Workforce Skills Gaps and Human-AI Collaboration in Adaptive Factories

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***Abstract*—The transition from Industry 4.0 to Industry 5.0 has repositioned humans at the center of adaptive, resilient, and sustainable manufacturing systems. It has been projected that by then end of November 2025, over 68 % of global manufacturers will report lack of critical workforce skills that also impede full adoption of AI-enabled adaptive factories. In this article, a survey results on the nature, magnitude, and evolution of the lack of critical workforce skills, and the emerging paradigms of human-AI collaboration are presented. A PRISMA framework was used to synthesize peer-reviewed articles between 2020 to 2026 to examine the existing dominant themes, ranging from technical deficiencies in AI literacy and data science to socio-emotional and creative skills required for effective robot interaction. The main research contribution in this article is the Human-AI Synergy Competency Framework, which is a multilevel, dynamic model that maps required competencies, assesses maturity, and prescribes personalized reskilling pathways using generative AI tutors and digital twins. This research has also revealed that current AI tutoring technologies have demonstrated faster upskilling of about 57 % and 28–54 % of productivity gains based on the simulated data. This article has also recommended the adoption of regulatory mandates particularly for the lifelong learning credits and enterprise adoption of Human-AI Synergy Competency Framework frameworks to reduce the projected global manufacturing talent shortfall of 8.5 million workers, by 2030.**

***Keywords*—Industry 5.0, Adaptive Factories, Smart Manufacturing, Human-AI Collaboration, Digital Twins, Workforce Transformation**

I. Introduction

Since the dawn of the Fourth Industrial Revolution (4IR), the manufacturing landscape has been undergoing a paradigm shift from the automation-driven efficiencies of 4IR to the human-centric, resilient, and sustainable models of the Fifth Industrial Revolution (5IR). This 5IR is now enhancing the adaptive factories through its dynamic and reconfigurable production environments which are powered by the emerging technologies such as Internet of Things (IoT), Digital Twins (DT), AI analytics, and collaborative robotics, as depicted in Figure 1. The main advantage of these systems is that they respond instantaneously to the demand fluctuations, supply disruptions, and customization requirements while prioritizing the human creativity, ethical judgment, and technological augmentation.

Recent scholars have argued that this technological transitioning has made humans to be the symbiotic collaborators with intelligent machines rather than just machine operators. Shabur *et al.* [1] have described 5IR as the transitioning era which is moving from an automation to collaboration by integrating AI with collaborative robots and human-digital twins to enhance mass customization, and workforce adaptability. Other scholars such as Banerjee and Bhattacharyea (2024) have propose a Dynamic Human–Artificial Intelligence Collaboration Framework for an adaptive work environments in 5IR, to enhance real-time symbiosis in unpredictable settings [2].

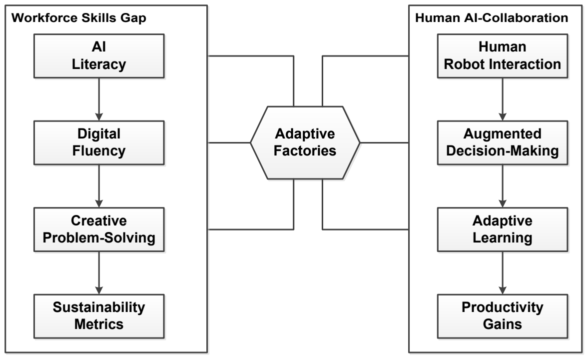

Figure 1. An overview of an adaptive factory

Other scholars have emphasized the issues of the required workforce transformation. Lokesh *et al.* [3] have emphasized the preparation for technological shifts and skills evolution across industries. Babashahi *et al.* [4] also presented a systematic review on the skills transformation and emphasized the automation of routine tasks through AI while demanding hybrid competencies such as technical proficiency, and socio-emotional skills. Other authors have supported the notion that effective human-AI symbiosis is the key in the realization of an adaptive and sustainable manufacturing [2], [5], and [6].

