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Literature Review of Industry 4.0 Technologies for Water Optimization in Steel Plants

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Abstract

This article presents a systematic literature review on the application of Industry 4.0 technologies in water optimization within the steel industry. Using the PRISMA protocol, 50 articles selected from international scientific databases, published between 2018 and 2026 were analyzed. Bibliometric analysis identified global trends, while qualitative analysis examined the core of studies centered on water management. It is demonstrated that the integration of enabling technologies such as the internet of things, artificial intelligence, digital twins, and cyber-physical systems, among others, enables real-time monitoring and failure prediction. The analyzed studies demonstrate a significant reduction in water withdrawal, effluent mitigation, and measurable economic gains. The literature points to gaps regarding implementation costs, the need for technical training, and the scarcity of empirical data in developing countries. It is concluded that digitalization is strategic for steel industry sustainability, recommending future studies on its convergence with Industry 5.0.

Keywords: Industry 4.0; Steel Industry; Water Efficiency; Sustainability

1. Introduction

As one of the world's most capital- and resource-intensive the steel sector plays a strategic role in the global economy. This assertion is corroborated by the 2024 Statistical Yearbook of the Brazilian Steel Institute [1], which identifies the automotive, civil construction, and distribution sectors as the most representative in steel consumption. This validates the view that the steel industry supplies modern civilization with essential raw materials [2] for the construction of buildings, vehicles, and household appliances.

It is strategic in naval engineering and the energy sector worldwide [3,4]. The connection with various sectors reinforces the role of the steel industry in the global economy [5]. The industrial sector faces significant pressure regarding the environmental impact it exerts. This factor is highlighted in the "Environmental Outlook 2025" document by the Organization for Economic Co-operation and Development (OECD) [6]. In this scenario, corporate management must integrate production processes and environmental management, placing environmental impact at the core of its activities [7].

Amid the various natural resources impacted by the steel industry, water stands out as a critical input [8], given the sector's high resource consumption profile [9]. Because energy-intensive sectors like steel manufacturing are major

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drivers of regional water demand, they offer the greatest potential for water-saving initiatives [10]. Water is essential for cooling, cleaning, and power generation processes within the sector [09,11].

Industry 4.0 emerges as a driver of technological transformation leveraged by the infrastructure based on the Internet of Things (IoT), big data, and artificial intelligence [12] to optimize consumption and monitor water quality in real time [13.14]. The adoption of these technological innovations not only improves operational efficiency (cost reduction and quality improvement) but also mitigates environmental impact, thereby promoting sustainability [15].

Addressing the need to integrate productive efficiency with sustainability, this article conducts a literature review on the intersection of Industry 4.0, the steel sector, and water management, seeking to identify how digital technologies can promote a more rational and sustainable use of water resources. The text is thus organized into sections that initially address the fundamentals of the steel industry and its water-related challenges, followed by the presentation of Industry 4.0 technologies applicable to the sector, and finally, the discussion of the results found in the selected literature.

2. Theoretical Framework

In the current context, the steel industry faces the challenge of adapting to the new technological determinants of the industrial revolution, which are composed of information technology infrastructure and the Internet of Things, with Big Data serving as their foundation [16].

The Fourth Industrial Revolution, or Industry 4.0, is characterized by the integration of physical and cybernetic systems, promoting the digitalization of manufacturing processes. This revolution is based on the integration of systems that allow for rapid responses and expand process capabilities [17], thereby reinforcing the importance of incorporating technologies that are part of Industry 4.0. Also, Industry 5.0 seeks to find the exact balance between autonomous/self-organizing cyber-physical systems and the employees within those same systems [12].

Among the technological pillars that support this transformation, the Industrial Internet of Things (IIoT), Cloud Computing, Big Data Analytics, Artificial Intelligence (AI), and Cyber-Physical Systems (CPS) stand out [18]. In the steel context, these enabling technologies allow for the conversion of traditional factories into "smart factories." For this integration to occur in real time and without production delays, the support of cloud computing infrastructures [19] combined with artificial intelligence-driven industrial networks is essential [20].

Cyber-Physical Systems (CPS), for example, are composed of physical subsystems equipped with computing and networking resources to monitor and control processes, in which the physical affects the computational and vice versa [21]. For this purpose, the use of new technologies in the industry will aid, as smart factories stand out as an innovative industrial model that utilizes cyber-physical systems to monitor processes, make decentralized decisions, and optimize production.

Digital twin technology acts as a virtual replica connected to cyber-physical systems, executing calculations and scenario simulations, thereby preventing operations from being interrupted. It becomes essential to the steel sector, as it enables continuous and precise analysis for decision-making, including when sensor failures or noise occur due to industrial environment conditions [22].

The processing of large volumes of data originating from IIoT and CPS occurs through Big Data Analytics, which aims to identify problems, predict operational failures, and optimize resources, transforming raw data into autonomous decisions [21]. Steel production demands large volumes of water, which is used in various ways, ranging from the cooling of machines, equipment, and products to descaling and gas washing processes [23, 24].

Pumping and treatment in industrial water circuits account for a considerable proportion of a plant's total electricity consumption; due to the water-energy nexus, efficient water management is critical [25]. To achieve this efficiency, process innovations and circular strategies are essential to enable safe reuse and the closure of the industrial water cycle [26].

The application of Industry 4.0 concepts to water resource management originated the term "Water 4.0" (or digital water), which refers to the intersection between water and Information and Communication Technologies (ICT) [27]. In steel mills, water optimization occurs through rigorous monitoring supported by AI, IIoT, and digital twin [28]. To ensure the reliability of this monitoring, Explainable Artificial Intelligence (XAI) has been applied to interpret water distribution network data transparently [29].

In integrated and semi-integrated plants, cooling water represents the largest share of water use, being fundamental for dissipating excess heat in stages such as hot and cold rolling, and in the cooling of blast furnaces [30]. Despite the large quantities of water withdrawn, a relatively small portion (often less than 10%) is effectively consumed, with losses occurring primarily through evaporation in cooling towers [30]. Historically, the sector has sought to increase its recirculation rates.

However, growing global scarcity and strict environmental legislation requires a regulatory support system and high capital investments to enable energy sustainability in the sector [31]. There are specific sector initiatives, such as the ResponsibleSteel certification, which demands rigor in resource management (including water) and emissions [32].

It is imperative that the sector transcends conventional treatment technologies, seeking real-time optimization. Literature highlights that water-related problems, ranging from scarcity and pollution to extreme events such as storms and floods, put life and socioeconomic progress at risk [33]. This scenario reinforces the urgency of integrated approaches to water resource management.

