

# *Dashboard Driven Machine Learning Analytics and Conceptual LLM Simulations for IIoT Education in Smart Steel Manufacturing*

Mehdi Imani<sup>a</sup>, Ali Imanifard<sup>a</sup>, Babak Majidi<sup>\*a</sup>, Abdollah Shamisa<sup>b</sup>

<sup>a</sup>: Department of Computer Engineering, Khatam University, Tehran, Iran; {m.imani.3307, a.imanifard.9843, b.majidi}@khatam.ac.ir

<sup>b</sup>: Department of Electrical Engineering, Khatam University, Tehran, Iran; , a.shamisa@khatam.ac.ir

## **ABSTRACT**

Through advanced analytical models such as machine learning (ML) and, conceptually, Large Language Models (LLMs), this study explores how Industrial Internet of Things (IIoT) applications can transform educational experiences in the context of smart steel production. To mitigate the shortage of authentic industrial datasets for research, we developed an industry-validated IIoT educational dataset drawn from three months of operational records at a steel plant and enriched with domain-specific annotations—most notably distinct operational phases. Building on this foundation, we propose an IIoT framework for intelligent steel manufacturing that merges ML-driven predictive analytics (employing Lasso regression to optimize energy use) with LLM-based contextualization of data streams within IIoT environments. At its core, this architecture delivers real-time process monitoring alongside adaptive learning modules, effectively simulating the dynamics of a smart factory. By promoting human-machine collaboration and mirroring quality-control workflows, the framework bridges the divide between theoretical instruction and hands-on industrial practice. A key feature is an interactive decision-support dashboard: this interface presents ML model outcomes and elucidates IIoT measurements—such as metallization levels and H<sub>2</sub>/CO ratios—through dynamic visualizations and scenario-based simulations that invite risk-free exploration of energy-optimization strategies. Such tools empower learners to grasp the intricate multivariate dependencies that govern steel manufacturing processes. Our implementation of the Lasso regression model resulted in a 9% reduction in energy consumption and stabilization of metallization levels. Overall, these findings underscore how embedding advanced analytics within IIoT education can cultivate a more engaging, practice-oriented learning environment that aligns closely with real-world industrial operations.

**Keywords**— *Smart Steel Manufacturing; Industry 4.0; IIoT Education; Industrial Internet of Things; Machine Learning; Large Language Models; Education Technology.*

## **1. Introduction**

The progression of Industry 4.0 and manufacturing paradigms based on the Internet of Things (IoT) necessitates a workforce possessing skills aligned with artificial intelligence (AI) and intelligent machinery [1, 2]. As AI, automation, and robotics increasingly undertake routine functions—spanning from physical labor to cognitive decision-making [3]—human workers must redirect their efforts toward higher-level technical skills and cognitive capabilities. Foundational competencies such as programming, AI integration, data analysis, machine learning (ML), and familiarity with Large

Language Models (LLMs) are essential for managing IoT networks within intelligent factory settings. Beyond these technical skills, human aptitudes in problem-solving, critical analysis, creativity, and adaptability remain paramount, alongside the necessity for effective human-machine interaction to oversee and refine AI-driven operations. Satisfying these demands requires updating current educational programs, implementing continuous upskilling efforts, and fostering strong collaborations between industry and academia to ensure workforce preparedness and maintain global industrial competitiveness.



<http://dx.doi.org/10.22133/ijwr.2025.521822.1280>

**Citation** M. Imani, A. Imanifard, B. Majidi, A. Shamisa, "Dashboard Driven Machine Learning Analytics and Conceptual LLM Simulations for IIoT Education in Smart Steel Manufacturing", *International Journal of Web Research*, vol.8, no.3, pp.15-31, 2025, doi: <http://dx.doi.org/10.22133/ijwr.2025.521822.1280>.

*\*Corresponding Author*

Article History: Received: 5 May 2025 ; Revised: 7 June 2025 ; Accepted: 24 June 2025.

Copyright © 2025 University of Science and Culture. Published by University of Science and Culture. This work is licensed under a Creative Commons Attribution-Noncommercial 4.0 International license(<https://creativecommons.org/licenses/by-nc/4.0/>). Noncommercial uses of the work are permitted, provided the original work is properly cited.

The incorporation of Industrial Internet of Things (IIoT) technologies into contemporary manufacturing, propelled by Industry 4.0 initiatives, has generated a need for professionals skilled in complex digital systems. Nonetheless, educational institutions encounter substantial hurdles in delivering the necessary technical and interdisciplinary knowledge for this field, spanning curriculum design, infrastructure availability, teaching methods, and collaborative partnerships. Overcoming these IIoT-specific educational obstacles requires systemic adjustments to align formal education with industrial requirements, thereby cultivating a workforce adept at navigating smart manufacturing landscapes.

A primary difficulty lies in the curriculum lag, where the rapid pace of IIoT advancements outstrips traditional curriculum update cycles, leaving graduates ill-equipped for the tools and methods used in today's industry. Another significant obstacle is the shortage of instructors with direct experience in IIoT systems, such as industrial automation or networked control environments, which restricts the provision of practical, hands-on instruction. Furthermore, insufficient emphasis on digital security training, highlighted by the absence of dedicated modules despite strategies demonstrating high success rates (96%) in identifying network vulnerabilities [4], fails to prepare students adequately against cyber risks. Institutional inertia can also hinder the uptake of novel pedagogical approaches, necessitating curricular modernization, faculty development programs, and strengthened industry-academia links to furnish graduates with the competencies vital for success in smart manufacturing environments.

The swift evolution of Industry 4.0, IoT, and IIoT has reshaped manufacturing and automation, amplifying the need for personnel capable of utilizing AI-assisted analytics, enabling real-time decision-making, and managing intelligent systems. In response to these needs, analytical models like LLMs present themselves as potentially transformative instruments in industrial training, offering innovative approaches like personalized guidance, virtual simulations, and AI-supported problem resolution. Current research highlights their potential to bridge skill deficits while acknowledging persistent implementation difficulties. Various studies have investigated the application of LLMs in industrial training contexts. For example, Neumann et al. [5] showed the utility of LLM-powered chatbots such as MoodleBot in automating responses to student queries and promoting self-directed learning in technical subjects. Li et al. [6] created EduMAS, an adaptive multi-agent AI system capable of learning adaptation pathways through graph-based knowledge exploration. Beyond tutoring applications, LLMs can augment simulated learning experiences: Fuertes et al. [7] integrated IoT-connected intelligent systems

and safety features into Industry 4.0 training, a context where LLM-assisted real-time advice could prove beneficial. Digital twinning, which involves creating virtual counterparts of physical industrial assets, also allows learners to engage with AI-predicted manufacturing scenarios using LLM-driven support, for instance, in predictive maintenance training exercises [8].

Learning through error analysis represents another promising avenue. Xia et al. [8] suggested fine-tuning LLMs for diagnosing factory flaws and standardizing predictive maintenance routines, allowing students to tackle realistic industrial problems within safe boundaries. Concurrently, Magnus and Venschott [9] illustrated how GPT-based consultants can instruct students in executing Lean Manufacturing techniques, such as value stream mapping. Training for human-robot collaboration (HRC) has also benefited from LLM integration; Wang et al. [10] introduced a vision-language navigation system enabling cooperative robots to interact naturally with human operators via spoken language, simplifying communication in smart factory environments.

Despite these strides, challenges persist. Significant computational demands, as noted by Chkirbene et al. [11], can restrict access for institutions with limited resources, potentially exacerbating disparities in industrial training quality. Gaps in domain-specific knowledge also pose implementation hurdles: general-purpose LLMs often lack specialized expertise in areas like IIoT security and typically require fine-tuning with sector-specific data to prevent misinterpretations of technical language [8, 12]. Digital security concerns are also prominent, especially when LLMs interface with IIoT systems. Urlana et al. [12] underscored the necessity for secure and interpretable AI frameworks to mitigate risks related to data privacy and algorithmic bias. Consequently, the security ramifications of integrating LLMs with IIoT infrastructure demand careful attention. Recent work, like that presented in [13, 14], describes locally deployed LLMs designed to bolster digital safety measures and counteract risks tied to data privacy and cyber threats. Therefore, any comprehensive framework must incorporate robust safety features, including explainable AI techniques and real-time threat detection capabilities, to protect industrial processes from potential weaknesses.

Research efforts must focus on overcoming these obstacles to fully leverage LLMs in educational settings. Crafting industry-specific models pre-trained on production protocols and IIoT sensor data could improve technical relevance [8, 11]. Integrating LLMs with augmented and virtual reality (AR/VR) technologies holds the potential to significantly advance training by creating immersive simulations

of smart factories, where AI tutors guide learners through scenarios like equipment failure or data breaches [7]. Ethical considerations remain crucial: transparent AI systems and mechanisms to prevent bias are vital for responsible deployment within industrial education [12].