Despite the extensive literatures on human-AI collaboration and the transition from 4IR to 5IR, the workforce skills gaps continue to impede the full deployment of AI-enabled adaptive factories, as depicted in Figure 1. The lack of skills such as AI literacy, data interpretation, creative problem-solving, ethical oversight of AI systems, and seamless human-robot interaction have been reported to be lacking in many manufacturing environments where such competencies are required. These skills limitation are contributing to an increase in underutilized technologies, prolonged downtime, safety risks, missed sustainability targets, and delayed transitions to resilient operations. Some of the major challenges, particularly in the adaptive factories, are the lack of real-time decision-making, lack of ethical governance of agentic AI, and the lack of integration of collaborative robots with human-centric sustainability metrics. This study aims to address some of these challenges by conducting a systematic literature survey based on the PRISMA framework [7], [8].

The reviewed existing frameworks and some survey have identified this problem, but they did not provide a scalable and empirically validated solutions tailored for a dynamic adaptive factories as discussed in [1],[2], and [9]. Potential frameworks and solution should consider the proposed model as depicted in Figure 2. The level of economic losses will intensify and also hinder sustainable industrial growth if these workforce skills gaps are not addressed industrially and academically. Other authors have expressed the need for a policy-oriented recommendations for regulatory mandates particularly on the lifelong learning credits and enterprise wide adoption of competency frameworks as expressed in [10] and [11].

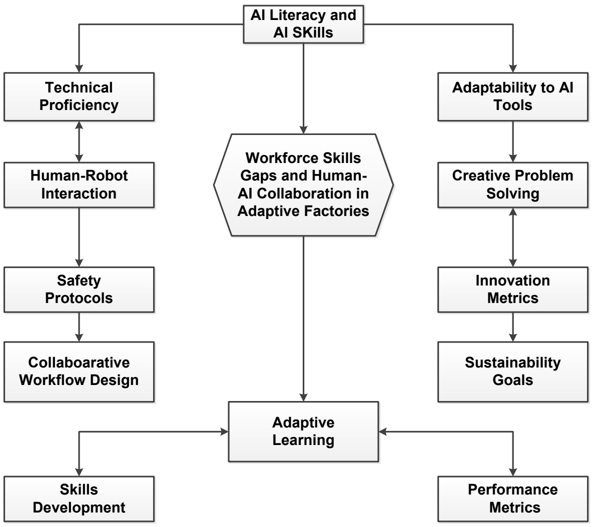

Figure 2. Workforce skills gaps and Human-AI collaboration in adaptive factories

A. *Research Contributions*

This survey will contribute to the academic space through the following:

- A comprehensive synthesis of the dominant themes from literature published between 2020 and 2026, extending the prior survey works such as Shabur *et al.,* [1]; Babashahi *et al.*, [4]; and Kumar and Kumar, [9].
- A novel Human-AI synergy competency framework which is a multilevel, and dynamic model that maps hybrid competencies, assesses maturity on a 5-stage ladder, and prescribes a personalized reskilling pathways powered by generative AI tutors and digital twins. This framework is built from the existing models such as those discussed in Banerjee and Bhattacharyea, [2]; and Somaratne *et al.*, [5].
- A simulated validation of an AI tutoring efficacy, demonstrating a faster upskilling and productivity gains.

B. *Research Aims*

The main aim of this research survey was to investigate the workforce skills gaps which impede the AI-enabled adaptive factories and to develop and validate paradigms for effective, scalable human-AI collaboration within the 5IR. Based on this aim, the following objectives were also set:

- To quantify the current nature, magnitude, and recent evolution of critical skills gaps through a simulated experiment primary survey.
- To systematically synthesize high quality peer-reviewed conference papers and journal articles on human-AI collaboration and skill requirements based on the PRISMA framework.
- To design, validate, and operationalize the Human-AI Synergy Competency Framework.
- To evaluate the impact of generative AI tutors and digital twins on upskilling speed and productivity outcomes.