3. Methodology

The development of the literature review was based on the PRISMA method, which aims to ensure the reliability and applicability of the findings through the methods and results of systematic reviews [34]. Access to the studies was provided via the Periodicals Portal of the Coordination for the Improvement of Higher Education Personnel (CAPES), with access granted by Fluminense Federal University (UFF). For the search, the international databases Scopus, Web of Science, and ScienceDirect were utilized. The database search was conducted between October 2025 and November 2025.

The basic flow for the execution of the methodology, as shown in Figure 1, consisted of performing the search according to the terms and databases cited in Table 1. This was followed by filtering the articles to identify those aligned with the objective of the study (presented in Figure 4) and the final organization of the articles to be presented.

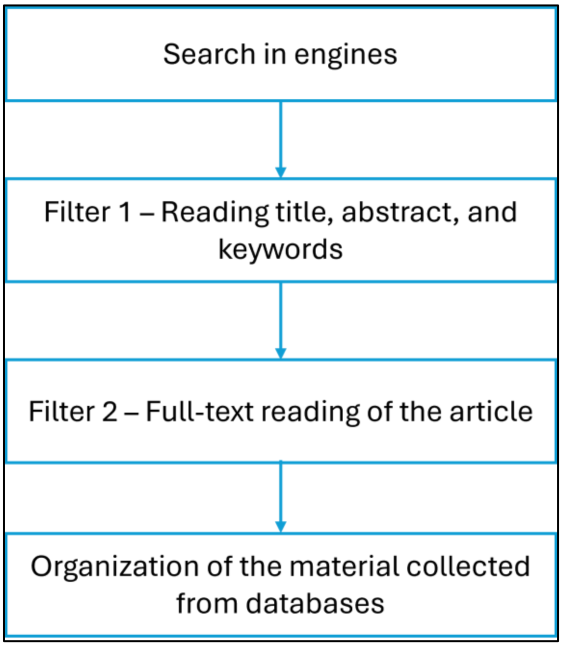

Figure 1 Steps established in the systematic literature review

In this study, the database search utilized the terms 'water efficiency', 'industry 4.0', and 'steel industry' in conjunction with the Boolean operator AND, which indicates that the search must return results containing the specified search terms. This approach yields a more concise set of articles for evaluation. The word order does not interfere with the obtained results. Table 1 presents the search terms combined with the AND operator:

Table 1 Terms used in database queries

Term	Databases searched
"Water efficiency and Industry 4.0"	Scopus, Web of Science, Science Direct
"Water efficiency and Steel Industry"	Scopus, Web of Science, Science Direct
"Industry 4.0 and Steel Industry"	Scopus, Web of Science, Science Direct

Seeking thematic relevance and source quality, the following decision criteria were employed:

- Linguistic criterion: Articles must be published exclusively in English.
- Temporal criterion: Articles must be published from 2018 onwards.
- Article access criterion: Only studies published under open access were included.
- Quality criterion: A top-down filtering approach was adopted to evaluate the article's contribution to the study's ecosystem, divided into two levels of eligibility:

Investigates the practical feasibility of Industry 4.0 in the steel industry. Rather than merely listing technologies, it is necessary to analyze the implementation bottlenecks and the actual environmental impact of these innovations.

For the core of the analysis, the selection criteria prioritize investigations where water efficiency is the central indicator of success. This includes the use of digital systems applied directly to water management.

Methodological note: This distinction in scope proved necessary due to the characteristics of the current literature. While the conceptual foundation and operational challenges of Industry 4.0 in the steel industry are widely documented, applications directly focused on water management in the steel industry represent an emerging and highly specific branch, which is addressed in depth by the core articles of this study.

To minimize potential biases as much as possible, the following premises were established in the development of this work:

- Use of more than one database.
- Critical analysis of the results produced by the search mechanism.
- Exclusion of duplicate records to prevent biases in the statistical analysis.

After conducting the search based on the established terms, 372 articles were identified. The search term “industry 4.0 and steel industry” yielded the largest number of related articles, with 207 articles listed, followed by the term “water efficiency and steel industry” with 104 articles, and subsequently the term “water efficiency and Industry 4.0” with 61 articles, as shown in Figure 2. This indicates an opportunity for further studies related to water efficiency and Industry 4.0.

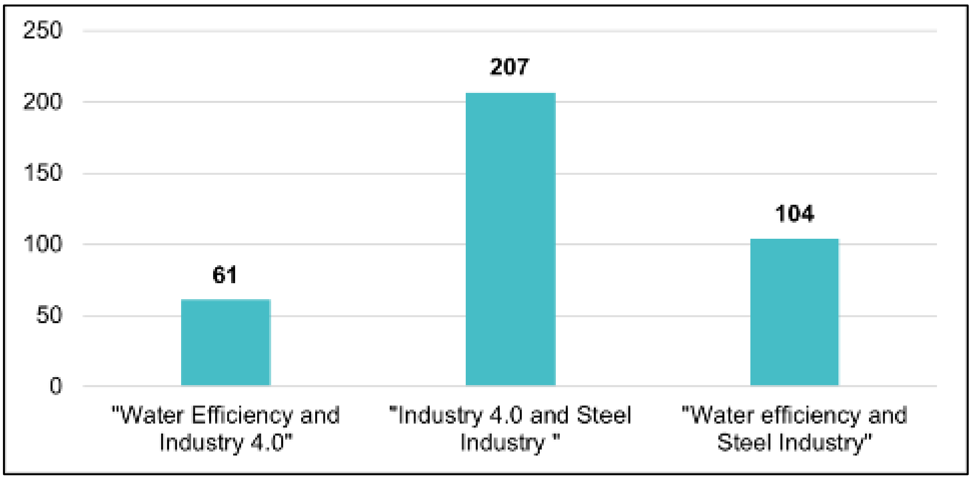

Figure 2 Number of articles retrieved based on the terms used in the search

An analysis was conducted regarding the search terms and the respective databases. As shown in Figure 3, it is possible to identify that the ScienceDirect database contributed 243 articles out of the 372 found, corresponding to approximately 65% of the total articles retrieved. Web of Science accounted for approximately 25% of the listed articles (n= 92), while the Scopus database contributed about 10% of the selected articles (n= 37).

The use of more than one database is fundamental, not only to avoid biases but also to increase the robustness and reproducibility of the results by providing a more comprehensive perspective from each data source.

