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Successful AI-Driven Human-Machine Interaction (HMI): Key Insights for the Engineering Workforce

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Abstract

This study examines a conceptual framework for the integration of AI-driven Human-Machine Interaction (HMI) into the engineering workforce, highlighting its role in facilitating the transition to Industry 5.0, which prioritizes human-centricity, sustainability, and resilience. Drawing on sociotechnical systems theory, the authors analyzed the interplay between social and technical components in workplaces and advocated for human-centric design, dynamic trust relationships, and collaborative sensemaking in AI-driven environments. Moving beyond existing literature reviews, this work introduces a central hypothesis that framing AI as a collaborative intelligence tool significantly improves utilization compared with framing it as a replacement tool. Also, we introduce a novel framework derived from a systematic literature synthesis and provide a detailed roadmap for empirical validation, including a proposed survey instrument. The discussion highlights the importance of AI as a collaborative intelligence tool that augments human skills rather than replaces them, thereby enabling engineers to focus on creativity, intuition, and strategic decision-making. It emphasizes the need for enhanced AI literacy, adaptive HMI designs, and organizational support to foster positive attitudes toward AI adoption and reduce resistance to change. This study concludes that successful AI integration requires framing AI as a tool to enhance human capabilities, supported by empathetic design, structured validation processes, and human resource development efforts to promote technology literacy and positive employee attitudes. This study aims to inform Human Resource Development (HRD) strategies for organizational AI adoption.

Introduction

The current era is defined by a deep collaboration between humans and machines (Wilson & Daugherty, 2024). The rapid advancement of technologies, particularly machine learning (ML) and AI, has transformed the global workforce at an unprecedented pace. Many organizations are now implementing AI to enhance productivity and reduce operational expenses, particularly for repetitive tasks in manufacturing. AI functions as a powerful tool to enhance organizational capabilities and individual performance rather than as a standalone solution. A key perspective in this field is that workers are not in competition with AI itself, but rather with other individuals who can effectively use AI as a productivity-boosting tool (Chamorro-Premuzic, 2024). As professional interactions move toward human-machine models, the way users engage with these technologies will determine whether the relationship enhances or restricts communication and efficiency (Chuang, 2024).

Improving Human-Machine Interaction (HMI) requires a comprehensive grasp of the distinct capabilities of both people and technology. Humans provide unique value in areas like intuition, creativity, empathy, and common sense—traits that current machines do not possess. While humans can navigate complex, novel situations and adapt rapidly, machines are bound by pre-programmed logic and require specific training for new activities. However, machines significantly outperform humans in accuracy, processing speed, and consistency, as they manage large datasets without succumbing to emotional bias or fatigue (Mourtzis et al., 2023; Sanders &

Wood, 2019). The growth of HMI is being fundamentally shaped by AI integration, which facilitates more intelligent systems by providing users with real-time analytics and predictive data. By 2025, more than 35% of HMI solutions are projected to incorporate AI to improve machine control (Pangarkar, 2025). Table 1 shows a breakdown of the key differences between traditional HMIs and AI-enhanced HMIs. However, realizing these gains requires addressing the critical sociotechnical challenges of employee resistance and low technology literacy. This market projection underscores the urgency for a conceptual framework to manage the sociotechnical transition effectively.

Table 1: Breakdown of key differences between traditional HMIs and AI-enhanced HMIs

HMI Feature	Traditional HMI (Static)	AI-Enhanced HMI (Dynamic)
Primary Focus	Manual control and data display (Wang et al., 2022)	Proactive, adaptive, and intelligent collaboration (Lu et al., 2022)
Interaction Dynamics	Reactive; initiated by the user	Proactive; provides adaptive interfaces and predictive insights (Mourtzis et al., 2023)
Data Application	Real-time monitoring of specific variables	Pattern detection within massive datasets
System Evolution	Static; requires manual intervention (Vogel-Heuser & Hess, 2016)	Dynamic; improves through machine learning (Pangarkar, 2025)
User's Role	Operator and controller (Sanders, 2019)	Strategic decision-maker and collaborator (Wilson, 2024)

To reach peak HMI performance, the strengths of both parties must be integrated. For example, machines can manage repetitive, time-intensive tasks, freeing humans to focus on strategic and creative goals. Additionally, machines can process data and present it in highly actionable formats. Achieving this synergy requires further advances in AI and ML to more closely mimic human decision-making processes. Algorithms can now analyze large datasets to identify patterns that optimize manufacturing, leading to reduced waste and higher output. These innovations have already improved workforce planning, quality management, and factory sustainability (Sanders & Wood, 2019; Özdemir & Hekim, 2018).

