Scientific and Cultural Organization (2024)** | France | Technical report | The **UNESCO** warns of the new digital divide caused by AI and proposes AI literacy as a universal and strategic right for global inclusion. |
| 7 | **PBIA,** Brazilian Artificial Intelligence Plan. 2024-2028 (2024) | Brazil | Technical report | The PBIA 2024–2028 sets guidelines for the ethical and strategic use of artificial intelligence in Brazil. The plan coordinates actions across infrastructure, education, the productive sector and government |
| 10 | **Morandini et al. (2023)** | Italy | Narrative review | Impact of AI on workers' skills and need for reskilling |
| 11 | OCDE, **Organization for Economic Co-operation and Development and,** SENAI, **National Service for Industrial Training** (2023) | Brazil | Technical report | The report highlights the urgency of aligning vocational training with technological demands through integrated strategies involving the productive sector, government, and education, fostering digital, cognitive, and socioemotional skills for the future of work. |
| 12 | Davenport & Ronanki (2018) | EUA | Descritive Analiti | Practical applications of AI in real-world organizations |
| 16 | Sidhu et al. (2024) | Bangladesh | Quantitative study | Comparative analysis of skill gaps in emerging economies |
| 19 | Shen & Zhang (2024) | China | Quantitative empitical study | Analyzes the impact of AI on employment, highlighting that its adoption can promote job creation when accompanied by educational reforms that reduce regional and sectoral inequalities. |
| 20 | Barreto et al. (2023) | Brazil | Literature review | Impact of AI on labor productivity in Brazil |
| 21 | Mendoza et al., 2022 | Filipinas | Quantitative study | Systematic review of digital skilling for adults |
| 22 | Oluwaseyi et al. (2023) | Nigéria | Literature review | Future transformations of industries and society with AI |
| 23 | Patel & Patel (2024) | Índia (Gujarat). | Survey-based study | Worker perceptions of AI in Indian manufacturing |
| 24 | Salminen et al. (2024) | Europe | Qualitative | Alignment of industry needs and education in AI training |
| 25 | Gatabazi et al. (2025) | EUA | Review Literature | Adoption of AI in global manufacturing industries |
| 26 | Oschinski, Crawford & Wu (2022) | EUA | Technical report | AI and the future of workforce training in the US |
| 27 | Krzywdzinski & Jürgens (2023) | Germany | Qualitative | Robotization and employment dynamics in German industries |
| 28 | CSET (2021) | EUA | Technical report | Policy recommendations for US AI workforce development |
| 29 | Alghamdi et al. (2023) | EUA | Quantitative | AI-enhanced education and workforce readiness in Nevada |
| 30 | Gulzar et al. (2024) | Pakistam | Survey-based study | AI training and high-performance work systems in Pakistan |
| 31 | Eusebio (2024) | Philipinas | Survey-based study | Acceptance of AI in manufacturing industries in the Philippines |

## 4. CONCLUSION

This study showed that AI literacy in the industrial sector still faces barriers that limit its effectiveness, particularly the absence of

evaluation metrics, the disconnection between training programs and shop floor practices, cultural resistance, the neglect of ethical and generational dimensions, and weaknesses in public policies.

For industrial managers, it is recommended to adopt validated diagnostic and competency identification tools for AI, capable of measuring existing skills and identifying gaps to be addressed, categorized by job profiles. In addition, training programs should be contextualized to shop floor routines, accessible to non-specialist workers, and designed to integrate both technical and human dimensions.

At the public policy level, clear and actionable measures are required. A first step is to establish validated tools to measure AI-related competencies, categorized by worker profiles, which can serve as a basis for targeted training. In parallel, governments should provide incentives for AI literacy programs tailored to small and medium-sized enterprises, since they are often excluded from large-scale initiatives. Finally, sustainable results depend on long-term national policies, aligned with industrial strategies and supported by partnerships with companies and educational institutions. For developing economies, these measures are particularly critical to reduce regional inequalities, strengthen SMEs, and ensure that industrial competitiveness advances together with socioeconomic inclusion.

At the educational level, universities and technical training centers should adapt their curricula to the real demands of industry, in collaboration with companies and policymakers. This integration helps align training content with productive practices, increasing the relevance of AI literacy programs and preparing workers for the critical and responsible use of AI.

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