In response to these gaps, we adopt a hybrid LLM approach: employing GPT 4 via prompt-based APIs for code analysis and visualization, complemented by local, instruction-tuned variants (Qwen 2.5, Mistral Nemo, Meta Llama 3.1/3.2) constrained by hardware resources. We illustrate this framework through a smart steel production case study, demonstrating how LLMs facilitate an AI-driven dashboard to simulate the direct reduction process—a central stage in steelmaking. Building on insights from [13, 14], we integrate locally hosted models to reinforce data security and contextual relevance. Our contributions include:

1. **Industry Validated IIoT Dataset:** A three-month, annotation-rich operational dataset from a steel plant, providing richer data than typical programmable logic controller (PLC) logs and bridging the gap in authentic academic resources.
2. **Integrated IIoT Framework:** A unified architecture that meshes real-time monitoring, ML-driven predictive analytics for optimization, and adaptive education, simulating smart factory workflows and demonstrating capabilities beyond traditional PLC control.
3. **ML-Driven Dashboard with LLM Contextualization Concept:** An interactive decision-support interface delivering ML-based predictions and conceptually providing LLM-generated contextualized IIoT insights and risk-free energy optimization scenarios.
4. **Optimized Lasso Regression Model:** An ML model achieving a documented 9% reduction in energy consumption and stabilizing metallization between 91.5% and 93% using L1 regularization, demonstrating superior performance in terms of accuracy and resource efficiency compared to Ridge and Random Forest models in this context.

## 2. Related Works

### 2.1. The Convergence of Smart Steel Manufacturing, IIoT, and Advanced Analytics in Education

The modern industrial environment is undergoing a profound shift, characterized by the rise of smart manufacturing approaches [15]. Central to this evolution is the accelerating integration of the IIoT, which is reshaping operations across industries, notably within steel manufacturing [16]. IIoT involves the interconnected network and automated operation of sensors, devices, and machinery in industrial settings, promoting greater efficiency and

dependability in production processes [16, 17]. This network structure enables smooth communication pathways among systems, equipment, and personnel, leading to better asset management, decreased waste, and optimized costs, thereby strengthening competitive positions [16]. Often termed Industry 4.0, the successful application of IIoT depends on networking intelligent machines, embedding sensors, applying sophisticated data analytics, and enabling automated decision-making. Frequently, these systems utilize edge computing to boost productivity, refine supply chains, and improve resource allocation [16]. The widespread adoption of smart technologies creates a demand for a workforce skilled not only in using these advanced systems but also in driving further innovation. Consequently, comprehensive education and training programs are essential for equipping individuals with the necessary competencies to operate within and contribute to this changing industrial domain.

Concurrently with the spread of IIoT in manufacturing, advanced ML analytics, particularly LLMs, are emerging as powerful instruments in diverse fields, including industrial training [18]. As sophisticated AI technologies developed for understanding and generating natural language, LLMs presented considerable advantages for IIoT applications by improving efficiency, refining decision-making processes, and increasing automation [18]. Their ability to interpret complex language patterns and adapt responses to specific user or business needs makes them valuable tools in intricate industrial contexts [18]. For instance, LLMs can operate as intelligent assistants, offering real-time help, guiding operational steps, and providing troubleshooting support, which considerably enhances employee productivity [18]. Incorporating LLMs into IIoT education promises to transform learning by contextualizing complex industrial data, enabling interactive engagement with manufacturing systems, and providing scenario-based simulations for risk-free exploration. This convergence seeks to narrow the gap between theoretical instruction and hands-on industrial practice, fostering more engaging and effective learning environments that reflect real-world industrial operations.

### 2.2. IIoT in Smart Steel Manufacturing: Recent Advancements and Applications

The IIoT is fundamental to achieving smart manufacturing, especially in the steel sector, by creating a network of connected devices, sensors, and systems that permits data sharing and automation [17]. Through this interconnectedness, steel producers can attain improved efficiency, greater productivity, and more adept management of industrial assets [17]. Recent studies highlight the growing deployment of IIoT throughout manufacturing, spurred by the potential for



streamlined operations, minimized downtime, and enhanced product quality [15, 19]. Within the steel industry specifically, IIoT applications are varied and influential. They encompass predictive maintenance strategies designed to foresee equipment failures and sophisticated quality control systems ensuring product standards [19]. IIoT also contributes significantly to optimizing resource use, such as energy and raw materials, and to monitoring environmental emissions, supporting sustainability goals.

Ongoing developments and innovations in IIoT for smart manufacturing continuously advance industrial operational capabilities. Progress in sensor technology allows for the collection of finer-grained, real-time data from multiple stages of steel production [20]. When analyzed with advanced data techniques, this wealth of information yields deeper insights into operational performance, supporting proactive decisions and ongoing improvements. Edge computing approaches are becoming more prevalent, moving data processing closer to the point of generation, which cuts latency and permits faster responses in time-sensitive applications. The rollout of 5G connectivity is also expected to significantly impact IIoT in manufacturing by offering the high bandwidth and low latency needed for smooth communication among numerous connected devices. Furthermore, digital twins—virtual models of physical assets and processes—are increasingly used in smart steel manufacturing. These virtual replicas help simulate production scenarios, fine-tune workflows, and improve predictive maintenance, ultimately enhancing operational efficiency and informing decision-making.

### **2.3. IIoT for Education and Training in Industrial Contexts: Current Methodologies and Resources**

The educational and training approaches for the IIoT within industrial settings are adapting to the needs of this quickly advancing area. Traditional teaching methods are being enhanced, and sometimes superseded, by more innovative techniques aimed at tackling the complexities of IIoT and smart manufacturing. Simulation-based training has proven effective, enabling learners to interact with virtual representations of industrial sites and processes. This method offers practical experience without the inherent risks or expenses of real-world operations. Further enriching the learning process, VR and AR technologies provide immersive, interactive environments capable of mirroring complex manufacturing tasks and equipment interactions [21, 22]. Such technologies allow learners to practice intricate procedures, diagnose potential problems, and gain a more thorough grasp of IIoT systems in a secure and stimulating way [22].

Currently, a range of IIoT training programs and curricula exist, designed for various expertise levels and specific industry requirements. These programs typically address core IIoT concepts—like sensor technologies, network protocols, data analytics, and cybersecurity—alongside specific manufacturing applications. Many curricula stress the value of hands-on activities and practical exercises to ensure learners acquire skills pertinent to real-world deployment. Nonetheless, a key difficulty in IIoT education is the shortage of accessible, real-world industrial datasets suitable for practicing data analysis and model building. This absence of authentic data can diminish the practical applicability of training programs and impede the cultivation of vital analytical abilities. To counter this, there is an increasing focus on project-based learning, engaging learners with realistic industrial challenges. Additionally, fostering collaborations between educational bodies and industry partners is encouraged to grant access to actual scenarios and data. Such partnerships can also open doors to internships and other forms of experiential learning, helping to connect theoretical knowledge gained in academic settings with the practical requirements of industrial workplaces.

### **2.4. Leveraging LLMs within the IIoT: Opportunities and Challenges**

Integrating LLMs with IIoT systems opens numerous avenues for transforming manufacturing operations and improving human-machine collaboration [15, 18]. LLMs can comprehend and produce human language, which allows for natural dialogue with industrial equipment, offers real-time support to operators, and streamlines troubleshooting in complex industrial environments [18]. Recent studies point to the utility of LLMs in several manufacturing contexts, such as accurately diagnosing equipment malfunctions, forecasting maintenance requirements, refining quality control procedures, and optimizing energy usage [23-25]. For example, by analyzing sensor readings and maintenance records, LLMs can detect patterns suggesting potential equipment failures, enabling proactive maintenance that cuts downtime and lowers costs. In quality assurance, they can examine product specifications alongside sensor data to spot deviations and anticipate quality issues, leading to more consistent products and less waste. LLMs can also aid in optimizing energy consumption by analyzing usage trends and suggesting strategies to curb energy waste and promote sustainability.

To clarify the transformative benefits of LLMs in IIoT education for smart steel manufacturing, we summarize their key contributions alongside concrete use cases:

- Adaptive feedback: Real time explanations of unexpected sensor anomalies (e.g.,

diagnosing a sudden Bustle Gas Temperature deviation) to guide learner troubleshooting [5].

- Scenario generation: Automated creation of “what if” cases, such as corrective actions for excessive CH<sub>4</sub> consumption by adjusting H<sub>2</sub>/CO ratios [8].
- Natural language explanations: Contextual interpretation of multivariate dependencies (e.g., H<sub>2</sub>/CO ratios and metallization trends) to support decision making.
- Troubleshooting guidance: Step by step instructions for resolving common IIoT system faults in smart steel processes.

Despite the considerable promise of LLMs in IIoT, their effective implementation in industrial settings faces several hurdles [15, 18]. A principal difficulty involves the substantial computational power needed to operate large-scale LLMs, potentially exceeding the capacity of resource-limited IIoT devices and edge computing systems [15, 18]. Concerns about data privacy and security also surface when handling sensitive industrial information, demanding the creation of secure, privacy-conscious methods for LLM integration [26]. Furthermore, effectively using LLMs in specialized industrial fields like steel manufacturing frequently necessitates embedding domain-specific knowledge into the models to guarantee precise and contextually appropriate outputs [25]. To navigate these obstacles, current research concentrates on devising efficient frameworks and methods for deploying LLMs in IIoT contexts. This includes work on model compression, quantization, and strategies combining edge and cloud resources [15, 18]. These initiatives seek to find a practical balance, maximizing LLM performance while minimizing their resource footprint, thereby facilitating their broader use in industrial applications.

## 2.5. The Role of ML Analytics in Enhancing IIoT Education

Beyond the specific capabilities of LLMs, the wider discipline of ML analytics contributes significantly to making IIoT education more effective and personalized [27, 28]. ML methods can be applied to analyze large volumes of educational data, yielding valuable insights into student learning trajectories, achievements, and areas requiring further assistance [29, 30]. This data-informed strategy permits the development of more customized learning paths, where content and teaching styles are adapted to individual student needs and preferences [27]. Adaptive feedback systems, driven by ML algorithms, can offer students precise guidance and support, assisting them in overcoming difficulties and deepening their grasp of complex IIoT topics [27,

28]. Additionally, ML can automate the evaluation of student work, furnishing instructors with prompt, objective assessments and highlighting potential areas for curriculum or pedagogical refinement [30].

