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Review

Robotics and Automation for Energy Efficiency and Sustainability in the Industry 4.0 Era: A Review

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Abstract

Robotisation is playing an increasingly important role in economic and technological life today. Industrial robotisation has a significant impact on the efficiency and productivity of manufacturing companies, and service robots are becoming more and more common in everyday life. The main objective of our research is to examine the impact of robotisation on energy consumption and sustainability, as well as the technological and corporate challenges facing the integration of robots. The research is based on a literature review, which we supplemented with a bibliographic analysis. In terms of methods, we relied on the Global Citation Score, Co-Coupling Network Analysis, and Burst Analysis. Our results suggest that research on industrial robotisation can be divided into complementary dimensions, ranging from engineering-level trajectory optimization and subsystem design to system-level modeling, macroeconomic sustainability analysis, and data-driven optimization. The findings highlight that the positive impacts of robotisation on both energy efficiency and carbon reduction can be maximized when these approaches are integrated into a systemic framework that connects micro- and macro-level perspectives.

Keywords: industrial robotisation; energy efficiency; sustainability; systematic literature review; Industry 4.0

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1. Introduction

Today, industrial robotisation has become one of the world's most important technological trends and a key driver in the transformation of the global economy [1]. The explosion of industrial robots in production units has significantly increased manufacturing efficiency, reduced production costs, and improved product quality [2]. However, these major changes have had a significant impact not only on the micro-economy, but also at the macro-economic level. The widespread use of robotisation not only brings direct productive benefits, but also profound economic changes to existing economic structures, labour markets, and socio-economic balances [3].

Alongside the Internet of Things (IoT), digital transformation, cyber-physical systems, and artificial intelligence, industrial robotisation is also one of the pillars of Industry 4.0 [4,5]. The basic principles of Industry 4.0 include the development of flexible production, digitalisation of manufacturing, and automation, of which industrial robots are an essential component [6,7]. Industry 5.0, on the other hand, puts people at the centre, attempting to combine automation with human work in a collaborative way [8]. Sustainability is an important element of this human–machine collaboration [9,10]. Thus, the manufacturing environment created through the Industry 5.0 paradigm is not only highly efficient but also sustainable and ethical [11].

Overall, the results indicate that the macroeconomic impact of industrial robotisation depends to a large extent on the country's or group of countries' basic economic structure and level of development, as well as their technological absorptive capacity [12–14]. For these reasons, it is of central importance that countries adopt economic policies that help to harness the potential of technological developments in a way that also ensures social and economic sustainability [15,16].

The study aimed to address two research questions.

RQ1. How do different dimensions of industrial robot research (engineering design, system-level modeling, macroeconomic analysis, and data-driven optimization) complement each other in shaping a comprehensive understanding of energy efficiency and sustainability?

RQ2. How can data-driven optimization approaches (e.g., machine learning, digital twins, genetic algorithms) be integrated with engineering-level design and macro-level sustainability assessments to create integrated models of energy-efficient robotisation?

For a deeper analysis of the effects of industrial robotics, a comprehensive Systematic Literature Review is essential to map and synthesize the state of the art in knowledge in a methodologically transparent and reproducible manner. This study also highlights the role of industrial robots in improving energy efficiency, reducing manufacturing energy intensity, and supporting the transition to low-carbon and sustainable production systems. Furthermore, as part of this research, we examine the macroeconomic impacts of industrial robotisation in detail, with a particular focus on economic growth, productivity, employment, innovation, and competitiveness. Drawing on the literature explored so far, we have attempted to identify the economic factors that most influence the economic success of industrial robot adoption in countries with different levels of economic development.

The first part of the article provides an introduction to the research topic and formulates research questions, the second major chapter presents the basic data and methods used in the research, the third part analyzes the results, and the last part summarizes and interprets the data obtained.

2. Materials and Methods

To identify scientific trends and research directions, we have used a methodology with two main parts. The first part is a Systematic Literature Review (SLR), during which we defined the research questions. This was followed by a query to create a database of key articles on the research topic. The methodological framework of the systematic literature review and bibliometric analysis applied in this study is illustrated in Figure 1. The queries used were the following:

TITLE-ABS-KEY("industrial robot *" OR "robotization" OR "robotisation")

AND

TITLE-ABS-KEY("energy efficiency" OR "energy saving" OR "energy consumption")

We used research from 2018 to 2025 that included the words defined in the query in the title, abstract, or keywords. Furthermore, only articles and reviews were considered, and these were limited to English-language publications. The keyword industrial robot and its variants and energy efficiency and its variants were used to create the query. As the subject area was already narrowed down, no other keywords were needed.

Scopus database was used for the research because, in addition to its broad, multidisciplinary coverage and high-quality, peer-reviewed journals, it has advanced search and bibliometric tools [17,18]. After performing the screening, we obtained 777 studies, of which 403 were articles, 358 were conference papers, and 16 were reviews.

