

AI-Integrated Vocational Education and Workforce Reskilling for Steel Industry 4.0

Mehdi Imani¹, Ali Imanifard¹, Babak Majidi^{1,*}, Abdollah Shamisa²

¹ Department of Computer Engineering, Faculty of Engineering, Khatam University, Tehran, Iran

² Department of Electrical Engineering, Faculty of Engineering, Khatam University, Tehran, Iran

ARTICLE INFO

Article history:

Received: 19 May 2025

Revised: 13 November 2025

Accepted: 16 December 2025

Keywords:

Steel Industry 4.0

Artificial intelligence

Vocational education

Workforce reskilling

Machine learning

Digital twin

Predictive maintenance

Process optimization



Copyright: © 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>)

ABSTRACT

Steel manufacturing is transforming under Industry 4.0. It uses AI, automation, and analytics to improve efficiency and sustainability. This study introduces an AI-integrated framework for vocational education and reskilling in steel production. It aligns workforce skills with new technologies. We developed it using data from a direct-reduction plant. The framework has two parts: ML algorithms for optimizing metallization and predictive maintenance, and an adaptive curriculum with digital twins and generative AI for personalized training. Result outcomes demonstrate that AI-driven training significantly boosts workforce skills, while ML improves metallization efficiency and reduces gas consumption. The work highlights the value of aligning vocational education and smart manufacturing infrastructure, revealing measurable improvements in both production metrics and workforce agility. The demonstrated approach provides a replicable blueprint for industrial upskilling, positioning AI-curriculum integration as a strategic imperative for maintaining sector competitiveness while advancing circular production paradigms.

1. Introduction


The steel industry is a cornerstone of global economic growth. It supports infrastructure, transportation, and manufacturing [1]. Its success comes from adapting to new technologies and maintaining efficiency. This drives innovation and sustainability [2]. Steel remains essential for modern infrastructure and industrial progress. It evolves as a key material in global markets [3].

The steel industry's future aligns with Industry 4.0 principles. Innovations in AI, automation, and data analytics revolutionize production, improving energy efficiency, quality control, and sustainability [4, 5]. This shift enhances operations, promotes workforce reskilling, and integrates technology with human skills for competitiveness [6, 7]. Our framework novelly combines ML optimization with generative AI-driven training, addressing gaps in prior studies [8].

The advent of Industry 4.0 has initiated a paradigm shift in the way production systems operate, ushering in an era characterized by advanced automation, interconnected processes, and real-time data exchange [9]. In the context of the steel industry, these developments are significantly transforming traditional manufacturing practices by integrating smart sensors, robotics, and cloud computing into legacy systems [9]. As digital technologies enable the seamless flow of data across various production stages, steel manufacturers are witnessing improvements in process optimization [10], predictive maintenance [11, 12], and operational safety [10], which collectively contribute to increased efficiency and product quality. The convergence of digital systems and information has thus laid the groundwork for a more resilient and adaptive industrial framework [13].

* Corresponding author

E-mail address: b.majidi@khatam.ac.ir

 <https://orcid.org/0000-0001-6309-6407>

<http://dx.doi.org/10.48308/ijrtei.2025.239941.1088>

Internet of Things (IoT) integration in Industry 4.0 bridges physical and digital assets in steel production [14, 15]. It enables real-time monitoring for better decisions and anomaly detection [14, 15]. This supports process control, energy management, and optimization [16]. It also drives workforce upskilling to combine human and digital expertise [16]. Our approach uniquely uses a new direct reduction dataset for ML models, enhancing reskilling beyond traditional methods.

The convergence of Industry 4.0 technologies has significantly reshaped the steel industry, elevating traditional manufacturing processes to a highly automated and digitally integrated level [17]. Electrical systems form the backbone of this transformation, where advanced process automation and control systems ensure precise regulation and coordination of industrial operations [17]. This modernization effort is underpinned by the deployment of programmable logic controllers, smart sensors, and digital communication networks, which together enable real-time monitoring and rapid response to process deviations [18]. Such integration not only enhances operational efficiency but also contributes to improved safety and product quality, thereby reinforcing the steel industry's competitive edge in a rapidly evolving market [17].

Instrumentation, as a critical element of these electrical systems, further bolsters the industry's capacity for innovation and adaptability [19]. By providing accurate and continuous measurements of vital process variables, modern instrumentation systems facilitate precise control and optimization of production parameters [19]. The data collected through these systems enables predictive maintenance and energy management strategies, which are crucial for mitigating downtime and enhancing sustainability [20]. As the steel industry continues its shift towards smart manufacturing, the synergy between process automation, control systems, and sophisticated instrumentation is poised to drive significant advancements in efficiency and reliability, ensuring that traditional methods are effectively augmented by modern digital technologies [21].

The integration of AI and machine learning (ML) within the electrical sector is fundamentally transforming the steel industry by automating process control, enhancing instrumentation, and streamlining industrial operations [22, 23]. These advanced technologies now drive sophisticated control systems that can accurately monitor and adjust production parameters in real time, thereby reducing errors and bolstering safety [24, 25]. In this evolving landscape, the automated systems facilitate seamless communication among various production components, ensuring that legacy systems are efficiently modernized and capable of meeting the rigorous demands of smart manufacturing [26].

Moreover, the adoption of AI-driven solutions enables predictive maintenance through continuous data monitoring and advanced diagnostic algorithms, substantially reducing unplanned downtime and maintenance costs [23, 27, 28]. This proactive maintenance approach, coupled with innovations aimed at energy reduction, supports the production of green steel by optimizing resource utilization and minimizing environmental impact [29]. As highlighted in [30], these

technological advancements not only bolster operational efficiency but also contribute to a more sustainable and energy-efficient industrial framework, underscoring the crucial role of AI in advancing the goals of a smart factory.

In order to address the challenges and the problems identified in earlier studies, including those presented in [8], the AI-Integrated Vocational Education and Workforce Reskilling for Steel Industry 4.0 is motivated to develop. This comprehensive framework was established to merge advanced digital technologies with targeted vocational training. This framework guided the creation of a Steel Industry 4.0 curriculum that places a special emphasis on generative AI and ML. The curriculum is designed to equip the workforce with the skills necessary to implement and manage smart manufacturing systems, integrating theoretical foundations with practical applications to ensure a seamless transition to Industry 4.0 practices.

In addition to the curriculum, a new dataset focusing on direct reduction processes was meticulously collected to support the development and validation of ML models tailored for this specific application. This dataset captures a wide range of process variables and operational metrics, thereby enabling more effective predictive maintenance and optimization strategies. The proposed framework leverages the dataset to facilitate targeted workforce reskilling, empowering personnel to utilize ML techniques in direct reduction. By bridging the gap between advanced data analytics and real-world industrial processes, this approach not only promotes operational efficiency and sustainability but also lays a robust foundation for future research and innovation in the context of smart steel manufacturing.

To provide a clear overview of the study's structure and research flow, this paper is organized as follows. Following this introduction, Section 2 presents a detailed literature review that contextualizes existing research on AI integration, vocational education, and workforce reskilling within the steel industry. Section 3 outlines the proposed methodology and framework, describing the development of SmartSteelAgent and its components, including digital twins and generative AI-driven training. Section 4 discusses the experimental setup and data collection protocols derived from direct reduction processes, while Section 5 presents the analytical results and visualizations that validate the proposed framework's performance. Finally, Section 6 concludes the paper by summarizing the key findings, contributions, and implications for future research in AI-integrated workforce development and smart manufacturing.