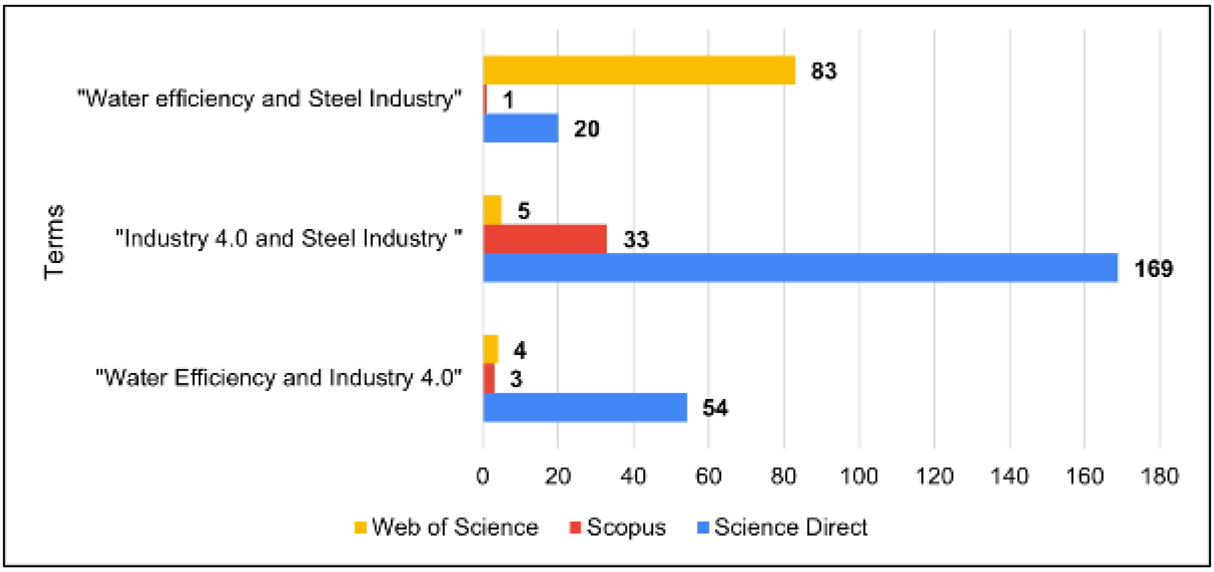

Figure 3 Number of articles found from the databases used in the search.

The initial identification phase of the literature review assessed 49 duplicate articles across the consulted databases, leaving 323 articles for analysis. Proceeding to the screening stage, an analysis of the titles, keywords, and abstracts was conducted, resulting in the exclusion of 186 articles that did not meet the aforementioned inclusion and exclusion criteria.

This left 137 articles for the second evaluation stage to be read in their entirety. Additionally, 17 articles could not be included in the analysis as they did not comply with the previously mentioned article access criterion. Consequently, 120 articles were read in full.

Of these, 70 studies were excluded due to non-compliance with the quality criteria, specifically: 22 for misalignment of objectives with the review, 22 for divergent focus, and 26 for insufficient data for information extraction. The inclusion stage comprised 50 selected articles aligned with the study's objectives, as depicted in Figure 4.

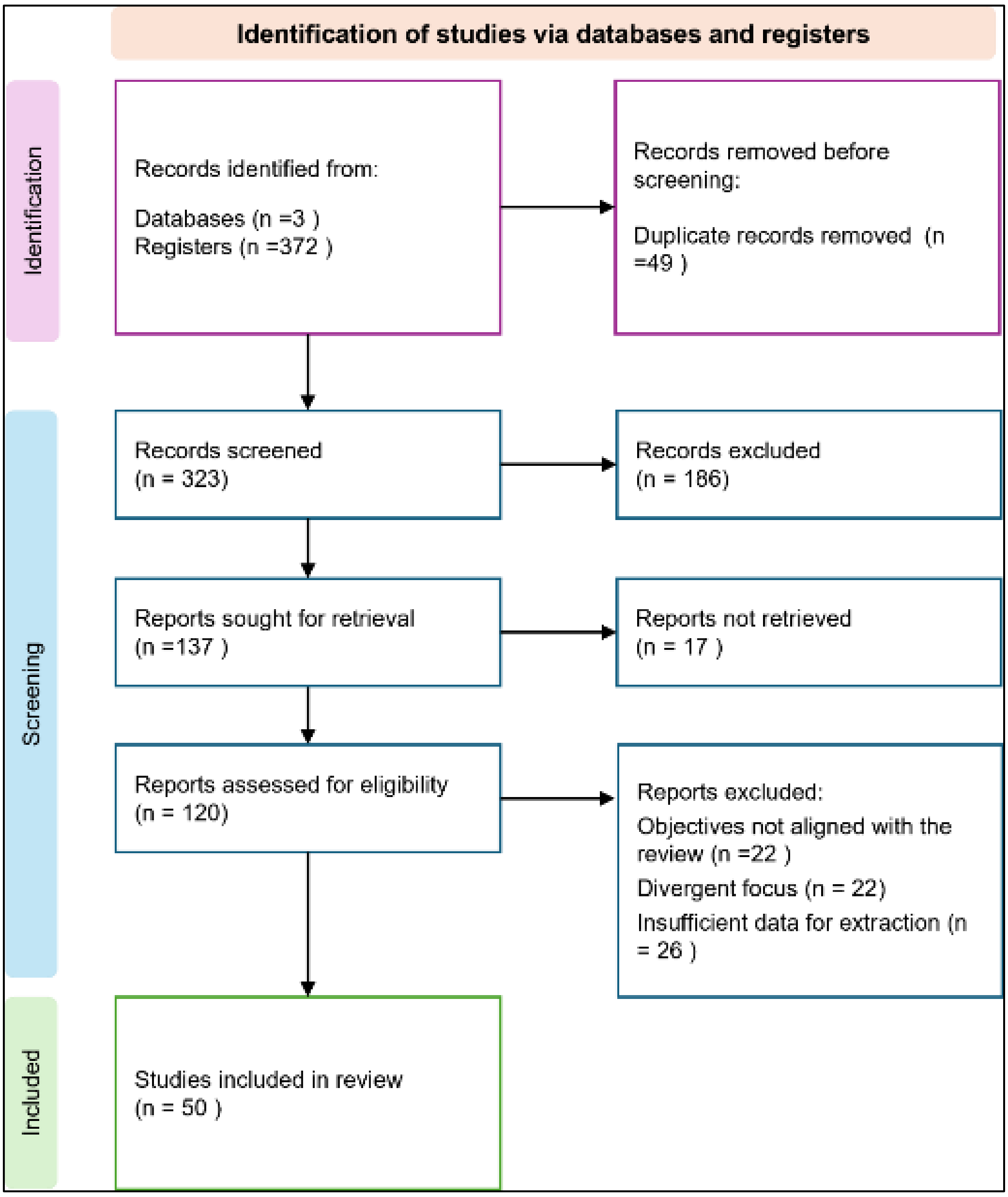

Figure 4 Flow diagram of the study identification, screening, and selection process according to PRISMA guidelines

A mapping and accounting of the continents that contributed to the article was carried out. The criterion used was fractional counting by co-author, where each article is equivalent to 1 point, divided among the authors. This ensured a statistical representation proportional to the contribution of each continent.

