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UPSKILLING AND RESKILLING STRATEGIES FOR EMPLOYEES IN INDUSTRY 5.0

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ABSTRACT

In the context of rapid technological advancements and evolving job requirements, organizations increasingly emphasize upskilling and reskilling initiatives to enhance workforce competencies. The present study examines the impact of upskilling and reskilling strategies on workforce competency levels among software professionals. A descriptive and quantitative research design was adopted to achieve the objectives of the study. Primary data were collected from 181 software employees working in Karnataka, specifically in the Bengaluru and Mysuru regions, using a structured questionnaire developed on a five-point Likert scale ranging from *5 = Strongly Agree* to *1 = Strongly Disagree*. The respondents belonged to the age group of 23–35 years, representing early- and mid-career professionals in the software industry. The sample consisted of 101 female and 80 male respondents, ensuring adequate gender representation. The data were analysed using appropriate statistical techniques to assess the relationship between upskilling and reskilling strategies and workforce competency levels across cognitive, social, and technical domains. The findings reveal that both upskilling and reskilling strategies have a positive and statistically significant influence on workforce competencies, with upskilling demonstrating a comparatively stronger impact. The study underscores the critical role of continuous skill development initiatives in enhancing employee capabilities and improving organizational adaptability in a dynamic digital environment. The results offer practical implications for human resource managers, learning and development professionals, and policymakers in designing effective workforce development frameworks for the software industry in Karnataka.

Introduction

As we move towards Industry 5.0, which emphasizes sustainability, human-centricity, and resilience, it is crucial to examine the readiness of educational institutions and industrial learning units to meet the demands of this new era (Caratozzolo et al., 2024). This human-centric paradigm shift necessitates a workforce equipped with advanced competencies, as technological evolution demands a corresponding evolution in employee skills to ensure equal employment opportunity and sustained productivity (Ghobakhloo et al., 2024; Oeij et al., 2024). Aligning workforce capabilities with these evolving industry requirements is essential for reducing skill disparities and fostering economic growth (Radhika & Kokil, 2024), as the ultimate objective extends beyond mere employment generation to encompass sustainable development and the nurturing of an environmentally conscious society (Dehbozorgi et al., 2024). Consequently, organisations must prioritise the reskilling and upskilling of their workforce to address the widening skills gap and prepare employees for the complexities of human-machine collaboration (Oeij et al., 2024; Samuels & Pelser, 2025). This involves not only technical proficiency but also the integration of cognitive skills, social values, and deepening digital competencies necessary to achieve synergies where humans and intelligent machines work in perfect symbiosis (Bieńkowska et al., 2025; Chrisanty et al., 2024). However, achieving this transition requires overcoming significant barriers to upskilling and reskilling, as current participation rates in adult training remain low, particularly among the sociodemographic groups that stand to benefit most (Oeij et al., 2024). Upskilling and reskilling are therefore regarded as critical strategies not merely to absorb the impact of these shifts but to actively seize the opportunities they present for a competitive and inclusive economy (Oeij et al., 2024). This review synthesizes current academic discourse to identify the prevailing strategies and challenges associated with workforce development, highlighting specific interventions such as experiential learning pathways and the role of formal education in addressing the documented mismatch between academic curricula and industry needs (Oeij et al., 2024; Radhika & Kokil, 2024). The literature indicates that while prior research underscores the necessity of skilled workforces, it often fails to adequately elucidate the evolving job dynamics and specific learning trajectories required during the Industry 5.0 transition (Oeij et al., 2024). To address this gap, the following section critically examines the multidimensional frameworks of workforce development, analyzing the specific knowledge, skills, and attitudes necessary for human-machine collaboration (Oeij et al., 2024).