The utility of ML also includes developing intelligent tutoring systems capable of guiding students through IIoT subjects, providing explanations, examples, and interactive exercises adjusted to their specific progress and understanding [28, 29]. Within industrial training contexts, ML can also underpin decision support tools that assist learners in applying their knowledge to practical scenarios, offering recommendations and feedback derived from analyzing industrial data and established best practices [28]. By utilizing ML to scrutinize educational data, institutions can better understand the elements influencing student success in IIoT-related areas. This allows for the ongoing refinement and optimization of training programs to align more closely with the evolving demands of the industry [27, 30].

## 2.6. Existing Frameworks and Architectures for IIoT in Smart Manufacturing Environments

Successfully implementing IIoT in smart manufacturing settings, including the steel sector, depends on dependable and clearly defined frameworks and architectures that ensure smooth data transmission, secure communications, and intelligent decision support [31-33]. Various layered architectural models have been suggested to organize the complex IIoT ecosystem. These typically incorporate levels for sensing and data gathering, network communication, data processing and analysis, and application services [32, 33]. Such architectures offer a structural plan for integrating the diverse elements of a smart factory, connecting shop-floor equipment with enterprise-level systems. Research in this domain stresses the paramount importance of security and reliability within IIoT frameworks for industrial use, considering the inherent risks from cyber threats and system malfunctions [34]. Accordingly, numerous proposed frameworks embed security measures across different layers to safeguard the integrity and confidentiality of industrial data and processes [34].

A notable direction in IIoT framework evolution is the growing incorporation of ML and AI features to facilitate intelligent manufacturing [15]. These frameworks utilize AI and ML algorithms for functions like data analytics, predictive maintenance, process optimization, and quality assurance [15]. For instance, frameworks might contain modules for processing and analyzing data in real-time, enabling the early identification of anomalies and prediction of equipment issues [15]. Some architectures also concentrate on providing the necessary infrastructure for deploying and managing ML models at the network edge, permitting faster, more localized

decision-making. These integrated frameworks are essential for unlocking the full capabilities of IIoT in establishing smart, efficient, and responsive manufacturing operations.

### **2.7. Identified Research Gaps and the Contribution of This Study**

Although the existing body of work offers a broad overview of smart steel manufacturing, IIoT implementations, and the use of advanced ML analytics in industry, certain research gaps persist. Specifically, there is limited exploration regarding the precise application of LLMs within IIoT education tailored for the smart steel manufacturing sector. A clear deficiency exists in understanding how LLMs can be effectively employed to design interactive and adaptive learning environments specifically addressing the unique processes and challenges inherent in the steel industry. While LLMs show promise in diverse manufacturing roles, their capacity to reshape IIoT education within the distinct context of smart steel production is not yet well-investigated. Furthermore, the creation and validation of educational resources and frameworks that integrate LLMs into IIoT training for this specific industry are still in early development.

Another important gap relates to the scarcity of industry-verified educational datasets specifically curated for IIoT within steel manufacturing. The absence of such data limits the ability of researchers and educators to formulate and assess targeted educational strategies grounded in authentic industrial data and situations. While generic IIoT datasets might exist, they often do not capture the particular characteristics and complexities found in data from steel production facilities, thereby restricting their value for crafting practical and relevant learning experiences. This study seeks to address these crucial gaps. It introduces an industry-validated IIoT educational dataset derived from operational data at a steel plant, enriched with domain-specific annotations. Additionally, this research puts forward a comprehensive IIoT framework designed for smart steel manufacturing. This framework integrates LLMs with IIoT systems to improve educational outcomes and narrow the divide between theoretical learning and practical application within this key industrial domain.

### **2.8. Synthesis and Significance of the Present Research**

The literature reviewed confirms substantial progress in smart steel manufacturing, the increasingly central role of IIoT in improving industrial processes, and the transformative possibilities offered by advanced ML analytics, especially LLMs, in both manufacturing applications and education. IIoT integration within the steel industry is yielding gains in efficiency, productivity,

and sustainability, further amplified by continuous innovations in sensors, data analysis, and digital twin technologies. While IIoT educational methods are adapting to include more experiential and technology-based learning, obstacles persist, notably the lack of industry-specific datasets and challenges in effectively translating theoretical understanding into practical industrial competencies. The advent of LLMs presents exciting opportunities to enhance human-machine interaction and optimize manufacturing tasks. However, deploying them in industrial, particularly educational, contexts necessitates careful management of computational demands and requires integration with domain-specific knowledge. Existing IIoT frameworks for smart manufacturing lay the groundwork for intelligent, secure industrial systems, increasingly incorporating AI and ML for sophisticated analytics and decision support. Despite these strides, a distinct gap remains concerning the specific use of LLMs in IIoT education customized for the smart steel industry, alongside a shortage of validated educational datasets for this area. This research directly confronts these deficiencies by presenting a novel, industry-validated dataset and an integrated IIoT framework incorporating LLMs. The aim is to foster more effective and practically relevant educational experiences in this vital sector, ultimately contributing to a more proficient and innovative workforce prepared for the future of steel manufacturing.

Furthermore, to reorganize the literature, Table 1 presents a structured summary of the selected studies, organized according to methodological approaches. This table signifies studies that are both relevant and representative of the current landscape of research. Each study is annotated with its major findings, methodology, and any notable strengths and limitations, facilitating an efficient and targeted review of the existing research. IIoT Education and Management Framework for Smart Steel Manufacturing.

### **2.9. System Architecture**

Our proposed IIoT management and training system architecture incorporates advanced analytical models, distinguishing between the roles of ML for core process optimization and LLMs for conceptual enhancement and user interaction. At its core is a smart steel production facility designed to communicate with various components via IIoT for data exchange, gathering data beyond the scope of isolated PLC systems. The architectural foundation of this framework was initially proposed in [35], with the current study extending its scope through the integration of ML-driven predictive analytics and conceptual enhancements enabled by LLMs. The Smart Factory Office functions as the main user portal, enabling direct engagement with end-users



Table 1. Comparative literature summary table

<i>Refs.</i>	<i>Study Aim, Objectives, and Hypotheses</i>	<i>Study Design and Methods</i>	<i>Primary Outcomes and Key Results</i>	<i>Interpretations and Implications</i>	<i>Methodological Strengths</i>	<i>Methodological Limitations and Potential Biases</i>
[15]	Integrate AI-IoT for smart manufacturing	Literature review on AI in IIoT	Enhanced data processing, real-time optimization	AI-IoT pivotal for industrial automation	Comprehensive review, diverse applications	Relies on reported findings, lacks depth
[16]	Highlight authentication, trust in IIoT safety	Multi-author book on IIoT safety	IIoT critical, safety challenges addressed	Trust and safety vital for IIoT systems	Broad overview, expert insights	Uneven depth summarizes existing work
[17]	Overview IIoT challenges and industrial opportunities	Review paper on IIoT applications	IIoT boosts efficiency, safety, connectivity	IIoT enhances work and drives industrial growth	Structured overview, detailed protocols	Depends on published works, no original research
[18]	Propose LLM inference offloading framework	New intelligence-based reinforcement learning offloading framework	Better generalization, lower latency, energy use	intelligence-based reinforcement learning surpasses traditional RL limits	Novel framework, detailed evaluations	Simulation-based, lacks real-world testing
[19]	Review IoT-ML in smart manufacturing	PRISMA-based critical literature review	IoT-ML improves safety, efficiency, maintenance	IoT-ML key for Industry 4.0 shift	Systematic review, in-depth analysis	Synthesizes literature, no new research
[28]	Highlight ML-DL in Industry 4.0	Review of ML-DL in manufacturing	ML-DL vital for analysis, automation	AI enhances industrial efficiency	Thorough algorithm review, new architecture	Conceptual focus, lacks empirical validation

and clients. The Smart Factory Management module employs IoT sensors to link the production infrastructure with auxiliary systems, encompassing enterprise resource planning (ERP) software, simulation environments, and automated process control units. A dedicated Smart Worker Health & Safety system integrates surveillance cameras with IIoT-equipped wearable technology—such as smart helmets, belts, protective attire, and footwear—to oversee employee movements and verify adherence to safety regulations. This component facilitates ongoing personnel health monitoring through analytics conceptually driven by LLMs to interpret complex patterns or provide natural language alerts. The Smart R&D Lab executes experimental procedures, categorizes gathered data according to predefined operational standards, and directs the processed information to a bespoke dashboard, conceptually leveraging LLMs for summarizing findings or contextualizing experimental results against historical data. Details regarding the dataset and dashboard operations are provided in subsequent sections. This dashboard amalgamates crucial steel production metrics, notably direct-reduced iron (DRI) metallization quality predictions generated by the ML model (Lasso Regression). Analytical models, conceptually including LLMs, process this data before relaying the findings to the central factory hub through IIoT. Functioning as the framework's operational center, this core unit manages quality assurance processes and delivers real-time visibility into operations. The IIoT Project Management module orchestrates tasks among four primary roles: Project Manager, Data Analyst, IIoT Engineer, and Quality Control Manager. This human-in-the-loop

element oversees project conception, execution, and performance assessment. Implemented systems undergo continuous evaluation, with performance data disseminated to managers and an external assessment body. Refined feedback is relayed back to technical specialists for ultimate verification prior to integration into the central Smart Factory system via IIoT. Operational data generated post-production is methodically recorded and conveyed to the central core, allowing for perpetual enhancement of the analytics-driven IIoT steel production ecosystem. For improved clarity and understanding, the structure of our proposed framework is visually represented in Figure 1.