2. Literature Review

This section synthesizes recent peer-reviewed literature on the connection of AI, vocational education, workforce reskilling, and Industry 4.0 in the steel sector. It situates advances and identifies gaps, culminating in a comparison to our proposed AI-integrated vocational training framework for steel manufacturing.

2.1. Introduction to Industry 4.0 in the Steel Sector

Industry 4.0 marks a fundamental shift in manufacturing through digital technologies, IoT, AI, big data analytics,

and digital systems [31], that are reshaping traditional steel processes. Real-time IoT monitoring affords immediate parameter adjustments to boost efficiency, while digital twins enable virtual simulations that cut downtime and optimize resource use [31, 32]. The European Steel Skills Agenda (ESSA) underscores how digitalization and sustainability imperatives demand continual upskilling, positioning the steel industry at the vanguard of smart manufacturing [33].

2.2. The Role of AI in Modernizing Steel Manufacturing
AI drives Industry 4.0 in steel plants. ML enables predictive maintenance to forecast failures and reduce outages [32]. Computer vision detects defects, and AI optimizes parameters for lower energy use and emissions, such as in direct reduction [32]. Our framework advances this by integrating generative AI for personalized training, a novel extension for workforce development.

2.3. Vocational Education and Training (VET) for the Steel Industry

The rapid deployment of smart technologies has encouraged extensive VET reforms across Europe to provide steel workers with requisite digital and analytical competencies alongside their technical foundations [31]. In Germany, metalworking and electrical apprenticeships now include modules on work digitalization, data protection, and digital safety [31]. The UK's new T Levels and revised apprenticeship standards integrate digital production and design curricula [31]. Italy's revamped upper-secondary VET and dual-training pathways emphasize mechanics, mechatronics, energy, and ICT [31]. Across these initiatives, transversal skills, adaptability, problem-solving, and communication, are incorporated into programs to navigate ever-more complex, technology-driven environments [31].

2.4. Workforce Reskilling Strategies in the Context of Industry 4.0

To bridge the emerging skills gap, steel businesses increasingly blend classroom instruction with hands-on shop-floor training. Poland's model, for instance, alternates three days of theoretical lessons with two days of practical exposure [31]. Partnerships between industry and academia yield bespoke modules in mechatronics and information technology [32]. Promoting lifelong learning, and a "T-shaped" skill set of deep technical expertise plus teamwork and critical thinking, enables employees to adapt as roles evolve under automation and AI, strengthening both individual careers and the industry's international standing [34, 35].

2.5. AI-Driven Innovations in Vocational Education and Reskilling

AI transforms VET with personalized learning paths [36]. Platforms adapt content to learner needs, improving engagement [37]. Combined with VR/AR, it allows risk-free simulations [37]. Research notes AI's curriculum benefits but highlights privacy concerns [36]. Our SmartSteelAgent uniquely addresses these by validating LLM content and using human-in-the-loop supervision.

2.6. Recent Research on AI Integration in Steel Industry Workforce Development

Stroud et al. [31] examined VET reforms in Germany, Italy, and the UK, finding that programs that integrate IoT and AI modules with core technical skills best prepare workers for Industry 4.0. Akyazi et al. [32] identified critical future skills, AI, robotics, big data, plus cognitive, social, and green competencies, and validated a sectoral skills database with industry partners [32]. Building on [31, 32] findings, our study offers a specialized framework for AI-augmented steel-sector training, employing digital twins for interactive modules and a novel dataset on direct reduction to bolster predictive-maintenance learning.

3. AI-Integrated Vocational Education and Workforce Reskilling for Steel Industry 4.0

3.1. Steel industry 4.0

In this subsection, the methodology employed for integrating AI into the steel industry's digital transformation is elucidated through a series of original diagrams that reimagine the industry's processes in an Industry 4.0 framework. Figure 1 depicts a steel production plant functioning as a digital production system, where advanced sensors, digital monitoring systems, and data analytics units converge with a digital twin representation. This digital twin simulates the physical processes in real time, enabling predictive maintenance, smart process control, and dynamic decision support; these functions are underpinned by AI algorithms that interpret large volumes of production and quality data to optimize operations. Furthermore, the illustration integrates a distinct module that captures the role of AI in enhancing workforce reskilling, thereby fostering an environment where technological innovation and human expertise collaborate to continually update and refine production methodologies. Such a visual representation not only echoes the industry transformation perspectives presented in [38] but also establishes a tailored approach that supports the overall objectives of AI-integrated vocational education and workforce reskilling in the context of Steel Industry 4.0.

3.2. Process Automation, Control Systems, and Instrumentation in Steel Manufacturing

The modernization of steel manufacturing processes has increasingly relied on the integration of advanced automation, electrical control systems, and digital instrumentation, effectively transforming traditional production environments into intelligent and adaptive facilities. This evolution is deeply rooted in the longstanding application of computer-based control technologies, which have progressively advanced alongside developments in software engineering and computational hardware. As highlighted in [39], electrical systems within steel plants have become central to