This shift requires a holistic approach that integrates technical proficiency with cognitive and social capabilities, as the realization of Industry 5.0 has far-reaching implications for workforce competencies and skills (Oeij et al., 2024). The European Commission's strategic initiative further underscores that the human worker is the most precious and limited resource in this transformation, requiring organisations to harness human intellect and skills to leverage advanced technologies effectively (Oeij et al., 2024). This harmonization of human potential with technological capabilities is essential, as employees must develop both soft skills and advanced technical competencies to function effectively within this human-centric environment (Vukelić et al., 2024). The establishment of human-robot collaboration demands a collaborative workplace, in which personalization in labor relations with employees is a key element, necessitating new skills, capabilities, and competencies from workers (Borchardt et al., 2022). One unsolved question is how to achieve the balance between the investment in new technologies and the huge costs to reskill workers, considering the potential need for yet unknown skills for HR to manage in the context of Industry 5.0 (Borchardt et al., 2022). Specifically, the financial burden of acquiring smart machines and providing comprehensive training for new roles presents a significant obstacle, as the high costs associated with upgrading production lines and developing specialized competencies can strain organizational resources (Adel, 2022). Furthermore, inadequate infrastructure to accommodate new technologies and the time required for reengineering processes can exacerbate these financial challenges, particularly if employees lack the forward-thinking mindset necessary for rapid adaptation (Maddikunta et al., 2021).

1. Literature Review

The transition toward Industry 5.0 necessitates a fundamental redefinition of workforce competencies, as identified in the conceptual framework for workforce skills which categorizes the primary beneficiaries into students and existing workers (Oeij et al., 2024). For incumbent employees, the literature emphasizes the importance of continuous internal training to enhance technical judgment and collaboration skills with intelligent systems (Aka, 2024; Ghobakhloo et al., 2024), while students require academic curricula that bridge the gap between theoretical knowledge and the practical demands of human-machine interaction (Oeij et al., 2024; Pinzone & Taisch, 2023). Specifically, Industry 5.0 demands a balanced approach that includes the ability to work with data, knowledge of interaction with computers and robots, and technical know-how in sustainable development and system complexity, alongside soft skills such as creative and critical thinking and green skills related to the environment (Borchardt et al., 2022). Higher education institutions must therefore rethink their strategies regarding lifelong learning and transdisciplinary education, incorporating modules on sustainability, resilience, and human-centric design to meet these complex demands (Borchardt et al., 2022). This transition is complicated by the fact that existing educational models often struggle to integrate the multidisciplinary skills and experiential learning necessary to equip learners with the required competencies (Hajime et al., 2025). To address these systemic shortcomings, recent studies propose the integration of teaching factories, living labs, and combined public-private learning ecosystems that actively simulate real-world industrial environments (Oeij et al., 2024). These immersive environments enable learners to apply theoretical concepts in practical settings, thereby bridging the distance between academic instruction and the operational realities of smart factories (Oeij et al., 2024; Pinzone & Taisch, 2023). Despite these advancements, current understanding remains limited regarding the specific workforce skills required for managerial or technical tasks, particularly the cognitive and relational capacities needed to navigate this human-centric environment (Oeij et al., 2024). Furthermore, the literature highlights the necessity of lifelong learning and transdisciplinary education supported