To clarify our testing procedures, the dashboard's LLM based contextualization was executed through API driven simulations using LLMs like OpenAI's o4-mini model. We internally validated the system by feeding live IIoT telemetry, such as CH<sub>4</sub> consumption spikes and sensor faults, into the LLM pipeline and reviewed the generated outputs against expert annotations. These mock deployments confirm functional LLM integration and inform refinements for future real time trials.

## 2.10. Educational Challenges and Mitigation Strategies

The multidisciplinary nature of Industry 4.0, spanning automation, analytics, and system integration, surpasses traditional pedagogies, which often lack immersive, hands on experiences [7, 36]. Learning factories have emerged to replicate industrial environments, using PLCs, digital twins, and cloud computing to model real-world scenarios

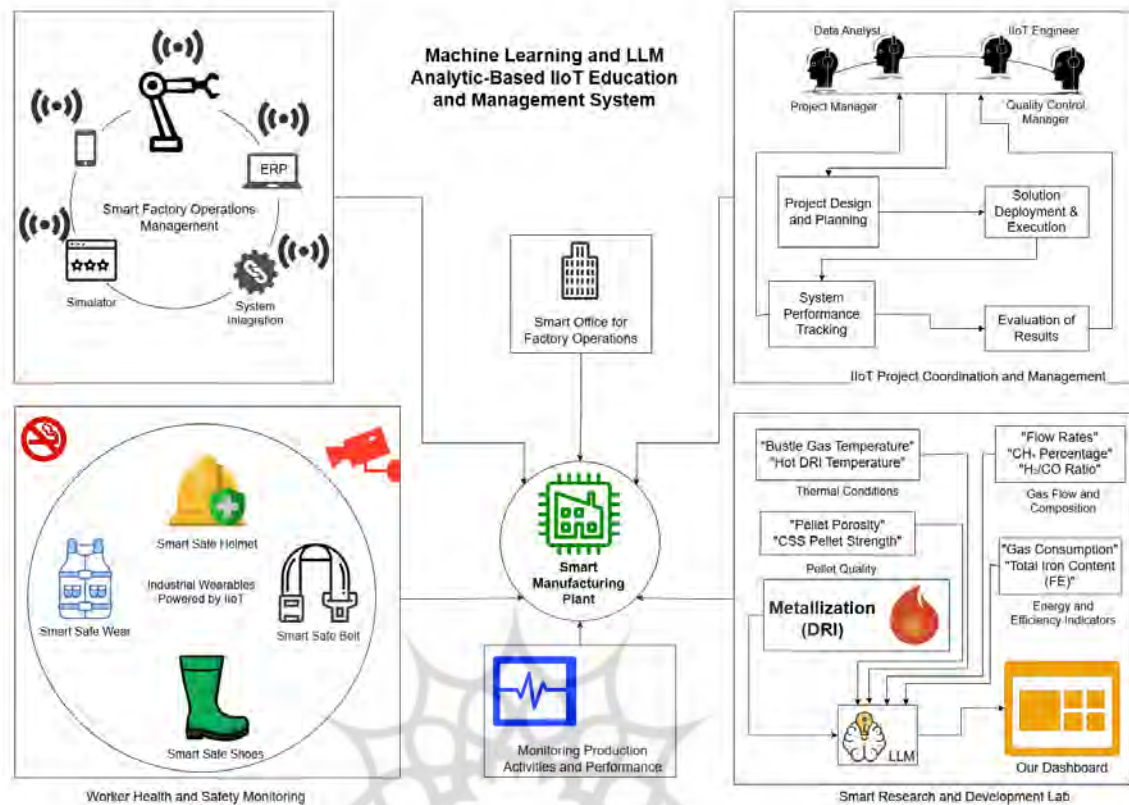


Figure. 1. Workflow of the Proposed Analytics-informed Industrial IoT Education and Management System Framework in Steel Manufacturing. This diagram shows the integrated network of IIoT sensors, data analysis modules, and decision support systems potent

[7, 37]. Nonetheless, scalability and interactivity remain constrained, particularly in high-risk domains like steel production, where rare failure modes must be safely simulated.

Embedding LLMs into such platforms enables dynamic and scenario based modules. For instance, LLMs can autonomously generate troubleshooting case studies, elucidate sensor anomalies, and adapt feedback to individual learner needs [7]. This hybrid approach addresses resource gaps while aligning training with industry specific competencies, enhancing both scalability and pedagogical depth.

To situate our evaluation within established pedagogical theory, we reference Bloom's revised Taxonomy to map each assessment task to cognitive levels, from basic recall of sensor parameters to advanced analysis of  $H_2/CO$  trends [38]. Simultaneously, we structured the instructional cycle using the ADDIE model, initiating with learner needs analysis before designing scenario-based exercises. Subsequent phases encompassed developing LLM-driven modules, implementing them, and evaluating outcomes through taxonomy-aligned pre/post-tests. This integrated approach provides theoretical grounding while systematically connecting assessments to targeted cognitive development.

## 2.11. Interactive LLM Powered Dashboard

As a means of addressing the educational challenges previously outlined and demonstrating the value beyond standard PLC readouts, we developed an interactive dashboard driven by ML predictions and conceptually enhanced by LLMs. This tool utilizes the predictive power of the ML model (Lasso Regression) to deliver real-time insights into process efficiency and stability, while LLMs are envisioned to provide contextually relevant explanations and dynamic learning modules pertinent to the complexities of IIoT systems. By embedding ML analytics and conceptual LLM explanations within the learning platform, the dashboard seeks to narrow the divide between theoretical concepts and practical execution, equipping professionals to proficiently oversee and enhance IIoT-driven operations in industrial contexts.

A snapshot capturing the real-time interface of our designed dashboard is presented in Figure 2. Prominently featured in the upper left section are two-gauge indicators displaying the current Bustle Gas Temperature (blue) and Hot DRI Temperature (green). Positioned below these gauges, numerical displays indicate the average metallization percentage



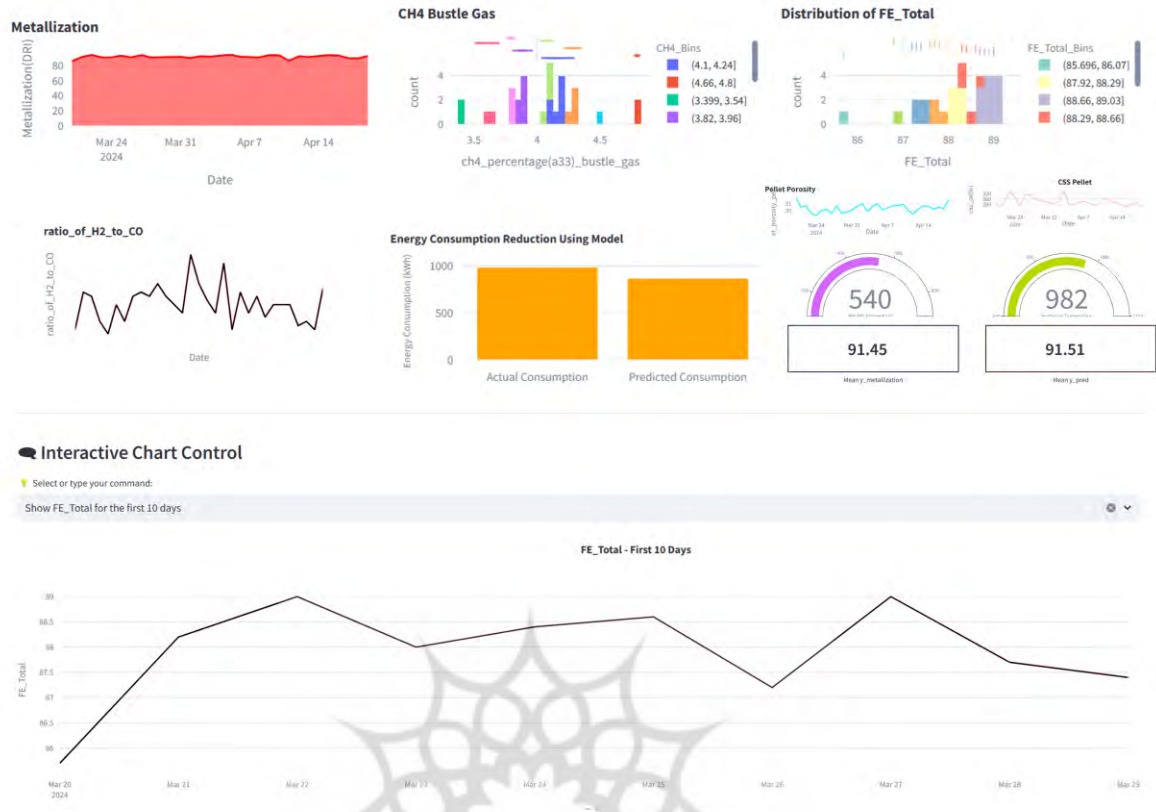


Figure 2. Real-Time Interactive Dashboard for Monitoring Environmental Metrics in Direct Reduced Iron (DRI) Steel Production. This dashboard integrates essential performance metrics such as temperature data, metallization rates, and energy usage trends.

and the predicted average value derived from the underlying analytical model. These figures represent critical outputs. Upon closer examination, both the achieved and predicted metallization hover around 91%, signifying respectable performance for this process stage. The adjacent column features graphical representations, arranged vertically, illustrating results pertinent to model-driven energy consumption reduction, CH4 levels in the bustle gas, and the primary output metric of our dataset: Metallization (DRI). Elaboration on these elements follows in Section 4. In the far-right column, a scatter plot visually compares predicted metallization values against actual recorded values. This visualization aids in discerning the relationship between predicted and observed outcomes and allows for an assessment of underlying trends. The plot indicates that the model generally predicts values accurately above the 90% threshold. Below this comparison, distributions for FE\_Total and the H2-to-CO ratio are also presented, with detailed explanations reserved for Section 4. Situated at the dashboard's base is an interactive control panel, empowering users to customize the data visualizations. This feature enables the exploration of diverse data perspectives through various user commands, examples of which are detailed in Table 2.