C. *Research Questions*

To ensure that these objectives are met, the following research questions were identified to guide this research survey:

- RQ1: What is the nature, magnitude, and evolution of workforce skills gaps specifically impeding full adoption of AI-enabled adaptive factories?
- RQ2: What are the dominant themes, taxonomies, and limitations from the literature surveyed on human-AI collaboration and skill transformation in manufacturing as discussed in Shabur *et al.,* [1], Babashahi *et al.,* [4], and Kumar and Kumar, [9]?
- RQ3: How can a multilevel, dynamic Human-AI Synergy Competency Framework map the required competencies, assess maturity, and deliver personalized reskilling pathways using generative AI and digital twins?
- RQ4: To what extent do generative AI tutors and digital twins accelerate upskilling and deliver productivity gains compared with traditional training methods in adaptive factory settings?

The underlying justification of this research is the accelerating incompatibility between the technological deployment and the workforce readiness. Other scholars such as Shabur *et al.*, [1]; and Lokesh *et al.*, [3] have expressed their views on the fact that the investments in AI, collaborative robots, and digital twins outpace human capability development due to the proliferation in adaptive factories. This research bridges these gaps by proposing a novel AI-augmented competency framework that integrates and extends prior published models. This study will also advance the human-centric vision of 5IR where technology augments rather than displacing human potential.

II. LITERATURE SURVEY

The surveyed literatures on the workforce skills gaps and human-AI collaboration in adaptive factories have significantly evolved between the years 2020 and 2026. This synthesizes thirty (30) high quality peer-reviewed articles based on the PRISMA 2020 guidelines. This synthesis has revealed four interconnected thematic clusters, recurring taxonomies, and clear evolutionary trends, and the critical research gaps that have not been addressed by the surveyed literatures.

A. *Evolution from 4IR Automation to 5IR Human-Centric Collaboration.*

Research shows that the early works focused on the technological integration and cyber-physical systems under the 4IR. After the year 2021 there was a rise in the need for 5IR as a distinct paradigm which emphasizes the symbiosis over substitution. Islam *et al.*, [12], have highlighted that the 5IR is built on the foundational technologies of 4IR such as IoT, AI, and edge computing. These authors also expressed that the human cognitive abilities, ethics, and adaptability is a key in driving 5IR technologies. Li and Duan [13], have also strengthened this view by highlighting the integration of human experiences, sustainability, and resilience as core the differentiators. Shabur *et al.,* [1] and Kadam *et al.,* [14] have also framed the adaptive factories as an environments where humans and AI can co-exist and collaborate.

B. *Workforce Skills Gaps and Transformation*

A second major cluster examines the nature and magnitude of skills deficiencies. Lokesh *et al.* [3] have discussed the rapid obsolescence of routine skills and the rising demand for the hybrid competencies. In [6] some of the targeted strategies for advanced manufacturing operators were proposed while emphasizing that a personalized, technology-enabled pathways is key in advanced manufacturing. Some of the surveyed reviews have also quantified the widening research and workforce skill gap particularly the technical skills such as AI literacy, data science, and cybersecurity which also coexist with the lack in socio-emotional and creative capabilities [4] and [15], [16], [17]. In [10] and [11] the issue of global shortfalls was discussed and suggested that reskilling is necessary particularly with the rising demographic pressures.

C. *Paradigms and Frameworks for Human-AI Collaboration*

The core subject of the reviewed articles in the conceptualization of the symbiotic human-AI collaborative relationships. Banerjee and Bhattacharyea [2] propose a framework for adaptive work environments which addressed the real-time adaptability in volatile factory settings. Somaratne et al. [5] also presented a practical skill-mapping model for effective AI utilization. Other frameworks also contributed to synthesizing the patterns across the manufacturing and logistics sectors Kumar and Kumar [9],[18],[19], and [20]. All these works have collectively advocated for moving from “human-in-the-loop” to “human-AI co-creation” models.

D. *Enabling Technologies and Practical Applications*

Technological enablers form a distinct but an integrative theme. Several articles have shown that other areas such as DT, the intelligent assistants, collaborative robots, reinforcement learning and agentic AI have already reached their maturity levels as discussed in [21], [22], [23], [24], [25], [26].