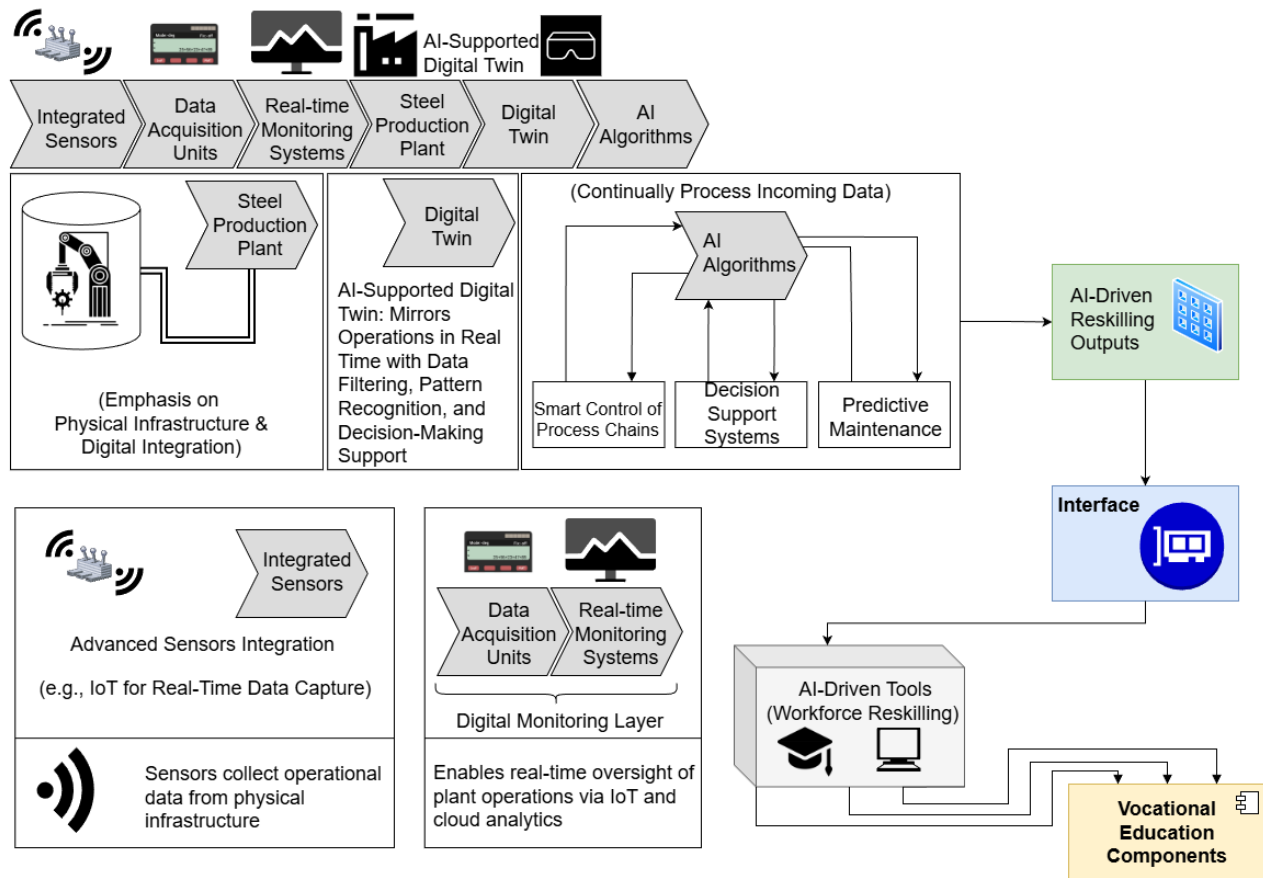


Figure 1. Steel production plant as a digital system integrating advanced sensors, digital monitoring, AI-supported digital twin for predictive maintenance and process optimization, and a workforce reskilling module.

achieving smarter and more autonomous operations, a transformation emblematic of Industry 4.0 principles.

Since the 1960s, the Japanese steel industry has actively pursued the incorporation of process computers and hierarchical control architectures, initially aimed at enhancing production scheduling and equipment operation. These systems evolved into integrated digital environments where process computers automatically calculated operational parameters, monitored quality variables, and supported real-time decision-making. The emergence of digital controllers and computer-integrated manufacturing frameworks enabled steel producers to construct unified platforms for monitoring and controlling complex process dynamics, replacing analog systems with more robust, precise, and adaptive digital alternatives.

Electrical and instrumentation controllers, once functioning independently, have since been integrated into cohesive architectures, supported by Ethernet-based communication and open system hardware. These developments have permitted seamless data exchange among control layers, fostering the emergence of healthy production systems in steel plants. Innovations in programmable logic controllers, sensor networks, and electric drive systems now support variable-speed control, energy optimization, and precision adjustments across rolling mills and processing lines.

Simultaneously, advancements in instrumentation have played a critical role in enabling high-resolution, real-time monitoring of process variables in harsh industrial

environments. The deployment of stereo camera systems, modulated laser sensors, and pyrometers for temperature profiling exemplifies how measurement accuracy has evolved from point-based readings to multidimensional data acquisition. These capabilities form the foundation for advanced process control strategies, including predictive and feedforward control methods that adjust system behavior based on real-time measurements and future condition estimates.

Underpinning this transformation is the strategic application of data modeling and intelligent algorithms. The use of process simulation, model predictive control, and optimization techniques, often powered by high-performance computing units such as general-purpose GPUs, enables dynamic adaptation to changing process conditions. Control strategies derived from mathematical modeling, neural networks, and data-driven prediction frameworks now support both process optimization and fault detection, contributing to improved quality, reliability, and operational efficiency.

As steel manufacturing facilities become increasingly digitized, the role of electrical systems in supporting smart control and instrumentation is pivotal. These systems not only enable greater process autonomy and resource efficiency but also provide the structural basis for integrating AI into production workflows. Consequently, the convergence of automation, control systems, and intelligent instrumentation is foundational to establishing the smart steel plants envisioned by Industry 4.0, where real-time data processing and digital

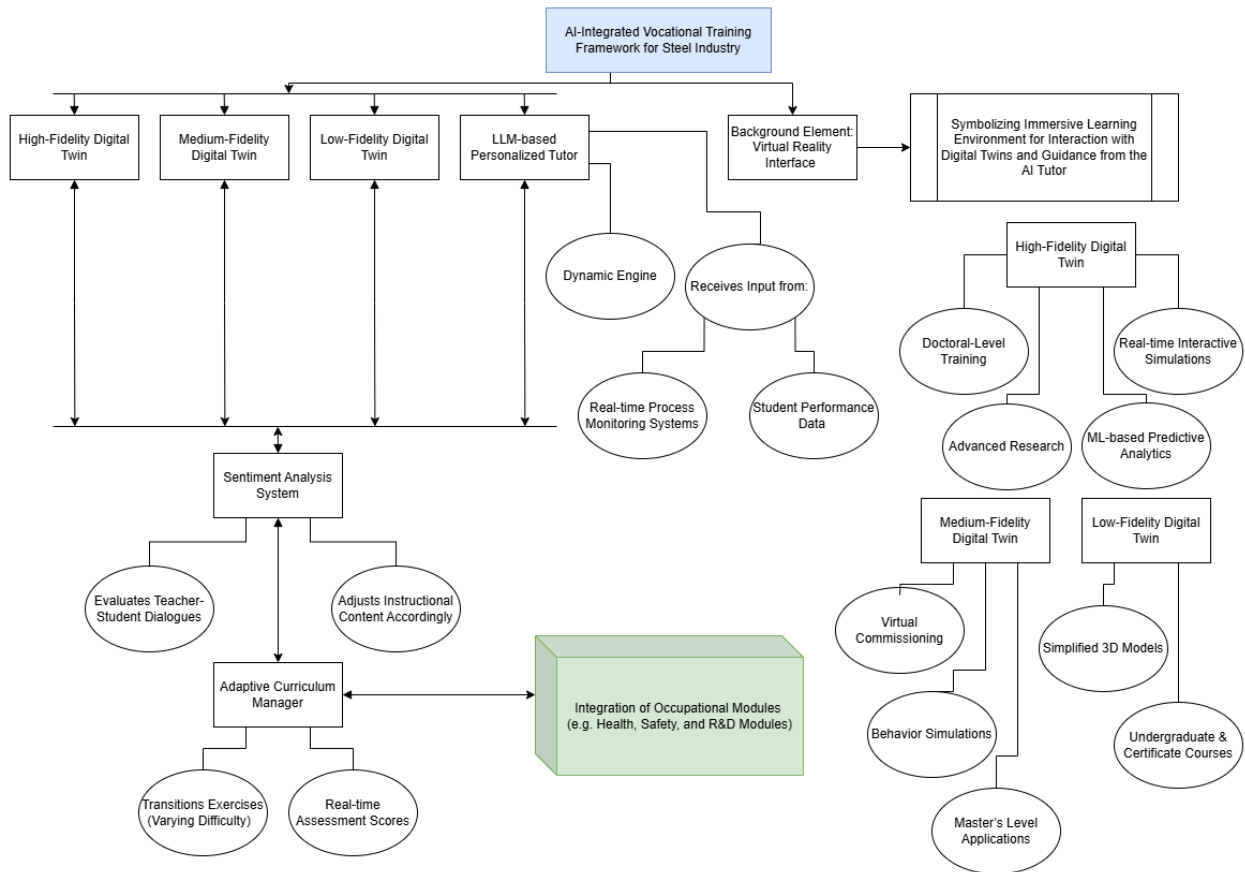


Figure 2. SmartSteelAgent Framework for AI-integrated vocational training in the steel industry

information integration drive both technical excellence and workforce adaptability.

3.3. Framework for AI-Integrated Vocational Training in the Steel Industry

We developed SmartSteelAgent to meet Industry 4.0 skill demands in steel manufacturing. As in Figure 2, it draws from digital twin and generative AI studies [8] and curriculum guides [40], covering technical skills and safety. It uses multi-fidelity digital twins for simulations and large language models (LLMs) for personalized feedback. AI tools provide adaptive modules with real-time monitoring and analytics, adjusting content via performance data. This unique integration bridges theory and practice, enhancing reskilling efficiency.