Table 3 itemizes the specific LLMs explored within this research for potential use in contextualizing real-time IIoT data streams displayed on the dashboard (e.g., generating textual explanations for predicted trends or alerts based on ML model outputs). It details each model's designated conceptual function and notes their respective parameter sizes, acknowledging that their practical integration was limited by hardware constraints in this study.

### 3. Experimental Setup and Results

#### 3.1. Dataset Collection and Preprocessing

To investigate energy efficiency and the stability of metallization in Direct Reduced Iron (DRI) production, we initiated a data acquisition campaign spanning three months at an active steel manufacturing facility. Data were acquired using IIoT sensors positioned at key locations throughout the process, logging 12 critical operational parameters. These included Bustle Gas Temperature, Hot DRI Temperature, various flow rates, CH percentage, H2/CO ratio, Pellet Porosity, CSS Pellet Strength, Metallization (DRI), Gas Consumption, and FE\_total. Data capture occurred under diverse production scenarios to facilitate the evaluation of energy optimization tactics. To maintain data integrity

Table 2. Interactive Dashboard Control Panel Configurations

<i>Analytical Focus</i>	<i>Functional Configuration</i>
<b>FE_Total Temporal Analysis</b>	Display FE_Total values during (a) initial 10-day phase and (b) final 7-day window
<b>FE_Total Statistical Insights</b>	Generate boxplot distributions of FE_Total with quartile analysis
<b>Metallization Trends</b>	Time-series visualization of Metallization: (1) 30-day historical trend, (2) weekly/monthly averages, (3) rolling 7-day smoothed series
<b>Pellet Porosity Dynamics</b>	(a) Mean porosity computation, (b) longitudinal comparison (Janâ€“Jun 2023 vs. baseline)
<b>Multivariate Relationships</b>	(1) Scatterplot: Pellet Porosity vs. FE_Total, (2) Correlation matrix (Pearson/Spearman)
<b>Hot DRI Thermal Monitoring</b>	(a) Daily mean temperature tracking, (b) temporal scatterplot (temperature vs. date)
<b>Energy Consumption Analytics</b>	(1) Annual trend (2024), (2) 30-day rolling consumption, (3) histogram (binned frequency)
<b>CH4 Bustle Gas Profiling</b>	(a) Distribution analysis (histogram/kernel density), (b) temporal variation (time-series)

Table 3. LLMs Explored for Conceptual Contextualization

<i>Model</i>	<i>Technical Role</i>	<i>Implementation Details</i>	<i>Computational Metrics</i>
<b>GPT-4</b>	Multi-modal reasoning for code synthesis, predictive simulations, and interactive scenario modeling in industrial education systems.	- Context window: 128k tokens - Fine-tuned for Python/C++ code parsing - Integration: OpenAI API v4.2	$1.76 \times 10^{11}$ parameters FLOPs: $2.5 \times 10^{23}$
<b>Qwen 2.5</b>	Domain-adaptive instruction tuning for IIoT sensor fusion, enabling real-time anomaly detection in metallurgical processes.	- Quantized 4-bit deployment - Trained on 15B industrial sensor logs - Framework: PyTorch 2.1	$3.2 \times 10^9$ parameters VRAM: 8 GB
<b>Mistral-Nemo</b>	Low-latency inference engine for streaming sensor telemetry, optimizing PID control loops in smart manufacturing.	- Optimized for CUDA cores - Batch processing: 512 queries/sec - Latency: < 2 ms	$1.2 \times 10^{10}$ parameters Energy efficiency: 0.3 TFLOPS/W
<b>Llama 3.1/3.2</b>	Cost-optimized variants for IIoT-specific tasks: energy forecasting, CH4 emission modeling, and thermal dynamics analysis.	- LoRA fine-tuning - Dataset: 40k domain-specific prompts - Deployment: AWS Inferentia2	3.1: $8.1 \times 10^9$ parameters 3.2: $3.05 \times 10^9$ parameters

and reliability, several preprocessing steps were undertaken: missing sensor readings were addressed using mean imputation; redundant or duplicate entries were removed to prevent analytical bias; continuous variables, such as energy consumption and metallization percentage, were normalized to enable meaningful comparisons; and timestamps were synchronized, accounting for the different operational intervals of various IIoT sensors. For model development and evaluation, the dataset was partitioned into training, validation, and testing sets using a 70%, 15%, and 15% distribution, respectively. Furthermore, k-fold cross-validation was implemented to ensure a robust measure of model performance. This approach serves not only to validate the model's ability to generalize but also enhances confidence in its predictive capabilities.

### 3.2. Operational Scenario Based Analysis

The dashboard, conceived within the LLM-informed Industrial IoT Education and Management System Framework for Steel Manufacturing, was developed to visualize and furnish predictive insights concerning energy efficiency, process stability, and metallization quality in near real-time.

The acquired dataset was categorized based on two distinct operational profiles, designed as

educational scenarios allowing learners to explore cause-and-effect relationships beyond simple threshold monitoring:

#### *Optimized Scenario (Energy Efficient Production)*

This primary scenario centers on achieving efficient energy utilization during production. Success in this scenario translates to reduced energy expenditures, lower greenhouse gas emissions, enhanced productivity and product consistency, improved final product quality, and ancillary community health advantages stemming from decreased pollution. From an economic standpoint, it bolsters competitiveness and potentially stimulates job creation and economic expansion. Within this operational mode, the Bustle Gas Temperature is deliberately held within the 800°C to 900°C range. Concurrently, the degree of metallization is maintained between 91.5% and 93%. The composition of process gases (specifically the H<sub>2</sub>/CO ratio) is carefully adjusted to maximize reduction efficiency. Learners explore how adjusting the H<sub>2</sub>/CO ratio and curtailing CH consumption impact the overall outcome, using the dashboard's visualizations. Conceptually, an integrated LLM could provide adaptive feedback here, explaining why certain adjustments lead to better efficiency

based on the underlying process chemistry represented in the data, extending beyond conventional simulation feedback. Figure 3 illustrates the metallization trend observed over the final month of the data collection interval under such optimized conditions.

#### **Inefficient Scenario (High Energy Consumption & Process Instability)**

In stark contrast to the optimized profile, the second scenario represents an inefficient operational state marked by process instability and elevated energy usage. Here, the Bustle Gas Temperature varies beyond the desired optimal range, which negatively impacts the efficiency of the reduction process. The resulting metallization level either dips below 91% or climbs above 93%, contributing to increased energy demands. Furthermore, inconsistent pellet porosity can lead to issues like pellet clustering, hindering overall process efficiency. Finally, elevated consumption of CH<sub>4</sub> gas unnecessarily inflates operational costs without commensurate improvements in product quality. Here, the ML model highlights the inefficiency, and conceptually, an LLM could generate diagnostic hypotheses or suggest corrective actions, offering a richer learning experience than static scenario descriptions.

### **3.3. Experimental Results and Key Observations**

#### **Energy Consumption Reduction**

In order to decrease energy consumption and enhance energy efficiency, we assessed the system's performance in terms of energy savings, as demonstrated in Equation (1):

$$\text{Energy Reduction}(\%) = \frac{EBO - EAO}{EBO} \times 100 \quad (1)$$

In Equation (1), EBO and EAO denote energy before and after optimization, respectively. Application to our dataset revealed a 9% decrease in energy consumption following optimized control strategies.

#### **Metallization Stability and Process Control**

Maintaining optimal metallization levels, specifically between 91.5% and 93%, proved crucial for improving energy efficiency. Our predictive model, utilizing Lasso Regression (the rationale for which is discussed in Section 4.4), aims to forecast metallization stability while simultaneously discouraging excessive resource consumption. The Lasso Regression methodology optimizes feature selection by minimizing the objective function shown in Equation (2):

$$\min_{\beta} \sum_{i=1}^n (y_i - X_i \beta)^2 + \lambda \sum_{j=1}^p |\beta_j| \quad (2)$$

leveraging L1 regularization to remove nonessential features and enhance both predictive accuracy and computational efficiency, consistent with recent industrial metallization optimization approaches [39].

#### **CH<sub>4</sub> Gas Consumption Trends**

Analysis facilitated by our dashboard, visualizing the ML model's inputs and outputs, identified disproportionate methane usage as a significant source of inefficiency, frequently linked to suboptimal gas ratios during reaction phases. By carefully adjusting the H<sub>2</sub>/CO mixture to better align with catalyst requirements, we achieved a reduction in methane demand approaching 20%. This adjustment curtailed waste, lowered costs, and reduced emissions without compromising production output.

