Positioning Industrial Engineering in the Era of Industry 4.0, 5.0, and Beyond: Pathways to Innovation and Sustainability

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Abstract

Industrial Engineering (IE) has continually evolved to optimize systems and processes, addressing the demands of an ever-changing industrial landscape. From its historical roots in work organization to its current role in Industry 4.0 and the emerging Industry 5.0 paradigm, IE has remained central to fostering innovation, efficiency, and sustainability. Industry 4.0 has revolutionized industrial systems through the integration of Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), and advanced data analytics, enabling real-time decision-making and resource optimization. Building on this foundation, Industry 5.0 shifts the focus to human-centric, ethical, and sustainable practices, leveraging advanced technologies such as cognitive digital twins, collaborative robots, and resilient systems to enhance human-machine collaboration and environmental responsibility. This study explores the evolution of IE, its foundational principles, and its critical role in addressing modern industrial challenges. It highlights strategies for advancing the IE profession and academic programs, ensuring their relevance in the digital era. Additionally, it identifies six future research directions, including Human-AI collaboration, Adaptive and resilient systems design, advanced sustainability models, ethical and inclusive systems design, digital twin integration, and quantum computing, as key enablers for driving innovation and achieving global sustainability goals. By bridging the technological advancements of Industry 4.0 with the human-centric and sustainable objectives of Industry 5.0, IE is positioned to lead the transformation of industrial systems, fostering a resilient, inclusive, and sustainable future.

Keywords: Industrial Engineering, Industry 4.0, Industry 5.0, Cyber-Physical Systems (CPS), Human-AI Collaboration, Sustainability, Resilient Systems, Digital Twins, Circular Economy, Smart Manufacturing, Quantum Computing

1. Introduction

Industrial Engineering (IE) lies at the intersection of engineering, management, and technological innovation, aiming to design, optimize, and sustain complex industrial systems (IS). Over its long history, IE has demonstrated a remarkable capacity to evolve in response to changing industrial demands [1,2]. From the optimization of manual labor in early civilizations to leveraging cutting-edge digital technologies today, IE has consistently focused on improving productivity, efficiency, and sustainability [3]. As a discipline, it has played a pivotal role in shaping industrial revolutions, from mechanization in the first Industrial Revolution to the introduction of lean systems and automation in the late 20th century [4,5].

In the current era, IS face unprecedented challenges and opportunities brought about by the rise of Industry 4.0 (I4.0), characterized by the integration of advanced technologies such as Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), and big data analytics (BDA) [6,7]. These technologies enable the creation of smart factories with capabilities for real-time monitoring, predictive maintenance (PdM), and autonomous decision-making [8,9]. Through the use of digital twins (DTs), for example, industries can simulate and optimize production processes, resulting in reduced downtime and enhanced resource efficiency [10]. However, the rapid adoption of these technologies has also brought about challenges, including cybersecurity risks, ethical dilemmas in AI usage, and the marginalization of human roles in automated environments [11,12].

Recognizing these challenges, Industry 5.0 (I5.0) has emerged as a response, emphasizing human-centric and sustainable IS. Unlike its predecessor, which prioritized automation and efficiency, I5.0 seeks to harmonize technology and human involvement by fostering collaboration between humans and intelligent systems [13]. Technologies such as Human-Robot Collaboration (HRC), cognitive DTs, and Explainable AI (XAI) enable workplaces that are safer, more inclusive, and more adaptive to human needs [14,15]. Moreover, I5.0 emphasizes the integration of sustainability principles into industrial practices, aligning with global initiatives such as the United Nations Sustainable Development Goals (SDGs) [16].

In this evolving context, IE is uniquely positioned to bridge the gap between technology and human-centric IS. Its core competencies in systems design, process optimization, and data-driven decision-making provide the necessary foundation for addressing modern industrial challenges. By integrating emerging technologies into traditional practices, IE can drive innovation in areas such as smart manufacturing, supply chain (SC) resilience, and adaptive production systems [17,18]. Furthermore, IE contributes to achieving sustainability by optimizing energy use, reducing waste, and enabling circular economy (CE) models [19,20].

This study seeks to position IE as a cornerstone in the era of I4.0, I5.0, and beyond by addressing several key objectives. First, it provides a historical perspective on the evolution of IE, tracing its journey from early practices to its current integration with advanced digital technologies. Second, it explores the principles of IE, contextualizing its foundational concepts within the frameworks of I4.0 and I5.0 to highlight their relevance in modern IS. Third, it discusses strategies for advancing the IE discipline, including enhancing its academic programs, fostering industry partnerships, and adapting to the rapidly changing industrial landscape [21,22].

The present study further identifies future research directions that are critical for advancing the discipline, including Human-AI collaboration (HAC), the design of adaptive and resilient systems, and the integration of quantum computing (QC) into industrial applications. For example, research into HAC aims to enhance the synergy between human expertise and AI-driven decision-making, ensuring greater trust, transparency, and adaptability in complex industrial environments [23–25]. Similarly, resilient system design focuses on enabling IS to withstand and recover from disruptions, whether from SC shocks or environmental challenges [26–28]. The potential of QC, meanwhile, offers transformative capabilities for solving optimization problems in manufacturing and supply chains that are currently beyond the reach of classical computing methods [29–31].

Through this comprehensive review, the study aims to demonstrate the critical role of IE in driving innovation, sustainability, and human-centric design in modern industries. The insights provided herein will serve as a roadmap for researchers, practitioners, and policymakers, offering actionable strategies to harness the full potential of IE in shaping the future of IS. Ultimately, the study highlights how IE is not only a field of study but a catalyst for addressing global challenges and advancing industrial transformation.

This paper is structured to provide a comprehensive exploration of IE in the context of I4.0, I5.0, and beyond. Section 2, *The Evolution of Industrial Engineering*, traces the historical trajectory of IE, highlighting its transformation from early work organization principles to modern digital and human-centric paradigms. Section 3, *Principles of Industrial Engineering*, identifies and elaborates on the foundational principles that guide the discipline, showcasing their relevance in addressing contemporary challenges. Section 4, *Advancing Industrial Engineering Discipline*, delves into strategies for strengthening the profession, with subsections 4.1 and 4.2 focusing on enhancing the IE profession's visibility and modernizing academic programs to reflect emerging industry demands. Section 5, *Future Research Directions*, outlines six critical areas of research that will shape the discipline's progression, including HAC, resilient systems, and QC. Finally, Section 6, *Conclusion*, synthesizes the insights presented and emphasizes the pivotal role of IE in fostering innovation, sustainability, and inclusivity in the modern industrial landscape.

2. The Evolution of Industrial Engineering

The evolution of IE is deeply rooted in historical advancements and societal needs, evolving through several key phases (Fig. 1). From its early foundations in ancient civilizations, where concepts of work organization and logistics were applied in large-scale projects like the construction of pyramids, to the mechanization of production during the Industrial Revolution, IE has consistently sought to improve efficiency and productivity [32]. Over time, the discipline embraced scientific management principles, pioneered by Taylor and the Gilbreths, which laid the groundwork for optimizing work processes through time and motion studies. As industries recognized the importance of human factors, the Human Relations Movement integrated worker satisfaction and ergonomics into IS [1].

In the mid-20th century, the Systems Approach and Operations Research (OR) expanded IE's focus to optimizing complex systems, aided by advancements in computing. This era introduced tools like linear programming, queuing theory, and simulation modeling, which remain central to modern IE practices [33–35]. The rise of automation and robotics in the 1970s and 1980s marked another transformative period, with the adoption of Computer-Integrated Manufacturing (CIM) systems, lean manufacturing (LM), and Just-in-Time (JIT) production. The globalization era further refined IE with lean thinking, Six Sigma (SS), and the need for efficient global SCs.

The emergence of I4.0 has brought about a revolution in IE by integrating Cyber-Physical Production Systems (CPPS), IIoT, drones, AI, and BDA [36–38]. These technologies enable real-time communication between machines, edge devices, and cloud systems, fostering smart manufacturing environments with distributed management functionalities [9]. However, the full potential of I4.0 lies not only in technological adoption but also in addressing the operational and safety challenges posed by such complex systems [39].

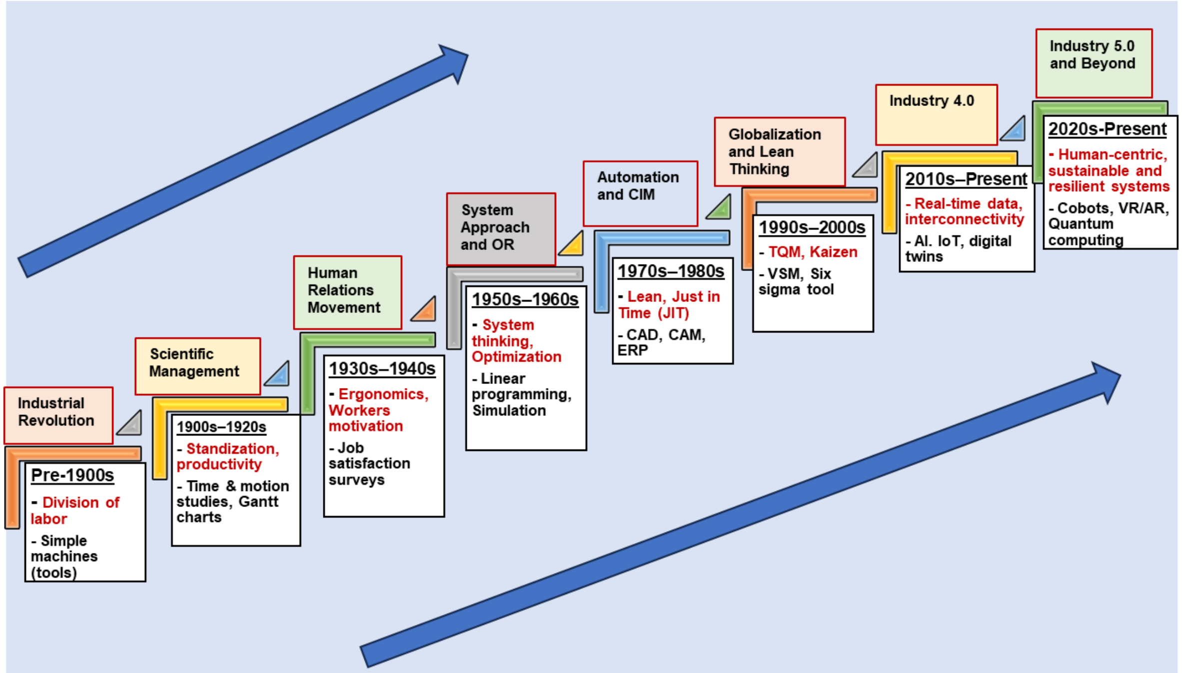

Fig. 1. Evolution of industrial engineering: key milestones, timelines, principles and tools

Building on these advancements, I5.0 introduces a new dimension that emphasizes human-centric and sustainable production systems. Unlike its predecessor, which focused on automation and efficiency, I5.0 integrates advanced technologies such as cognitive DTs and edge computing to enhance real-time decision-making and collaboration between humans and intelligent systems [40]. This paradigm shift fosters inclusivity, sustainability, and resilience in industrial operations, aligning with broader socio-economic and environmental goals [16,41].

In I4.0, IIoT platforms have become essential for monitoring and optimizing production processes, facilitating PdM and efficient resource allocation. For instance, integrating blockchain with IIoT has proven effective in creating transparent and sustainable SCs by providing real-time tracking and incentivizing eco-friendly practices [42]. However, challenges such as task scheduling in cloud-fog-edge environments and ensuring system reliability through advanced fault-tolerant mechanisms remain critical research areas [43].

I5.0 builds upon these advancements by leveraging technologies like Safety 4.0, which integrates AI, IoT, and robotics to enhance workplace safety and productivity [43]. Moreover, the incorporation of sustainable and resilient practices into IS is a cornerstone of this new era, as seen in the development of secure communication frameworks and privacy-preserving systems for real-time industrial data exchange [40]. These innovations ensure operational efficiency while prioritizing ethical considerations and worker well-being.

The adoption of I4.0 and I5.0 principles across various sectors has highlighted the dynamic capabilities required for successful integration. Research has identified key enablers such as sensing, seizing, and reconfiguring resources to adapt to rapidly changing environments [44]. Furthermore, innovative solutions like immersive virtual environments for operator training and cognitive DTs for real-time process optimization exemplify the transformative potential of these technologies [16,45].

Despite these advancements, significant gaps remain in fully realizing the potential of I5.0. Issues such as cybersecurity in interconnected systems, data privacy, and the ethical implications of AI-driven decision-making need to be addressed [46]. Additionally, the integration of these technologies in developing regions presents unique challenges, including limited infrastructure and skill gaps, which must be overcome to achieve inclusive and sustainable industrial growth [41].