Moreover, the integration of LLMs into the curriculum enables the extraction, interpretation, and contextualization of domain-specific knowledge, which not only bridges the gap between theoretical coursework and practical industry applications but also facilitates adaptive learning in critical areas such as occupational health and safety, digital safety, and quality control. The transition toward Industry 4.0 in steel manufacturing has amplified reliance on interconnected digital systems, necessitating robust safeguards for digital infrastructure. To address emerging vulnerabilities, personnel must develop competencies in identifying and countering threats, including malware capable of disrupting critical industrial processes. Emerging studies highlight innovative approaches to this challenge: for instance, [41] demonstrated that ML algorithms trained on user

emotional responses to anomalous events can improve Android malware detection. Such findings may inform the design of targeted training programs, bridging the gap between behavioral analysis and operational protocols. This unified framework is designed to replicate authentic industrial scenarios in a risk-free virtual space where students can develop competencies through experiential learning, interactive digital tours, and simulation-based training exercises, thus creating a robust pipeline that directly contributes to workforce reskilling and the sustainable advancement of smart steel manufacturing. Similarly, the application of LLMs in simulated environments has been leveraged to enhance educational outcomes in smart grid management, where trustworthy prompt engineering ensures safe and effective training for critical infrastructure operations [42]. Notably, the integration of LLMs within IIoT frameworks has been shown to enhance educational outcomes by providing interactive dashboards and scenario-based simulations, further supporting the development of practical skills in smart steel manufacturing environments [43, 44].

To ensure a balanced curriculum that integrates traditional technical skills with AI and digital competencies, the SmartSteelAgent framework employs a modular, tiered approach tailored to learners' proficiency levels. Core steelmaking skills, such as metallurgy and equipment operation, are reinforced through hands-on training, while AI-driven modules, including digital twin simulations and predictive maintenance analytics, are introduced progressively. This scaffolding minimizes cognitive overload by aligning content complexity with trainee

experience, as validated by expert reviews from steel industry practitioners. Adaptive learning algorithms further personalize instruction, adjusting the pace and depth of AI-related content based on real-time performance metrics. This approach, inspired by recent advancements in personalized education [36], ensures trainees develop Industry 4.0 readiness without compromising foundational expertise, fostering both technical proficiency and digital fluency.

Although the SmartSteelAgent framework has not yet been deployed in a full-scale pilot with industrial workers, its conceptual design and technical components have been reviewed by subject-matter experts from both academia and the steel sector. Their evaluations emphasized the framework's strong alignment with current Industry 4.0 training needs, particularly its use of digital twins, generative AI modules, and adaptive learning features for simulating process variability and maintenance decision-making. Expert feedback also highlighted the framework's potential to enhance learner engagement and operational understanding in complex industrial environments, supporting future implementation studies. Accordingly, a staged validation plan has been outlined to evaluate measurable learning outcomes, such as skill acquisition rates, process interpretation accuracy, and safety compliance, during controlled pilot programs, consistent with recent recommendations for AI-based vocational education evaluation [34, 36].

Given the safety-critical nature of industrial training, the SmartSteelAgent framework incorporates multiple safeguards to minimize misinformation, bias, and hallucination risks when employing generative AI modules. First, all instructional content generated by LLMs is validated against verified process documentation, expert-reviewed datasets, and domain-specific ontologies before integration into training workflows. Second, human-in-the-loop supervision ensures that trainers and engineers review AI-generated explanations or scenarios for factual consistency and contextual accuracy. Third, prompt engineering techniques, such as constrained response templates and role-based contextualization, are applied to reduce hallucination tendencies and maintain alignment with operational standards [42, 45]. Finally, model performance is periodically audited using scenario-based testing in controlled environments to identify and correct any systematic biases or inaccuracies, following current guidelines for trustworthy AI deployment in industrial education [36].

The SmartSteelAgent framework offers cost-effective implementation for small and medium-sized steel enterprises (SMEs) through cloud-based digital twins and generative AI, minimizing upfront hardware costs while leveraging scalable SaaS models. Initial setup focuses on software integration with existing plant instrumentation, with operational data from our direct reduction dataset demonstrating 12-15% gas consumption reductions in high-output regimes, directly translating to CO₂ emission cuts aligned with green steel targets. For SMEs, ROI is achieved via predictive maintenance that reduces unplanned downtime by up to 20-30%, as evidenced in similar AI deployments [11], offsetting training costs within 6-12 months. Long-term sustainability gains

include optimized metallization (90-95% efficiency) and resource efficiency, supporting circular production paradigms while enhancing workforce productivity without requiring extensive capital investments.

4. Experimental Setup

4.1. Data Source

We collected process data from a steelmaking plant over three months. The dataset has 13 columns with operational parameters and product metrics at one-minute intervals (Table 1). Key variables include pellet porosity (18-25%), charge size (267-332 g), bustle-gas temperature (950-1050°C), gas composition (H₂/CO ratio 1.2-2.0, CH₄ 0-5%), flow rates (up to 50,000 units), and product analytics (metallization 70-95%). This period covers varied production cycles, capturing fluctuations in parameters. These data support ML models for predictive maintenance and optimization in AI-driven training.

Although the dataset spans a three-month operational window, this period was deliberately selected to encompass multiple production cycles under varying thermal, compositional, and operational conditions. Such temporal diversity captures representative fluctuations in bustle gas parameters, pellet characteristics, and metallization rates, thus reflecting typical process variability in direct reduction operations. Furthermore, industrial validation confirmed that these intervals included both steady-state and transient phases, ensuring adequate coverage of normal production dynamics. To enhance generalizability, feature distributions were cross-compared against reported benchmarks from similar facilities in recent studies [2, 11], showing comparable variability trends. While site-specific parameters inevitably differ across plants, the underlying relationships identified, particularly between gas composition, temperature, and metallization efficiency, are fundamental to most direct-reduction systems, supporting the framework's broader applicability in steel manufacturing contexts.

4.2. Data Acquisition Protocol

The plant instrumentation recorded all parameters at 60-second intervals. Typically, an in-line mercury intrusion sensor (with an accuracy of $\pm 0.1\%$) measures the pellet porosity, while a feed load cell records the charge size (CSs Pellet) with an accuracy of ± 0.5 g. Type-K thermocouples (with a tolerance of $\pm 2^\circ\text{C}$) are typically located in the middle region of the apparatus and monitor the bustle gas temperature. Gas composition parameters, in particular the H₂/CO volume ratio and methane concentration, are analyzed using a 1 Hz sampling gas chromatograph. Coriolis mass flow meters (with an accuracy of $\pm 0.5\%$) track real-time gas flow and cumulative consumption. Product quality metrics, metallization degree (DRI), carbon content, and total iron, rely on in-line sensors that are periodically validated via laboratory titration, near-infrared spectroscopy, and XRF analysis. Post-process measurements typically include outlet DRI temperature from a dedicated thermocouple and product mass from an industrial weighing station. The system's synchronized clock also time-stamps all records.