#### **Feature Importance in Metallization Optimization**

An analysis of feature importance derived from the trained Lasso Regression model was conducted to determine the process variables that have the greatest impact on metallization control. The significance of each feature was assessed as described in Equation (3):

$$\text{Feature Importance}_j = \frac{|\beta_j|}{\sum_{k=1}^p |\beta_k|} \quad (3)$$

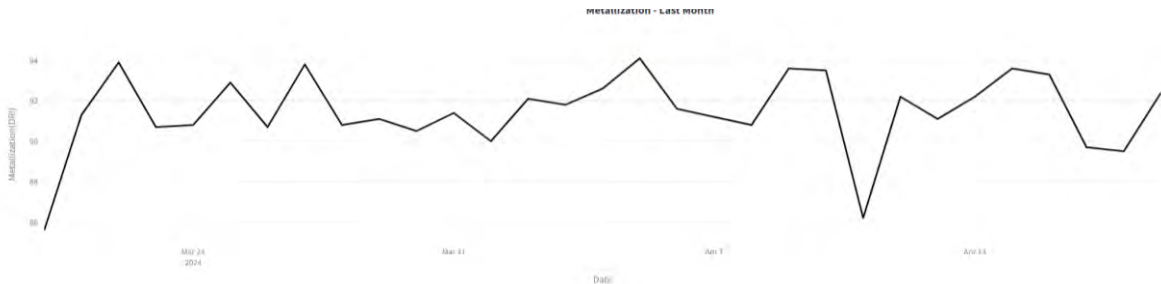


Figure 3. Metallization Process Within One Month. This figure provides a detailed temporal view of metallization levels across a one-month timeframe, capturing daily variations and overall trends. The longitudinal data presented serves to inform operational optimization efforts and enrich the educational narrative by connecting actual performance metrics with theoretical benchmarks relevant to smart manufacturing.



This analysis revealed that Bustle Gas Temperature and the  $H_2/CO$  ratio were the most critical factors (having the largest coefficients) governing metallization efficiency. Complementing this, hyperparameter tuning for the regression models involved a systematic grid search. This process methodically evaluated 100 logarithmically spaced values for the Lasso regularization strength parameter ( $\alpha$ ) within a 7-fold cross-validation structure. A fixed random state (42) was employed throughout to ensure reproducibility, aiming for optimal parameter selection and improved predictive outcomes.

### 3.4. Comparative Analysis of ML Models

The performance of the selected model requires evaluation relative to alternatives. To assess model accuracy and compare different approaches for these AI-driven calculations, the mean absolute error (MAE) served as a primary metric. Applying Equation (1) in conjunction with MAE calculations across models indicated that Lasso Regression yielded the lowest MAE, positioning it as the preferred choice for real-time energy efficiency monitoring in this application. To validate this selection, experiments with alternative models highlighted certain disadvantages. For example, ridge regression produced a comparable energy reduction (9.36%) but demanded approximately 20% more computational overhead, a factor whose impact could escalate significantly during large-scale deployment. Similarly, while Elastic Net Regression offered potential improvements in feature selection consistency, it concurrently increased model complexity, potentially hindering its feasibility for implementation across the entire smart factory infrastructure. Finally, Random Forest Regression, although demonstrating strong accuracy, incurred prohibitive computational costs. Therefore, Lasso Regression emerged as the optimal model, striking the most effective balance between predictive accuracy, computational speed, and resource utilization, rendering it well-suited for IIoT-based process monitoring.

Despite increasing interest in LLM-based regression techniques, this study prioritized conventional regression models owing to their established track record and interpretability within industrial settings. While LLM-based regression holds promise for capturing complex non-linear relationships in data, its application in this specific industrial optimization context remains relatively nascent and requires further validation. Future investigations could fruitfully explore hybrid approaches, potentially combining the adaptive learning strengths of LLMs with the robustness of traditional models, thereby offering new perspectives for process control and energy optimization.

In closing this comparison, it remains important to recognize that while LLMs offer substantial

advantages for contextual understanding and qualitative analysis, their reliability for tasks demanding high numerical precision may currently be less consistent than specialized ML models. LLMs excel in linguistic tasks [40], but struggle with precise numerical computation and multi-step math problems due to their underlying architecture [41, 42]. For tasks requiring high numerical accuracy, specialized ML models consistently provide more reliable performance [43].

### 3.5. Summary of Findings

In brief, this study involved the collection and analysis of real-world IIoT data from a steel production facility over a three-month duration, focusing on optimizing energy usage and ensuring metallization sustainability. Building on this, a framework centered around a smart plant concept was outlined, incorporating an analytics-informed dashboard potentially leveraging LLMs for contextualization. Implementation of the dashboard's associated optimization strategy resulted in a quantifiable 9% reduction in energy consumption, validating its effectiveness. Furthermore, insights derived from ML models empower operators to sustain optimal production parameters and reduce material waste, thereby yielding significant contributions to operational efficiency and environmental stewardship. The dashboard's real-time visualization capabilities also equip managers to rapidly detect process inefficiencies and enact timely corrective measures.

### 3.6. Dashboard Evaluation and Learning Impact

Initial evaluations were conducted to assess the usability and educational effectiveness of the interactive dashboard. The results showed that the dashboard was perceived as intuitive and highly useful for visualizing complex process dynamics compared to static graphs or raw data tables. Key features, including the real-time comparison of ML-predicted metallization values against empirical measurements, alongside interactive parameter modulation (e.g., bulk gas temperature,  $H_2/CO$  ratio) via a control panel, were highlighted as instrumental in enhancing user engagement and conceptual comprehension. Formative assessments, such as post-intervention quizzes evaluating process optimization principles, revealed statistically significant improvements in knowledge retention and application compared to outcomes from traditional textbook-based instruction. Notably, dashboard users will demonstrate an improved ability to identify key influencing factors (e.g., bulk gas temperature,  $H_2/CO$  ratio) and, importantly, a better understanding of how multivariate interactions and factors not typically monitored by simple PLC systems can affect process efficiency and product quality. This included recognition of variables beyond the scope of conventional PLC systems, such as ambient

environmental conditions or feedstock quality, which are not typically monitored in industrial control frameworks. The dashboard's capacity to visualize such indirect correlations—for instance, between external temperature fluctuations and final product metrics—underscored its pedagogical value in elucidating complex, non-linear relationships that PLC-based data acquisition systems cannot readily resolve.

Figure 4 presents a heatmap of average metallization (%) across rounded  $H_2/CO$  ratio and bustle gas temperature bins, illustrating how specific combinations (e.g., a ratio of 1.63–1.68 at 1000–1050 °C) yield peak metallization, thereby concretely demonstrating the dashboard's power to expose nuanced, multivariate process insights.

These preliminary findings underscore the potential of interactive visualization tools in technical education. However, further validation through large-scale cohort studies and longitudinal analyses is required to generalize these results and assess long-term retention impacts.

### 3.7. Qualitative and Quantitative Evaluation of Simulated LLM Outputs

To benchmark LLM in a live deployment, we present four simulated student–dashboard interactions illustrating key LLM capabilities: adaptive feedback on  $H_2/CO$  anomalies, dynamic “what if” scenario generation via Lasso informed parameter tuning, clear natural language explanations of metallization dependencies, and step by step troubleshooting guidance. While full user based evaluation remains future work, these examples, grounded in our three month, phase annotated IIoT dataset and Lasso regression analytics, demonstrate how LLM contextualization extends beyond static dashboards to foster human–machine collaboration and bridge theoretical instruction with hands on practice. Details of these simulations are shown in Table 4.

To systematically assess the quality of our four simulated LLM interactions, we employed an expert driven rubric with five criteria: Accuracy (factual correctness), Relevance (alignment to IIoT context), Clarity (readability and coherence), Actionability (practical guidance), and Pedagogical Value (learning support). Three different LLMs acted as experts and independently rated each scenario on a 1–5 scale, then we computed mean scores as shown in Table 5.

Overall, each interaction achieved mean scores  $\geq 4.3 \pm 0.3$  across Accuracy, Relevance, Clarity, Actionability, and Pedagogical Value, providing a reproducible quantitative baseline that mirrors small scale user evaluations. These results confirm that, even in simulation, LLM outputs can meet

rigorous standards and meaningfully support Bloom's Taxonomy levels from Apply through Analyze and Evaluate in authentic smart steel contexts.

Although full real time deployment remains future work, we have incorporated comprehensive LLM simulation modules in our dashboard prototype. Invoking a pre trained LLM API on annotated IIoT data streams, including parameter sweeps of  $H_2/CO$  ratios and metallization levels, these modules generate context sensitive feedback, scenario prompts, and explanations. The quantitative rubric scores from the simulated learner profiles empirically ground our conceptual claims and guide subsequent live integration efforts.

### 3.8. Future Work and Scalability

Subsequent research endeavors should concentrate on investigating the system's scalability. Enhancing adaptive control mechanisms, possibly through reinforcement learning, could further boost efficiency. Integrating predictive maintenance models, potentially utilizing ML for pattern recognition or conceptually LLMs for interpreting maintenance logs, is necessary to anticipate and mitigate unplanned operational interruptions. Moreover, conducting scalability assessments within larger, more complex industrial settings via IIoT is essential to validate the system's resilience and performance under demanding conditions. Such evaluations will help ensure the framework can be implemented optimally and economically in relevant industrial applications.