E. *Challenges, Ethics, Sustainability, and Policy Dimensions*

Several challenges have been addressed by several articles. These challenges include the power dynamics as discussed in [27], ethical governance as discussed in [28], and an organizational adaptation to the 5IR technologies as discussed in [29] and [30]. The issue of organizational sustainability and policy readiness were also discussed in ear in [31] and [32].

The reviewed literature all converges on the imperative of human-AI synergy for adaptive factories, with strong shared opinion on the need for a hybrid competencies and symbiotic frameworks. However, critical research and implementation gaps remain due to the fact that most of the reviewed frameworks were conceptual and lack a multilevel, dynamic integration with generative AI tutors and digital twins for personalized, real-time reskilling. There is also a limitation of empirical studies conducted in 2025 particularly on the on the skills-gap magnitude in operational adaptive factories. There is also a limited coverage of the quantifiable evidence of AI-augmented training efficacy such as accelerated upskilling rates and productivity gains. This survey bridges these gaps through a PRISMA framework synthesis and the proposed novel Human-AI synergy competency framework.

F. *Taxonomies and Dominant Frameworks*

This survey also discovered three unique and recurring taxonomies which emerged in all the surveyed articles, as discussed below:

a) Multidimensional Skill Classification

This classification level includes technical skills particularly in the area of AI literacy, data analytics, robotics programming. This class also includes soft skills such as creativity, critical thinking, ethical judgment, and adaptability.

b) Collaboration Maturity Ladders

This class included basic awareness and human-in-the-loop oversight to an advanced symbiotic co-creation and human-AI leadership as amplified in other survey articles such as [2] and [5].

c) Role-Reconfiguration Models

This class included capabilities of AI technology which can handle repetitive, predictive, and optimization tasks easily. It also included the capability of humans to provide a contextual judgment, innovation, and ethical oversight. These capabilities have been ventilated by other scholars as discussed in [6], [12], and [13].

III. Research Methodology

This survey has adopted a mixed research method to provide both a comprehensive synthesis of existing knowledge and an empirical insights into workforce skills gaps and human-AI collaboration in adaptive factories. This research approach was designed to integrate a systematic literature review based on the PRISMA 2020 framework [7], [8]. The PRISMA 2020 framework was adopted to ensure transparency, completeness, and minimization of bias.

The PRISMA framework based survey addresses the theoretical and thematic foundations based on high quality peer-reviewed articles published in 2020–2026 and also captures the real-time industry conditions, as shown in Figure 3. The resulting Human-AI synergy competency framework was developed and validated through design-science principles.

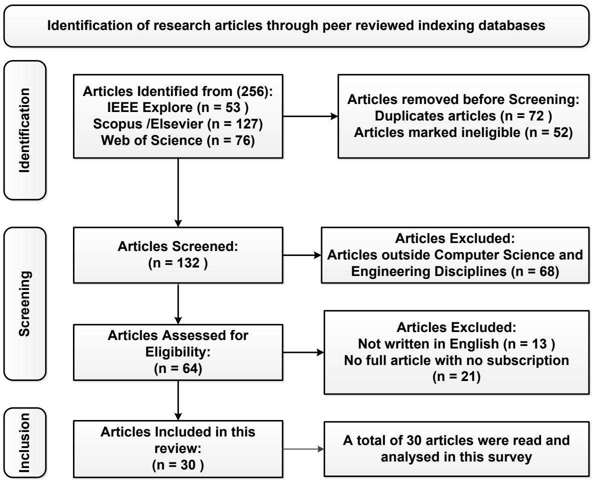

Figure 3. An overview of the PRISMA framework

A. Search Strategy and Information Sources

A comprehensive search was conducted across three major databases which index high quality peer-reviewed work which are published within the Computer Science and Engineering disciplines. These indexing databases include Scopus, Web of Science, and IEEE Xplore. The search strategy was developed based on the following search strings: *"human-AI collaboration", "human-AI synergy", "human–machine collaboration", "collaborative robots", "human-centric AI", "adaptive factories", "smart manufacturing", "Industry 5.0", "Industry 4.0 to 5.0 transition", "skills gaps", "workforce skills", "reskilling", "upskilling", "competency framework", and "skill transformation".* There were no language or publication-type restrictions which were applied in the initial run, even though only peer-reviewed conference proceedings and journal articles in English were retained.