by digital technologies to foster the cognitive, social, and environmental competencies essential for this transition (Borchardt et al., 2022; Oeij et al., 2024). Beyond cognitive and social competencies, the literature underscores the critical importance of resilience and personal qualities, as the ability to adaptively overcome difficulties and maintain control over decisions is paramount for navigating the challenges of this new industrial paradigm (Borchardt et al., 2022). To operationalize these competencies, researchers have developed comprehensive frameworks that outline specific directions for skill development, distinguishing between the abilities required to create an Industry 5.0 work environment and those needed to function within it (Oeij et al., 2024). These frameworks suggest that successful adaptation requires a human-centric approach where companies invest in both technological assets and human capital, ensuring that workers benefit from the digital transition through active involvement in the process (Oeij et al., 2024). Learning Factories have emerged as a particularly effective pedagogical tool to address these gaps, providing secure, regulated environments for hands-on experience with industrial processes and emerging technologies (Hajime et al., 2025; Milisavljevic-Syed et al., 2023). These environments are designed to support regional small and medium-sized enterprises by reducing regional disparities, as industrial progress tends to concentrate in innovative regions, leaving lagging areas at risk of skill deficits and technological unemployment (Milisavljevic-Syed et al., 2023). To mitigate these risks, recent scholarship emphasizes the need for Learning Factories to incorporate sustainability and resilience into their design, thereby addressing the environmental and social dimensions often overlooked in Industry 4.0 digitalization efforts (Milisavljevic-Syed et al., 2023). This shift towards a human-centric paradigm requires a fundamental redefinition of workforce competencies, moving beyond the technical efficiency focus of Industry 4.0 to encompass the broader societal goals of resilience and sustainability (Oeij et al., 2024). To operationalize these requirements, the "Industry 5.0 Skills Palette" has been introduced to provide a structured understanding of the specific competencies employees must acquire, addressing the current lack of clarity regarding the precise skill sets needed for this transition (Oeij et al., 2024; Pinzone & Taisch, 2023). This palette categorizes essential capabilities into distinct domains, emphasizing that the industrial Operator 5.0 must not only possess the technical attributes of their predecessors but also demonstrate the ability to manage increasing complexity, engage in simultaneous tasks, and maintain openness to change (Mattsson et al., 2023). This evolution reflects a broader shift in manufacturing work roles, where the scope expands from purely technological management to driving innovation, resilience, and sustainability in a human-centered manner (Pinzone & Taisch, 2023). Central to this human-centered approach is the concept of Human Capital 5.0, which defines the workforce as an intangible asset possessing embedded values such as knowledge, creativity, and innovation necessary to achieve scalable personalization and competitiveness (Aheleroff et al., 2022). However, realizing this potential requires a transformative shift in organizational culture and policy frameworks that prioritize sustainability, human-centricity, and resilience over pure efficiency (Oeij et al., 2024). This paradigm shift necessitates that organizations move beyond traditional efficiency metrics to adopt a wider perspective that encompasses human, resilience, and sustainability factors in their strategic planning (Oeij et al., 2024). Consequently, organizations must expand their conventional economic indexes with additional Industry 5.0 indicators to measure progress in these areas (Oeij et al., 2024). These indicators should encompass metrics for human-centricity, such as employee well-being, autonomy, and engagement, alongside measures of organizational resilience that assess the capacity to withstand disruptions like supply chain shocks or economic crises (Kővári, 2024; Oeij et al., 2024).