Industry 4.0, introduced in 2011, focuses on integrating digital and physical systems to enable high-level automation through technologies such as the Internet of Things (IoT) and digital twins (Wang et al., 2022; Vogel-Heuser & Hess, 2016; Soori et al., 2023). It has improved production flexibility and supports remote operations and personalized manufacturing. Industry 5.0 builds on this by emphasizing the synergy between humans and machines and prioritizing sustainability, resilience, and human-centricity (Xu et al., 2021). This paradigm introduces Human-Centric Smart Manufacturing (HCSM), which values human expertise, flexibility, and creativity (Lu et al., 2022). This approach leverages the unique strengths of both humans and machines to foster innovation. Success in Industry 5.0 depends on HMI, as worker roles continue to evolve. An optimized HMI ensures that operators receive the necessary support, with machines serving as extensions that aid decision-making and improve human well-being through intuitive assistance.

Purpose of Study

The realization of AI-driven productivity gains in the workplace is consistently hindered by low employee receptivity and resistance to change, underscoring the shift from human-human to effective HMI as a critical sociotechnical challenge. To better understand this barrier, our research focuses on

1. Identifying key principles for successful AI-driven HMI from the engineering workforce insights, and
2. Establishing a robust, empirically testable hypothesis concerning employee behavior based on the sociotechnical systems (STS) theory.

Drawing on practical insights into human resource development (HRD) and organizational psychology, this study examines the nuanced perceptions and decision-making processes that employees use when interacting with AI-driven HMI systems at work.

Deductive reasoning is used to formulate specific predictions and develop hypotheses, which can be tested with data to draw conclusions and support valid inferences in future research. For this study, the process (1) began with identifying gaps and problems based on a general understanding of HMI, and (2) made assumptions to create a hypothesis from existing theory. This top-down logical approach provides practical guidance for designing a coherent, rigorous study on the continued development of AI-Driven HMI (Robinson & Bailey-Rodriguez, 2023).

The core hypothesis of this research is that *employee perception of AI as an 'augmentation tool' (designed to augment skills) is a stronger predictor of AI-driven HMI utilization than the perception of AI as a 'productivity-efficiency tool' (designed to replace tasks)*. This hypothesis is positioned early to guide the subsequent theoretical development and framework construction.

This paper employs a deductive qualitative methodology to synthesize existing literature and form specific predictions. The synthesis process followed a top-down logical approach: (1) identification of gaps in HMI receptivity within Industry 5.0 literature; (2) selection of sources based on STS theory and HCSM (e.g., Lu et al., 2022; Xu et al., 2021); and (3) integration of organizational psychology principles (e.g., Maslow's hierarchy) to create a testable framework. Sources were selected for their relevance to the engineering workforce's transition from Industry 4.0 to 5.0 and their focus on human-centeredness.

Theoretical Framework

For this study, STS theory is used to understand human-technology relations and explain the interaction between social support and technological infrastructure in the workplace (Cummings & Worley, 2014). The STS theory integrates social and technical aspects (as interdependent parts of a complex system) and explains how human workers (as self-organized units) optimize a system that encompasses people, technology, infrastructure, culture, processes, and metrics (Ang et al., 2024). The sociotechnical system integrates human, machine, environmental, work-activity, and organizational structures and processes toward a common goal (Carayon et al., 2015). Its goal is to account for the optimal interaction between a *social subsystem*, which involves the coordination and management of individuals and teams, and a *technology subsystem*, which includes equipment, technology, and work organization (Carayon et al., 2015). The STS perspective facilitates systematic review, explains dynamic interaction, promotes joint optimization, focuses on human-centered design, and highlights the influence of macro-level factors (such as policy context and community) within a complex, goal-oriented system. (Dell et al., 2021). Researchers have used STS theory to

- analyze the complex interplay between technical and social components in health care delivery (Chisholm & Ziegenfuss, 1986),
- develop contemporary organizational development interventions that focused on self-leading work groups performing interrelated technological tasks (Appelbaum, 1997),
- develop the conceptual framework of workplace safety (Carayon, 2015),
- optimize the conduct of systematic reviews (Dell et al., 2021),
- enhance enterprise resource planning systems on organizational productivity (Chiawah et al., 2022), and
- advance human-robot collaboration for organizational development in construction (Ang et al., 2024).