Therefore, the evolution of IE from its historical foundations to I4.0 and I5.0 represents a profound transformation. By focusing on advanced technologies, human-centric designs, and sustainability, IE is poised to lead the next wave of industrial innovation, addressing global challenges and shaping a more inclusive and resilient future.

3. Principles of Industrial Engineering

This section presents the foundational principles of IE as they relate to the evolving paradigms of I4.0 and I5.0 (Fig. 2). These principles were identified through a comprehensive literature review conducted using the ScienceDirect database, focusing primarily on publications from 2024 and 2025, with some inclusion of relevant works from 2023. The analysis encompasses a wide range of journals, which were ranked according to the number of selected publications that contributed to the discussion. Fig. 3 visually depicts this ranking, highlighting journals such as *Journal of Manufacturing Systems*, *Computers & Industrial Engineering*, and *Journal of Cleaner Production* as the most frequently referenced sources. By examining these principles through a contemporary lens, this section aims to demonstrate their relevance in addressing the challenges and opportunities of modern industrial systems.

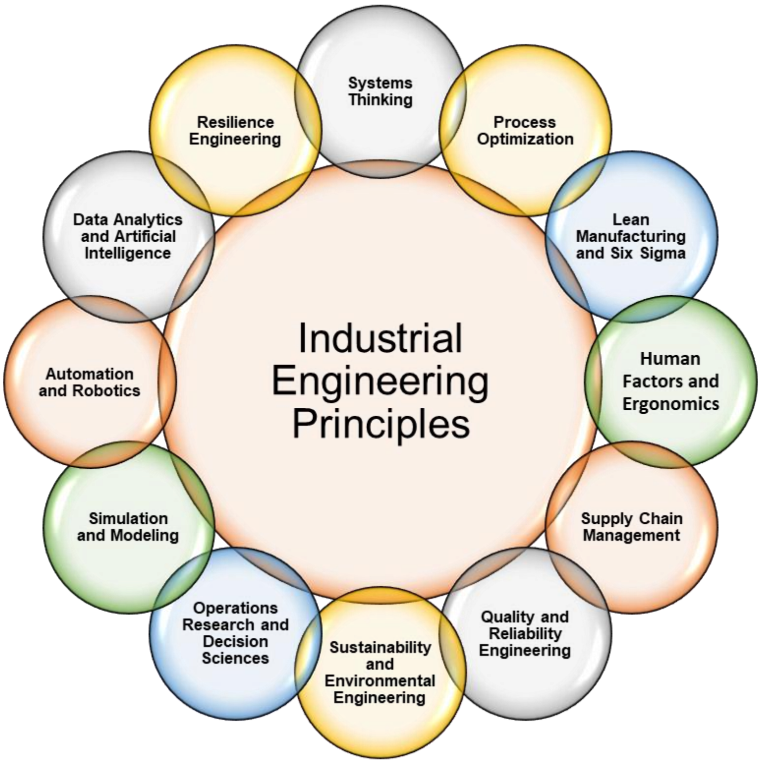

Fig. 2. Twelve key principles of industrial engineering in the context of Industry 4.0 and Industry 5.0

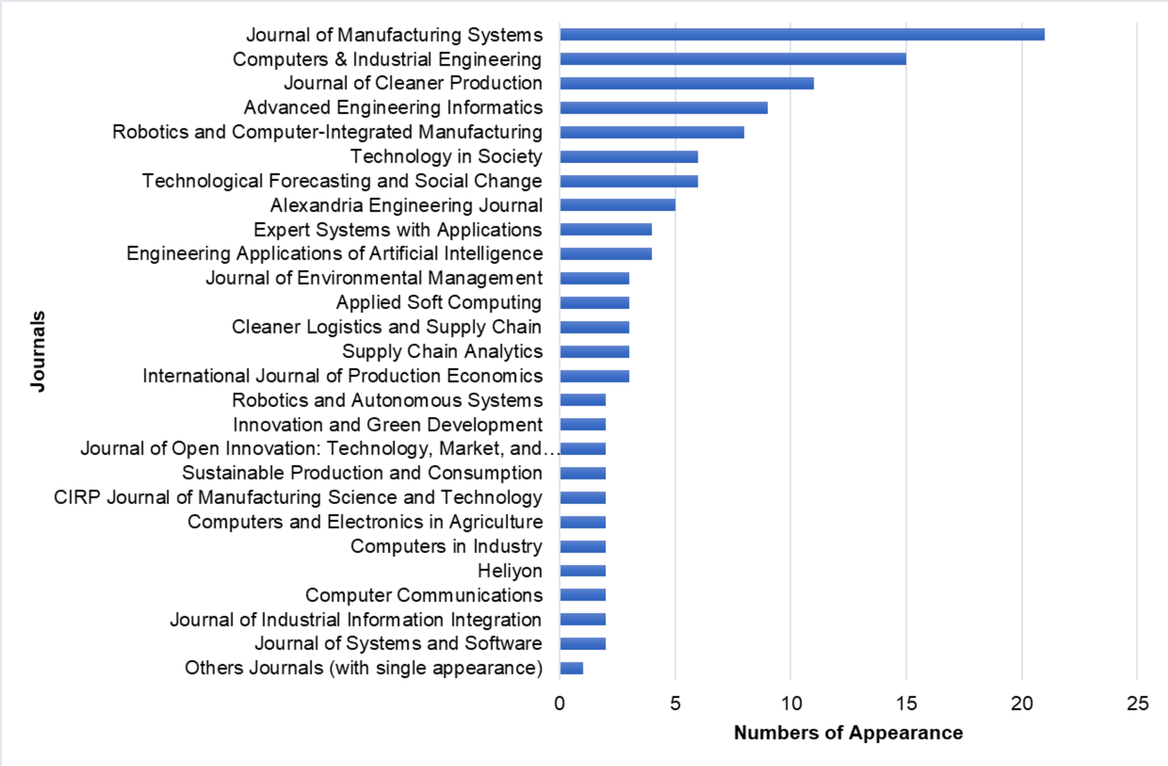

Fig. 3. Ranking of journals based on the number of selected publications contributing to the discussion of industrial engineering principles in the context of I4.0 and I5.0.

3.1 Systems Thinking

The IE has long been underpinned by systems thinking, a holistic approach that enables the analysis, optimization, and management of complex systems. This foundational principle has gained renewed significance with the advent of I4.0, characterized by the integration of CPS, IoT, and DTs. These technologies have fundamentally reshaped industrial operations by enabling real-time data exchange, PdM, and dynamic system optimization [47]. As the industrial landscape evolves toward I5.0, the focus shifts to human-centric system designs, emphasizing collaboration between humans and machines. This transition indicates the importance of balancing technological advancements with human well-being and sustainability to create resilient and adaptive IS [28].

In I4.0, CPS serves as the cornerstone of innovation, bridging the physical and digital realms to enable intelligent, interconnected systems [48]. These systems, such as CPPS, utilize sensor data and control algorithms to enhance manufacturing efficiency, scalability, and flexibility [49]. For example, CPS enables smart factories to dynamically optimize production processes in response to real-time data. However, ensuring the security and reliability of CPS remains a pressing challenge amid escalating cyber threats. Solutions like the PB-fdGAN framework enhance Collaborative Intrusion Detection Systems (CIDS) by leveraging federated learning to detect threats while preserving data privacy [47]. Blockchain-enabled decentralized systems, such as TRIPLE, further bolster CPS by ensuring secure and trusted communication, thereby improving system reliability and decision-making [50]. The integration of DTs enhances these capabilities by providing real-time monitoring and predictive analytics, enabling precise energy management and process optimization [51,52].

While I4.0 focuses on technological convergence, I5.0 emphasizes the human element, fostering environments where humans and machines collaborate seamlessly. This shift is exemplified by the rise of Industrial Metaverses, where virtual and physical systems interact to support enhanced decision-making and productivity [53]. Human-centric system designs are increasingly supported by frameworks like the Extended Iterative Process Sequence Exploration (eIPSE), which automates production step configurations in CPPS, minimizing inefficiencies and improving reproducibility [54]. Furthermore, I5.0 integrates sustainable practices, such as IoT-enabled ultra-precision machining (UPM), which employs real-time error compensation and multi-objective optimization to align manufacturing processes with ecological and societal goals [55].

The transition to smart factories is largely driven by systems optimization, encompassing resource allocation, process scheduling, and energy management. Innovations like the Energy DT simulate and adjust production parameters in real-time, leading to significant cost and energy savings [51]. Similarly, smart SCs leverage IoT and BDA to achieve end-to-end visibility and predictive insights. Blockchain technology (BT) enhances these SCs by improving transparency and traceability, ensuring resilience and sustainability even in the face of global disruptions [56].

Despite the strides made, several challenges persist in adopting systems thinking in IE. Managing the complexity of control software variants in CPPS development requires multidisciplinary coordination and advanced tools [49]. Additionally, securing reliable communication in 5G-enabled CPS ecosystems is critical to mitigating the risk of system failures [57]. To address these challenges, formal verification methods such as Timed Computation Tree Logic (TCTL) are increasingly employed to validate the operational reliability of frameworks like FedGA-Meta under diverse scenarios [58].

Notably, systems thinking remains pivotal in advancing IE practices for both I4.0 and I5.0. By integrating CPS, IoT, and human-centric frameworks, the industrial sector is evolving to achieve greater resilience, sustainability, and collaboration. Continued research and innovation, coupled with robust security mechanisms and formal verification techniques, will enhance the reliability and optimization of these systems, paving the way for future breakthroughs.

3.2 Process Optimization

The IE is dedicated to enhancing efficiency, productivity, and quality in production systems. At its core lies process optimization, a principle that has advanced significantly with the rise of I4.0 and I5.0. These industrial revolutions have introduced cutting-edge technologies to streamline operations, reduce waste, and improve overall system performance. While I4.0 focuses on data-driven, technology-enabled improvements, I5.0 emphasizes human-machine collaboration (HMC) and sustainable, customized production.

In I4.0, technologies like the IoT, AI, and Machine Learning (ML) enable smart manufacturing by collecting and analyzing vast amounts of real-time data. This data-driven approach facilitates informed decision-making and precise process control. IoT enhances real-time monitoring by capturing high-dimensional, nonlinear data, which is crucial for optimizing manufacturing systems. For instance, IoT-enabled platforms in heat pump manufacturing use multivariate time series data to identify key variables through causal inference, improving model accuracy and reducing monitoring costs [59]. Similarly, AI frameworks such as ECS-Net leverage 1D Convolutional Neural Networks (1DCNN) to achieve a 93.7% fault detection rate in wind power systems, significantly reducing energy loss [60]. In HVAC systems, AI-driven Artificial Neural Networks (ANN) dynamically adjust indoor conditions, leading to a 16% efficiency gain [61]. Simulation tools like Tecnomatix Plant Simulation further enhance system performance by allowing manufacturers to test production scenarios, achieving a 15% improvement in flexibility and output [62]. DTs, by creating real-time virtual replicas of physical systems, optimize production processes such as laser-directed energy deposition (DED), enabling precise control of temperature profiles for improved material properties [63].

While I4.0 prioritizes technological convergence, I5.0 introduces a human-centric approach, focusing on hybrid automation and mass personalization. Advanced scheduling systems integrate heuristic algorithms and deep reinforcement learning to optimize multi-stage manufacturing processes, minimizing waste and enabling manufacturers to efficiently meet unique customer demands [64]. Dynamic SC optimization, driven by hybrid models that combine IoT and BT, improves inventory and cost management while ensuring sustainability [65]. Moreover, AI-enabled frameworks such as EWDO-LSSVM enhance predictive accuracy for smart irrigation systems, enabling personalized agricultural solutions with an 87.5% accuracy [66]. These advancements showcase the potential of I5.0 to foster greater collaboration between humans and machines while aligning manufacturing processes with ecological and societal goals.

Applications of process optimization span diverse areas in I4.0 and I5.0. In smart buildings, Convolutional Neural Network (CNN)-IoT frameworks optimize energy management by predicting usage, detecting inefficiencies, and improving demand response with an 88% prediction accuracy [67]. IoT-based DWM-Evac models enhance fire emergency evacuation by leveraging real-time data for dynamic path planning, reducing evacuation times by 25 seconds compared to traditional methods [68]. In additive manufacturing (AM), the combination of CNN and the NSGA-II algorithm optimizes 3D printing parameters, resulting in a 53% improvement in mechanical performance [69].