2. Objectives

This study aims to identify the specific upskilling and reskilling strategies necessary to equip the workforce with the cognitive, social, and technical competencies required for the transition to Industry 5.0 (Aheleroff et al., 2022; Oeij et al., 2024). The transition to Industry 5.0 represents a fundamental shift from the technology-centric focus of Industry 4.0 to a human-centric paradigm that prioritizes sustainability, resilience, and worker well-being (Łupicka & Jeszka, 2025). This paradigm shift necessitates a fundamental redefinition of workforce competencies, as current understanding remains limited regarding the specific skills employees need to acquire to contribute to this transformation (Pinzone & Taisch, 2023). Specifically, this research seeks to investigate the organizational prerequisites for continuous learning and re-skilling that are essential for integrating new technologies while mitigating employee resistance toward change (Olsson et al., 2024). By examining the intersection of organizational policy and individual development, this research addresses the gap between theoretical skill requirements and practical implementation mechanisms (Oeij et al., 2024). Furthermore, this study aims to evaluate the effectiveness of current educational frameworks, such as Learning Factories, in bridging the gap between academic knowledge and the dynamic demands of the industrial sector (George, 2024; Saniuk & Grabowska, 2022).

3. Scope of the Study

This research is delimited to the examination of upskilling and reskilling strategies within the context of continuing engineering education divisions and industry learning and development units, specifically focusing on the competencies required for engineers and technical professionals to thrive in Industry 5.0 environments (Caratozzolo et al., 2024). The literature review examines the theoretical foundations and empirical evidence surrounding workforce transformation, highlighting the misalignment between current university pedagogy and evolving corporate demands due to outdated curricula ("Humanizing Businesses for a Better World of Work," 2024). The misalignment is further compounded by ineffective pedagogical methods that fail to engage learners with the practical, hands-on experiences necessary for modern industrial environments (Radhika & Kokil, 2024).

4. Research Methodology

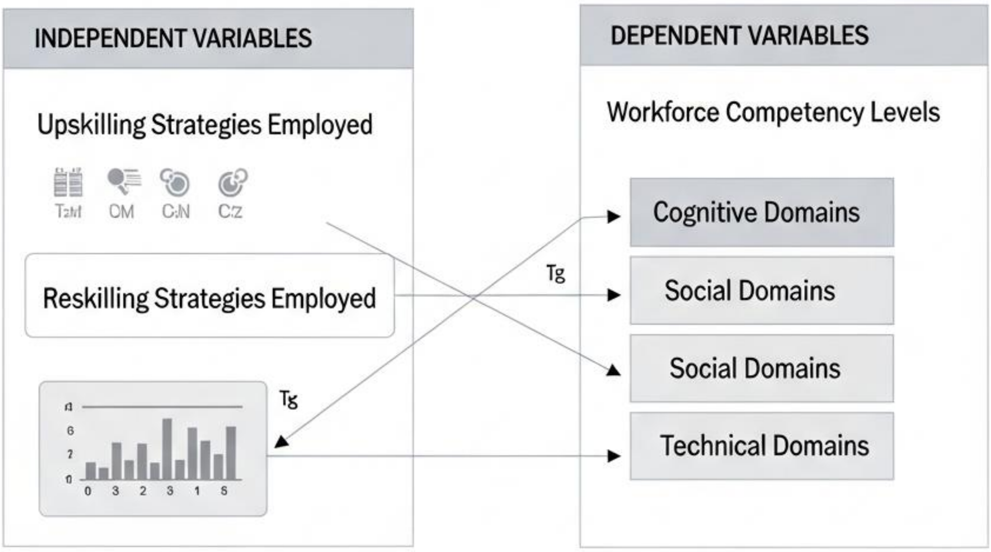
This study employs a mixed-methods approach to investigate the efficacy of upskilling and reskilling strategies, beginning with a comprehensive literature review to identify current best practices and perceived gaps in Industry 5.0 education and training (Caratozzolo et al., 2024). This review is further enriched and triangulated through consultations with academics, experts, and practitioners to address the scarcity of scattered literature across scientific disciplines (Oeij et al., 2024). This interdisciplinary approach is essential to synthesize fragmented insights into a cohesive framework, as the manufacturing sector still needs to be fully integrated with AI and lacks research addressing the full spectrum of operational and societal implications (- & -, 2024). The literature review systematically examines the theoretical underpinnings of workforce transformation, identifying the critical competencies and pedagogical frameworks necessary for the transition to

Industry 5.0. To complement the theoretical analysis, the study incorporates qualitative insights from expert discussions and practitioner interviews, which serve to validate and contextualize the findings derived from academic sources (Oeij et al., 2024). These consultations engaged practitioners, companies, and networks to discuss the perceived relevance of Industry 5.0 and its key elements, including human-centricity, resilience, and sustainability (Oeij et al., 2024).

5. **Variables:**

The independent variables include the specific upskilling and reskilling strategies employed, such as Learning Factories and interdisciplinary training programs, while the dependent variables consist of workforce competency levels in cognitive, social, and technical domains as well as organizational readiness for Industry 5.0 adoption (Gomes et al., 2025; Hajime et al., 2025; Radhika & Kokil, 2024). The literature review examines the theoretical underpinnings of workforce transformation, identifying the critical competencies and pedagogical frameworks necessary for the transition to Industry 5.0. The literature review systematically examines the theoretical underpinnings of workforce transformation, identifying the critical competencies and pedagogical frameworks necessary for the transition to Industry 5.0.