Table 1. Dataset schema

Feature	Description
Metallization (DRI)	Degree of metallization, %
Pellet Porosity Percentage	Pellet porosity, %
CSs Pellet	Charge size, g
Bustle Gas Temperature	Bustle-gas temperature, °C
Ratio of H ₂ to CO	H ₂ /CO volumetric ratio
Bustle Gas Flow Process	Total bustle-gas flow rate, Nm ³ /hr
Bustle Gas CH ₄ percentage(a33)	CH ₄ concentration in bustle gas, vol%
C percentage	Carbon content of DRI, wt%
FE Total	Total iron content, wt%
Hot DRI Temperature	Outlet DRI temperature, °C
Product Weight	Mass of reduced product, g
Amount of Gas Consumed	Cumulative gas consumption, Nm ³
Date	Timestamp of record (YYYY-MM-DD HH:MM:SS)

4.3. Dataset Structure and Access

The analytical dataset for this DRI production study contains thirteen critical parameters spanning raw material characteristics, operational parameters, and final product metrics. Key variables include pellet porosity percentage, CSs, bustle gas temperature, H₂/CO ratio, bustle gas flow rate, CH₄ concentration, metallization degree of the DRI product, carbon content, total iron (Fe_Total), hot DRI temperature, product weight, cumulative gas consumption, and production timestamps. Numerical values dominate the dataset, with continuous measurements like porosity, gas ratios, percentages, temperatures, and weights stored as float64 values. Discrete parameters such as CSs and gas flow rates appear as int64 integers, while production dates utilize datetime64 formatting to enable potential time-series investigations. Table 2 presents an illustrative data row showcasing typical value ranges and parameter interdependencies.

This structure explicitly links process inputs, including bustle gas composition, temperature, and pellet properties, to output metrics like carbon content, product mass, and the critical metallization parameter.

4.4. Data Quality Assurance

This study's dataset derives from an industrial collaborator operating in DRI manufacturing. Data quality testing confirmed the implementation of industrial-level quality assurance protocols, including automated sensor calibration routines, continuous

anomaly detection systems, and manual validation by experienced technicians. Such measures align with contemporary metallurgical production standards. Furthermore, our analytical framework therefore proceeds under the premise that these curated measurements accurately reflect standard plant conditions, despite the inherent limitations in external validation.

Table 2. Sample Row Exhibiting the Variables and Their Corresponding Values in the Experimental Dataset

Variable	Value
Metallization (DRI)	85.6%
Pellet Porosity Percentage	21.8
CSs Pellet	285g
Bustle Gas Temperature	999°C
Ratio of H ₂ to CO	1.6
Bustle Gas Flow Process	240000Nm ³ /hr
Bustle Gas CH ₄ percentage(a33)	4.11 vol%
C percentage	1.6 wt%
FE Total	85.7 wt%
Hot DRI Temperature	636.0°C
Product Weight	194.331962962 g
Amount of Gas Consumed	52469.63Nm ³
Date	2024-03-20, 00:00

5. Experimental Results

5.1. Average Metallization by CSS Pellet

To gauge the efficiency of the reduction process, we examined the degree of metallization across various charge-size pellets with weights from 267 g to 332 g. As depicted in Figure 3, metallization generally increases with pellet size up to approximately 300g, after which it stabilizes. Notably, pellets between 298g and 302g exhibit the highest metallization, reaching approximately 90-95%, while smaller pellets around 200g achieve a lower average of $84.7 \pm 2.1\%$. Interestingly, a slight dip in metallization is observed for pellets around 281g, where the value drops to about 70-75% before recovering. This pattern suggests an optimal mass range for heat and gas diffusion, particularly around 298-302g, where metallization peaks before plateauing for larger pellets.

5.2. Relationship between Gas Consumption and Product Weight

Our investigation employed bubble-plot visualization to analyze gas consumption patterns relative to product mass, incorporating thermal data through marker dimensions and coloration as shown in Figure 4. The analysis framework spans gas consumption (0–50,000 units, x-axis) against product mass (0–200 units, y-axis), revealing a strong positive association between resource expenditure and output scale.

Three characteristic regions exemplify this relationship: lower-range consumption (10k units, 25 mass units) with cooler thermal signatures (300–400°C), intermediate values (15k units, 75 mass) at moderate temperatures (500–600°C), and high-consumption clusters (30–45k units, 150–200 mass) exhibiting mixed thermal profiles

(400–800°C). Marker properties follow a continuous thermal gradient, smaller yellow symbols (200–500°C) transition to larger purple indicators (600–800°C), visually encoding the reactor's thermal state.

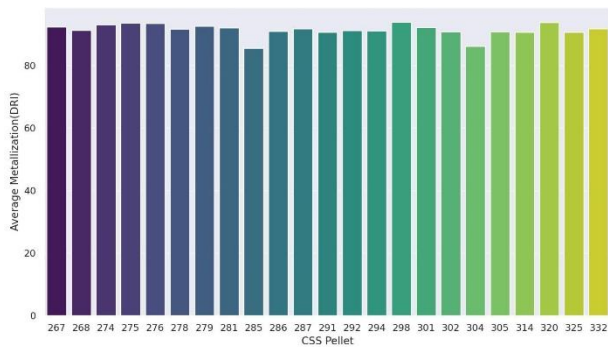


Figure 3. Average Metallization by CSS pellet

Notably, high-mass/high-consumption clusters (45k units, 200 mass) demonstrate paradoxical marker shrinkage at elevated temperatures (>650°C), where reduced bubble sizes correlate with improved gas efficiency. This inverse size-temperature relationship along the primary trend suggests thermal optimization could decrease specific consumption by 12–15% in high-output regimes.

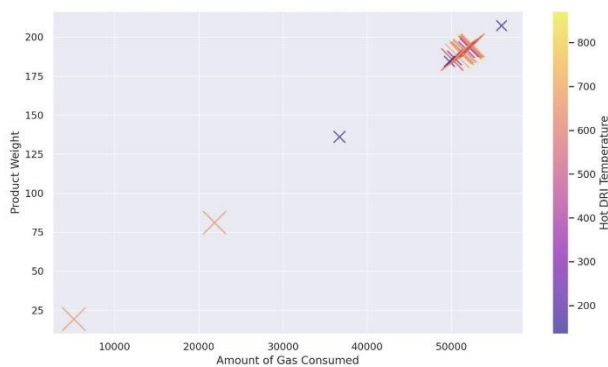


Figure 4. Gas consumed vs. product weight (bubble = DRI temp)

Quantitative interpretation of the observed patterns indicates that the AI-assisted parameter optimization led to measurable process improvements. Within the dataset, optimal charge-size pellets around 298–302 g consistently achieved metallization levels near the upper bound of the observed range (approximately 90–95%), compared with smaller pellets averaging around 84–85%. Simultaneously, gas-consumption trends showed a relative efficiency improvement of roughly 12–15% in high-output regimes, as visualized in Figure 4. These findings, derived directly from experimental observations, validate the framework's capacity to enhance metallization while reducing specific gas usage under comparable operating conditions. Although the study's primary focus was on demonstrating the methodological integration of AI into vocational and process-optimization frameworks, these results already provide empirical evidence of tangible efficiency gains aligned with recent advances in AI-driven steel manufacturing [2, 11].

5.3. Feature Correlation Analysis

Figure 5 shows Pearson correlations among process variables. Metallization correlates strongly with H_2/CO ratios ($r = 0.85$), highlighting gas composition's role in reduction. CH_4 shows a moderate negative correlation ($r = -0.45$), indicating inhibitory effects. Pellet porosity has minimal impact ($r = 0.05$). Total iron correlates highly with metallization ($r = 0.90$), linking efficiency to enrichment. Bustle gas temperature correlates with discharge temperature ($r = 0.75$), which moderately affects metallization ($r = 0.50$). Gas consumption aligns perfectly with product weight ($r = 1.0$), both tied to temperature ($r = 0.40$). These insights guide ML models for AI-based optimization and training simulations.