In the era of I4.0 and I5.0, process optimization remains a cornerstone of industrial advancements. By harnessing IoT, AI, simulation, and hybrid automation, industries are achieving unprecedented levels of efficiency, flexibility, and sustainability. These technologies position IE as a vital discipline in modern manufacturing, driving the transition toward smart, human-centered, and sustainable IS.

3.3 Lean Manufacturing and Six Sigma

Lean Manufacturing (LM) and Six Sigma (SS) have long been essential methodologies in IE, aiming to eliminate waste, improve operational efficiency, and ensure high-quality outcomes. While LM focuses on streamlining processes by reducing non-value-adding activities, SS employs data-driven methods to minimize variation and defects [70]. With the emergence of I4.0 and I5.0, these principles have evolved, integrating advanced digital technologies and human-centered approaches to further enhance efficiency, sustainability, and adaptability in modern IS [71].

The advent of I4.0 has revolutionized LM by incorporating digital technologies such as IoT, AI, big data, and CPS. This evolution, known as Lean 4.0, enables real-time data collection and analysis to optimize workflows, identify inefficiencies, and reduce waste [72]. IoT sensors, for instance, monitor machine performance to facilitate PdM, minimizing downtime and improving productivity. BDA further streamlines operations by identifying bottlenecks and enhancing production flexibility. Costa et al. [73] demonstrated the integration of LM and I4.0 through ISM-MICMAC analysis, identifying critical variables for a structured framework to achieve environmental sustainability. This alignment not only enhances operational efficiency but also supports global sustainability goals.

In I5.0, LM evolves into a more human-centric framework, emphasizing collaboration between human expertise and advanced automation. This paradigm leverages human creativity and intuition to address complex problems that automated systems cannot resolve. For example, Tetteh et al. [74] explored Lean 4.0 adoption in Ghana's pharmaceutical sector, highlighting the importance of integrating human decision-making with digital tools. Their findings highlight how management commitment and the synergy between human expertise and automation drive long-term quality and performance improvements.

The SS, when combined with I4.0 technologies, enables precise quality control through advanced analytics and real-time monitoring. DTs, for instance, simulate production processes, allowing for early defect detection and optimization. Nakandala et al. [71] emphasized that lean practices drive I4.0 adoption by fostering exploitative learning, which enhances operational performance through defect reduction and consistent quality control. By leveraging these technologies, SS ensures that manufacturing processes meet stringent quality standards while maintaining efficiency.

Sustainability has emerged as a key focus in the evolution of LM. Sustainable Lean Six Sigma (SLSS) frameworks, such as the one proposed by Utama and Abirfatin [75], integrate lean principles with green initiatives to improve the Manufacturing Sustainability Index (MSI). Tools like Sustainable Value Stream Mapping (Sus-VSM) and Failure Mode and Effect Analysis (FMEA) help identify and mitigate inefficiencies while promoting environmentally friendly practices. Similarly, Sodkomkham et al. [76] demonstrated how Material Flow Cost Accounting (MFCA) and IoT can enhance water use efficiency in the beverage industry, aligning Lean's waste reduction philosophy with environmental sustainability.

Leadership and organizational culture play a crucial role in successfully implementing Lean principles in the digital age. Gatell and Avella [77] identified lean leadership competencies such as customer orientation, continuous improvement, and problem-solving as vital for fostering a culture of innovation and adaptability. Additionally, Saradara et al. [78] proposed a framework that integrates Lean Project Delivery Systems (LPDS) with CE principles, enhancing resource efficiency and minimizing waste throughout a product's lifecycle.

The application of Lean 4.0 and SS extends beyond traditional manufacturing to sectors such as healthcare, logistics, and construction. Javaid et al. [79] illustrated how Lean 4.0 reduces medical errors and waste in healthcare, improving overall efficiency. In the construction industry, Dara et al. [70] demonstrated the use of Lean tools like JIT and Total Quality Management (TQM) to minimize inefficiencies in precast production processes. These applications highlight the versatility of Lean and SS in driving efficiency and quality across various industries.

Despite their benefits, integrating Lean and SS with I4.0 technologies presents challenges, including high implementation costs, resistance to change, and a lack of digital skills among workers. Bueno et al. [72] emphasized the need for clear frameworks and success factors to overcome these barriers. In I5.0, the challenge lies in balancing automation with human-centric approaches. Salvadorinho et al. [80] stressed the importance of fostering a culture that respects human input while leveraging technology to achieve sustainable and efficient operations.

The integration of LM, SS, and I4.0 technologies signifies a transformative shift in IE. By adopting real-time digital tools and fostering human-centered approaches, industries can achieve unparalleled levels of efficiency, quality, and sustainability. As research and implementation frameworks evolve, I5.0 offers exciting opportunities to redefine operational excellence, blending technology and human expertise for a more adaptive and resilient industrial future.

3.4 Human Factors and Ergonomics

Human Factors and Ergonomics (HFE) is a cornerstone of IE, dedicated to designing systems that optimize human performance while ensuring safety, comfort, and well-being. As industries transition from I4.0 to I5.0, the role of HFE has expanded to address both the usability of advanced technologies and the holistic well-being of workers. This evolution shows the importance of intuitive user interfaces, collaborative robots (cobots), and ergonomically optimized workplaces, ensuring that human-system interactions are efficient, safe, and supportive [81].

In I4.0, the integration of advanced technologies such as the IoT, AI, and DTs has created highly interconnected manufacturing systems. While these innovations enhance productivity, they also introduce complexities in human-system interactions, necessitating the design of user-friendly interfaces. Smart interfaces simplify these interactions by reducing cognitive overload and improving decision-making. For instance, multi-robot collaborative wire arc AM systems benefit from calibration methods that transform complex spatial data into manageable user interfaces [82]. Similarly, visual-inertial fusion systems enhance human motion tracking in collaborative environments, improving efficiency and reducing errors [81]. DTs, pivotal in I4.0, allow operators to monitor and control processes with precision, but their effectiveness depends on presenting data in clear, comprehensible formats. Integrating DTs with immersive technologies like Virtual Reality (VR) creates intuitive environments, enabling seamless interactions with virtual models and bridging the gap between complex data and actionable insights [83].

I5.0 builds upon these technological advancements by shifting the focus toward human-centric manufacturing. This paradigm integrates worker well-being into industrial processes through ergonomically sound workplaces, cobots, and technologies that support mental and physical health. Cobots, designed to work alongside humans, perform repetitive or physically strenuous tasks, reducing injury risks and enhancing productivity. These robots, equipped with AI, optimize task execution in real time, ensuring smooth HRC and minimizing idle time [84]. In assembly lines, cobots assist with hazardous or complex tasks, demonstrating their potential to enhance both safety and operational efficiency [85]. Worker fatigue, a significant concern in high-intensity environments, can be addressed through dynamic fatigue models that evaluate physical and cognitive exhaustion levels. Task reallocation based on these models ensures safe and efficient operations by redistributing workloads between humans and robots when fatigue thresholds are reached [86].

Smart factories in I5.0 further integrate cognitive and physical ergonomics to create adaptive work environments that prioritize safety and efficiency. VR tools are increasingly used to design ergonomic workstations, allowing real-time assessments of physical and cognitive risks. Fu et al. [87] developed a VR-based framework for modular construction manufacturing, which ensures ergonomic risks remain within acceptable ranges. Similarly, Augmented Reality (AR) provides real-time task guidance, helping workers maintain proper posture and reduce strain during repetitive tasks. AR-assisted layouts overlay visual instructions onto physical workspaces, ensuring precise task execution and minimizing errors [88].

Beyond physical ergonomics, I5.0 emphasizes cognitive and emotional well-being through human-centric design principles. Human Digital Twins (HDTs) represent a novel approach to integrating human characteristics into manufacturing systems, providing personalized feedback on posture, movement, and workload. This reduces the risk of musculoskeletal disorders while optimizing performance [89]. HDTs align with the goals of I5.0 by preserving privacy and focusing on worker well-being. Additionally, technologies like Augmented Reality Head-Up Displays (AR-HUDs) improve situational awareness and reduce mental workload in high-stress environments, such as aviation or complex manufacturing systems [90]. Adaptive transparency in automated systems further enhances operator trust and decision-making by providing clear, comprehensible feedback [91].

Despite significant advancements, fully integrating HFE principles into I5.0 presents challenges. Ethical concerns, such as ensuring data privacy in systems like HDTs, require careful consideration. Bridging the technological gap between physical and virtual systems is essential for seamless HRC. Moreover, managing the cognitive load associated with complex interfaces is critical to maintaining worker efficiency and safety. Future research should focus on developing standardized ergonomic frameworks, enhancing AI-driven HRC systems, and fostering interdisciplinary collaboration to address these challenges [92,93].

To this end, HFE plays a vital role in advancing IE as the industry transitions from I4.0 to I5.0. By designing user-friendly interfaces, integrating cobots, and prioritizing worker well-being, HFE ensures that technological advancements benefit both industrial efficiency and human needs. These innovations enhance productivity while fostering a safe, inclusive, and resilient industrial ecosystem, marking a significant step toward achieving the human-centric goals of I5.0.

3.5 Supply Chain Management

Supply Chain Management (SCM) is a critical principle of IE, dedicated to optimizing the flow of goods, services, information, and finances from raw material suppliers to end consumers. In recent years, the advent of I4.0 and I5.0 has reshaped SCM by integrating advanced technologies to improve efficiency, resilience, and sustainability. This transformation has enabled SCs to address modern challenges such as global disruptions, environmental concerns, and the evolving expectations of consumers [94,95].

The I4.0 paradigm revolutionizes SCM through digitization and interconnected systems, utilizing technologies such as blockchain, the IoT, and real-time analytics. Blockchain enhances transparency and security by providing immutable transaction records, which is particularly valuable in sectors like agri-food and pharmaceuticals, where traceability and trust are crucial [94]. IoT devices enable real-time monitoring and PdM, minimizing disruptions and improving operational efficiency [96]. For example, blockchain-based traceability systems in the agri-food sector have been shown to enhance logistics and inventory management, while simultaneously boosting consumer confidence in product authenticity [97]. Moreover, Supply Chain Digital Twins (SCDTs) create virtual models of SC processes, enabling businesses to simulate disruptions and implement proactive measures to ensure resilience [98]. AM complements these advancements by decentralizing production, reducing dependency on complex SCs, and enhancing agility. This approach not only promotes customization but also mitigates the risks associated with SC disruptions [99–101].

Building on the technological foundation of I4.0, I5.0 introduces a human-centric and sustainable approach to SCM. This paradigm emphasizes collaboration between humans and intelligent systems to create adaptive SCs that address environmental, social, and economic challenges. Circular Supply Chain (CSC) models exemplify this shift by focusing on resource recovery and waste reduction. Frameworks like m-TISM and MICMAC facilitate the development of closed-loop systems that enhance sustainability and profitability, as seen in solar photovoltaic recycling initiatives [102,103]. I5.0 further prioritizes resilience, with food SCs designed to withstand climate challenges and ensure food security [104]. Blockchain-driven traceability systems ensure product authenticity while aligning with consumer demand for sustainable goods, enhancing both operational efficiency and environmental responsibility [105]. Additionally, strategies like reverse logistics and DTs optimize resource utilization and reduce environmental impacts, aligning with global sustainability goals [106].

The incorporation of emerging technologies like Additive Digital Molding (ADM) illustrates the potential of I5.0 to foster both agility and sustainability in SCs. By combining digital reverse engineering, AM, and plastic injection molding, ADM empowers small and medium-sized enterprises (SMEs) to localize production and reduce dependence on global sourcing. This not only enhances business flexibility but also supports SDGs by minimizing resource waste [107]. Blockchain, IoT, and DTs play a central role in driving these transformations. Blockchain secures SC data, reducing fraud and improving trust, while IoT enables real-time tracking and predictive analytics, reducing lead times and enhancing customer satisfaction [60,96,108]. DTs allow businesses to simulate and optimize SC processes, ensuring more informed decision-making and greater operational efficiency [98,109,110]. Meanwhile, CSC models encourage the transition from linear to circular frameworks, prioritizing resource reutilization and waste recovery to support sustainable manufacturing [111,112].

Despite the promising benefits, the integration of I5.0 principles into SCM faces challenges. Financial constraints, technological barriers, and the need for organizational readiness often hinder the seamless adoption of these innovations. Overcoming these obstacles requires proactive management support and stakeholder engagement. Frameworks like interpretive structural modeling (ISM) and hybrid optimization models have proven effective in addressing critical challenges and enhancing SC resilience [102,113]. Successful case studies further demonstrate the transformative potential of these advancements. Blockchain-based traceability systems in the agri-food sector improve product quality and reduce food waste, contributing to a decarbonized SC [104,114,115]. In the pharmaceutical industry, multi-objective optimization models balance cost, environmental impact, and social factors, improving overall resilience and efficiency [116]. Similarly, in the electric vehicle (EV) sector, blockchain facilitates the recycling of retired power batteries, ensuring traceability, profitability, and reduced environmental impact [117].