The European continent stood out in terms of contribution, having about 63% of the co-authors. Thus, representing the absolute leadership of the articles analyzed. Following is Asia with about 28% of the articles, followed by the American continent (3% for North America and 6% for South America). The African continent and Oceania had no representation in this study, obtaining 0%. Indicating that there are very few studies conducted in developing countries.

To organize the selected studies, the STArt tool (version 3.3 beta 3), developed by LaPES at the Federal University of São Carlos (UFSCar), was utilized. This tool was developed to assist researchers in conducting systematic literature reviews through the various stages and activities required by this methodology [35].

In this study, the tool's function was to generate the systematic review protocol, which was detailed herein through the selection criteria and potential biases, as well as to execute the filtering selections mentioned in Figure 4. Finally, it facilitated the export of the selected articles to an Excel file containing the following fields: author(s), year of publication, publisher, keywords, and abstract.

Additionally, Zotero (version 9.0.5) was used for reading PDFs, organizing articles by keywords, and generating bibliographic references according to the required citation style.

4. Methodology

Based on the selection protocol established in the Methodology, 50 scientific articles that meet the quality and thematic relevance criteria were consolidated. To understand the state of the art in this thematic intersection, a bibliometric analysis was initially conducted based on the most frequently cited keywords by the authors. Subsequently, a bibliographic analysis of the theoretical content of the articles related to the most cited keywords was performed, with the aim of presenting the findings, gaps, and achievements.

Finally, an intersection will be made based on the full reading of the 50 articles, seeking those that have a direct connection with the guiding axes of this study (Industry 4.0, steel industry, and water management), which will be presented in Table 3 and will undergo a more in-depth analysis in this study.

For the execution of the bibliometric analysis of the keywords, it was evident that 3 articles did not have keywords explicitly stated in the file; therefore, they were not included in this stage of the study. Due to this, the keywords of a total of 47 articles were analyzed.

A terminological normalization of the keywords was performed using the Zotero tool. After normalization, an RIS extension file containing the bibliographic metadata of the references used in this study was exported.

To visualize the most cited terms, a term co-occurrence map was generated using the VOSviewer tool, version 1.6.20. The construction of the map utilized the RIS file exported from Zotero and the creation of a thesaurus file [36].

The initial intention was to cite the 10 most used keywords by the authors of the selected studies; however, to ensure accuracy and avoid bias, 14 keywords were selected due to a tie in the occurrence of the terms.

Below is the content of the thesaurus, which seeks a unified categorization for synonymous terms. See Table 2.

Table 2 Terms used in database queries

Unified Term	Mapped Original Terms
Smart Manufacturing	Smart Factory, Intelligent Manufacturing, Smart Manufacturing
Industry 4.0	Industry 4.0, Industrie 4.0
Cyber-Physical Systems	Cyber Physical System, Cyber-Physical Systems, Cyber-Physical System (CPS)
Carbon Neutrality	Carbon-neutrality, Carbon Neutrality
Digital Twin	Digital Twin, Digital Twins
Digital Technologies	Digital technology, Digital Technologies, Digital Technologies (DTS)

Through the VOSviewer software, it was possible to map the relationships among the most frequent terms. The term map presents four distinct thematic clusters that fully align with the objective of this study and will be analyzed individually below. See Figure 5.

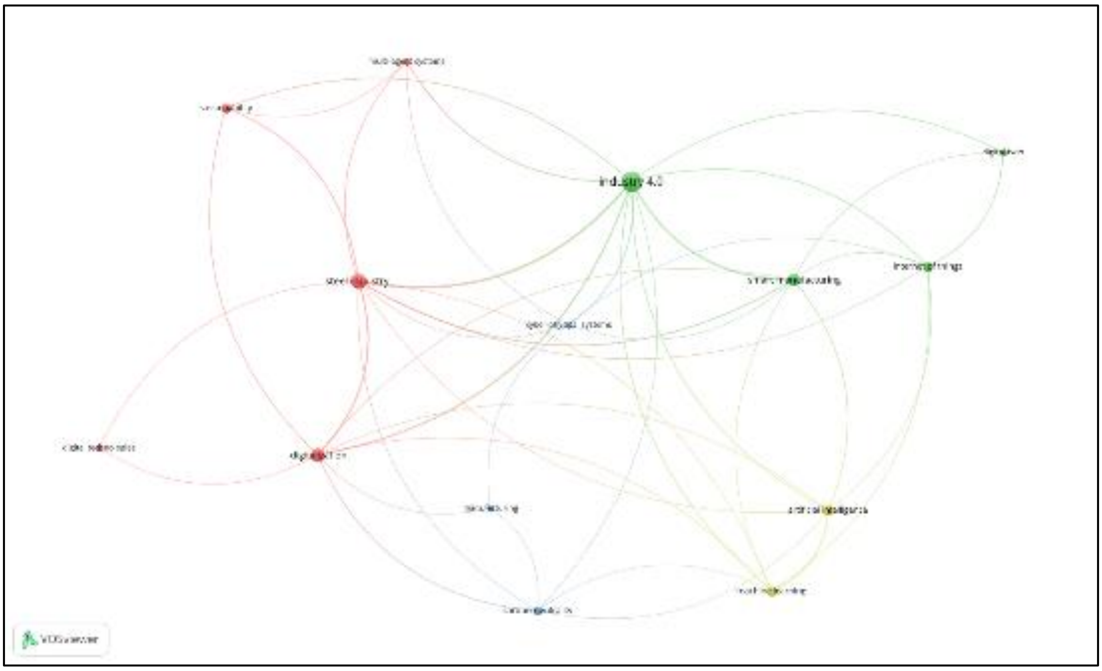

Figure 5 Keyword co-occurrence map showing the most recurrent terms in the literature

The nodal cluster is the green cluster, and the term 'Industry 4.0' has a direct association with most of the terms displayed in the map, from which the other related elements branch out. There is a strong connection with the terms 'smart manufacturing', 'internet of things', and 'digital twin'. This scenario is justified by the studied literature, which indicates that factories already possessing some form of automation [37, 28] seek to integrate enabling technologies such as digital twins and the internet of things to establish a facility that meets Industry 4.0 requirements.

The term 'steel industry' is linked to the terms 'sustainability', 'digitalization', 'digital technologies', and 'multi-agent systems', which constitute the red cluster. Within this grouping, it is possible to identify how issues of digitalization, its associated technologies, and sustainability are prominent in the steel industry, utilizing the technological enabler 'multi-agent systems' to provide solutions for these steel industry-related areas.