Figure 1: Research frame between Independent variables & dependent variables



According from the image 1, The image presents a conceptual research framework illustrating the relationship between *independent variables* and *dependent variables* in the context of workforce development.

On the left side, the **Independent Variables** are shown as:

- *Upskilling Strategies Employed*
- *Reskilling Strategies Employed*

These represent the organizational initiatives and training interventions designed to enhance employees' knowledge, skills, and capabilities. Upskilling focuses on improving existing competencies, while reskilling emphasizes developing new skills to adapt to changing job roles or technological transformations.

On the right side, the **Dependent Variables** are grouped under *Workforce Competency Levels*, which are further categorized into:

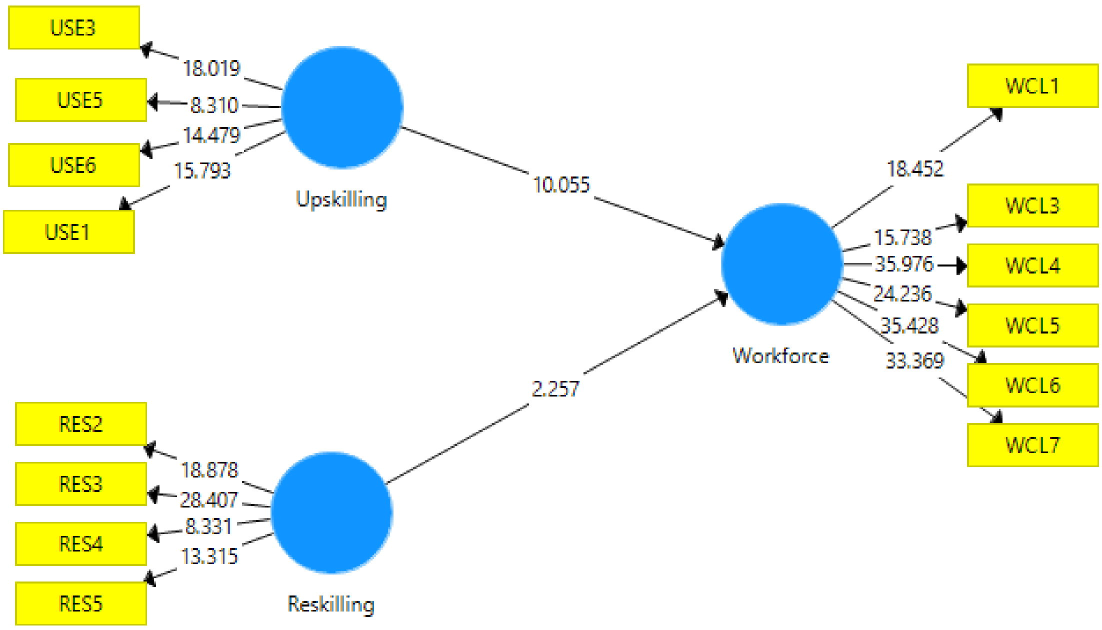
- **Cognitive Domains** – reflecting knowledge acquisition, analytical thinking, problem-solving ability, and understanding of concepts.
- **Social Domains** – representing communication skills, teamwork, adaptability, collaboration, and interpersonal effectiveness.
- **Technical Domains** – indicating proficiency in job-specific technical skills, digital tools, and operational expertise.

The arrows connecting the independent variables to the dependent variables indicate a direct causal relationship, suggesting that both upskilling and reskilling strategies significantly influence the overall competency levels of the workforce across cognitive, social, and technical dimensions.