The integration of I4.0 and I5.0 technologies into SCM represents a paradigm shift, transforming traditional SCs into systems that are more efficient, adaptive, and sustainable. By leveraging innovations such as blockchain, IoT, DTs, and CE principles, SCM achieves unprecedented levels of transparency, efficiency, and environmental responsibility. These advancements firmly position SCM as a vital component of IE, playing a pivotal role in addressing global challenges and driving sustainable development for the future.

3.6 Quality and Reliability Engineering

Quality and reliability engineering (QRE) form the bedrock of IE, aiming to ensure consistent performance, defect reduction, and operational excellence across production systems. With the emergence of I4.0 and I5.0, these principles have undergone a significant transformation, leveraging advanced technologies to optimize maintenance and quality assurance processes. PdM and real-time quality control (RTQC) have become key enablers of efficient and sustainable manufacturing, while human-augmented systems in I5.0 emphasize collaboration between humans and intelligent systems to enhance production outcomes.

In I4.0, PdM plays a crucial role by utilizing IoT, BDA, and AI to forecast equipment failures and schedule maintenance proactively. By continuously analyzing data from sensors monitoring machine conditions, PdM reduces unexpected downtimes, improves productivity, and minimizes operational costs [118]. Advanced frameworks like MachNet, which leverage deep learning, adapt to diverse PdM scenarios, enabling accurate health state (HS) and remaining useful life (RUL) predictions [119]. IoT-enabled condition monitoring systems further enhance PdM by tracking critical machine parameters, such as engine speed and fuel consumption, providing real-time insights for robust decision-making [120]. ML algorithms, including LSTM and Random Forest, have demonstrated exceptional accuracy in predicting failures, addressing data heterogeneity, and improving system reliability [121]. These advancements make PdM indispensable in modern manufacturing, ensuring optimal resource utilization and uninterrupted operations.

Real-time quality control systems, another cornerstone of I4.0, leverage BDA and ML to detect deviations during production processes instantly. These systems enable zero-defect manufacturing (ZDM) by employing anomaly diagnostics, drift detection, and advanced techniques such as XAI to enhance transparency in fault diagnosis [122]. Tools like DTs simulate and monitor production processes in real time, allowing manufacturers to optimize quality assurance and operational efficiency [123]. XAI methods, such as Local Interpretable Model-Agnostic Explanations (LIME), provide interpretable fault explanations, empowering operators to make informed decisions and maintain consistent product quality [124]. These systems exemplify how I4.0 technologies enable continuous quality improvement through data-driven insights.

I5.0 builds on the advancements of I4.0 by integrating human intuition, creativity, and decision-making with intelligent systems to foster human-centric and sustainable manufacturing. Human-augmented quality assurance systems utilize tools such as AR and AI to enhance inspection processes and improve product customization. AR interfaces provide real-time visualization of complex data, enabling operators to make quick and accurate decisions in challenging manufacturing environments [125]. Frameworks like Maintenance 5.0 emphasize sustainable and socially responsible operations by combining AI-driven tools with human-centered strategies. For instance, PackMASNet, a continual learning-based model, optimizes quality inspections while minimizing resource consumption, ensuring sustainability in mass customization scenarios [126]. These human-augmented systems align with I5.0's goals of achieving both technological innovation and worker well-being.

Maintenance 5.0 integrates predictive capabilities with human-centric approaches to achieve sustainable maintenance in ZDM environments. This framework highlights the importance of addressing environmental, social, and human factors in QRE [127,128]. Advanced decision support systems, which combine predictive insights with anomaly explanations, allow operators to take timely corrective actions, ensuring optimal machine performance and reducing waste [129]. By fostering collaboration between humans and intelligent systems, Maintenance 5.0 sets the stage for sustainable and adaptive manufacturing systems.

TQM remains a foundational approach to quality assurance in IE, and its integration with I4.0 technologies has significantly transformed traditional practices. Real-time data acquisition, advanced analytics, and ML enable evidence-based decision-making and continuous process improvement. Studies demonstrate that combining lean and agile SCM practices with TQM enhances productivity and sustainability, although challenges like data fragmentation and sensor integration persist [130,131]. In I5.0, TQM incorporates human-centered methodologies that emphasize employee training, leadership, and cultural shifts, ensuring that quality systems remain adaptive to dynamic production environments [132].

With the integration of I4.0 and I5.0 technologies, QRE are undergoing a transformative evolution. PdM, real-time quality control, and human-augmented systems are redefining traditional practices, enabling higher efficiency, sustainability, and resilience in manufacturing. Future research should focus on bridging the gap between advanced data-driven methods and human-centric approaches to foster seamless integration, ensuring that IS continue to achieve optimal performance and adaptability in the face of evolving challenges.

3.7 Sustainability and Environmental Engineering

IE plays a pivotal role in promoting sustainability and environmental stewardship by developing energy-efficient, resource-optimized systems that address global environmental challenges. Under the principles of sustainability and environmental engineering (SEE), IE integrates human, financial, technological, and environmental resources to create eco-friendly industrial practices. The convergence of I4.0 and I5.0 technologies has transformed these principles, introducing innovative pathways to achieve sustainability through energy efficiency, CE frameworks, and low-carbon manufacturing.

I4.0 technologies, including the IoT, AI, BDA, and DTs, enable industries to enhance production efficiency while minimizing environmental impact. By facilitating real-time monitoring, PdM, and smart resource allocation, these technologies significantly reduce energy consumption and material waste. For instance, Santos and Sant'Anna [133] demonstrated how I4.0 tools assist Small and Medium Enterprises (SMEs) in optimizing production processes, reducing waste, and fostering sustainability. Similarly, the sawn rubberwood industry in

Thailand adopted Resource Efficient and Cleaner Production (RECP) methodologies, achieving a 28.31% reduction in raw material intensity and a 76.23% increase in eco-efficiency [134]. These examples highlight how I4.0 technologies align industrial operations with global sustainability goals, emphasizing energy-efficient and resource-optimized production systems.

Building upon the technological advancements of I4.0, I5.0 focuses on human-centric, resilient, and sustainable manufacturing practices. This paradigm emphasizes the integration of CE principles, which promote waste reduction, resource recirculation, and low-carbon production processes. Ghobakhloo et al. [135] outlined a strategic roadmap for I5.0, demonstrating its potential to enhance sustainable manufacturing through functions such as value network integration and sustainable business model innovation. The CE framework shifts industrial practices from linear to circular models, reducing waste and maximizing resource utilization. Bressanelli and Saccani [136] introduced the C-Readiness tool, which helps firms assess their readiness for CE practices and prioritize decarbonization actions. In Thailand's rubberwood industry, for example, sawdust was repurposed as fuel, significantly lowering the sector's carbon footprint and enhancing resource efficiency [134].

Electronic waste (e-waste) management exemplifies the challenges and opportunities of integrating circular economy principles with I5.0 technologies. Darzi [137] proposed a framework combining the Best-Worst Method (BWM) and Fuzzy Vlse Kriterijumsk Optimizacija Kompromisno Resenje (F-VIKOR) to evaluate e-waste mitigation strategies. The study highlighted take-back practices as a critical approach for extending product lifecycles and reducing environmental harm, aligning with CE principles. Similarly, addressing carbon emissions through circular strategies like remanufacturing and material reuse is essential for sustainable manufacturing. Wandji et al. [138] demonstrated the use of product State of Health assessments to determine optimal take-back periods, yielding environmental and economic benefits. Furthermore, Liu [139] introduced a carbon emission quota allocation model using data envelopment analysis (DEA) to ensure equitable carbon rights distribution, promoting balanced industrial development and sustainability.

Sustainable business models and decision-making tools are crucial for facilitating the transition to environmentally conscious industrial practices. Sharma et al. [140] identified key drivers for achieving carbon neutrality in Indian manufacturing firms, highlighting the importance of sustainable business values and supportive government policies. Meanwhile, Nikolakis et al. [141] proposed an eco-efficiency indicator combining life cycle assessment (LCA) and cost analysis (CA), offering manufacturers a quantitative methodology to implement CE practices. Additionally, Corsini et al. [142] examined the interplay between consumers and manufacturers in shaping a systemic circular transition, emphasizing the need for active stakeholder engagement to close the gap between circular demand and supply.

Human-centric values are central to I5.0, creating resilient manufacturing systems that integrate advanced technologies with human expertise. Khan et al. [143] explored the role of green human capital (GHC) and green environmental strategic capabilities (GESC) in promoting CE practices among SMEs, demonstrating how these capabilities support the transition from linear to circular models. These studies emphasize the importance of fostering a culture of sustainability within organizations to enhance both environmental performance and economic viability.

The integration of I4.0 and I5.0 technologies under IE's SEE principles offers unprecedented opportunities for industries to achieve sustainable, energy-efficient, and resource-optimized production systems. By adopting CE frameworks and leveraging advanced decision-making tools, industries can reduce energy consumption, minimize waste generation, and lower carbon emissions. The journey toward a sustainable future requires collaborative efforts, technological innovation, and a steadfast commitment to environmental stewardship.

3.8 Operations Research and Decision Sciences

IE, grounded in the principles of Operations Research and Decision Sciences (OR&DS), plays a vital role in addressing complex industrial challenges. These disciplines drive the design, optimization, and control of systems across sectors, ensuring resource efficiency and informed decision-making. The rise of I4.0 has accelerated the adoption of smart technologies, while I5.0 emphasizes ethical considerations, sustainability, and HMC. Together, these paradigms are reshaping industrial systems to be more adaptive, inclusive, and sustainable.

I4.0 has introduced advanced optimization algorithms for resource allocation, scheduling, and system control. DT technology has revolutionized real-time decision-making by enabling data-driven simulations that optimize operational efficiency [144]. In manufacturing, tools like Deep Reinforcement Learning (DRL) have improved job-shop scheduling with automated guided vehicles (AGVs), offering scalable solutions to complex production environments [145]. PdM has also seen advancements, with AI-driven models like Long Short-Term Memory (LSTM) and Random Forest optimizing machine uptime and reducing costs [146]. Federated learning frameworks further enhance energy-efficient and privacy-preserving data processing in industrial IoT environments, highlighting the importance of real-time adaptability in smart manufacturing [147]. These innovations demonstrate how I4.0 technologies enhance system performance and operational resilience through dynamic and predictive capabilities.

While I4.0 focuses on automation and connectivity, I5.0 prioritizes ethical and societal considerations, emphasizing sustainability and human-centric design. Ethical AI practices, for instance, have been shown to foster user trust and accelerate technology adoption in sectors like tourism and healthcare [148]. Sustainability frameworks, such as CE integration, link environmental performance with operational efficiency by promoting resource recirculation and waste reduction [149]. AI-driven smart building systems align technological innovation with community involvement and regulatory compliance, ensuring a balance between progress and societal well-being [150]. Moreover, strategies for green and resilient manufacturing offer a blueprint for sustainable competitive advantages, particularly in developing economies [41]. These developments highlight the shift from technology-centric models to human-centric frameworks, ensuring that industrial progress serves broader societal and environmental goals.

The integration of AI into OR&DS has revolutionized traditional decision-making processes, providing enhanced accuracy, transparency, and scalability. XAI models, such as those utilizing SHAP and LIME, allow stakeholders to interpret complex data, ensuring trust in AI-driven decisions [151]. Hybrid optimization models, which combine ML with techniques like Monte Carlo simulations, have improved cost-effectiveness and resilience in SCM [152]. AI applications in humanitarian operations have demonstrated the potential of configurational analysis to optimize coordination during crises, offering scalable and efficient solutions [153]. Decentralized learning models, driven by edge computing, further enhance energy usage and resource allocation in smart cities, showcasing the versatility of AI in modern IS [147]. These AI-driven approaches illustrate the potential of OR&DS to provide actionable insights, streamline operations, and improve system resilience.

Despite these advancements, there are emerging research areas that warrant further exploration. Hybrid models that integrate physical and data-driven approaches, such as those applied to lithium-ion battery lifecycle analysis (LCA), offer improved prediction accuracy [154]. Scalable optimization models, like the Heterogeneous Graph Scheduler (HGS), are essential for accommodating diverse manufacturing environments [145]. The need for trust and transparency in AI-driven technologies, particularly in healthcare and wearable devices, is critical for user acceptance and compliance [155]. Moreover, interdisciplinary collaboration that aligns digital capabilities with organizational culture can foster innovation and accelerate the adoption of new technologies [156]. Addressing these gaps will enable OR&DS to further drive innovation in I4.0 and I5.0 ecosystems, ensuring these systems are both technologically advanced and ethically sound.