Subsequently, two peripheral clusters can be observed, which are nevertheless of essential importance for the realization of the other segments. The yellow cluster indicates strong trends of 'artificial intelligence' and 'machine learning' in the industry, making it a fundamental grouping for the emergence of an Industry 4.0 that achieves carbon neutrality, as represented in the green and blue clusters, respectively.

The terms 'cyber-physical systems', 'manufacturing', and 'carbon neutrality' belong to the blue cluster, evidencing that complete integration is possible through the use of cyber-physical systems in manufacturing. Its positioning is central on the map, and its connections, albeit subtle, assist the industry in its objective of achieving sustainability and maintaining a strategic position in the competitive market.

The terms presented in the map in Figure 5 have been compiled and can be viewed in Table 3, which presents the unified category of the terms, their occurrence within the scope of this study, and the related studies.

Table 3 List of the 14 Most Cited Author Keywords

Unified category of terms	Citation count	Bibliographic reference
Industry 4.0	21	[1, 5, 12, 18, 19, 37, 38, 39, 42, 46, 48, 47, 49, 50, 51, 52, 53, 58, 59, 61, 62]
Steel Industry	12	[5, 12, 21, 39, 45, 48, 50, 51, 52, 56, 61, 62]
Digitalization	10	[1, 21, 43, 47, 48, 49, 51, 56, 65, 66]
Smart Manufacturing	8	[4, 5, 19, 42, 51, 55, 58, 61]

Artificial Intelligence	6	[4, 14, 41, 48, 57, 58]
Internet of Things	5	[5, 9, 20, 41, 59]
Machine Learning	5	[14, 20, 48, 57, 58]
Sustainability	5	[50, 56, 60, 62, 65]
Carbon Neutrality	4	[11, 40, 43, 48]
Cyber-physical Systems	3	[5, 18, 54]
Digital Twin	3	[9, 42, 59]
Digital Technologies	3	[21, 44, 63]
Manufacturing	3	[13, 43, 54]
Multi-agent Systems	3	[18, 61, 62]

Based on the listed studies, it can be inferred that the steel industry is one of the primary foundational industries [4], influencing a chain of sectors that depend on steel to maintain active production [38] and the global economy [39]. Due to its importance, it is a sector directly impacted by issues such as recent climate changes [40], public policies [11], [41], the demand for a more competitive industry [42], [5], and the presence of political uncertainties [43].

These are the pressing demands that the industry must address to align its operations with the United Nations' Sustainable Development Goals (SDGs) [44], become more sustainable [11], position itself strategically [45], and achieve a competitive advantage [46]. To mitigate such challenges, the industry has been undergoing the transition from Industry 3.0 to Industry 4.0 [47], and the literature has identified several determining factors that can impact this digital transformation. Case studies of major steel companies, such as ArcelorMittal, Thyssenkrupp, and Tata Steel, have also been presented [48].

Regarding cultural and structural barriers, problems such as organizational inertia [21], data silos [49], unqualified personnel [21], [50], the absence of AI specialists [50], and the loss of tacit knowledge [51] were detected. This produces an organizational scenario exacerbated by uncertainty regarding ROI (Return on Investment) [21], [52] and the fact that environmental innovations in R&D are asymmetrically distributed in sectoral funding [21]. To overcome these structural and financial gaps, the adoption of open innovation emerges as a vital strategy for sharing risks and attracting external human capital [12].

It was identified that the implementation of technologies often occurs in a fragmented manner without strategic changes [53], resulting in poor data traceability [54]. The risk aversion fosters concerns regarding cyberattacks [21], [55], the theft of digital secrets [35], and the risks associated with connecting a factory to the cloud [56].

Various solutions are presented across the steel industry segments, particularly regarding the incorporation of new enabling technologies. For example, the use of machine learning has enabled cycle reduction and early failure prediction in metal alloy design [4], cold rolling planning and routing [45], chemical analysis using virtual sensors [57], the blocking of incorrect materials upon detecting anomalies in steel rolling [58], the use of genetic algorithms for industrial symbiosis integration aimed at reducing environmental emissions [48], and the use of non-linear modeling for real-time salinity and contaminant monitoring [14]. By combining AI with SCADA systems, direct thermal control in industrial furnaces was achieved [2].

Aligned with improved prediction, monitoring, and control [18], [2] of the plant, enabling technologies such as digital twins and the internet of things allow for the simulation of production scenarios [59] without the need to interrupt manufacturing activities. Furthermore, integrating IoT with big data enables the reduction of failures and energy consumption [9].

Another distinct procedure observed was the use of digital twins combined with augmented reality, which elevates operators to the level of 'smart operators' by providing real data available during crisis situations for rapid decision-making in the industrial environment [59]. Additionally, it is indicated that the digital twin relies heavily on internet of things networks and 5G architecture [19].

Fundamental to this process is the internet of things, as it is responsible for collecting the physical data of the plant [59], which can be utilized in areas such as reverse logistics [80], material flow costing and lean manufacturing [60]. The integration of these enabling technologies is made possible by cyber-physical systems, which connect the physical plant to the virtual environment, enabling autonomy, minimizing human intervention, and responding dynamically to environmental conditions [54], for instance, through the flexibilization and optimization of industrial furnaces [61]. With the objective of enhancing product sales, there is the possibility of new services replacing traditional business models [18]. It is noteworthy that brownfield industries present an obstacle, as legacy systems must coexist with CPS [18].

For this integration to achieve maximum efficiency in smart manufacturing, the literature highlights the transition from centralized control to decentralized architectures, enabled by Multi-Agent Systems (MAS). In this model, the plant's own machines and resources are represented by autonomous virtual agents that communicate with each other in Peer-to-Peer networks, dynamically negotiating task allocation to respond to failures without the need for constant human intervention [21] or a central server [62]. Under the governance of innovation leaders, such as the Chief Digital Officer (CDO) [63], this technological convergence is directed toward the consolidation of this entire technological apparatus, converging toward the global objective of transitioning to a green economy and achieving carbon neutrality [64].

The use of artificial intelligence combined with IoT and big data has proven capable not only of generating financial savings and energy efficiency but also of enabling the circular economy, the repurposing of harmful by-products, and the optimization of natural resources by detecting leaks and applying intelligence to effluent treatment [13], as well as minimizing raw material waste [65], thus configuring itself as an essential factor for mitigating CO_2 emissions in the steel industry [64].

Some of the promising results found in these studies indicate that the use of digital twins saved 3% of the unit energy cost [9]. With the use of IoT and lean management, it was possible to increase the production rate in the steel plant by more than 24%. Machine learning simulations of coke oven gas resulted in a 70% reduction in sulfide toxicity, in addition to saving the steam flow of the boilers [5]. Digitized monitoring for leak detection yielded a 30% saving in water [66]. These data demonstrate that digital maturity and the use of AI-based modeling simultaneously reduce harmful emissions and consumption in the industrial energy matrix [63, 56].