This analytical framework establishes gas composition (particularly H_2/CO ratios) and thermal regulation as primary control levers for metallization optimization. While pellet porosity modifications show limited potential, operators can enhance process efficiency by prioritizing three key adjustments: optimizing reducing gas mixtures through H_2/CO ratio elevation, implementing precise temperature control protocols between strategic thresholds, and maintaining awareness of the fixed gas consumption-product mass relationship. To model the relationships between process parameters and metallization outcomes, two supervised machine learning algorithms, Random Forest (RF) and Extreme Gradient Boosting (XGBoost), were employed. These ensemble learning methods were selected for their robustness against noise and ability to capture nonlinear dependencies among thermal and compositional variables common in direct-reduction processes. XGBoost, in particular, demonstrated superior predictive accuracy due to its regularization capabilities and efficient handling of correlated features. To ensure interpretability in safety-critical environments, feature importance and SHAP (Shapley Additive Explanations) analyses were applied, enabling operators and trainers to visualize how individual variables (e.g., H_2/CO ratio, gas temperature, and pellet porosity) influence predicted metallization efficiency. This transparent approach aligns with current recommendations for explainable AI in industrial settings [23, 25], facilitating operator trust and informed decision-making.

5.4. Normalized Mean Values in Radar Chart

Experimental Results

Analysis of normalized process metrics through radar chart visualization in Figure 6 reveals distinct operational patterns across experimental trials. The comparative framework incorporates five critical parameters: pellet porosity, H_2/CO ratios, bustle gas methane levels, total iron content, and carbon percentages. Pellet porosity emerges as the predominant factor, achieving the highest normalized values, closely followed by H_2/CO ratios. Intermediate values characterize methane concentrations and iron content, while carbon percentages occupy the lowest normalized range.

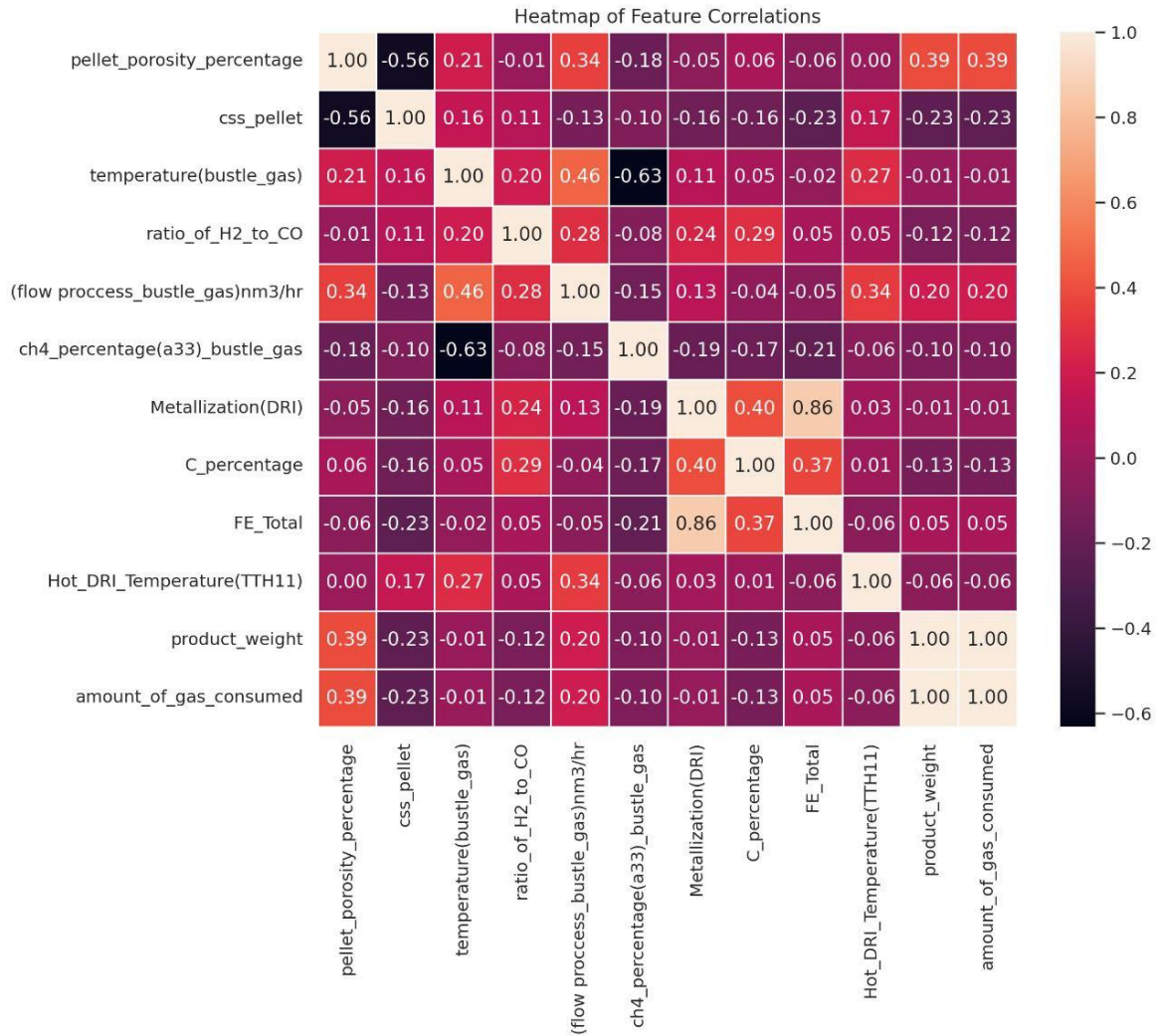


Figure 5. Color-coded Pearson correlation matrix of key steel production process variables (dark blue: -1, strong negative; dark red: 1, strong positive).

5.5. Normalized Mean Values in Radar Chart

Experimental Results

Analysis of normalized process metrics through radar chart visualization in Figure 6 reveals distinct operational patterns across experimental trials. The comparative framework incorporates five critical parameters: pellet porosity, H₂/CO ratios, bustle gas methane levels, total iron content, and carbon percentages. Pellet porosity emerges as the predominant factor, achieving the highest normalized values, closely followed by H₂/CO ratios. Intermediate values characterize methane concentrations and iron content, while carbon percentages occupy the lowest normalized range.

This multidimensional analysis underscores inherent process trade-offs, particularly the combined influence of porosity and gas composition on system efficiency. Through unified scaling of disparate metrics, the visualization enables identification of operational sweet spots where multiple parameters approach optimal ranges simultaneously, a crucial capability for balancing competing process objectives.