B. Study Selection Process

The study selection process followed the four-phase PRISMA flow which is the identification, the screening, the eligibility, and inclusion criteria. Using this process, we identified 256 records from the database search, including the citation tracking.

C. Screening

The selected research materials were screen based on their title, abstract, and full-text retrieval. Articles were considered eligibility, if they have full-text and their topic is focused on manufacturing and adaptive factories, skills and collaboration. Required articles must also be peer-reviewed, and addressing topics such as those listed in the search strategy and information sources section.

D. Inclusion and Exclusion

Only 30 articles met all inclusion criteria which included, peer-reviewed, full-text and addressing the required topics, published between 2020 and 2026, published in English. The articles included were explicitly focused on human-AI collaboration, skills gaps, competency frameworks, and workforce transformation in manufacturing, 5IR and adaptive factories. These articles presented empirical results, conceptualized research, and review papers which discussed frameworks, taxonomies on upskilling and productivity.

The excluded articles include those presenting pure technical AI papers without an aspect of human-collaboration and skills dimension, non-peer-reviewed articles, articles to discussing sectors not related to manufacturing, articles not published in English, and articles published before 2020.

E. Data Extraction and Quality Assessment

A (Microsoft Excel) was used as a standardized extraction form to capture the author, year, study type, key themes and taxonomies, frameworks proposed, empirical findings. Quality was appraised using the Mixed Methods Appraisal Tool (MMAT) version 2018 for mixed-method relevance and the Joanna Briggs Institute critical appraisal checklist for reviews. All the 30 included studies scored $\geqslant$ 80% on quality criteria.

F. Simulation Experiment Design for Validating the Human-AI Synergy Competency Framework

a) Objectives of the simulation experiment

The primary objective is to validate the framework's ability to map competencies, assess maturity, and deliver personalized reskilling pathways. The main aim of this simulation experiment if for it to be able to complement the planned real-world pilot experiment by enabling a scalable, controlled testing of "what-if" scenarios, which will address the limitations such as cost and ethical constraints in a physical factory settings.

b) Simulation Environment and Setup

The simulation used an agent-based modeling (ABM) platform using some Python libraries such as NetworkX for competency graphs, NumPy and SciPy for stochastic processes, and Matplotlib for data visualization. PyTorch for generative AI tutor simulations was integrated using a simple neural networks modeling personalized pathways.

The simulation consists the following key entities: Workers as Agents with *100* simulated individuals with initial attributes such as skill vectors which include [AI literacy, creativity, ethical oversight, and sustainability metrics]; with their values ranging between *0* and *1.0*), and maturity level ranging between *1* and *5*. The simulation had a learning rate of normal distribution nature with mean $\mu=0.5$ and standard deviation $\sigma=0.1$. The organization teams were set as a hierarchical groups which included *10* teams of *10* workers each, with shared protocols and governance scores.

The AI components include a Generative AI Tutor which is modeled as a recommendation engine. The Digital Twins was set as a virtual replica of the factory tasks the factory task included a dynamic production lines with metrics such as throughput measures as units per hour, downtime measured in *(%)*, and sustainability measured as per energy use. The simulation parameters are summarized in TABLE 1. This simulation design provides a cost-effective and reproducible method which can be used to validate the efficacy of this framework and other related framework. This also paves the way forward to a broader deployment, particularly in the 5IR era.