With these, IE, through the integration of OR&DS, is central to the transformations brought about by I4.0 and I5.0. Advanced optimization algorithms and AI-driven frameworks enable real-time adaptability, dynamic scheduling, and predictive analytics, while the human-centric focus of I5.0 ensures alignment with societal and environmental priorities. This synergy fosters innovation, resilience, and inclusivity, creating sustainable industrial ecosystems. However, challenges such as AI interpretability, scalability, and ethical integration must be addressed through continued interdisciplinary research. By leveraging technological advancements and prioritizing ethical decision-making, IE can lead the way toward a future that balances operational excellence with societal and environmental well-being.

3.9 Simulation and Modeling

Simulation and modeling (SM) are foundational tools in IE, offering critical insights into the behavior of complex systems and facilitating optimized decision-making. With the rise of I4.0 and the subsequent shift toward I5.0, the application of these tools has expanded significantly, enabling real-time monitoring, HMC, and personalized production. These advancements leverage cutting-edge technologies such as DTs, AM, and HRC to improve system efficiency, enhance safety, and ensure sustainability.

In the context of I4.0, DTs have become central to real-time system modeling and performance prediction. These virtual replicas synchronize with their physical counterparts, enabling real-time simulations, monitoring, and optimization of production processes. For example, DTs in AM facilitate defect detection and process optimization in real time. Makanda et al. [157] introduced FULAM, a federated unsupervised learning method that detects anomalies in Fused Filament Fabrication (FFF) machine vibration data while addressing data privacy and heterogeneity concerns. Additionally, DTs support dynamic scheduling in Mass Personalization Manufacturing (MPM), enabling real-time adjustments to meet diverse customer demands. Kosse et al. [10] proposed a Semantic DT-based Dynamic Scheduling Framework for precast concrete production, which effectively manages uncertainties through real-time data exchange. Enhanced process control is another critical application, with Zhang et al. [158] demonstrating a DT-enabled framework that dynamically adjusts assembly process parameters, significantly improving product quality.

I5.0 builds on these technological advancements by emphasizing human-centricity and promoting seamless HMC. SM in this paradigm focus on replicating human-machine interactions to enhance productivity, safety, and personalization. HRC benefits from DT-based simulations that optimize safety and collaborative strategies. Baratta et al. [14] explored DT frameworks for improving HRC safety, while Liu et al. [159] developed a maturity assessment framework for DTs in collaborative assembly tasks. Psarakis et al. [15] demonstrated how visual cues in HRC environments enhance collaborative fluency, emphasizing the importance of intuitive interaction modalities. Personalized manufacturing systems are another focus of I5.0. Zhang et al. [160] introduced a model combining modular design with personalized production, optimizing SC efficiency and customer satisfaction. Furthermore, reinforcement learning-based systems, as proposed by Qin et al. [161], enable dynamic scheduling in job shop environments, adapting to stochastic changes and improving production efficiency. Human-centric simulations also play a crucial role in fatigue and ergonomic assessment, ensuring worker safety and comfort in HRC environments. Lambay et al. [162] reviewed ML approaches for detecting operator fatigue, highlighting the importance of ergonomic task design and real-time feedback systems.

SM have also revolutionized AM by addressing challenges such as nozzle clogging and inconsistent print quality. Data-driven modeling techniques, such as Shi et al.'s [163]

Personalized Feature Extraction (PFE) algorithm, enable real-time anomaly detection in AM imaging data, significantly improving print quality and process reliability. These advancements enhance AM's potential for personalized manufacturing, aligning with I5.0's goal of mass customization.

Despite these advancements, challenges remain in fully leveraging the potential of SM in I4.0 and I5.0. Data privacy and sharing continue to be major concerns, particularly in centralized systems. Federated learning frameworks like FULAM provide promising solutions by enabling collaborative learning without compromising data security [157]. Human-Machine Interfaces (HMIs) present another challenge, as they must be intuitive and adaptable to enhance HRC. Sanfilippo et al. [164] stressed the need for a structured approach to integrating sensory modalities for effective collaboration. Additionally, uncertainty in dynamic production environments requires robust simulation models to ensure reliable system performance. Zhang et al. [165] proposed a multi-objective discrete bees algorithm to balance assembly lines under uncertain conditions, illustrating the importance of advanced modeling techniques.

Generally, SM are integral to the successful implementation of I4.0 and I5.0 principles. Technologies like DTs, AM, and HRC enable real-time system optimization, personalized production, and enhanced human-machine synergy. To fully realize the potential of these advancements, future research should address challenges related to data privacy, system interoperability, and human-centric design. By overcoming these hurdles, SM will continue to drive innovation, efficiency, and sustainability in IS.

3.10 Automation and Robotics

Automation and robotics (AR) are fundamental principles of IE, driving transformative advancements in production systems through their integration with I4.0 and I5.0 technologies. These paradigms leverage cutting-edge innovations, such as AI, the IoT, and robotics, to revolutionize efficiency, precision, and sustainability in industrial processes. From fully automated production lines to cobots working alongside humans, the evolution of AR demonstrates their pivotal role in reshaping modern industries.

I4.0 emphasizes the development of fully automated and interconnected production lines powered by AI, big data, and IoT. These systems enhance productivity by automating repetitive tasks, minimizing human intervention, and improving precision and speed. For example, optimized robotic energy consumption strategies have been shown to boost productivity while mitigating geopolitical risks that affect AI-driven industrial outputs [166]. Advances in robotic control, such as inverse kinematics solutions for six-degree-of-freedom robots, have further improved computational efficiency and accuracy, enabling more complex and adaptive automation [167]. Additionally, automation has significant ecological benefits. Studies reveal that industrial robots reduce ecological footprints across various sectors, contributing to environmental quality improvements on a global scale [168–170]. Moreover, the integration of robotic disassembly systems in CE initiatives highlights the sustainability potential of automation by promoting resource recovery and waste reduction [171].

Building on these advancements, I5.0 introduces a human-centric approach, focusing on cobots that work seamlessly alongside humans. This paradigm not only enhances productivity but also prioritizes worker well-being and safety. Cobots are designed to be contextually intelligent and socially adept, enabling them to interact with human workers in dynamic environments. For instance, advanced robotic systems that utilize infrared-thermal imaging improve safety in HRC settings by detecting potential hazards in real-time [172]. In industries like healthcare and manufacturing, cobots reduce operator workload while maintaining high safety and performance standards. However, balancing robotic efficiency with human-centered safety and adaptability remains a critical challenge, as highlighted by studies on safe human-robot interactions (HRI) [173].

The environmental and economic impacts of robotics are profound, with industrial robots driving green innovation and economic growth. Robots have been shown to reduce carbon emissions, particularly in capital-intensive industries, facilitating the transition to low-carbon green economies [174]. In regions like Belt and Road Initiative countries, robot integration significantly boosts green industrial performance, aligning industrial practices with sustainability goals [175]. Furthermore, robotics complement human labor by increasing labor income shares and addressing challenges posed by aging populations in labor-intensive sectors [176–178]. These advancements highlight the role of automation in promoting economic resilience and sustainability.

Emerging technologies and advanced applications are expanding the scope of robotics in industrial settings. Integrating robotics with AI-driven systems, such as DTs and blockchain, enables real-time process optimization and enhances HRC [179]. For instance, blockchain-integrated extended reality (XR) systems have improved gearbox assembly processes by facilitating efficient data exchange and collision avoidance [180]. Similarly, NeRF-based 3D modeling enhances safety in industrial environments by optimizing robotic navigation and preventing collisions [181]. Beyond traditional industries, robotics is also making strides in space exploration. AI-enabled robotic systems have demonstrated capabilities for in-orbit satellite assembly, showcasing the versatility of automation across diverse applications [182].

Despite these advancements, the transition from I4.0 to I5.0 presents several challenges. Ensuring safety in HRI and addressing ethical concerns are critical areas for further research. Developing socially responsible robots, enhancing collaborative safety measures, and optimizing energy use are essential to overcoming these challenges [183]. Emerging innovations such as embodied AI and cooperative tele-recovery strategies show promise for addressing current limitations and fostering more effective HRC [184,185].

AR are essential drivers of efficiency, sustainability, and innovation in IE. As I5.0 gains momentum, the focus on human-centric and collaborative technologies will redefine the relationship between humans and machines. This evolution promises to foster a more sustainable, inclusive, and resilient industrial future, where automation supports both technological progress and societal well-being.

3.11 Data Analytics and Artificial Intelligence

The integration of Data Analytics and AI (DA&AI) within IE marks a transformative step in optimizing manufacturing and production systems. This principle underpins the progression from I4.0, which emphasizes automation and digitization, to I5.0, which seeks to restore a human-centric, sustainable industrial paradigm. By harnessing the power of big data, ML, and AI-driven decision-making, industries can enhance process efficiency, minimize waste, and build resilient, adaptive systems.

In I4.0, big data and predictive analytics play a pivotal role in process optimization. The framework relies on CPS, the IoT, and real-time data collection, enabling actionable insights for PdM, inventory management, and production planning [5]. PdM, for instance, leverages data from IoT sensors to forecast equipment failures, thereby reducing downtime and maintenance costs [186]. DTs, which replicate physical systems in virtual environments, facilitate advanced simulations to optimize production workflows, identify bottlenecks, and enhance overall efficiency [21]. Furthermore, tools like cloud computing enable seamless integration of data from multiple sources, supporting JIT manufacturing and smart inventory management [22]. Virtual manufacturing platforms, enhanced by RFID technology, provide real-time visibility into SCs, driving improvements in operational efficiency and product quality [187]. These digital advancements foster autonomous decision-making, allowing AI systems to continuously analyze data streams and make process adjustments with minimal human intervention.

As industries transition to I5.0, the focus shifts from automation to human-centric manufacturing. This paradigm emphasizes ethical AI practices to ensure transparency, accountability, and alignment with societal values [188]. Unlike I4.0, which often marginalizes human roles, I5.0 fosters collaboration between humans and machines. Trustworthy AI (TAI) frameworks address critical concerns such as bias, explainability, and ethical implications, ensuring that AI-driven systems are safe and reliable [189]. HRC underscores this approach, with human safety and psychological well-being as top priorities [12]. XAI enhances trust by offering transparent models that help operators understand AI-driven decisions, thereby improving decision-making on the shop floor [190].

Human-Centric Smart Manufacturing (HCSM) exemplifies the vision of I5.0, where human intuition and AI capabilities are integrated to maximize productivity and safety. Human Digital Twins (HDTs) provide real-time insights into workers' physical and cognitive states, enabling personalized adjustments to workloads and environments to reduce fatigue and enhance performance [17]. Cobots, exemplify this human-centric focus by handling repetitive or hazardous tasks, while humans focus on creative and decision-intensive responsibilities [191]. This symbiotic relationship ensures that the human element remains central, improving job satisfaction and reducing psychological risks.

The applications of DA&AI in IS are diverse and impactful. Predictive modeling and maintenance systems use real-time sensor data to identify potential equipment failures, reducing disruptions and costs [192]. AI also supports sustainable manufacturing by optimizing resource use and reducing emissions, aligning with environmental, social, and governance (ESG) goals [19,193]. AM, enhanced by AI, improves material selection and print parameter optimization, enabling efficient production of lightweight and durable components for sectors such as aerospace and healthcare [194,195]. Energy optimization is another critical application, with AI systems demonstrating significant potential in reducing carbon emissions and improving total factor productivity in industrial operations [196]. Furthermore, HDTs enable comprehensive fatigue and stress monitoring, ensuring worker safety and optimizing performance in real time [17].

The integration of AI and big data also contributes to ethical governance and sustainability. Transparent decision-making processes, supported by AI-driven tools, enhance circular economy practices by optimizing resource utilization and reducing waste [197]. This alignment with SDGs fosters a more resilient and socially responsible industrial ecosystem [198].

With these regards, the evolution from I4.0 to I5.0 reveals the transformative potential of DA&AI in IE. While I4.0 has revolutionized operational efficiency through automation and digitization, I5.0 emphasizes human-centric values, ethical AI, and sustainable manufacturing. Future research should focus on refining HAC, addressing ethical challenges, and developing frameworks for adaptive, human-centered IS. By leveraging big data and AI, IE is poised to redefine the factory of the future, fostering seamless integration of human and machine capabilities for a more sustainable and inclusive industrial landscape.