Table 4 Articles integrating or mentioning Steelmaking, Water Management, and Enabling Technologies for Industry 4.0

Author(s), year	**Enabling technologies**	**Article description**
Fang et al., 2025	CPS, AI	Operational guidance system using modeling and AI to optimize desulfurization and wastewater in the steel industry.
Iannino et al., 2021	Sistemas multi-agentes	Proposes and simulates a novel hybrid peer-to-peer architecture combined with a multi-agent system.
Colla et al., 2021	Big Data, ML, AI, Simulation	Vision for implementing circular economy via big data and ML for sustainability in the steel industry.
Perera et al., 2023	AI, ML, monitoring	Review of AI-based soft sensors to predict parameters in process industries.
Gajdzik & Wolniak, 2022	Industry 4.0, Digital strategies	Framework for R&D&I activities and expenditure analysis in the Polish steel industry (I4.0).
Li et al., 2024	Multi-source data integration	Method for spatial estimation of industrial water use using multi-source data.

From the systematic review comprising 50 studies, 6 stood out for containing information relevant to the core of this work (Industry 4.0, steel industry, and water management). Table 4 above presents the authors, keywords, and a description of the studies, which will be explored in depth below.

This work seeks to understand the role of industry 4.0 as a strategic enabler, through enabling technologies, to achieve effective water management, aligning productivity and sustainability in the manufacturing environment.

The development of industry 4.0 in the steel industry is intrinsic to sustainability, as the use of enabling technologies aims at the conservation of raw materials and energy, carbon management, and the promotion of the circular economy [12], and complementarily, industrial symbiosis [48].

Concepts such as green innovation and open innovation are in synergy with industry 4.0 because digitalization is utilized to achieve innovations in clean technologies and to enable interactions with external partners. Another interesting concept addressed for the viability of a sustainable steel industry is "Environment 4.0", which consists of the application of industry 4.0 technologies such as digitalization, machine learning, big data, artificial intelligence, and others, to improve the environmental footprint of production processes. In this scenario, sustainability becomes managed via data and digitalization, ultimately contributing to the achievement of the United Nations Sustainable Development Goals [48].

A strategy to reach this level is to maintain rigor in the collection of industrial data and information. This collection can occur via cyber-physical systems, which, combined with the internet of things, provide real-time data that can be analyzed by machine learning algorithms. These algorithms can, in turn, be used to update digital twins and thereby obtain predictive insights.

However, in a manufacturing environment, there are critical infrastructure limitations, as the use of physical sensors may not be suitable for hostile work environments, which are characterized by the need for constant maintenance, high costs, and measurement delays [57]. One of the proposed solutions is the use of soft sensors, which are virtual sensors consisting of AI-driven mathematical models capable of estimating complex parameters in real time using easily measurable process variables [57]. Another solution is the use of a centralized database server that collects, updates, and stores information in real time. This leaves the verification of measurements to software agents that query the database and are capable of performing asynchronous message exchanges with each other, thus eliminating the need for human oversight for verification. Consequently, this allows for a faster response in cases of failure or unexpected maintenance [62].

Regarding practical results in water management, there is the use of AI combined with the Aspen Plus simulation software, which employs modeling based on historical plant data, namely: flow variation, and the quantities of H_2S and CO_2 in coke oven gas. Obtained through CPS and IoT, this makes it possible to predictively calculate the injection of low-ammonia liquid and low-pressure steam. This approach calculates the exact fluid demand in real time, reducing H_2S emissions into the atmosphere by 75%. The result is that the plant can operate against atmospheric emissions, but the discharged water continues to rigorously meet environmental specifications for PH, ammonia (NH_3), and HCN [5].

Satellite and multi-sensor data enabled the measurement of water consumption; in the industrial sector, it was evidenced that this is one of the major factors affecting water use, highlighting the need to monitor and improve recycling rates, and to establish reuse and wastewater metrics to achieve a circular economy [10].

The chronic delay in traditional physical sampling is one of the main bottlenecks for fluid management in the steel industry. Replacing these methods with soft sensors and predictive models alters this dynamic, converting raw operational data into instantaneous demand estimates [57]. A practical example of this application is found in the work of Fang, where automation reduced the steam flow from 5.4 tons per hour to 4.0 tons per hour, optimizing the direct reuse of effluents within the production line itself. The closing of water circuits functions as a strategic defense against water scarcity, preventing unplanned downtime and financial losses in the plant [48].

5. Conclusion

This article conducted a systematic literature review to investigate the potential of industry 4.0 technologies for water optimization in the steel industry. The analysis of the literature demonstrated that technologies such as the internet of things, artificial intelligence, digital twins, cyber-physical systems, and other enabling technologies allow for real-time monitoring, failure prediction, and circular water management, significantly reducing the withdrawal of natural resources while keeping the sector more competitive and sustainable.

The incorporation of technologies is a complex and analytical process, involving constant evaluation of the cost-benefit ratio of the adopted solutions. It is noteworthy that industrial modernization does not require the massive adoption of all available tools, but rather the careful selection of those aligned with the operational reality of each plant.

In hostile environments such as the blast furnace, for example, the literature demonstrates that the replacement of high-cost physical sensors with soft sensors and the implementation of predictive thermodynamic simulation software constitute highly viable practical strategies, capable of reconciling high thermal productivity with stringent water recirculation goals.

For the success of this transition, there is a critical conditioning element, the human factor, which, in the face of numerous technological changes and innovations, faces a gap in technical skills. Consequently, workforce training and preparation become determining barriers or facilitators for the full utilization of the mapped technological potential.

The review also identified limitations in current literature. A large proportion of the studies focuses on theoretical proposals or pilot projects in specific regions (Europe and Asia), revealing a gap regarding large-scale application in developing countries, as well as concerning implementation costs versus long-term financial returns specifically for water resources.

For future research, it is recommended to conduct empirical studies that quantify the ROI of Industry 4.0 solutions focused on steel mills. Furthermore, it is recommended to explore the integration of these technologies with Industry 5.0, focusing on the human aspect and the social resilience of communities impacted by water usage. The transition to Steel 4.0 proves to be inevitable and beneficial, aligning economic competitiveness with the preservation of global water resources.

Compliance with ethical standards

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During the preparation of this work, the authors utilized the Gemini Pro tool to assist in the structuring of tables, generating insights on topics, proofreading, and translating from Portuguese to English. Following the use of this tool, the authors reviewed, edited, and assume full responsibility for the content and originality of the final text.

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Instituto Aço Brasil. (2024). Anuário Estatístico 2024. Instituto Aço Brasil, Rio de Janeiro, Brasil.