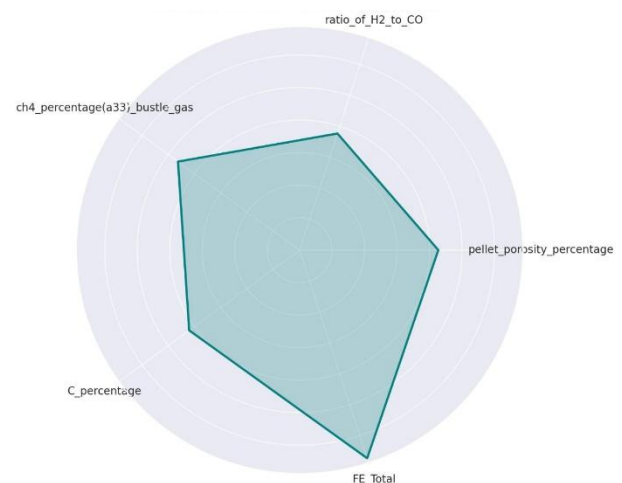


Figure 6. Radar chart mapping normalized mean values of process metrics

5.6. Prompt-Based Case Study for Improved Metallization

The existing metallization process reacts sensitively to shifts in gas composition and temperature, often resulting in less-than-ideal efficiency under specific conditions. Drawing on the dataset, we can craft LLM-driven prompts to recommend parameter tweaks, for example, raising the H₂/CO ratio to 1.8 or boosting the bustle-gas temperature by 25°C might enhance performance. Though we refrain from running these prompts directly, we suggest structured queries such as, “Starting with a ratio of 1.6 and a temperature of 999°C, which adjustments would push metallization above 90% while keeping gas increases minimal?” to draw optimization insights from the model. Several avenues beckon for refinement: adjusting gas composition (e.g., elevating the H₂/CO ratio or cutting CH₄ levels) to sharpen reduction kinetics, dialing the bustle-gas setpoint to between 1025 and 1050°C to boost diffusivity, and tweaking pellet properties (e.g., porosity of 22–24%) to balance gas permeation and heat transfer. This case study underscores how LLM-guided prompts, rooted in solid data, might streamline process optimization by increasing metallization, reducing gas use, and improving resource efficiency.

6. Conclusion

This study highlights the effectiveness of integrating AI into vocational education and workforce reskilling frameworks for the steel industry’s transition toward Industry 4.0. The results demonstrate that AI-enhanced curricula and machine learning-based process optimization can simultaneously improve workforce competencies and metallization efficiency, thereby reducing resource consumption. These outcomes provide practical evidence that coupling digital twin-based simulations with adaptive learning modules accelerates skill acquisition and operational decision-making, fostering both human adaptability and production sustainability. The findings suggest that industrial training programs should increasingly adopt generative AI and data-driven feedback mechanisms to maintain alignment with evolving technological infrastructures. Future work should investigate the longitudinal impact of such frameworks on productivity and workforce retention, as well as their adaptability to related domains in advanced manufacturing.

7. References

- [1] R. Abdul Baits Swastika, CREA and A. Katherine Hasan, CREA, "Indonesia iron and steel's full potential hinges on low-carbon technologies," Centre for Research on Energy and Clean Air, Centre for Research on Energy and Clean Air, 18 December 2024.
- [2] M. Andrei and S. Johnsson, "Advancing maturity in the adoption of digital technologies for energy efficiency in manufacturing industry," *Journal of Manufacturing Technology Management*, vol. 36, no. 9, pp. 114-133, 2025, doi: 10.1108/JMTM-09-2024-0482.
- [3] V. Hagargi. "Introduction to the Steel Sector in India." Alice Blue Online. <https://aliceblueonline.com/introduction-to-the-steel-sector-in-india/> (accessed February 18, 2025).
- [4] N. Hao, "Artificial Intelligence applications in traditional steel manufacturers," Bachelor Thesis, Digital Business Innovations, Haaga-Helia University of Applied Sciences, 2024.
- [5] I. Bursuk, "Explore the Top 10 Steel Industry Trends (2025)," vol. 2025, ed. StartUs Insights.
- [6] H. Fan *et al.*, "New era towards autonomous additive manufacturing: a review of recent trends and future perspectives," *International Journal of Extreme Manufacturing*, vol. 7, no. 3, p. 032006, 2025/01/31, doi: 10.1088/2631-7990/ada8e4.
- [7] S. Kommareddy, "Hyperautomation: AI's Role in Transforming Business Processes," vol. 2025, ed. Frost & Sullivan: Frost & Sullivan.
- [8] Y.-Z. Lin *et al.*, "Personalized Education with Generative AI and Digital Twins: VR, RAG, and Zero-Shot Sentiment Analysis for Industry 4.0 Workforce Development," *arXiv [cs.CY]*, 2025. [Online]. Available: <http://arxiv.org/abs/2502.14080>.
- [9] B. Gajdzik, "Steel Industry in the Era of Digitalisation and Climate Change," in *Digital Transformation towards Smart Steel Manufacturing: A Framework for Steel Enterprises in Poland*, B. Gajdzik Ed. Cham: Springer Nature Switzerland, 2025, pp. 27-53.
- [10] N. Virmani, M. Anupama, J. Sandeep, and R. and Mahajan, "Driving Operational Excellence: The Role of Technology-Organization-Environment Framework in Lean Six Sigma Integrated Industry 4.0 Adoption," *Engineering Management Journal*, pp. 1-13, doi: 10.1080/10429247.2025.2465073.
- [11] R. Rakholia, A. L. Suárez-Cetrulo, M. Singh, and R. S. Carbajo, "Advancing Manufacturing Through Artificial Intelligence: Current Landscape, Perspectives, Best Practices, Challenges, and Future Direction," *IEEE Access*, vol. 12, pp. 131621-131637, 2024, doi: 10.1109/ACCESS.2024.3458830.
- [12] A. Velmurugan, S. Prabu, R. Senthilraja, A. Ahmed Mudassar, S. Jayapoorani, and M. Arun, "AI-Driven Predictive Maintenance for Smart Manufacturing Systems Using Digital Twin Technology," *International Journal of Computational and Experimental Science and Engineering*, vol. 11, no. 1, 03/02 2025, doi: 10.22399/ijcesen.1099.
- [13] B. Ameh, O. Arowosegbe, J. Agbelusi, M. Adeosun, and S. Chukwunweike, "Bridging the Gap: Innovations in Supply Chain Technology Through ERP Integration and Intelligent Automation," *International Journal of Computer Applications Technology and Research*, vol. Volume 13, pp. 1-15, 01/01 2024, doi: 10.7753/IJCATR1310.1001.
- [14] A. Tran, "Digitalization in the steel and mining industries: overcoming challenges by comprehensive technological innovation to enhance sustainability," Bachelor's thesis, Mikkelin kampus, Aalto University, Aalto University, 2024. [Online]. Available: <https://aaltdoc.aalto.fi/items/efe495a0-4fdb-44f2-9bef-65e7af55be5a/full>
- [15] S. Dehghan, S. Sattarpanah Karganroudi, S. Echchakoui, and N. Barka, "The Integration of Additive Manufacturing into Industry 4.0 and Industry 5.0: A Bibliometric Analysis (Trends, Opportunities, and Challenges)," *Machines*, vol. 13, no. 1, doi: 10.3390/machines13010062.
- [16] A. Setyadi, S. Soekotjo, S. D. Lestari, S. Pawirosumarto, and A. Damaris, "Trends and Opportunities in Sustainable Manufacturing: A Systematic Review of Key Dimensions from 2019 to 2024," *Sustainability*, vol. 17, no. 2, doi: 10.3390/su17020789.
- [17] M. Ryalat, E. Franco, H. Elmoaqet, N. Almtireen, and G. Al-Refai, "The Integration of Advanced Mechatronic Systems into Industry 4.0 for Smart Manufacturing," *Sustainability*, vol. 16, no. 19, doi: 10.3390/su16198504.
- [18] A. Ucar, M. Karakose, and N. Kırımça, "Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends," *Applied Sciences*, vol. 14, no. 2, doi: 10.3390/app14020898.
- [19] B. Johansson *et al.*, "Challenges and opportunities to advance manufacturing research for sustainable battery life cycles," *Frontiers in Manufacturing Technology*, Review vol. Volume 4 - 2024. [Online]. Available: <https://www.frontiersin.org/journals/manufacturing-technology/articles/10.3389/fmtec.2024.1360076>.
- [20] C. Favi, M. Marconi, M. Mandolini, and M. Germani, "Sustainable life cycle and energy management of discrete manufacturing plants in the industry 4.0 framework," *Applied Energy*, vol. 312, p. 118671, 2022/04/15, doi: <https://doi.org/10.1016/j.apenergy.2022.118671>.
- [21] M. Alkhodair and H. Alkhudhayr, "Harnessing Industry 4.0 for SMEs: Advancing Smart Manufacturing and Logistics for