6. Data Analysis

The reliability and convergent validity of the constructs—**Reskilling, Upskilling, and Workforce**—were assessed using Cronbach's Alpha, rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE). The results demonstrate that all constructs meet the recommended measurement model criteria. For **Reskilling**, Cronbach's Alpha (0.946) and Composite Reliability (0.959) indicate excellent internal consistency, far exceeding the recommended threshold of 0.70. The rho_A value (1.057) also reflects strong construct reliability. The AVE value of 0.854 is well above the minimum criterion of 0.50, confirming a high level of convergent validity and suggesting that the indicators explain a substantial proportion of variance in the construct. The **Upskilling** construct shows acceptable to good reliability, with Cronbach's Alpha (0.723), rho_A (0.727), and Composite Reliability (0.829) all exceeding the minimum acceptable limits. The AVE value of 0.550 meets the recommended threshold, indicating adequate convergent validity. Although the reliability metrics are comparatively lower than those of Reskilling and Workforce, they remain within acceptable ranges for empirical research. For the **Workforce** construct, Cronbach's Alpha (0.919), rho_A (0.921), and Composite Reliability (0.937) demonstrate strong internal consistency and construct reliability. The AVE value of 0.714 exceeds the threshold of 0.50, confirming satisfactory convergent validity and indicating that the indicators effectively represent the underlying construct. Overall, the measurement model exhibits **strong reliability and adequate convergent validity** across all constructs, supporting their suitability for subsequent structural model analysis.

Image 2, Relations between upskills & Reskilling for Employee workforce productivity



According to the image 2, The structural model results reveal that both **reskilling** and **upskilling** strategies have a statistically significant and positive influence on **workforce competency levels**. The path coefficient for **Reskilling → Workforce** (Original Sample, $O = 0.131$) indicates a positive relationship, suggesting that reskilling initiatives contribute to improvements in workforce competencies. The *t*-statistic of 2.257 exceeds the critical value of 1.96, and the associated *p*-value of 0.024 is below the 0.05 significance level. This confirms that the effect of reskilling on workforce competency is statistically significant, although the magnitude of the effect is relatively modest. In contrast, **Upskilling → Workforce** demonstrates a substantially stronger effect, with a path coefficient of 0.494. The high *t*-value (10.055) and a *p*-value of 0.000 indicate a highly significant relationship. The low standard deviation (0.049) further suggests consistency and robustness in the estimated effect. Overall, the findings indicate that while both reskilling and upskilling significantly enhance workforce competencies, **upskilling emerges as the more influential driver**. This highlights the critical role of continuous skill enhancement in strengthening workforce capabilities, while reskilling remains an important complementary strategy for adapting to evolving job requirements.

7. Results

The systematic literature review identified twelve critical influencing factors that shape the required competencies for Industry 5.0 education, including automation, connectivity, data ethics, artificial intelligence, and lifelong learning (Borchardt et al., 2022). These factors are organized into four main dimensions: Resilient Manufacturing, Green Industrial Transformation, Digital Human Work, and Technological Systems, which collectively define eighteen distinct skills areas essential for successful integration (Pinzone & Taisch, 2023). Within the Resilient Manufacturing dimension, competencies such as adaptive problem-solving and crisis management are paramount, enabling organizations to maintain operational continuity amidst disruptions (Borchardt et al., 2022). Similarly, the Green Industrial Transformation dimension emphasizes environmental stewardship and circular economy principles, requiring professionals to develop competencies in sustainable resource management and eco-innovation to minimize industrial ecological footprints (Leitenbauer et al., 2025). The Digital Human Work dimension addresses the collaborative dynamics between humans and intelligent machines, necessitating advanced social competencies and ethical awareness to navigate the complexities of human-robot collaboration (Borchardt et al., 2022). This collaboration requires employees to possess the ability to think and reason rationally while maintaining the physical and mental conditions necessary to work safely and effectively with new technologies (Gajdzik, 2023). The Technological Systems dimension encompasses a broad range of technical enablers, such as Comprehensive Automation Testing, Data-Driven Analysis Technologies, and Intelligent Manufacturing, which require personnel to possess deep engineering knowledge and technological proficiency (Lo et al., 2024). These technical proficiencies must be complemented by a socio-technical evolution that redefines the role of operators as the focal point of manufacturing and production systems (Yitmen & Almusaed, 2024). This human-centric paradigm shift necessitates that educational institutions adopt a multi-pronged approach to readiness, characterized by curriculum integration of advanced technologies, pedagogical innovation towards active learning, and robust industry collaboration to provide real-world exposure (Bushuyev et al., 2024). This multi-pronged approach is necessitated by the finding that traditional lecture-based, content-heavy instruction models no longer suffice; instead, learning environments must become flexible, immersive, and closely aligned with real-world industrial practices (Hajime et al., 2025).