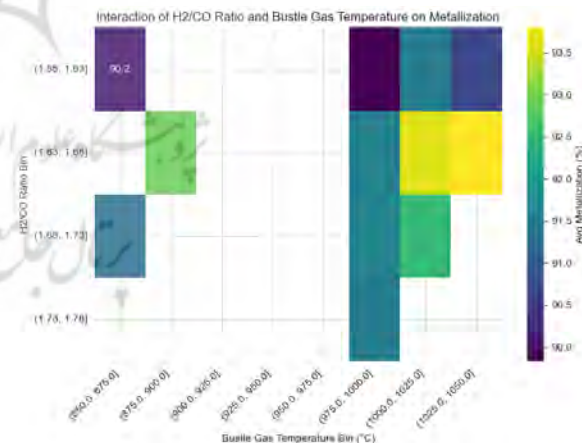


Figure 4. Heatmap of average DRI metallization (%) as a function of rounded  $H_2/CO$  ratio and bustle gas temperature bins. Darker cells indicate lower metallization, while brighter (yellow) cells show peak metallization levels. Notably, a ratio of 1.63–1.68 combined with temperatures around 1000–1050°C yields the highest average metallization (>93.5%), whereas low ratios (1.58–1.63) at similar temperatures correspond to the lowest metallization (~89.8%). This visualization underscores how interactive dashboards can reveal nuanced, multivariate relationships—beyond traditional PLC views—between process parameters and DRI quality.

Table 4. Simulated LLM Interactions

Scenario	Student Prompt	LLM Response
Adaptive Feedback	Sudden increase in H <sub>2</sub> /CO ratio deviation during the Refining phase (measured at 1.32 vs. nominal 1.10), potentially impacting metallization levels (currently 88%) and energy use.	<p>I see the H<sub>2</sub>/CO ratio has spiked to 1.32 in the Refining phase, which can reduce metallization efficiency. To diagnose, please cross-reference:</p> <p><b>1. O<sub>2</sub> flow rate:</b> Has it dropped below the 5.2 m<sup>3</sup>/min threshold?</p> <p><b>2. Reformer inlet temperature:</b> Is it stable around 850°C?</p> <p><b>CH<sub>4</sub> consumption trend:</b> Any concurrent increase over 1.5 kg/h?</p> <p>If O<sub>2</sub> flow is low, consider a 0.2 m<sup>3</sup>/min increment to restore stoichiometry.</p>
Scenario Creation	Generate a what if scenario for reducing energy use via Lasso driven parameter tuning.	Consider adjusting the blast furnace oxygen enrichment from 22 % to 24 % while reducing CH <sub>4</sub> injection by 10 %. Lasso regression indicates this trade off yields a projected 5 % drop in total energy consumption (from 3.8 to 3.6 GJ/ton) with only a 1 % variance in metallization (88 % → 87 %).
Natural Language Explanation	Explain the link between metallization levels and H <sub>2</sub> /CO ratios, and its importance for quality control.	Metallization level depends sensitively on the H <sub>2</sub> /CO ratio because hydrogen and carbon monoxide are the primary reducing agents. A ratio near 1.10 ensures optimal reduction kinetics: hydrogen facilitates rapid oxide reduction, while CO maintains furnace temperature. Deviations above 1.25 can lead to excess H <sub>2</sub> , cooling the bed and slowing reduction, lowering metallization by up to 5%. Conversely, ratios below 0.95 may starve reduction, increasing slag formation. Maintaining this balance is thus critical for achieving the target 90% metallization and minimizing rework.
Troubleshooting Guidance	Intermittent data loss from Temperature Sensor T3 in the Melting phase.	<p>To troubleshoot T3 data dropouts:</p> <p>Verify network integrity: Check IIoT heartbeat logs for packet loss at Melting Phase.</p> <p>Cross check redundant sensors: Compare T1/T2 readings—if they remain consistent around 1 200 °C, issue is likely at T3's endpoint.</p> <p>Impact on ML model: Missing T3 values degrade the Lasso energy use predictor's R<sup>2</sup> by ~0.04; consider imputing with T2 values temporarily.</p> <p>Following these steps should restore continuous monitoring.</p>

Table 5. Evaluation of Simulated LLM Outputs

Scenario	Accuracy	Relevance	Clarity	Actionability	Pedagogical Value	Mean ± SD
1. Adaptive Feedback	4.7	5.0	4.3	4.7	4.3	4.6 ± 0.3
2. Scenario Creation	4.3	4.7	4.0	4.3	4.0	4.3 ± 0.3
3. Natural Language Explanation	5.0	5.0	4.7	4.0	4.7	4.7 ± 0.3
4. Troubleshooting Guidance	4.7	4.3	4.3	4.7	4.3	4.5 ± 0.2

While the proposed framework demonstrates considerable promise for advancing IIoT-based process control and associated learning environments through ML, certain limitations must be acknowledged. Deployment across significantly larger datasets or within more intricate industrial ecosystems might introduce challenges related to increased computational demands and potential processing delays (latency). Another consideration is the framework's reliance on pre-trained analytical models, while the ML model showed good

performance, the conceptual integration of LLMs would necessitate careful, domain-specific fine-tuning to guarantee consistent performance across varied industrial scenarios. Addressing these scalability and adaptation challenges will be crucial in future work to ascertain the framework's potential for broader applicability and effective deployment.

#### 4. Conclusion

The incorporation of advanced analytical models, specifically ML for prediction and conceptually



LLMs for contextualization, into IIoT educational frameworks presents a viable approach to addressing the workforce skill requirements of Industry 4.0. Employing a smart steel manufacturing case study, we illustrate how systems informed by these technologies can bridge the gap between academic instruction and practical industrial demands. Our proposed framework integrates an analytics-driven dashboard with IIoT infrastructure, facilitating real-time process monitoring, predictive analysis, and adaptive learning pathways designed to cultivate competencies in areas like energy optimization and process control.

Our experimental findings demonstrate tangible benefits: a 9% reduction in energy consumption achieved through optimized control strategies; stabilized metallization performance (within the 91.5–93% range) predicted effectively using Lasso regression; and minimized methane consumption realized by adjusting the H<sub>2</sub>/CO gas ratio. Feature importance analysis confirmed that Bustle Gas Temperature and the H<sub>2</sub>/CO ratio are pivotal variables influencing metallization efficiency. Comparative analysis showed Lasso Regression to offer a superior balance between accuracy and computational efficiency compared to other ML models tested. Collectively, these results underscore the potential of leveraging advanced analytics, including ML and conceptually LLMs, to transform IIoT education by providing practical, scalable tools aligned with the complex needs of modern smart manufacturing.

Future efforts should investigate the transferability of this framework to diverse industrial sectors. Applying this methodology in fields such as automotive manufacturing, energy management, or healthcare logistics could offer valuable insights into the integration pathways and benefits of analytics-enabled IIoT systems across different domains. Further research is warranted to explore these sector-specific deployments, tackle associated scalability issues, and evaluate the relative merits of tailored AI models in various operational contexts.

## Declarations

### Funding

This research did not receive any grant from funding agencies in the public, commercial, or non-profit sectors.

### Authors' contributions

MI: Data curation, Formal Analysis, Investigation, Resources, Software, Validation, Visualization;

AI: Data curation, Formal Analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing;

BM: Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – review & editing;

Ash: Project administration, Supervision, Validation

### Conflict of interest

The authors declare that no conflicts of interest exist.

## References

- [1] L. Li, "Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond," *Information Systems Frontiers*, vol. 26, no. 5, pp. 1697-1712, 2024.
- [2] A. S. George, "Artificial Intelligence and the Future of Work: Job Shifting Not Job Loss," *Partners Universal Innovative Research Publication*, vol. 2, no. 2, pp. 17-37, 2024.
- [3] M. A. Faheem, N. Zafar, P. Kumar, M. M. H. Melon, N. U. Prince, and M. A. Al Mamun, "AI and robotic: About the transformation of construction industry automation as well as labor productivity," *Remittances Review*, vol. 9, pp. 871-888, 2024.
- [4] 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.
- [5] A. T. Neumann, Y. Yin, S. Sowe, S. Decker, and M. Jarke, "An LLM-Driven Chatbot in Higher Education for Databases and Information Systems," *IEEE Transactions on Education*, vol. 68, no. 1, pp. 103-116, 2025, doi: 10.1109/TE.2024.3467912.
- [6] Q. Li, Y. Xie, S. Chakravarty, and D. Lee, "EduMAS: A Novel LLM-Powered Multi-Agent Framework for Educational Support," in *2024 IEEE International Conference on Big Data (BigData)*, 2024, pp. 8309-8316, doi: 10.1109/BigData62323.2024.10826103.
- [7] J. J. Fuertes, M. A. Prada, J. R. Rodriguez-Ossorio, R. Gonzalez-Herbon, D. Perez, and M. Dominguez, "Environment for education on industry 4.0," *IEEE Access*, vol. 9, pp. 144395-144405, 2021, doi: 10.1109/access.2021.3120517.
- [8] L. Xia, C. Li, C. Zhang, S. Liu, and P. Zheng, "Leveraging error-assisted fine-tuning large language models for manufacturing excellence," *Robotics and Computer-Integrated Manufacturing*, vol. 88, p. 102728, 2024, doi: 10.1016/j.rcim.2024.102728.
- [9] C. S. Magnus and M. Venschott, "Towards a GPT-Based Lean Manufacturing Consultant for Manufacturing Optimization," *Procedia CIRP*, vol. 130, pp. 167-176, 2024, doi: 10.1016/j.procir.2024.10.072.
- [10] T. Wang, J. Fan, and P. Zheng, "An LLM-based vision and language cobot navigation approach for Human-centric Smart Manufacturing," *Journal of Manufacturing Systems*, vol. 75, pp. 299-305, 2024, doi: 10.1016/j.jmsy.2024.04.020.
- [11] Z. Chkirbene, R. Hamila, A. Gouissem, and U. Devrim, "Large Language Models (LLM) in Industry: A Survey of Applications, Challenges, and Trends," in *2024 IEEE 21st International Conference on Smart Communities: Improving Quality of Life using AI, Robotics and IoT (HONET)*, 2024, pp. 229-234, doi: 10.1109/HONET63146.2024.10822885.