The STS theory has been widely used in the social and behavioral sciences (Musa et al., 2024; Winter et al., 2014). Ang et al. (2024) conducted a case study on the design and development of human-robot teams in construction and identified the importance of research-practice-policy partnerships and collaborations, using STS approaches, to navigate the challenges of rapidly evolving technological landscapes.

The STS theory emphasizes the importance of the human aspect of technological innovation at work and provides a useful lens for analyzing the complexity of human-machine integration (Lee & Lee, 2022). According to Pasmore et al. (2019), advanced technology is outpacing the development of new organizational designs, creating a gap between available tools and their effective use. Drawing on sociotechnical thinking in machine-driven work settings, they concluded that the needs of human beings and social systems should be understood and addressed through technical capabilities. To drive organizational innovation and facilitate technology transfer, human factors in technology design and users' ability to use AI tools should be considered (Ang et al., 2024). *People* are a core component of Davis et al.'s (2014) socio-technical hexagon model, which emphasizes the importance of interrelationships among components in understanding complex systems.

Integrating human and AI forces, known as collaborative intelligence, into STS theory can help to address the dynamics of AI-reshaped human behaviors, communication modes, and work processes (Ang et al., 2024). Ang et al. (2025) adapted STS principles to examine the unique challenges of designing and developing human-robot teams (i.e., systems in which humans and intelligent robots collaborate socially and interdependently to achieve shared goals). They introduced a comprehensive framework of 34 STS principles, including 26 adapted principles (e.g., adaptability, autonomy, boundary controls, joint optimization, and continuous learning) and 8 newly proposed principles (i.e., agile & responsive thinking, adaptive autonomy, cognitive workload management, collaborative sensemaking, ethical considerations, trustworthiness, transparency and explainability, unpredictability management) to address gaps in traditional STS thinking. In response to the complexities of human-robot collaboration, they revised the STS framework to place greater emphasis on human-centric design, dynamic trust relationships, collaborative sensemaking, and risk management of AI uncertainties (Ang et al., 2025).

The application of STS provides a comprehensive framework for understanding and improving the systematic review process. By considering both social and technical elements, researchers can make informed decisions about integrating new technologies into their workflows, ultimately enhancing the quality and impact of their reviews.

Adaptive HMI in the Modern Industrial Context

Sustainability and resilience are central to Industry 5.0 and remain long-term objectives for the manufacturing sector (Yang et al., 2024). Within this framework, manufacturing employees should be viewed through two lenses (Janssen et al., 2019; Yang et al., 2024). First, highly skilled professionals remain central to HCSM environments. As factories become more complex, these workers must develop deeper expertise to manage precision systems. HMI systems should act as assistants that reduce physical strain while amplifying their skills' impact. Conversely, as systems become more integrated, some operators may act as "non-professional users" in certain contexts. Supporting these users requires HMI designs rooted in empathy, personalization, and enhanced interactivity to reduce cognitive load, improve well-being, and foster creativity (Sanders & Wood, 2019).