8. Discussion

The findings underscore that effective upskilling requires a fundamental shift from passive knowledge acquisition to active, experiential learning models that integrate digital twins and collaborative robotics to bridge the gap between theoretical concepts and practical application (Caratozzolo et al., 2024; Hajime et al., 2025). Specifically, learning factories and simulation-based environments have emerged as vital pedagogical tools that allow participants to not only familiarize themselves with technologies like additive manufacturing and human-robot collaboration but also learn how to select and implement appropriate AI applications within their own workspaces (Gyulai et al., 2023). This transition to experiential learning is critical because the integration of technologies such as robotics, automation, and the industrial internet of things fundamentally alters the relationship between humans and machines from command-and-control to collaborative partnership (Peppler et al., 2022). In this collaborative paradigm, humans must possess the technical acumen to understand and manage autonomous systems while maintaining the adaptability to address maintenance needs or technical issues as they arise (Jensen et al., 2024). Consequently, engineering education providers must foresee the potential of digital transformation in teaching and skill-developing activities to ensure graduating engineers are highly aligned with the demands and attributes needed by prospective industrial employers (Hazrat et al., 2023). This alignment requires a curriculum that combines timeless didactic traditions such as mastery-based and project-based learning with novel elements like student-centred active learning, visualization, and gamification, while refocusing engineering skills on human qualities such as creativity, empathy, and dexterity (Bühler et al., 2022). Furthermore, the integration of generative AI and immersive technologies into educational frameworks is essential for addressing the widening skillset gaps and ensuring the workforce is adequately prepared for the human-centric demands of Industry 5.0 (Caratozzolo et al., 2024; Lin et al., 2024). The PRISM framework offers a structured and adaptable approach to experiential learning, supporting the upskilling of the current workforce and empowering the next generation of engineers to thrive in a rapidly changing industrial landscape (Lin et al., 2024). This framework leverages generative AI to create personalized, rapid, and immersive skill mastery experiences through the use of Digital Twins and sentiment analysis, thereby ensuring learning efficiency and scalability (Lin et al., 2024). By aligning digital twin fidelity levels with Bloom's Taxonomy and the Kirkpatrick evaluation model, such frameworks provide a measurable pathway for technical education across undergraduate, master's, and doctoral levels (Lin, Alhamadah, et al., 2024; Lin, Patel, et al., 2024). This alignment is further evidenced by experimental validation where GPT-4 achieved a 91% F1 score in zero-shot sentiment analysis of teacher-student dialogues, demonstrating the capability of AI-driven systems to monitor learner comprehension and dynamically adjust content to meet course objectives (Lin, Alhamadah, et al., 2024; Lin, Patel, et al., 2024). Building upon these adaptive capabilities, the Multi-Fidelity Digital Twin framework systematically aligns simulation complexity with cognitive development stages to ensure robust skill acquisition across different educational levels (Lin et al., 2024). This comprehensive structure guides learners from foundational understanding to creative application, effectively addressing measurable learning outcomes and behavioral change while fulfilling industrial education objectives (Lin, Alhamadah, et al., 2024; Lin, Patel, et al., 2024). Such comprehensive frameworks must ultimately prepare engineers to become curious collaborators capable of navigating complex multistakeholder ecosystems through a continuous process of learning, unlearning, and relearning (Bühler et al., 2022).