[2] Pepe C, Farella G, Bartucci G and Zanoli SM. (2025). Recent innovations in computer and automation engineering for performance improvement in the steel industry production chain: A review. Energies, 18(8).

[3] Rissman J, Bataille C, Masanet E, Aden N, Morrow WR, Zhou N, Elliott N, Dell R, Heeren N, Huckestein B, Cresko J, Miller SA, Roy J, Fennell P, Cremmins B, Koch Blank T, Hone D, Williams ED, de la Rue du Can S and et al. (2020). Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070. *Applied Energy*, 266, 114848.

[4] Geng X, Wang F, Wu HH, Wang S, Wu G, Gao J, Zhao H, Zhang C and Mao X. (2023). Data-driven and artificial intelligence accelerated steel material research and intelligent manufacturing technology. Materials Genome Engineering Advances, 1(1), e10.

[5] Fang MC, Ward JD, Lee HY, Hsieh CT, Hsieh YC, Lee CL, Lin SC, Huang TH and Chou WT. (2025). An operation guidance system for a commercial-scale coke oven gas desulfurization process. Separation and Purification Technology, 373, 133533.

[6] OECD. (2025). OECD Economic Outlook, Volume 2025 Issue 1: Preliminary version. OECD Publishing, Paris, France. [https://doi.org/10.1787/83363382-en, Last accessed on 11/19/2025])

[7] Gajdzik B, Wolniak R and Grebski W. (2023). Electricity and heat demand in steel industry technological processes in industry 4.0 conditions. Energies.

[8] CSN. (2023). Relato Integrado 2023. CSN, São Paulo, Brasil, 196.

[9] Ma S, Ding W, Liu Y, Ren S and Yang H. (2022). Digital twin and big data-driven sustainable smart manufacturing based on information management systems for energy-intensive industries. Applied Energy, 326, 119986.

[10] Li, M., Guo, B., Zhang, J., & Zhang, Z. (2024). High-resolution estimation of industrial water use in Beijing-Tianjin-Hebei based on multi-source data. Ecological Indicators, 158, 111479. https://doi.org/10.1016/j.ecolind.2023.111479

[11] Sharma M, Vadalkar S, Antony R, Chavan G and Tsagarakis KP. (2024). Can Industry 4.0-enabled smart manufacturing help firms in emerging economies move toward carbon-neutrality? Computers & Industrial Engineering, 192, 110238.

[12] Gajdzik B and Wolniak R. (2022). Framework for R&D&I activities in the steel industry in popularizing the idea of industry 4.0. Journal of Open Innovation: Technology, Market, and Complexity, 8(3), 133.

[13] Fu W, Bakar AA and Tan YS. (2025). Towards Sustainable Water Management in Manufacturing - A Review of Various Facets of Water Efficiency and Effectiveness. Procedia CIRP, 135, 319–325.

[14] Maqsood Q, Fatima R, Rafaqat F, Mehmood T, Ali SW and Hussain M. (2025). Revolutionizing water and wastewater treatment: Data-driven approaches for advanced solutions. Desalination and Water Treatment, 324, 101432.

[15] Fernandes J, Reis LP and Silva SE. (2023). Digital supply chain: Roadmap development and application based on Industry 4.0 principles. IFAC-PapersOnLine.

[16] Gajdzik B. (2019). Steel industry 4.0 in the perspective of forecasted quantities of steel production in the world. Zeszyty Naukowe. Organizacja e Zarządzanie / Politechnika Śląska, 134.

[17] Alhammadi A, Alsyouf I, Semeraro C and Obaideen K. (2024). The role of industry 4.0 in advancing sustainability development: A focus review in the United Arab Emirates. Cleaner Engineering and Technology, 18, 100708.

[18] Iannino V, Denker J and Colla V. (2022). An application-oriented cyber-physical production optimisation system architecture for the steel industry. IFAC-PapersOnLine.

[19] Chen J and Zhou J. (2018). Revisiting industry 4.0 with a case study. In: Proceedings of the IEEE I.

[20] Chahed H, Usman M, Chatterjee A, Bayram F, Chaudhary R, Brunstrom A, Taheri J, Ahmed BS and Kassler A. (2023). AIDA—A holistic AI-driven networking and processing framework for industrial IoT applications. Internet of Things, 22, 100805.

[21] Branca TA, Fornai B, Colla V, Murri MM, Streppa E and Schroeder AJ. (2020). The challenge of digitalization in the steel sector. Metals, 10(2), 288.

[22] Ponsard C, De landtsheer R and Palm B. (2018). Accurate reasoning using imperfect digital twins: A steel industry case study. ERCIM News, 115, 9–10.

[23] Araújo JA. (2011). O conceito de água virtual aplicado à fabricação de laminados de aço. In: Anais do 19º Simpósio Brasileiro de Recursos Hídricos.

[24] Colla V, Matino I, Branca TA, Fornai B, Romaniello L and Rosito F. (2017). Efficient Use of Water Resources in the Steel Industry. Water, 9(11), 874.

[25] Oliveira MC, Iten M, Matos HA and Michels J. (2019). Water-energy nexus in typical industrial water circuits. Water, 11(4), 699.

[26] Karkou E, Angelis-Dimakis A, Parlapiano M, Savvakis N, Siddique O, Vyrkou A, Sgroi M, Fatone F and Arampatzis G. (2024). Process innovations and circular strategies for closing the water loop in a process industry. Journal of Environmental Management, 370, 122748.

[27] Alexandra C, Daniell KA, Guillaume J, Saraswat C and Feldman HR. (2023). Cyber-physical systems in water management and governance. Current Opinion in Environmental Sustainability, 62, 101290.

[28] Šverko M, Grbac TG and Mikuc M. (2022). SCADA systems with focus on continuous manufacturing and steel industry: A survey on architectures, standards, challenges and industry 5.0. IEEE Access, 10, 109395–109430.

[29] Brentan BM, Menapace A, Oberascher M, Herrera M and Sitzenfrei R. (2025). Enhancing explainable AI with graph signal processing: Applications in water distribution systems. Water Research, 285, 124022.

[30] Silva Netto EPD. (2023). Redução e reutilização de água na siderurgia. Technology Sciences, 5(1), 1-7.

[31] Sambodo MT, Silalahi M and Firdaus N. (2024). Investigating technology development in the energy sector and its implications for Indonesia. Heliyon, 10(6).

[32] Sutoova A and Koca F. (2022). Corporate social responsibility standards: Is it possible to meet diverse customer requirements? Management Systems in Production Engineering, 30(1), 54–61.

[33] Varbanov PS, Jia X and Lim JS. (2021). Process assessment, integration and optimisation: The path towards cleaner production. Journal of Cleaner Production, 281, 124602.