To thrive in the future of work, technology literacy and critical thinking are crucial. Technology literacy involves the ability to use, understand, manage, and evaluate technology effectively, encompassing problem-solving and adaptability. A literate individual understands how technology works and its impact on society (Long & Magerko, 2020). Key dimensions of technology literacy include (1) understanding fundamental technical concepts and principles, (2) applying critical thinking to technical issues and making informed decisions, (3) having the ability to use digital tools to manage systems and achieve goals, and (4) having the capacity to learn and adjust to emerging tools. AI literacy specifically impacts acceptance by reducing fear, building trust, and fostering positive attitudes toward adoption (Long & Magerko, 2020). It also improves HMI effectiveness by enhancing user experience and reducing training hurdles. Furthermore, powerful AI tools are only effective if they are actually used. Workers' motivation and action are driven by individual needs (Venkatesh et al., 2012). According to Maslow's hierarchy, the need for job security can motivate individuals to upskill (Maslow, 1954; Werner, 2022). However, if an employee feels their needs for self-actualization or belonging are already met, they may see no reason to adopt new AI tools, leading to negative attitudes toward HMI engagement. It is important to differentiate between attitude (an internal feeling or opinion) and behavior (an external action or response to the environment). While attitudes are internal influences, they can become stable and difficult to change, potentially creating barriers to AI implementation or counterproductive work behaviors (Fishbein & Ajzen, 1975, p. 216).

The Impact of AI-Driven HMI on the Engineering Field

The integration of AI-driven HMI is fundamentally reshaping engineering by transitioning traditional workflows into sophisticated sociotechnical systems in which humans and machines function as strategic partners. Unlike traditional automation, AI-driven HMI serves as an intuitive extension of the engineer's expertise. This shift requires a critical evolution from 'task-execution' to 'system-orchestration', necessitating enhanced technology literacy to leverage AI as a productivity-boosting partner rather than a replacement. These advanced HMI systems provide proactive, predictive insights and manage repetitive, data-intensive tasks, thereby empowering engineering professionals to dedicate their unique human strengths, such as creativity, intuition, and complex problem-solving, to higher-level strategic goals. Ultimately, the impact on the engineering workforce is marked by a critical need for enhanced technological literacy and upskilling, ensuring that practitioners can leverage AI effectively to boost productivity and innovation, rather than viewing it as a replacement for human talent. Through empathetic and adaptive design, AI-driven HMIs aim to reduce engineers' cognitive workload, thereby significantly improving operational efficiency and overall worker well-being.

To understand and navigate the complexities of AI-Driven HMI in a rapidly changing world, several critical gaps must be addressed.

- *Adaptability and Ethics*: There is a need for more research on fostering employee resilience and ensuring the ethical use of HMI at the individual and organizational levels (Chamorro-Premuzic, 2024; Gold et al., 2024).
- *Integration Methodologies*: Scientific research on frameworks for merging AI into existing workflows while maintaining positive employee sentiment is currently limited.
- *HRD Strategic Support*: Research into HRD initiatives that enhance HMI effectiveness—specifically those that promote employee autonomy and self-actualization—is inadequate (Ardichvili, 2022).

Exploring the intersection of HMI and AI in engineering reveals how "adaptive" systems move beyond static dashboards to become active teammates. These systems adjust based on the user's specific cognitive load, task goals, and technical literacy. For instance, an adaptive HMI for a CNC machinist differs from one for a quality control (QC) engineer. An adaptive HMI recognizes that a machinist and a QC engineer interact with the same physical reality, the manufactured part, through entirely different functional lenses (Srinivasa et al., 2013). For CNC Machinists focused on operational performance and safety, the HMI prioritizes real-time execution and management of physical constraints. When AI detects a slight increase in spindle vibration and heat during high-speed milling, the HMI shifts from a general status view to a Predictive Maintenance Overlay. This overlay highlights the specific tool path causing stress and suggests a 10% reduction in feed rate to prevent tool breakage. For seasoned machinists, it may show raw vibration data, while for newer operators, it could use a color-coded "Heat Map" with a prompt: “Tool wear approaching threshold. Swap tool at next cycle stop?” Meanwhile, for QC Engineers focused on validation and root cause analysis, the HMI emphasizes historical data and compliance. When a similar vibration event occurs, the QC engineer receives a notification on their tablet. The HMI then displays a Statistical Process Control Dashboard, indicating deviations from the nominal dimensions of the last five parts produced during the event, rather than the real-time spindle speed. The AI correlates the vibration data with results from the Coordinate Measuring Machine, showing that despite the vibrations, the parts stayed within acceptable tolerances, and this is relayed as a “Risk Assessment” rather than an "Operational Warning."