9. Conclusion

This study has demonstrated that preparing the workforce for Industry 5.0 requires a transformative educational approach that integrates immersive technologies, human-centric pedagogies, and adaptive learning frameworks to bridge the gap between theoretical knowledge and practical application (Caratozzolo et al., 2024; Lin et al., 2025). The research highlights that effective upskilling strategies must leverage advanced tools like generative AI and digital twins to create scalable, personalized learning environments that address the widening skill gaps in modern manufacturing (Lin et al., 2024, 2025). By implementing multi-fidelity digital twin simulations that map to Bloom's Taxonomy, educational institutions can establish foundational cyber-physical knowledge for undergraduate students while facilitating advanced analytical skills for master's level learners (Lin et al., 2024, 2025). Furthermore, doctoral candidates must be equipped with high-fidelity digital twins that enable complex evaluation and creative problem-solving tasks, ensuring they possess the strategic oversight necessary for leading resilient and sustainable industrial systems (Lin, Alhamadah, et al., 2024; Lin, Patel, et al., 2024). These high-fidelity simulations, when integrated with retrieval-augmented generation and zero-shot sentiment analysis, enable personalized learning pathways that dynamically adjust to learner needs, achieving over 86% accuracy in classifying student-teacher interactions to optimize training outcomes (Lin et al., 2025a, 2025b). The findings suggest that combining these adaptive technologies with human-centric design principles fosters a collaborative ecosystem where engineers can develop the creativity, empathy, and dexterity required to optimize human-machine interactions and address the sustainability objectives of Industry 5.0 (Caratozzolo et al., 2024; Lin et al., 2025). Ultimately, the successful transition to Industry 5.0 depends on a strategic alignment between technological innovation, education, and sustainability that empowers workers to navigate the evolving industrial landscape (Goggins et al., 2013; Leitenbauer et al., 2025). This alignment necessitates a fundamental shift from traditional, siloed approaches to collaborative and interdisciplinary learning models that prioritize lifelong learning and continuous upskilling for engineers and learning development professionals (Caratozzolo et al., 2024). Future research should therefore focus on the longitudinal impact of these AI-driven educational frameworks on workforce retention and the practical efficacy of human-centric manufacturing implementations in real-world industrial settings (Dehbozorgi et al., 2024; Goggins et al., 2013). Such investigations are critical to validate the long-term benefits of integrating generative AI and digital twin technologies into standard curricula, ensuring that these pedagogical innovations translate into sustained competitive advantages for industrial organizations. Additionally, the integration of low-fidelity Digital Twins with virtual reality-based training exercises, guided by generative AI teaching assistants, represents a scalable method for delivering immersive Industry 4.0 workforce development that can be adapted for Industry 5.0 requirements (Lin et al., 2024, 2025). These AI-driven assistants provide real-time guidance through audio and text interfaces, utilizing sentiment analysis to assess learner comprehension and tailor the educational experience accordingly (Lin et al., 2025). By addressing ethical concerns and navigating technical challenges, educators and technologists can collaboratively harness the power of generative AI to create innovative and inclusive learning environments that emphasize social-emotional learning and human connection alongside personalization (Guettala et al., 2024). This holistic approach ensures that as industries evolve toward greater human-machine collaboration, the workforce is equipped not only with technical proficiency but also with the adaptability and ethical reasoning necessary to drive sustainable innovation (Caratozzolo et al., 2024; Rajumesh, 2023). Future research endeavors should also include a comprehensive assessment of the regulatory and policy implications governing generative AI integration in manufacturing, proposing recommendations for effective policy development (Ghobakhloo et al., 2024). Specifically, policymakers must establish guidelines that ensure AI technologies remain human-oriented, attuned to human capabilities, incentives, and feedback to support the cooperative interfaces and dynamic task allocation required for Industry 5.0 (Gode et al., 2025). These regulatory frameworks must also address the ethical considerations surrounding data privacy, algorithmic transparency, and the socio-economic impacts of automation to ensure that the benefits of Industry 5.0 are distributed equitably across the workforce (Ghobakhloo et al., 2024).

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