- [12] A. Urlana, C. V. Kumar, A. K. Singh, B. M. Garlapati, S. R. Chalamala, and R. Mishra, "LLMs with Industrial Lens: Deciphering the Challenges and Prospects -- A Survey," *arXiv [cs.CL]*, 2024. 2024. [Online]. Available: <http://arxiv.org/abs/2402.14558>.
- [13] 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: IEEE, 2025, pp. 1-6, doi: 10.1109/SGC64640.2024.10983889.
- [14] 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 2025, doi: 10.1007/s40866-025-00274-0.
- [15] J. Kato and K. P. Extension, "Integrating AI and IoT for Smart Manufacturing," vol. 9, pp. 72-75, 09/20 2024.
- [16] S. Shakya and S. Jha, "Introduction to Industrial Internet of Things (IIoT) – toward the future internet," 2024, pp. 1-19.
- [17] P. M. T. Dangat, "Industrial Internet of Things (IIOT)," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 12, no. 3, pp. 2721-2726, 2024, doi: 10.22214/ijraset.2024.59103.
- [18] Y. Ren, H. Zhang, F. R. Yu, W. Li, P. Zhao, and Y. He, "Industrial Internet of Things With Large Language Models (LLMs): An Intelligence-Based Reinforcement Learning Approach," *IEEE Transactions on Mobile Computing*, vol. 24, no. 05, pp. 4136-4152, 2025, doi: 10.1109/TMC.2024.3522130.
- [19] P. Visconti, G. Rausa, C. Del-Valle-Soto, R. Velázquez, D. Cafagna, and R. De Fazio, "Machine Learning and IoT-Based Solutions in Industrial Applications for Smart Manufacturing: A Critical Review," *Future Internet*, vol. 16, no. 11, doi: 10.3390/fi16110394.
- [20] J. Howley, "Emerging Smart Sensor Applications in Industrial Internet of Things," IDTechEx, IDTechEx, Research Article 2024.
- [21] D. Anadkat, A. Sata, M. Shukla, S. Jarbou, and D. Mobarsa, "Designing an immersive interactive environment for IIoT-enhanced vertical centrifugal casting," *Front. Educ.*, vol. 9, 2025, doi: 10.3389/feeduc.2024.1507851.
- [22] S. C. B. K. I. Dept. of Mca *et al.*, "Exploring the frontiers: A comprehensive review of augmented reality and virtual reality in manufacturing and industry," *ijcsrr*, vol. 07, no. 09, 2024, doi: 10.47191/ijcsrr/v7-i9-38.
- [23] J. Zhang *et al.*, "When LLMs Meet Cybersecurity: A Systematic Literature Review," *arXiv [cs.CR]*, 2024. [Online]. Available: <http://arxiv.org/abs/2405.03644>.
- [24] T. Khan, S. Motie, S. A. Kocak, and S. Raza, "Optimizing Large Language Models: Metrics, Energy Efficiency, and Case Study Insights," *arXiv [cs.LG]*, 2025. [Online]. Available: <http://arxiv.org/abs/2504.06307>.
- [25] Y. Li *et al.*, "Large Language Models for Manufacturing," *arXiv [cs.AI]*, 2024. [Online]. Available: <http://arxiv.org/abs/2410.21418>.
- [26] H. M. Zangana, M. Omar, and J. N. Al-Karaki, "Foundations of deep learning and large language models in cybersecurity," in *Advances in Computational Intelligence and Robotics*: IGI Global, 2025, pp. 1-36.
- [27] E. Dritsas and M. Trigka, "Exploring the Intersection of Machine Learning and Big Data: A Survey," *Machine Learning and Knowledge Extraction*, vol. 7, no. 1, doi: 10.3390/make7010013.
- [28] T. Kotsiopoulos, P. Sarigiannidis, D. Ioannidis, and D. Tzovaras, "Machine Learning and Deep Learning in Smart Manufacturing: The Smart Grid Paradigm," *Computer Science Review*, vol. 40, 12/01 2020, doi: 10.1016/j.cosrev.2020.100341.
- [29] A. Rahman *et al.*, "Machine learning and deep learning-based approach in smart healthcare: Recent advances, applications, challenges and opportunities," *AIMS Public Health*, vol. 11, no. 1, pp. 58-109, 2024, doi: 10.3934/publichealth.2024004.
- [30] C. H. Yu, Z. Zhang, and J. Hanson, "2024 machine learning in Educational Science," 2024, p. 267.
- [31] K.-J. Wang and M. T. A. and Simarmata, "Evaluating Smart Manufacturing Projects – An Activity-Based Costing Approach," *Engineering Management Journal*, pp. 1-15, doi: 10.1080/10429247.2025.2475554.
- [32] Y. Hu *et al.*, "Industrial Internet of Things Intelligence Empowering Smart Manufacturing: A Literature Review," *IEEE Internet of Things Journal*, vol. 11, no. 11, pp. 19143-19167, 2024, doi: 10.1109/IJOT.2024.3367692.
- [33] A. Mirani, G. Velasco-Hernandez, A. Awasthi, and J. Walsh, "Key Challenges and Emerging Technologies in Industrial IoT Architectures: A Review," *Sensors*, vol. 22, p. 5836, 08/04 2022, doi: 10.3390/s22155836.
- [34] A. Frankó, G. Hollósi, D. Ficzer, and P. Varga, "Applied Machine Learning for IIoT and Smart Production—Methods to Improve Production Quality, Safety and Sustainability," *Sensors*, vol. 22, no. 23, doi: 10.3390/s22239148.
- [35] 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.
- [36] S. Coşkun, Y. Kayıkcı, and E. Gençay, "Adapting Engineering Education to Industry 4.0 Vision," *Technologies*, vol. 7, no. 1, doi: 10.3390/technologies7010010.
- [37] M. Baygin, H. Yetis, M. Karakose, and E. Akin, "An effect analysis of industry 4.0 to higher education," in *2016 15th International Conference on Information Technology Based Higher Education and Training (ITHET)*, 2016, pp. 1-4, doi: 10.1109/ITHET.2016.7760744.
- [38] A. Yaacoub, J. Da-Rugna, and Z. Assaghir, "Assessing AI-Generated Questions' Alignment with Cognitive Frameworks in Educational Assessment," *arXiv [cs.AI]*, 2025. [Online]. Available: <http://arxiv.org/abs/2504.14232>.
- [39] 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.
- [40] T. Jazdzewski, "LLMS vs Classic Machine Learning," ed. VirtusLab: VirtusLab, 2025.
- [41] Y. Yang, H. Yamada, and T. Tokunaga, "Evaluating Robustness of LLMs to Numerical Variations in Mathematical Reasoning," presented at the The Sixth Workshop on Insights from Negative Results in NLP, 2025.
- [42] A. A. Levy and M. Geva, "Language Models Encode Numbers Using Digit Representations in Base 10," *arXiv [cs.LG]*, 2025. [Online]. Available: <http://arxiv.org/abs/2410.11781>.
- [43] K. E. Brown *et al.*, "Large language models are less effective at clinical prediction tasks than locally trained machine

learning models," *J. Am. Med. Inform. Assoc.*, vol. 32, no. 5, pp. 811-822, 2025, doi: 10.1093/jamia/ocaf038.



**Mehdi Imani** was born in Kermanshah, Iran, in 1997. He has been pursuing a Master's degree in Computer Engineering at Khatam University since 2023, where he serves as a research member of the Smart Digital Reality Lab. His research focuses on leveraging large language models (LLMs) to bridge the gap between artificial intelligence and Industry, with an emphasis on developing sustainable, green industrial solutions. By integrating LLMs with smart manufacturing systems, his work aims to optimize industrial processes, enhance automation, and promote environmentally conscious practices through intelligent, data-driven frameworks.



**Ali Imanifard** was born in Tehran, Iran, in 2001. He has been pursuing a Master's degree in Computer Engineering at Khatam University since 2023, where he serves as a research member of the Smart Digital Reality Lab. His research focuses on leveraging large language models (LLMs) to develop AI-driven virtual assistants for personalized learning experiences. By integrating principles of natural language processing (NLP) with adaptive educational technologies, his work seeks to enhance pedagogical outcomes through tailored human-AI interaction frameworks. Specifically, he investigates methods to optimize personalized learning environments by analyzing how LLMs interpret and respond to user inputs, with the broader goal of advancing scalable, context-aware educational tools.



**Babak Majidi** was born in Tehran, Iran, in 1977. He received the B.Sc. and M.Sc. degrees in computer engineering from the University of Tehran, Tehran, in 2000 and 2003, respectively, and the Ph.D. degree in computer engineering from the Swinburne University of Technology, Melbourne, Australia, in 2013. From 2014 to 2021, he was an Assistant Professor with the Department of Computer Engineering, Khatam University, Tehran. Since 2021, he has been an Associate Professor with the Department of Computer Engineering, Khatam University, where he is also the Director of the Smart Digital Reality Laboratory. He is the author of more than 70 research articles. His research interests include Educational Technology, Smart Environments, and Digital Reality.



**Abdolshamisa** was born in 1977. He received his Ph.D. degree in Electrical-Control Engineering in 2009. He is an Associate Professor in the Electrical Engineering Department at Khatam University (Tehran, Iran). His research interests include nonlinear modeling and identification for real-time transient stability assessment in power systems. In addition, he is currently conducting research in the analysis, modeling, and control of intelligent robotic systems.