[34] Page MJ, Moher D, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW, Mayo-Wilson E, McDonald S and McKenzie JE. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. BMJ, 372, n160.

[35] Fabbri S, Silva C, Hernandes E, Octaviano F, Martimiano L and Beluca A. (2016). Improvements in the StArt tool to better support the systematic review process. In: Proceedings of the 20th International Conference on Evaluation and Assessment in Software Engineering (EASE '16). ACM, New York, 1-6.

[36] van Eck NJ and Waltman L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, 84, 523–538.

[37] Martins MS, de Paula GM and Botelho MRDA. (2021). Technological innovations and industry 4.0 in the steel industry: Diffusion, market structure and intra-sectoral heterogeneity. Revista Brasileira de Inovação, 20.

[38] Gajdzik B, Wolniak R and Grebski W. (2024). Changes in the steel chain in Industry 4.0. Some results of survey on the Polish steel market. Production Engineering Archives.

[39] Iannino V, Mocci C and Colla V. (2021). A hybrid peer-to-peer architecture for agent-based steel manufacturing processes. IFAC PapersOnLine, 54(1), 528-533.

[40] Jiao YJ, Jiang KJ, Chen S, Xiang PP and He CM. (2024). Water use in the industrial sector based on the IPAC model under the carbon-neutral transformation path in China. Advances in Climate Change Research, 15(6), 1130-1146.

[41] Baskaran D and Byun HS. (2025). Future-proofing CO2 mitigation towards a circular economy: A systematic review on process integration and advanced tools. Environmental Science and Ecotechnology, 26, 100587.

[42] Cimino A, Longo F, Mirabelli G, Solina V and Verteramo S. (2024). An ontology-based, general-purpose and Industry 4.0-ready architecture for supporting the smart operator (Part II – Virtual Reality case). Journal of Manufacturing Systems, 73, 52-64.

[43] Mallik AK. (2023). The future of the technology-based manufacturing in the European Union. Results in Engineering, 19, 101356.

[44] Hariyani D, Hariyani P and Mishra S. (2025). Digital technologies for the Sustainable Development Goals. Green Technologies and Sustainability, 3(3).

[45] O'Connor L. (2026). A comparative review of material supply chains and sustainability pathways in steel and battery technologies. The Extractive Industries and Society, 25, 101814.

[46] Saniuk A and Saniuk S. (2018). Current state and future perspectives of steel production. In: Proceedings of the 27th International Conference on Metallurgy and Materials. Tanger Ltd, Ostrava, Czech Republic, 1808–1813.

[47] Gajdzik B and Wolniak R. (2021a). Transitioning of steel producers to the steelworks 4.0 – literature review with case studies. Energies.

[48] Colla V, Pietrosanti C, Malfa E and Peters K. (2021). Environment 4.0: How digitalization and machine learning can improve the environmental footprint of the steel production processes. Matériaux & Techniques, 108(5-6), 507.

[49] Gajdzik B and Wolniak R. (2021b). Digitalisation and innovation in the steel industry in Poland-selected tools of ICT in an analysis of statistical data and a case study. Energies.

[50] Pourmehdi M, Paydar MM, Ghadimi P and Azadnia AH. (2022). Analysis and evaluation of challenges in the integration of Industry 4.0 and sustainable steel reverse logistics network. Computers and Industrial Engineering, 163.

[51] Chirumalla K. (2021). Building digitally-enabled process innovation in the process industries: A dynamic capabilities approach. Technovation.

[52] De Paula GM, Martins MS and Botelho MRA. (2024). New insights into the diffusion of I4.0 in the Brazilian Steel Industry: speed of adoption, effects on innovation systems, and financial results. Revista Brasileira de Inovação.

[53] Gajdzik B. (2022). Key directions in changes from steelworks 3.0 to steelworks 4.0 with analysis of selected technologies of digitalizing the steel industry in Poland. Management Systems in Production Engineering.

[54] Cui X. (2021). Cyber-Physical System (CPS) architecture for real-time water sustainability management in manufacturing industry. Procedia CIRP, 99, 543–548.

[55] Milisavljevic-Syed J, Thames JL and Schaefer D. (2020). The digitization of design and manufacturing: A state-of-the-art report on the transition from strategic vision to implementation in industry. Procedia CIRP, 93, 575–580.

[56] Kumar R, Kumar D, Ramtiyal B, Vijayvargy L and Bisht S. (2024). Assessing feasibility of design constraints for mills in planning and scheduling of cold rolling: A case of steel industry. International Journal of System Assurance Engineering and Management, 15(4), 1519-1535.

[57] Perera YS, Ratnaweera DAAC, Dasanayaka CH and Abeykoon C. (2023). The role of artificial intelligence-driven soft sensors in advanced sustainable process industries: A critical review. Engineering Applications of Artificial Intelligence, 121, 105988.

[58] Redchuk A and Walas Mateo F. (2022). New business models on artificial intelligence—The case of the optimization of a blast furnace in the steel industry by a machine learning solution. Applied System Innovation, 5(1).

[59] Attaran S, Attaran M and Celik BG. (2024). Digital twins and industrial internet of things: Uncovering operational intelligence in industry 4.0. Decision Analytics Journal, 10, 100398.

[60] Sodkomkham T, Ratanatamskul C and Chandrachai A. (2024). A novel integrated material flow cost accounting (MFCA)- IoT-lean management system approach to improving water use efficiency and reducing costs in the beverage industry. Cleaner Environmental Systems, 15, 100232.

[61] Iannino V, Colla V, Denker J and Goettsche M. (2019). A CPS-based simulation platform for long production factories. Metals, 9(10), 1025.

[62] Iannino V, Mocci C and Colla V. (2021). A hybrid peer-to-peer architecture for agent-based steel manufacturing processes. IFAC-PapersOnLine.

[63] Ma X, Wen Z, Li W and Taghizadeh-Hesary F. (2025). Enhancing energy conservation and carbon emission reduction synergies through digital technology: Firm-level evidence from China. Energy Reports, 13, 3686–3699.

[64] Branca TA, Fornai B, Colla V, Murri MM, Streppa E and Schroeder AJ. (2021). Current and future aspects of the digital transformation in the European Steel Industry. Matériaux & Techniques, 108(5-6), 508.

[65] Nyamekye P, Lakshmanan R, Tepponen V and Westman S. (2024). Sustainability aspects of additive manufacturing: Leveraging resource efficiency via product design optimization and laser powder bed fusion. Heliyon, 10(1).

[66] Puschnigg S, Patauner D, Böhm H, Doujak E and Müller C. (2025). Digitalization and hydropower integration in water supply systems: Unlocking energy potential, efficiency, and resilience. Cleaner Engineering and Technology, 29, 101098.