3.12 Resilience Engineering

Resilience engineering (RE) is a fundamental principle within IE, designed to enhance the robustness and adaptability of systems in the face of disruptions, failures, and dynamic operating conditions. As IS transition from I4.0 to I5.0, RE evolves to address the complexities of human-centric and environmentally sustainable operations. This progression emphasizes the importance of designing systems that prioritize safety, operational continuity, and sustainability while fostering HMC and ecological responsibility.

In the context of I4.0, RE focuses on enhancing the robustness of smart factories through the integration of advanced technologies such as the IoT, AI, and CPS. These technologies enable real-time monitoring, PdM, and automated recovery processes. For example, Masuduzzaman et al. [199] proposed a framework combining unmanned aerial vehicles (UAVs) and automated guided vehicles (AGVs) to detect toxic gases in smart factories. This system employs multi-access edge computing (MEC) for secure data transmission and real-time response, demonstrating a resilient approach to industrial safety. Similarly, Jin et al. [200] illustrated how smart decline strategies in urban planning can enhance adaptive capacity, offering insights applicable to IS for managing resource constraints and operational risks.

The transition to I5.0 shifts RE toward human-centric and sustainable goals. This paradigm emphasizes the need for adaptive systems that protect human operators while minimizing environmental impacts. Alabdulatif et al. [11] highlight the importance of integrating CPSs with robust security and privacy measures to address vulnerabilities in interconnected ecosystems. Resilient adaptive manufacturing systems, as discussed by Mo et al. [201], enable programmable logic controllers (PLCs) to reconfigure automatically based on shifting production demands, reducing system downtime and human error. Additionally, the industrial metaverse framework proposed by Guo et al. [202] supports resilience in digital and social dimensions, facilitating immersive, adaptive industrial operations that align with I5.0's emphasis on human-machine synergy.

Applications of RE span various domains. In smart production systems, Singh et al. [203] presented a biodiesel production framework that minimizes energy consumption and carbon emissions while maintaining high-quality output. Resilience in this system is achieved through automated inspection and remanufacturing, optimizing resource use and minimizing waste. Robust ML models, such as the Trusted Connection Dictionary Learning (TCDL) method proposed by Huang et al. [204], enhance fault detection and operational safety in IS by addressing label noise and ensuring reliable condition monitoring. Energy resilience is another critical area, as Wang et al. [205] demonstrated through a robust demand response (DR) framework for industrial microgrids, which enhances flexibility and reduces costs under fluctuating electricity prices. In manufacturing, adaptive control methods such as the robust predictive control for infinite-dimensional systems described by Zhang et al. [206] ensure stability and efficiency in dynamic environments, a key requirement for modern production processes.

Despite these advancements, RE in I5.0 faces several challenges. Security and privacy remain critical as CPSs and IoT devices become more pervasive, requiring robust authentication protocols and advanced cryptographic techniques to protect data integrity and prevent cyberattacks [207]. Human-centric design (HD) is another priority, necessitating intelligent scheduling systems that ensure worker safety and comfort while maintaining productivity [18]. Sustainable practices are equally vital; Lockan and Kansara [208] emphasized the need for renewable energy integration in industrial processes, advocating for robust optimization methods to manage uncertainties and enhance resilience in energy systems.

The RE is a cornerstone in the evolution of IS, bridging the technological innovations of I4.0 with the human-centric and sustainable objectives of I5.0. By integrating adaptive control, robust ML, and sustainable energy solutions, RE supports the development of secure, adaptive, and environmentally responsible industrial ecosystems. These advancements not only enhance operational efficiency but also align with broader societal and ecological goals, paving the way for a resilient and sustainable industrial future.

4. Advancing Industrial Engineering Discipline

IE operates at the intersection of several engineering and management disciplines, often overlapping and conflicting with fields (both engineering and non-engineering disciplines) such as Mechanical Engineering, Electrical Engineering, Computer Science, and Operations Management, as depicted in Fig. 4 and Fig. 5. While this interdisciplinary nature allows IE to tackle complex, system-level challenges, it also leads to conflicts and blurred boundaries with rival disciplines. These conflicts typically arise in areas such as process optimization, automation, and data-driven decision-making, where multiple fields claim expertise [209–211]. The comparison Table 1 and Table 2 highlight these overlaps, showcasing where IE distinguishes itself by integrating technical, human, and organizational elements, and where conflicts can hinder its clear identity. Understanding these dynamics is essential for positioning IE as a unique and indispensable discipline in academia and industry.

The IE profession and its academic programs must evolve to remain relevant and competitive in a rapidly changing industrial and technological landscape [212,213]. Strengthening the profession requires promoting its unique capabilities, embracing emerging technologies, and enhancing its societal impact. Simultaneously, positioning the IE degree in universities involves modernizing curricula, fostering industry partnerships, and improving the visibility of career opportunities [214,215]. This section discusses strategies for advancing both the profession and academic programs to ensure their continued growth and relevance in the era of I4.0 and beyond.

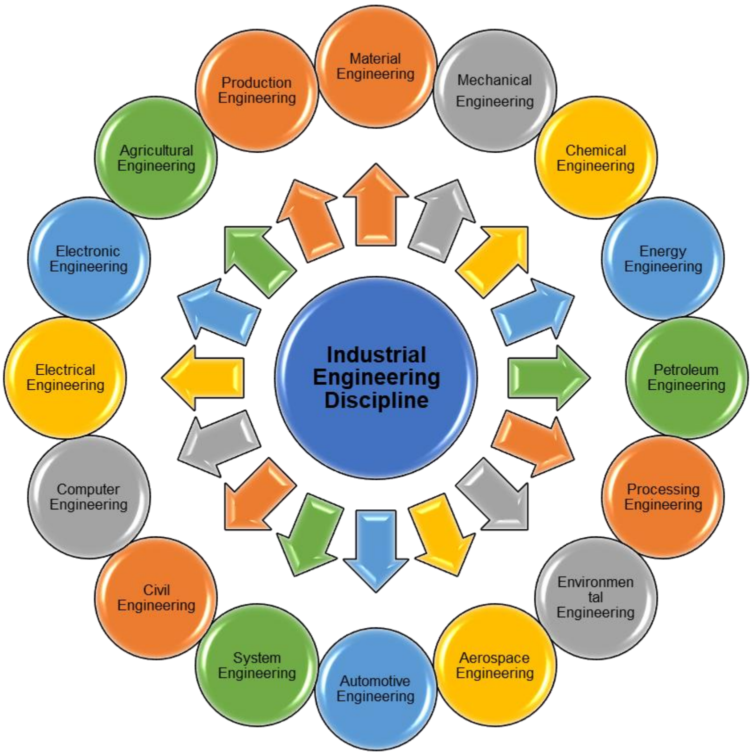

Fig. 4. Intersection of industrial engineering with various engineering disciplines

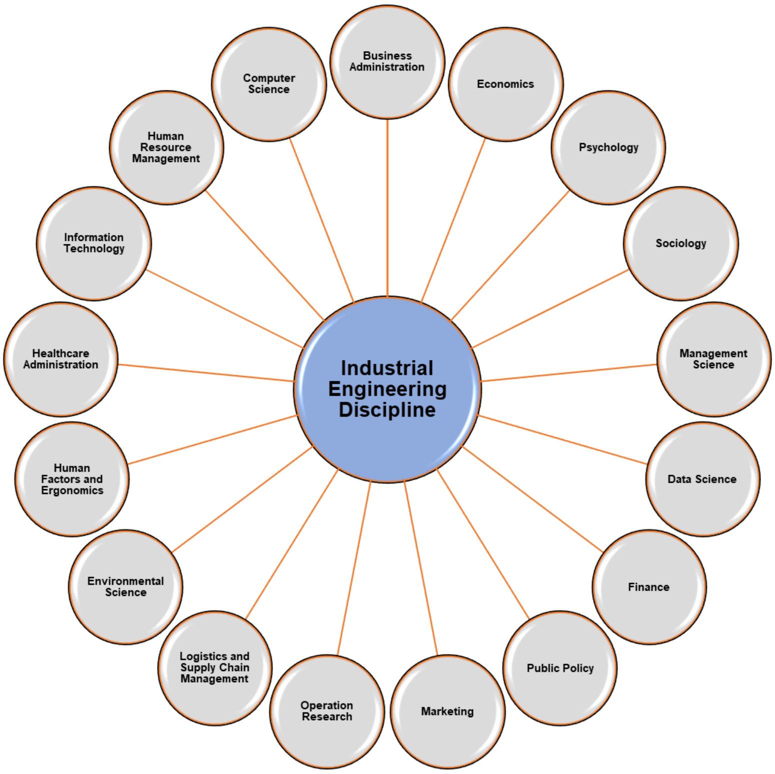

Fig. 5. Intersection of industrial engineering with non-engineering disciplines

Table 1
Key overlapping and conflicting areas between IE and engineering disciplines

Discipline	Overlap with IE	Conflict with IE	Tools/Principles
Materials Engineering	Manufacturing processes, quality control	Focus on material properties vs. system efficiency	SPC, electron microscopy
Energy Engineering	Energy optimization, sustainability	Macro-scale energy systems vs. operational energy use	Energy audits, simulation
Agricultural Engineering	Process optimization, supply chain management	Farm-level productivity vs. industrial logistics	GIS, process flow diagrams
Production Engineering	Lean manufacturing, system optimization	Technical depth vs. broader system focus	VSM, CAD/CAM
Chemical Engineering	Process design, safety	Molecular-scale focus vs. operational optimization	Aspen Plus, Arena
Processing Engineering	Workflow optimization, sustainability	Sector-specific focus vs. general optimization	Process simulators, Six Sigma
Mechanical Engineering	Machine design, manufacturing systems	Component-level focus vs. system-level optimization	FEA, SolidWorks
Electrical Engineering	Power systems, automation	Focus on electrical infrastructure vs. operational systems	Power flow analysis, PLCs
Electronic Engineering	Control systems, circuit design	Focus on microelectronics vs. industrial-scale systems	PCB design tools, SCADA
Computer Engineering	Embedded systems, real-time control	Hardware/software integration focus vs. system-wide efficiency	Embedded system design, FPGA tools
Civil Engineering	Facility layout, construction management	Structural design focus vs. operational efficiency	BIM, structural analysis software

Manufacturing Engineering	Production processes, advanced manufacturing	Machine-specific vs. workflow/system-wide optimization	CAM, CNC programming, industrial robotics
Systems Engineering	System integration, lifecycle optimization	High-level design vs. process-level focus	Systems modeling, MBSE
Petroleum Engineering	Process optimization in oil extraction and refining	Reservoir-specific focus vs. system-level efficiency	Reservoir simulation, drilling optimization
Environmental Engineering	Waste management, sustainability practices	Environmental impact focus vs. operational efficiency	Life Cycle Assessment (LCA), air quality models
Automotive Engineering	Vehicle production, automation in assembly lines	Component-level optimization vs. system-wide workflow	CAD/CAE, vehicle simulation, crash analysis

Table 2
Key overlapping and conflicting areas between IE and non-engineering disciplines

Discipline	Definition	Overlap with IE	Conflict with IE	Tools/ Techniques	Applications
Business Administration	Focuses on managing business operations, finances, and strategies.	Operations management, supply chain optimization	Strategic focus vs. operational efficiency	SWOT analysis, financial modeling	Operations planning, resource management
Economics	Studies how societies allocate scarce resources to produce goods and services.	Cost-benefit analysis, resource optimization	Macro-level policy focus vs. micro-level operational focus	Game theory, econometrics	Pricing strategies, production planning
Psychology	Explores human behavior and mental processes.	Human factors, ergonomics, and workplace productivity	Individual behavior focus vs. system-level optimization	Cognitive load analysis, task analysis	User interface design, workstation layout
Sociology	Examines social behavior, institutions, and cultural dynamics.	Team dynamics, organizational behavior	Focus on social systems vs. industrial processes	Social network analysis, surveys	Workforce collaboration, leadership development
Management Science	Applies analytical methods to solve business problems.	Decision-making, operations research	Theoretical focus vs. practical implementation	Linear programming, decision trees	Scheduling, logistics, project management
Data Science	Extracts insights from large datasets using computational and statistical methods.	Data-driven decision-making, predictive analytics	Algorithm focus vs. system integration	Machine learning, data visualization	Predictive maintenance, process optimization
Finance	Manages money, investments, and financial planning.	Cost analysis, investment in industrial technologies	Profit focus vs. operational efficiency	ROI, NPV, discounted cash flow	Capital budgeting, financial feasibility analysis