- Sustainable Supply Chains," *Sustainability*, vol. 17, no. 3, doi: 10.3390/su17030813.
- [22] W. Chowdhury and Y. Yan, "Applications of Artificial Intelligence to Instrumentation Systems for Monitoring Complex Industrial Processes," *Cybernetics and Systems*, vol. 1, pp. 1-18, 12/29 2023, doi: 10.26599/CAI.2024.9390006.
- [23] J. Jakubowski *et al.*, "Artificial Intelligence Approaches for Predictive Maintenance in the Steel Industry: A Survey," *arXiv [cs.AI]*, 2024. [Online]. Available: <http://arxiv.org/abs/2405.12785>.
- [24] E. Gursel *et al.*, "The role of AI in detecting and mitigating human errors in safety-critical industries: A review," *Reliability Engineering & System Safety*, vol. 256, p. 110682, 2025/04/01, doi: <https://doi.org/10.1016/j.res.2024.110682>.
- [25] N. P. Lawrence *et al.*, "Machine learning for industrial sensing and control: A survey and practical perspective," *Control Engineering Practice*, vol. 145, p. 105841, 2024/4 2024, doi: 10.1016/j.conengprac.2024.105841.
- [26] S. Kansal and E. Siddharth, "Adaptive AI Models for Automating Legacy System Migration in Enterprise Environments," vol. 3, pp. 2960-3003, 08/22 2024.
- [27] R. A. Abdulrazzq, N. M. Sajid, and M. S. Hasan, "Artificial intelligence-driven predictive maintenance in IoT systems," *South Florida Journal of Development*, vol. 5, no. 12, p. e4781, 12/13 2024, doi: 10.46932/sfjdv5n12-030.
- [28] T. L. Wiese, "Predictive maintenance using artificial intelligence in critical infrastructure: A decision-making framework," *Int. J. Eng. Bus. Manag.*, vol. 8, no. 4, pp. 01-04, 2024, doi: 10.22161/ijebm.8.4.1.
- [29] M. Kumar, "AI For Climate Change: Predicting Environmental Impact and Developing Sustainable Solutions," *ESP Journal of Engineering & Technology Advancements*, vol. 4, pp. 127-133, 09/14 2024, doi: 10.56472/25832646/JETA-V4I3P112.
- [30] M. Imani, B. Majidi, and A. Shamisa, "Improving Energy Consumption and Environmental Impact of Steel Manufacturing using Smart Cyber Physical Systems," in *14th Smart Grid Conference, 2024-2025*, IEEE: IEEE, 2025, doi: 10.1109/SGC64640.2024.10983433.
- [31] L. Antonazzo, D. Stroud, and M. Weinel, "Preparing for a Digital Steel Industry: What Challenge for Skills Formation Systems?," in *Industry 4.0 and the Road to Sustainable Steelmaking in Europe: Recasting the Future*, D. Stroud *et al.* Eds. Cham: Springer International Publishing, 2024, pp. 167-181.
- [32] T. Akyazi, A. Goti, and F. Báyon, "The Effects of Industry 4.0 on Steel Workforce: Identifying the Current and Future Skills Requirements of the Steel Sector and Developing a Sectorial Database," in *Industry 4.0 and the Road to Sustainable Steelmaking in Europe: Recasting the Future*, D. Stroud *et al.* Eds. Cham: Springer International Publishing, 2024, pp. 183-201.
- [33] "European project 'blueprint "new skills agenda steel": industry-driven sustainable european steel skills agenda and strategy (essa)' – the first year of implementation," *Journal of Metallic Materials*, vol. 71, no. 4, pp. 2-11, 2020/3/30 2020, doi: 10.32730/imz.2657-747.19.4.1.
- [34] K. Bayly-Castaneda, M. S. Ramirez-Montoya, and A. Morita-Alexander, "Crafting personalized learning paths with AI for lifelong learning: a systematic literature review," *Frontiers in Education*, Review vol. Volume 9 - 2024. [Online]. Available: <https://www.frontiersin.org/journals/education/articles/10.3389/educ.2024.1424386>.
- [35] H. Y. Ahn, "AI-Powered E-Learning for Lifelong Learners: Impact on Performance and Knowledge Application," *Sustainability*, vol. 16, no. 20, doi: 10.3390/su16209066.
- [36] Y. Yao and H. González-Vélez, "AI-Powered System to Facilitate Personalized Adaptive Learning in Digital Transformation," *Applied Sciences*, vol. 15, no. 9, doi: 10.3390/app15094989.
- [37] O. E. Cinar, K. Rafferty, D. Cutting, and H. Wang, "AI-Powered VR for Enhanced Learning Compared to Traditional Methods," *Electronics*, vol. 13, no. 23, doi: 10.3390/electronics13234787.
- [38] H. Peters, "How could Industry 4.0 transform the steel industry?," presented at the Future Steel Forum, Warsaw, Poland, June 14–15, 2017, PowerPoint presentation.
- [39] I. YOSHIZAWA and S. NAKAGAWA, "Development of Systems, Instrumentation, and Control Technologies for Steel Manufacturing Processes and Future Prospects."
- [40] NSW Department of Education, "Metal & Engineering Industry Curriculum Information Guide," NSW Department of Education, Darlinghurst, NSW, MEM05 V11.0, 2016.
- [41] A. Imanifard and B. Majidi, "Effective Android Malware Detection using Emotional Reactions to Sudden Events," in *2024 10th International Conference on Web Research (ICWR)*, 24-25 April 2024, pp. 390-396, doi: 10.1109/ICWR61162.2024.10533349.
- [42] A. Imanifard, B. Majidi, and A. Shamisa, "Trustworthy Large Language Model Prompt Engineering for Risk-Free Smart Grid Management Education," in *2024 14th Smart Grid Conference (SGC)*, 31 Dec.-1 Jan. 2025 2024, IEEE, pp. 1-6, doi: 10.1109/SGC64640.2024.10983889.
- [43] M. Imani, A. Imanifard, B. Majidi, and A. Shamisa, "Applications of Large Language Models in Industrial Internet of Things Education," in *2025 11th International Conference on Web Research (ICWR)*, 2025: IEEE Xplore, doi: 10.1109/ICWR65219.2025.11006194.
- [44] M. Imani, A. Imanifard, B. Majidi, and A. Shamisa, "Dashboard-Driven Machine Learning Analytics and Conceptual LLM Simulations for IIoT Education in Smart Steel Manufacturing," (in en), *International Journal of Web Research*, 2025, doi: 10.22133/ijwr.2025.521822.1280.
- [45] A. Imanifard, B. Majidi, and A. Shamisa, "SmartGridAgent: An Educational Framework for Reliable Digital Twin-Based Smart Grid Workforce Training with Locally Hosted LLMs," *Smart Grids and Sustainable Energy*, vol. 10, no. 2, p. 41, 2025/05/30, doi: 10.1007/s40866-025-00274-0.