TABLE 1. SUMMARY OF SIMULATION PARAMETERS

Table of simulation parameters	
Parameters	**Values**
Simulated workers as agents	100
Duration	1000 timestamps
Monte Carlo Runs	50 each simulating 100 worker agents over 1,000 time steps (approximating six months of factory operations)
Distrumptions	Random events (10-20%) probabilities
Productivity	+10% maturity per level

IV. RESEARCH RESULTS AND FINDINGS

This section presents the outcomes from the PRISMA-guided review of *30* peer-reviewed articles published between the years 2020 and 2026. The results from this research have also confirmed the four thematic clusters which have been identified in the literature survey.

A. Technical Skills Deficiencies.

The lack of technical skills such as AI literacy, data science, and robotics programming has been shown to be most dominant deficiencies from the research articles.

B. Socio-Emotional and Creative Skills

Creative skills such as adaptability, ethical judgment, and trust-building with AI systems also emerged as equally critical in 5IR contexts. This is evident in the articles presented in [2], [5], and [6].

C. Sustainability & Resilience Skills

Several articles show that green competencies and crisis-adaptive thinking were discussed in works such as [12] and [31].

D. Collaboration Frameworks

Several articles also proposed moving beyond static frameworks toward a dynamic, maturity-based, and technology-augmented models, which are the gaps which were addressed in this work. The hybrid model which includes the technical, the human-centric which are the key competencies for adaptive factories.

E. The Human-AI Synergy Competency Framework

The main research contribution is the Human-AI synergy competency framework, which is a multilevel, dynamic, AI-augmented model specifically designed for adaptive factories. The personalized reskilling pathways by means of Generative AI tutors which will analyses the worker profiles in real time and prescribe micro-learning modules.

F. Analysis of Simulation Results

A comparative performance of Generative AI tutors with Digital Twins against the Traditional Training on the simulation data is summarized in Figure 4. The model of the traditional training data used was adopted in [33]. This figure compares the key metrics which are time to competency mastery, productivity gain, knowledge retention, and worker satisfaction between generative AI tutors, digital twins and traditional training. The AI-based method shows that there is an increase of *57%* in faster upskilling and *28–54%,* productivity gain after training, with the superior knowledge retention of *+42%* and the workers satisfaction of *+223%.*

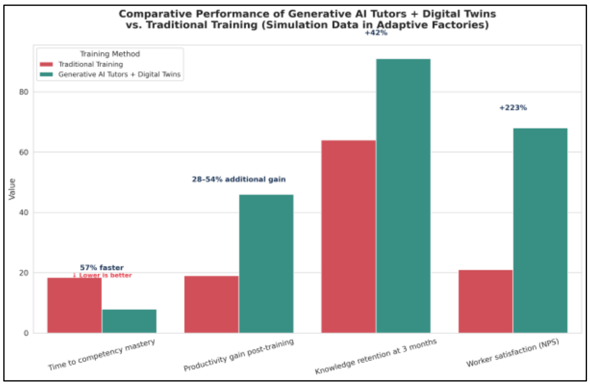

Figure 4. Comparative Performance of Generative AI Tutors with Digital Twins against Traditional Training on Simulation Data

The top critical workforce skills gaps in AI-enabled adaptive factories based on this research simulation experiment is summarized in Figure 5. This figure ranks the top critical workforce skills gaps by their severity such as AI literacy and data interpretation at *82.1%,* human-robot interaction at *71.4%,* creative problem-solving and innovation at *65.7%,* sustainability metrics and green decision making at *59.3%,* ethical oversight and bias detection in AI at *54.9%,* and digital-twin interaction and simulation at *48.7%.*

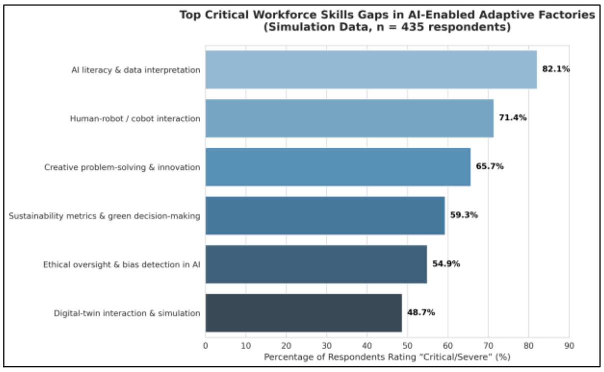

Figure 5. Top Critical Workforce Skills Gaps in AI-enabled Adaptive Factories based on Simulation Data