Discipline	Definition	Overlap with IE	Conflict with IE	Tools/ Techniques	Applications
Environmental Science	Studies interactions between humans and the environment.	Sustainability practices, waste reduction	Environmental conservation focus vs. production efficiency	Life Cycle Assessment (LCA), carbon footprint analysis	Green manufacturing, resource conservation
Healthcare Administration	Manages operations and policies in healthcare systems.	Process optimization, patient flow management	Patient care focus vs. industrial process optimization	Lean healthcare, workflow analysis	Hospital operations, resource allocation
Information Technology (IT)	Develops, implements, and manages computer systems.	Automation, digital systems for process control	Technical focus on software/hardware vs. system-level optimization	ERP systems, database management	Manufacturing execution systems, supply chain tracking
Human Resource Management	Manages employee relations, recruitment, and organizational development.	Workforce planning, employee productivity	Employee satisfaction focus vs. system efficiency	Employee performance tracking, time studies	Workforce scheduling, training programs
Logistics and Supply Chain Management	Focuses on the flow of goods, services, and information.	Inventory management, transportation optimization	Tactical-level operations vs. strategic system optimization	Inventory models, network design	Distribution, procurement, demand forecasting
Marketing	Studies market research, consumer behavior, and promotion strategies.	Customer-centric product design, demand forecasting	Consumer behavior focus vs. production and resource optimization	Conjoint analysis, market segmentation	Product development, sales forecasting
Public Policy	Develops and implements governmental and institutional regulations.	Regulatory compliance, safety standards	Policy formulation focus vs. operational execution	Policy analysis, regulatory impact assessments	Safety protocols, industry regulations
Computer Science	Studies computational theory, algorithm design, and software development.	Automation, data analysis, and optimization tools	Software focus vs. system-wide integration	Programming, machine learning, algorithm development	Real-time control systems, IoT integration
Human Factors and Ergonomics	Examines human capabilities and limitations in system design.	Workstation design, human-machine interaction	Human-centric focus vs. broader system efficiency	Task analysis, anthropometric studies	Ergonomic tools, safety-critical systems
Operations Research (OR)	Uses advanced analytical methods to optimize decision-making.	Optimization models, resource allocation	Purely mathematical focus vs. practical system constraints	Linear programming, simulation modeling	Supply chain optimization, transportation planning

4.1 Strengthening the IE Profession

The IE profession plays a pivotal role in optimizing complex systems, yet it often struggles with recognition and visibility compared to rival disciplines. To strengthen IE, it is essential to emphasize its unique ability to bridge the gap between engineering principles and business practices, focusing on systems thinking, process optimization, and human-centered design [216]. The advent of I4.0 and emerging paradigms like I5.0 present an unprecedented opportunity for IE to establish itself as a leading discipline by addressing contemporary challenges such as digital transformation, sustainability, and HMC. Fig. 6 illustrates four key strategies for strengthening the IE profession in the evolving industrial era, which are further discussed in this section.

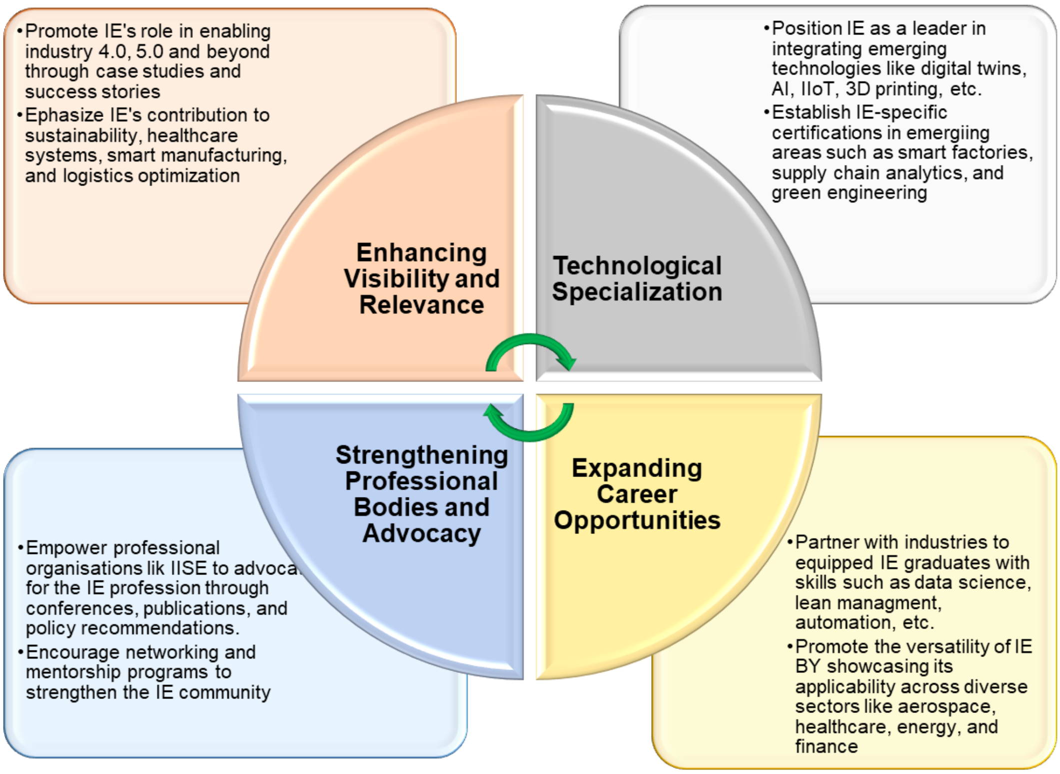

Fig. 6. Strategies for strengthening IE profession in the evolving industrial Era

One of the critical steps to strengthening IE is enhancing its technological specialization. Industrial engineers must be equipped with advanced skills in areas such as DTs, IoT, AI, and BDA [215]. By integrating these technologies into IE curricula and professional practices, the field can expand its relevance and demonstrate its critical role in enabling smart manufacturing, SC resilience, and adaptive systems [213,217]. Establishing industry-specific certifications in these technologies can further enhance the professional credibility of IE practitioners [218].

In parallel, IE programs must adapt to market demands by offering dynamic and interdisciplinary curricula. Courses that incorporate sustainability metrics, LM, advanced simulation, and PdM are vital for preparing graduates to tackle modern industrial challenges. Embedding experiential learning through internships, capstone projects, and industry collaborations ensures that students gain practical exposure and develop problem-solving skills that are immediately applicable in the workforce [219–222].

Strengthening professional advocacy is equally crucial. Organizations such as the Institute of Industrial and Systems Engineers (IISE) should continue to lead efforts in promoting the profession through conferences, publications, and policy advocacy. Encouraging industrial engineers to engage in research and innovation, especially in high-impact areas such as healthcare systems, energy optimization, and CE practices, will further demonstrate the profession's societal and economic value [223–225].

Strategic partnerships with industry, government, and academic institutions are essential for advancing the IE profession. These collaborations can provide funding for cutting-edge research, create co-operation opportunities, and position IE as a key contributor to national and global development strategies. By focusing on these areas, the IE profession can solidify its position as a cornerstone of modern engineering and a driver of innovation in the digital age [226,227].

Furthermore, integrating the concepts of Learning Factory, Operator 4.0, Operator 5.0, and Education 4.0 is crucial for strengthening IE profession. Learning Factories provide a hands-on environment where students and professionals can bridge the gap between theoretical knowledge and practical applications of advanced manufacturing systems [228]. These facilities enable the development of skills in real-time problem-solving, data-driven decision-making, and digital transformation [229]. The transition to Operator 4.0 emphasizes the augmentation of human capabilities through advanced technologies such as exoskeletons, AR, and AI-based assistance, fostering a symbiotic relationship between humans and machines [230]. Moving further, Operator 5.0 envisions a human-centric approach, promoting well-being, creativity, and collaboration within smart manufacturing ecosystems [231]. Education 4.0 complements these advancements by adopting flexible, student-centered learning paradigms that leverage digital tools, gamification, and experiential learning [232,233]. Together, these concepts foster an IE workforce that is adaptive, resilient, and equipped to navigate the challenges of I5.0, ultimately contributing to the growth and evolution of the profession.

4.2 Positioning the IE Degree within Academic Institutions

Positioning the IE degree effectively within academic institutions is critical to ensuring its relevance and competitiveness in an era of rapid technological advancement. The unique interdisciplinary nature of IE, combining engineering principles, systems optimization, and business insights, provides a solid foundation for addressing contemporary challenges. However, strategic actions are required to enhance its visibility, attract high-caliber students, and compete with well-established academic programs [232,234]. As illustrated in Fig. 7, positioning the IE degree within universities must align with the evolving industrial landscape, emphasizing the integration of emerging technologies and interdisciplinary approaches to meet industry demands.

A key strategy is the continuous evolution of the IE curriculum to reflect modern industry demands. Universities must integrate courses that emphasize emerging technologies such as DTs, IoT, AI, and ML, aligning them with traditional IE strengths like OR, systems engineering, and LM. Additionally, sustainability and CE principles should be woven into the curriculum, showcasing IE's role in fostering environmentally responsible and socially impactful systems [221].

Practical, hands-on learning is another critical factor for positioning the IE degree. Universities should offer experiential opportunities such as internships, cooperative education programs, and industry-sponsored capstone projects. These experiences not only prepare students for real-world challenges but also enhance their employability, making the degree more attractive to prospective students and their future employers. Moreover, the inclusion of advanced simulation tools like ARENA, Aspen Plus, and SolidWorks can help students master cutting-edge technologies and methods used in modern industries [235].

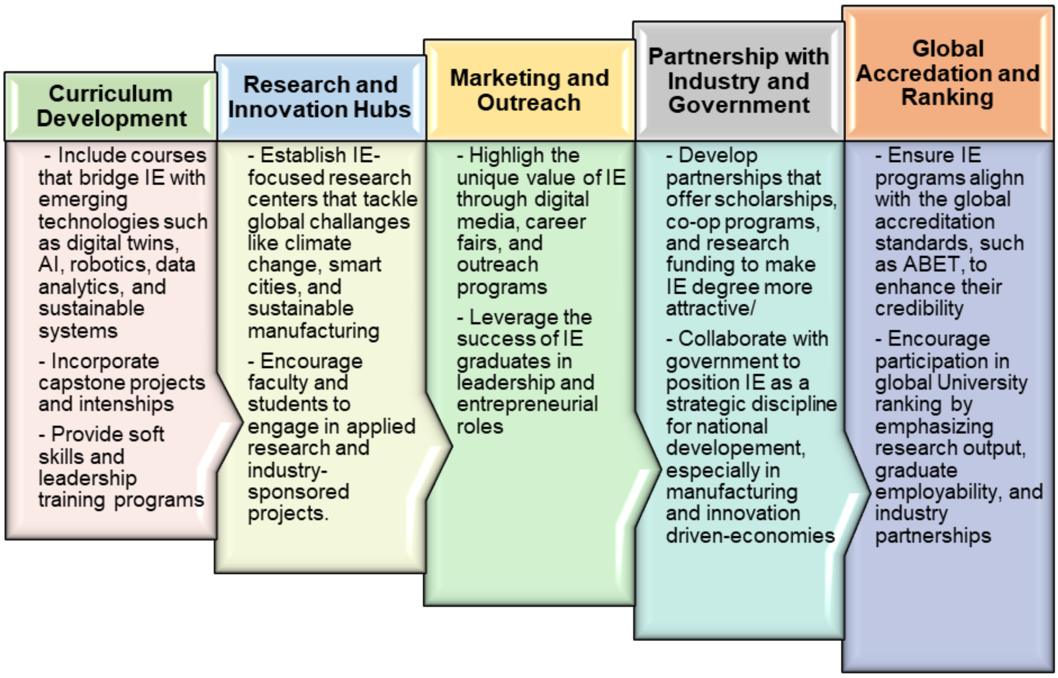

Fig. 7. Positioning the IE degree within academic institutions to align with the evolving industrial landscape.

To further elevate the IE degree, universities must foster partnerships with industries and government agencies. Such collaborations can create pathways for funded research, provide students with access to state-of-the-art facilities, and align academic programs with market needs. Establishing joint initiatives, such as research and development (R&D) hubs focused on smart manufacturing, logistics, and energy systems, would not only enhance the reputation of IE programs but also contribute to regional and national development [227,231].

Marketing and outreach efforts are equally important in positioning the IE degree. Universities should actively promote success stories of their IE graduates who have excelled in leadership, entrepreneurship, or innovative roles across various sectors. Highlighting the diversity of career opportunities available to IE graduates, such as roles in SCM, healthcare systems, and data analytics, can help dispel misconceptions about the scope of the degree and attract a broader pool of students [236–238].