Collaborative sensemaking is the process by which a human and an AI combine their unique strengths, the AI's pattern recognition and the human's “big picture” or “out-of-the-box” reasoning, to understand an ambiguous event. For example, when an AI flags a potential anomaly in a chemical process, “collaborative sensemaking” (Dian et al., 2025) works as follows. In a continuous-flow chemical reactor (Hassan et al., 2025), an AI detects a 5% rise in pressure in a secondary cooling loop and initiates a Collaborative Process. Instead of just issuing an alarm, the AI provides a Justification Map that shows the flow rate is stable despite the pressure increase, suggesting sensor drift or a minor blockage rather than a pump failure. The engineer, drawing on their understanding of AI capabilities, recognizes that the AI might overlook external factors and prompts the system to check the ambient temperature sensors from the past hour. The AI detects a spike in outdoor temperature that corresponds with the increase in pressure. This prompts the engineer to conclude that the sun is warming an uninsulated section of the piping, leading to thermal expansion. The AI supports this conclusion by modeling the thermal load. As a result, rather than suggesting an expensive shutdown of the plant, the team decides that the process can safely proceed with a minor adjustment to the set-point to accommodate the afternoon heat.

Key Aspects and Needs of the Current Engineering Workforce

The current engineering workforce faces a fundamental need for enhanced technological and AI literacy, extending beyond basic operational knowledge to encompass critical thinking, independent problem-solving, and the ability to evaluate the ethical and societal impacts of new tools (Martinez, 2025). To navigate the transition to AI-driven environments effectively, workers require robust organizational support and resources that foster adaptability and confidence in making informed decisions in complex scenarios. A critical driver of this transformation is the individual's motivation to upskill and reskill, often rooted in core psychological needs, such as job security, and institutional conditions, such as autonomy (Suengkamolpisut & Sukustit, 2025). When these needs are recognized, employees are more likely to remain open-minded about technological change and proactive in their learning. Furthermore, as industrial environments become more complex, the workforce must balance specialized technical expertise with the ability to interact with an empathetic, personalized HMI that accommodates varying levels of manufacturing knowledge (Rahman et al., 2025). Cultivating a positive internal attitude is essential, as these deep-seated perceptions gradually influence external work behavior and ultimately determine the success of human-machine collaboration within the modern sociotechnical landscape.

Key Principles of Successful AI-Driven HMI for Future Engineering Workforce

The foundation for successful AI-driven Human-Machine Interaction within the future engineering landscape rests on the core principle of framing technology as a collaborative intelligence tool designed to augment human skills rather than a productivity-efficiency tool aimed at replacing tasks. Achieving this synergy requires a holistic sociotechnical approach that balances tangible infrastructure with intangible processes, such as social norms and optimized work workflows, to create a truly supportive environment for digital transformation. Furthermore, successful implementation depends on designing interfaces that are intuitive, empathetic, and capable of providing real-time feedback, thereby reducing engineers' cognitive workload and enhancing their overall well-being in an Industry 5.0 context. By grounding these interactions in established theoretical frameworks such as the technology acceptance model and sociotechnical systems theory, organizations can foster a resilient workforce that views AI as an extension of their own expertise rather than a competitive threat.

The US government is actively pursuing policies and investments to transform the workforce for high-tech manufacturing. Organizations and human resource leaders should keep up with technological developments and promote a positive attitude toward AI tools. However, only 21% of human resource leaders are actively involved in the organization's AI strategy due to a lack of necessary AI expertise (Harvard Business Review Analytic Services, 2025). A lack of understanding of employees' attitudes (particularly when negative) towards AI tools may create barriers to AI implementation (Lichtenthaler, 2020) and lead to counterproductive work behaviors (Taşgit et al., 2023).

Empirical research that measures employees' attitudes, behaviors, and needs toward HMI is crucial. An AI-driven HMI analysis tool can incorporate the social, technological, and environmental aspects (as illustrated in Table 2) within the STS Framework. An example from a social aspect could be "I found AI features in performing my tasks very helpful, regardless of what other people think." Another example from a technological perspective is: "I expect AI-driven HMI can predict my actions and provide personalized recommendations based on my needs for job efficiency." An environmental aspect can be examined, such as "our organizational culture is positive on using AI-driven features within HMIs." For perceived augmentation, an item might be: "Using AI-driven features in my work allows me to focus on the more creative aspects of my job." Therefore, we argue that the three-aspect framework of STS can be used to analyze the complexity of human-machine integration and promote the success of AI-driven HMI. Table 3 operationalizes the three key aspects of our framework, providing specific components, justifications, and measurement approaches.