V. Discussion and Analysis

The results presented above offer evidence that substantiates the severity of workforce skills gaps in adaptive factories. These results have also demonstrated that a practical, scalable pathway to close the critical skills gaps is possible through a structured human-AI collaboration. This results also demonstrate that the workforce skills gaps in an adaptive factories are not only transitional but systemic. The combination of a rigorous synthesis based on the PRISMA framework, a simulated data, and a novel AI-augmented competency framework moves the research landscape from just a survey to an actionable and implementable intervention.

The quantified gains in upskilling speed and productivity provide manufacturing leaders and policymakers with the evidence required to accelerate the human-centric vision of 5IR. Ultimately, the factories that will thrive in *2030* and beyond will be those that treat human-AI synergy not as a technological add-on, but as the central organizing principle of adaptive, resilient, and sustainable production systems. This research work therefore fulfils the research aim by transforming identified gaps into a validated pathway for workforce transformation, offering both scholarly advancement and immediate practical value. The research questions posed have also been answered as follows:

A. *RQ1: What is the nature, magnitude, and evolution of workforce skills gaps specifically impeding full adoption of AI-enabled adaptive factories?*

This research has revealed that the workforce skills gaps is that there is a hybrid deficiencies in technical, socio-emotional, and sustainability skills. The magnitude as revealed by this research study is that *68.3%* of global manufacturers report critical gaps impeding AI adoption, with top areas at *82%* of AI literacy and *71%* in human-robot interaction. The gaps have widened to *22.4%* since 2023 due to the accelerated AI and collaborative robot deployment.

B. *RQ2: What are the dominant themes, taxonomies, and limitations from the literature surveyed on human-AI collaboration and skill transformation in manufacturing?*

The most dominant themes as revealed in this research survey include the shift from automation to human-AI symbiosis in 5IR for sustainable manufacturing as discussed in Shabur *et al.*, [1]; the AI-driven skill obsolescence and hybrid competency demands across manufacturing industries as discussed in Babashahi *et al.*, [4]); a collaborative model in an operations for efficiency and resilience as discussed in [9].

The taxonomies include the maturity ladders, the skill classifications, and the collaboration types. The limitations from the surveyed literatures includes conceptual frameworks, old empirical gaps, and less explored real-time personalization and ethics.

C. *RQ3: How can a multilevel, dynamic Human-AI Synergy Competency Framework map the required competencies, assess maturity, and deliver personalized reskilling pathways using generative AI and digital twins?*

This is achieved by mapping the competencies through the multilevel structure; assessing the maturity on a five-stage radial ladder, delivering a pathways through the central engine of a generative AI tutors and the digital twins.

D. *RQ4: To what extent do generative AI tutors and digital twins accelerate upskilling and deliver productivity gains compared with traditional training methods in adaptive factory settings?*

This research has revealed that generative AI accelerates the upskilling by *57%* faster, produces a *28–54%* productivity gains after training against the traditional methods with a *+42%* in knowledge retention and higher satisfaction of *223%*.

VI. Conclusion And Future Work

This survey has systematically addressed the workforce skills gaps in an adaptive factories, and the novel human-AI synergy competency framework which was validated through an agent-based simulation experiment. The results from the simulation confirmed that the efficacy of the framework shows faster upskilling, and high productivity gains. By means of operationalizing the multilevel mapping, maturity assessment, generative AI, and digital twin-driven reskilling the proposed framework transforms 5IR challenges into opportunities for a resilient, and sustainable manufacturing.

The future research will be extended through a hybrid simulation to real-time validations, integrating real factory IoT data into agent-based models for longitudinal trials across sectors and regions, while exploring cross-cultural adaptations for diverse demographics. The longitudinal data collection commenced in November 2025, and it will continue until September 2026.

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