Lastly, aligning IE programs with global accreditation standards, such as those set by ABET, ensures credibility and quality assurance. Participation in global university rankings, driven by research output, graduate employability, and industry impact, can further enhance the degree's prestige. By adopting these strategies, universities can firmly establish the IE degree as a forward-looking, impactful, and indispensable academic program in the modern industrial landscape [239,240].

5. Future Research Directions

The evolution of IE requires a robust research agenda to address emerging challenges and opportunities in an increasingly complex and technological world. This section outlines six promising areas for future research (Fig. 8): Human-AI Collaboration, Adaptive and Resilient Systems Design, Advanced Sustainability Models, Digital Twin Integration, Ethical and Inclusive Systems Design, and Quantum Computing in IE. These areas are crucial for driving innovation and ensuring that IE remains at the forefront of industrial transformation.

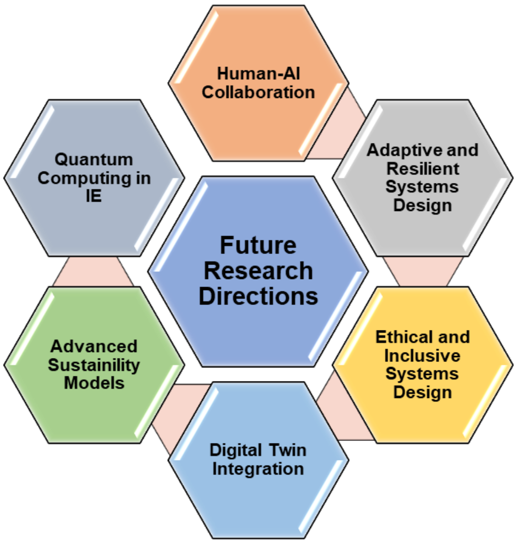

Fig. 8. Future research directions for driving innovation and sustainability in IE

5.1 Human-AI Collaboration

The integration of AI into IS has profoundly transformed decision-making and process management, fostering significant advancements in productivity, safety, and adaptability. However, the full potential of AI lies in seamless collaboration with human expertise, emphasizing a symbiotic relationship where both human and machine capabilities enhance each other [25]. This collaboration, central to Industry 5.0, prioritizes human-centric intelligent manufacturing systems by leveraging AI technologies such as generative AI and large language models (LLMs). These technologies offer human-like interaction, reasoning, and decision-making capabilities, thus enhancing design, production, and service processes [241].

Human-AI coevolution, defined as a continuous feedback loop where human decisions influence AI models and vice versa, plays a pivotal role in modern industrial settings. This dynamic creates opportunities for tailored, data-driven solutions but also introduces complex systemic outcomes that require further exploration [242]. For instance, LLMs demonstrate potential as collaborative partners, aiding human operators in perception, learning, decision-making, and execution. These advancements not only support real-time process optimization but also address safety and operational challenges by minimizing human error [243].

In safety-critical industries, AI-driven predictive and prescriptive models have shown promise in reducing human errors, thus enhancing reliability and operational resilience [243]. Future research should explore intelligent interfaces and tools that improve trust and transparency in human-AI interactions, particularly in industries where decision-making accuracy is critical. Such tools can facilitate safer working environments and more efficient operations by integrating real-time data analysis and human judgment [241].

Generative AI also offers significant potential for managerial practices, improving decision-making efficiency and fostering innovation. Studies indicate that high-quality information provided by conversational AI agents leads to better organizational performance and technological adaptation [244]. Moreover, AI-enabled systems are essential for sustainable manufacturing, as they support green SC collaboration and CE practices, thereby enhancing environmental outcomes [245].

The development of frameworks that optimize HAC is imperative for maximizing these benefits. As I5.0 continues to evolve, further research should focus on creating adaptive AI systems that align with organizational goals, foster worker satisfaction, and promote resource-efficient, cost-effective production paradigms [25]. Such advancements will cement the role of HAC as a cornerstone of sustainable, human-centric industrial operations.

5.2 Adaptive and Resilient Systems Design

The design of adaptive and resilient systems is paramount for industrial operations to withstand disruptions, adapt to evolving conditions, and recover efficiently. As industries move toward I5.0, the focus shifts to human-centric and flexible production systems that integrate real-time feedback and decision-making capabilities. I5.0 emphasizes the dynamic allocation of resources and the seamless blending of physical and virtual environments, exemplified by the Industrial Metaverse, which enables collaborative and adaptive manufacturing processes [246].

Adaptive systems must respond dynamically to uncertainties such as SC disruptions, cyber-attacks, and environmental changes. Resilience can be enhanced through methodologies like redundancy optimization, PdM, and risk assessment, supported by advanced tools like multi-agent systems (MASs) and fault detection algorithms for robust consensus under adversarial conditions [28]. Real-time data-driven decision-making is critical for maintaining operational stability and performance.

Emerging technologies such as AR further strengthen adaptability by providing real-time, human-centric guidance on the shop floor. AR systems offer step-by-step intuitive support, optimizing human-machine interactions while reducing cognitive load and assembly errors [247]. Additionally, the integration of ML and advanced analytics in multiscale modeling enables adaptive simulations for large-scale engineering problems, ensuring scalability and robustness in industrial applications [248].

Future research should focus on frameworks that combine human-centric design, real-time monitoring, and multi-objective optimization to enhance the resilience of cloud service processes, enabling rapid recovery and robustness in distributed design tasks. These advancements will not only optimize resource allocation but also ensure the seamless operation of adaptive systems in the face of disruptions, fostering a resilient and efficient industrial ecosystem [246,247].

5.3 Advanced Sustainability Models

As sustainability becomes a critical priority for industries, future research in IE must emphasize the development of advanced sustainability models that quantify environmental, economic, and social impacts. I4.0 technologies, such as AM, BDA, IoT, cloud computing, and AI, have emerged as pivotal enablers for sustainable manufacturing. These technologies account for a significant portion of the sustainability efforts in modern industries, as they facilitate efficient resource utilization, waste minimization, and energy-efficient production processes [249].

A key focus of sustainability models is the integration of CE principles, which promote resource reuse and recycling while minimizing waste and energy consumption. These models should embed decision-making frameworks that align with global sustainability goals, such as the United Nations SDGs. By employing advanced metrics, such as the Technology Driven Sustainability Index (TDSI), industries can effectively measure and track their sustainability progress along their I4.0 transformation journey [249].

Moreover, the decoupling of economic growth from environmental degradation remains a pressing challenge for energy-intensive manufacturing sectors. Under the I4.0 paradigm, edge-cloud cooperation and BDA can be leveraged to develop integrated sustainability benchmarks, providing real-time information for assessing the relationship between economic growth and carbon emissions. These benchmarks enable industries to monitor and optimize their production processes, reducing their carbon footprint while enhancing economic and social sustainability [19].

Future research should focus on designing holistic sustainability models that incorporate environmental, economic, and social dimensions. By integrating advanced technologies and decision-making tools, these models can empower industries to reduce their environmental impact, foster social responsibility, and drive sustainable economic growth, thus contributing to the achievement of the SDGs.

5.4 Ethical and Inclusive Systems Design

The rise of I5.0 emphasizes the need for human-centric IS, where ethical considerations and inclusivity play a central role. Future research should focus on designing frameworks and methodologies that prioritize equitable access to technology, worker well-being, and the minimization of social inequalities in industrial operations. TAI serves as a cornerstone in achieving this vision, ensuring that the integration of AI in industrial systems remains transparent, accountable, and participatory [189].

Ethical system design should address issues such as fairness, privacy, autonomy, and transparency. In the context of Human-Centered AI (HCAI), these principles foster trust and ensure that AI applications enhance, rather than replace, human capabilities [250]. Moreover, adopting a human-centric approach to HRC on manufacturing floors requires ethical frameworks that promote psychological safety and emphasize accountability in design and innovation processes [12].

Inclusivity metrics should be integrated into system evaluations to ensure that industrial technologies benefit all stakeholders, including marginalized communities. These metrics can be used to assess the ethical implications of design decisions and identify gaps in accessibility and equity. Personalized and ethical AI practices, which have demonstrated success in enhancing user adoption in fields like tourism, also hold significant potential in fostering inclusivity in industrial contexts [148].

By embedding these ethical and inclusive principles into the core of IS design, the IE field can drive the creation of systems that are efficient, sustainable, and socially responsible. This alignment will not only enhance worker well-being but also contribute to broader societal goals, reinforcing the importance of fairness, equity, and inclusivity in shaping the future of I5.0.

5.5 Digital Twins Integration

DTs are revolutionizing industrial operations by bridging the physical and digital realms, offering real-time insights and predictive capabilities. As I5.0 evolves, the integration of DTs into IS becomes increasingly critical. Future research should focus on seamlessly embedding DTs across the entire product lifecycle, from design and manufacturing to operation and end-of-life management. This requires developing interoperable DT platforms, enhancing data accuracy, and implementing secure real-time synchronization between physical and virtual systems [251].

The potential of DTs is further amplified when integrated with the industrial metaverse, which creates a data-centric and semantic-enhanced framework for factory-scale applications. By enabling dynamic knowledge synchronization and optimizing data flow, the industrial metaverse can transform material tracking and process monitoring in manufacturing [251]. Furthermore, advancements in human-centric systems, such as Human Digital Twins (HDTs), offer comprehensive frameworks for monitoring worker well-being, enhancing safety, and optimizing HRC [17,252].

Integrating DTs with advanced simulation tools, IoT sensors, and ML enhances their ability to predict and optimize system performance. For example, in AM, DTs coupled with ML have improved process monitoring, defect detection, and real-time decision-making [253]. Additionally, adopting standardized frameworks, such as the Asset Administration Shell (AAS), ensures dynamic monitoring and control, enabling comprehensive I4.0 scenarios, as demonstrated in smart warehouse systems [254].

Addressing challenges such as real-time data synchronization, secure data transfers, and behavioral modeling is essential to fully realize the potential of DTs. Ethical concerns, including data privacy and consent, must also be prioritized for widespread adoption. By advancing these capabilities, DTs will enable industries to optimize processes, reduce downtime, enhance product quality, and contribute to the broader goals of sustainability and operational efficiency [83,255].

5.6 Quantum Computing in IE

Quantum computing (QC) offers transformative potential for solving complex optimization problems that are currently beyond the reach of classical computing. In the context of IE, QC can revolutionize areas such as SC optimization, manufacturing process simulations, and energy-efficient production systems. For instance, breakthroughs in quantum convex optimization and ML could provide innovative solutions to challenges in power system planning and operation [31]. Similarly, quantum-enhanced algorithms for resource allocation and predictive analytics could improve the precision and efficiency of sustainable agricultural systems [256].

Recent advancements also highlight the applicability of quantum metaheuristic algorithms in addressing large-scale industrial challenges, including energy efficiency and path planning [257]. Furthermore, quantum simulations could enhance the design and performance of IS by offering unprecedented computational power and parallelism [29]. However, significant research is needed to address practical implementation challenges, scalability, and the development of quantum-safe environments [258]. By harnessing QC's potential, IE can unlock new frontiers of innovation and efficiency.

6. Conclusion

IE has continually evolved to meet the demands of a changing world, from its early foundations in work organization and logistics to its pivotal role in the digital and sustainable revolutions of I4.0 and I5.0. This transformation has been driven by the integration of advanced technologies, including AI, IoT, DTs, and QC, which have revolutionized production systems, SCs, and decision-making processes. I4.0 introduced CPS and data-driven automation, while I5.0 builds on these advancements to emphasize human-centric, ethical, and sustainable industrial practices. The discipline's ability to optimize complex systems and adapt to emerging challenges positions it as a leader in driving industrial innovation and sustainability. Resilience engineering, data analytics, automation, and sustainability models have demonstrated the potential to enhance operational efficiency, reduce environmental impacts, and foster HMC. Moreover, IE's interdisciplinary nature enables it to address critical global challenges such as resource scarcity, climate change, and the need for inclusive economic growth.

Advancing the IE profession and academic programs is essential to maintain its relevance and impact. By modernizing curricula, fostering industry partnerships, and promoting the profession's unique contributions, IE can attract top talent and remain a cornerstone of technological and societal progress. Furthermore, addressing ethical considerations, bridging digital divides, and enhancing cybersecurity will ensure that IE leads the way in building resilient, sustainable, and inclusive industrial ecosystems. IE stands at the nexus of innovation and sustainability, uniquely equipped to shape the future of industry. By embracing technological advancements and prioritizing human-centric and ethical practices, the discipline is poised to lead the transformation of IS, addressing global challenges and contributing to a sustainable and inclusive future. This evolution marks a pivotal moment for IE, positioning it as a key driver of progress in the digital and sustainable era.

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Declaration of Conflicting Interest

The author has no known competing financial interests or personal relationships to declare that could have appeared to influence the work reported in this paper.

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