Table 2: Key Aspects of Successful AI-Driven HMI based on the STS Theory

AI-Enhanced HMI	**Key Aspects of Successful AI-Driven HMI**		
	Social Aspect: (Society Dynamics, Human Behaviors, Subjective Norms)	**Technological Aspect:** (Methods, Work Design, Techniques, Equipment)	**Environmental Aspect:** (Support System)
Proactive, adaptive, and intelligent collaboration	Connect to actual work; comfortable to partner w/AI	Change job functions & work tasks	Clear policies & guidelines
Proactive; provides adaptive interfaces & predictive insights	Confidence to follow; accept (or refuse)	Predict actions & provide personalized recommendations	Customized interfaces
Pattern detection within massive datasets	Partner with AI to enhance job efficiency and creativity	Troubleshoot issues	Training programs to build AI literacy
Dynamic; improves through machine learning	Comfortable to consult an AI-driven feature in the HMI for assistance	Personalized support or guidance	Positive organizational culture; accessible environment
Strategic decision-maker and collaborator	Improve the efficiency of the manufacturing process	AI-driven HMI suggestion or alert	Support from leaders and top management

Table 3: Operational Components of Successful AI-Driven HMI

Aspect	Operational Components of Successful AI-Driven HMI		
	Operational Component	**Theoretical Justification**	**Measurement Approach**
Social	Perceived Augmentation	Collaborative Intelligence (Ang et al., 2024)	Likert scale: 'AI supports my creative intuition'
Technical	Adaptive Autonomy	Cognitive Load Theory (Ang et al., 2025)	System Usability Scale (SUS) for AI alerts
Environmental	Psychological Safety	STS Theory (Carayon et al., 2015)	Survey on leadership support for AI-literacy
Integration	Workflow Alignment	Work Design (Sanders & Wood, 2019)	Task analysis of AI-human handoffs
Policy	AI Literacy	Standardized certification programs for ML interface use.	Quiz: Mastery of predictive interface principles.

Thus, as we mentioned, we hypothesize that *employees' perception of AI as an 'augmentation tool' (designed to augment skills) is a stronger predictor of HMI utilization than their perception of AI as a 'productivity-efficiency tool' (designed to replace tasks)*. The AI-driven HMI may refer to the use of AI technologies (e.g., natural language processing, image recognition, and generative AI) to identify defects, with the HMI then alerting or providing information for decision-making. A comprehensive survey instrument should be designed to test this hypothesis by assessing the three key aspects of successful AI-driven HMI and to measure employees' attitudes, behaviors, and core needs regarding AI utilization, thereby providing a much-needed tool for both researchers and practitioners.

Proposed Empirical Validation Roadmap

To validate the proposed hypothesis and framework, a multi-stage empirical study is proposed:

1. *Survey Instrument Design*: A 15-item questionnaire will be developed, adapting scales from the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2012) and the System Usability Scale (SUS). Items will measure 'Perceived Collaboration' vs. 'Perceived Replacement'.
2. *Validation Process*: Beyond Cronbach's alpha for internal consistency, the study will conduct Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to establish construct validity. Model fit will be assessed using TLI, CFI, and RMSEA (acceptable thresholds of > 0.90 and <0.08, respectively).
3. *Pilot Case Study*: A pilot study within a smart manufacturing facility (Industry 4.0/5.0 transition) will be used to gather initial data from N=30 engineering professionals to refine the instrument.

Discussion and Alternative Explanations

While this framework prioritizes employee perception, alternative factors may exert greater influence on HMI utilization. For instance, 'Technical Reliability' is a prerequisite; if an AI system provides inaccurate data, utilization will fail regardless of positive attitudes (Mourtzis et al., 2023). Furthermore, 'Organizational Mandates' might force utilization through strict policy, although this may lead to counterproductive work behaviors if human-centric needs are ignored (Taşgit et al., 2023). Future research should measure these variables to assess the relative weight of perception compared with structural and technological factors.

A critical component of successful HMI integration is recognizing the traditional diversity markers within the engineering workforce. As of 2023, the share of women in engineering occupations was only 15% in the United States, a figure that has grown slowly over the last three decades. This representation is further fragmented when viewed through a racial lens: White women represent 9.1% of the total engineering workforce, followed by Asian women at 4.8%, while Hispanic or Latina women account for 1.6%, and Black women comprise a mere 0.5%. In the specialized field of artificial intelligence, women comprise only about 22% to 30% of the global talent pool, with representation dropping to less than 15% at senior executive levels. These disparities highlight the urgent need for HMI designs and HRD initiatives that are inclusive of the diverse lived experiences and perspectives of a heterogeneous workforce (Feldman & Cherry, 2024).

Implications for HRD Practices

Effective performance is often driven by positive attitudes and clear objectives, whereas negative mindsets can lead to disengagement and hinder successful AI adoption. To nurture a strong AI culture, HRD professionals should assess employees’ perspectives, intentions, and behaviors toward AI. They can implement *AI-driven learning management systems* to support personalized learning and anticipate talent and performance needs, thereby advancing organizational human capital. Real-time *AI coaching* also plays a crucial role in enhancing both individual and team performance and supporting ongoing behavioral change. Importantly, organizations should establish *AI policies* that reflect their values and ethical standards, providing guidance and support for employees’ judgment and decision-making.

When designing training that positions AI as a tool for human augmentation, HRD professionals should prioritize practical, people-oriented, and collaborative approaches. For example, they can *redefine roles* to highlight uniquely human strengths (such as creativity and empathy) and to establish human oversight processes in which humans review and approve crucial decisions, reinforcing human accountability. They can *revise job descriptions* to emphasize critical thinking and strategic decision-making, with AI as a supportive resource. They can also *foster AI literacy* through interactive, experiential learning and train employees to critically evaluate AI outputs, strengthening their ability to spot bias or errors. Moreover, to reduce anxiety and build confidence when engaging with AI, HRD professionals can *develop a psychologically safe environment* by cultivating a culture where leaders advocate for AI adoption and employees feel comfortable expressing opinions and challenging AI outputs without fear of consequences, and ensuring employees understand how AI works, its limitations, and best practices for using it effectively.

Conclusions and Recommendations

This study presents a preliminary conceptual framework for understanding the human factors that govern successful AI integration, providing vital guidance for HRD initiatives and informing best practices for AI implementation within organizations. While limited by a lack of primary empirical data, the framework provides a structured pathway for future researchers to test sociotechnical principles in engineering education and workforce development. A significant conclusion drawn from this synthesis is that employees are far more likely to embrace AI when it is framed as a collaborative intelligence tool that augments their inherent skills rather than a productivity-efficiency tool designed to replace their roles. Furthermore, successful integration requires an AI infrastructure and a shift toward Human-Centric Smart Manufacturing, where technology serves as an assistant to enhance human well-being and foster organizational resilience. It is recommended that organizations address the gap in human resource leadership, as active HR involvement is vital to managing the sociotechnical transition (Harvard Business Review, 2025).

Future research can employ quantitative methods to measure employees' attitudes, behaviors, and needs regarding AI and HMI in the workplace, and to examine the organizational challenges of implementing AI-driven HMI. To support this, it is recommended that organizations actively address the current gap in human resource leadership, as increasing the involvement of these professionals is vital for promoting positive attitudes and managing the sociotechnical transition. Researchers are also encouraged to investigate HRD initiatives that promote the effective implementation of AI-driven HMIs in the workplace. Efforts should prioritize developing AI literacy to reduce fear and mistrust, and focus on empathetic design and structured validation processes to ensure that HMI systems meet the diverse needs of both professional and non-professional users within the engineering workforce. Furthermore, enhancing diversity can be achieved by adopting empathetic design approaches that focus on understanding and addressing the emotional, cognitive, and physical needs of a wide range of AI users. Future empirical validation could investigate how variables such as age, educational background, and cultural attitudes toward technology might moderate the relationship between AI perception and HMI utilization.

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