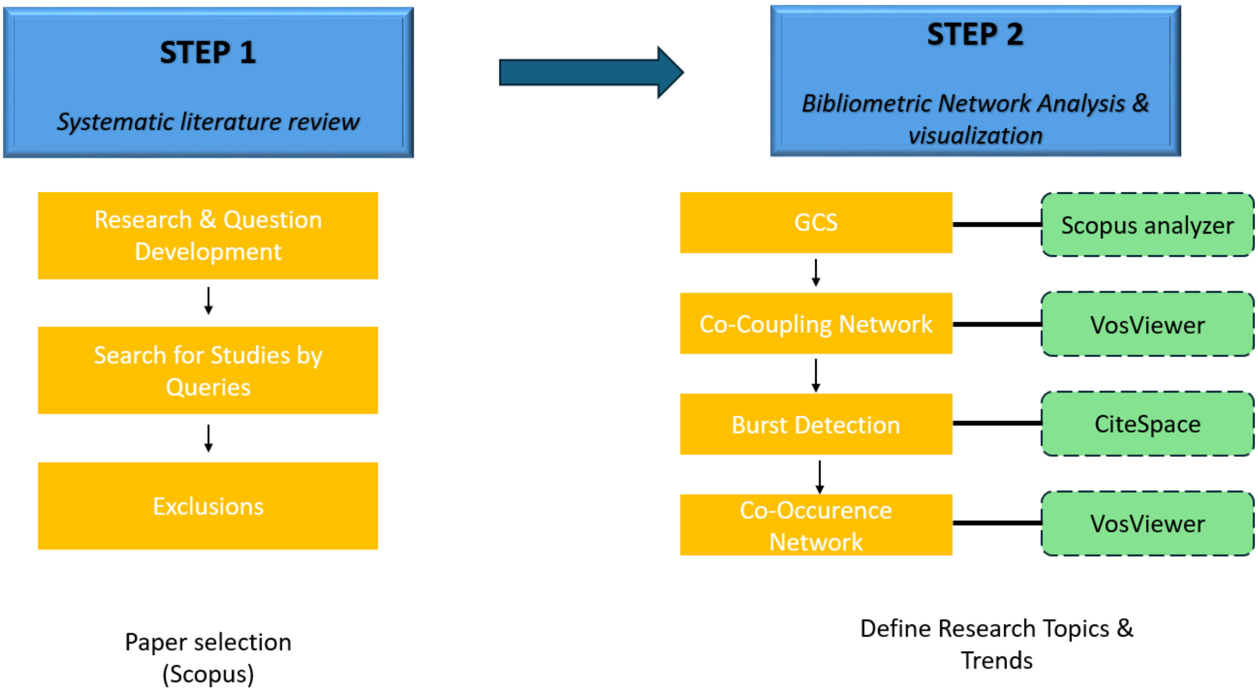

Figure 1. Methodological framework of the systematic literature review and bibliometric analysis.

After creating the database, the next major step is the bibliometric network analysis and visualisation [19]. Here, we first determined the Global Citation Score (GCS) [20], which ranks the most influential research on the topic based on the number of citations. The next step was the application of the Co-Coupling Network (CCN). This method enabled us to categorize the most influential articles into clusters based on the citations between publications, utilizing the GCS ranking. Then, using the Burst Detection method, we identified the keywords of high interest among researchers within specific time intervals, i.e., numerous articles were generated that dealt with the keyword in question. The Burst Detection method was performed with the CiteSpace (version 6.3.R1 (64-bit) Basic) app, which helps to identify these time-varying trends. The Co-Occurrence Network (CONK) technique was used to map co-occurrence patterns of keywords. The CCN and CONK maps were visualized using VosViewer; with this app, we were able to visualize the relationships between keywords and authors and identify correlations between different research areas.

The results have allowed us to draw conclusions about future research directions and identify potential research opportunities. The diagrams and network visualisations created using the methods provide an excellent tool for gaining a deeper understanding of key parts of the literature. The research carried out will not only provide a theoretical overview but will also be complemented by quantitative bibliometric analyses.

3. Results-Bibliometric Network Analysis & Visualisation

3.1. Global Citation Score

The Global Citation Score (GCS) method considers all citations in the database created using Scopus. The GCS is calculated by first aggregating the citations of all publications and then dividing this value by the number of years since the research was published, thereby reducing any bias. This approach allows us to examine trends over time that reveal the long-term relevance of a particular publication in a given field. Using the GCS indicator, publications can be compared based on data such as authors, institutions, or even keywords, thus supporting the evaluation of research performance. The GCS can be used to examine the relationship between articles based on citations, which can be used to map the network of scientific research on a particular topic. It can also identify a list of articles that are leading within a given discipline. The top 10 articles in our topic according to the GCS are listed in Table 1. As all the articles examined are drawn from a reliable database, the structured and controlled approach ensures the necessary credibility and comparability.

Table 1. Top 10 most cited articles based on Global Citation Score (GCS) related to industrial robotics and automation for energy efficiency and sustainability (2018–2025).

Publications	Year	Citations	GCS
Technology-driven carbon reduction: Analyzing the impact of digital technology on China's carbon emission and its mechanism [21]	2024	110	55
How does artificial intelligence affect pollutant emissions by improving energy efficiency and developing green technology [22]	2024	82	41
Carbon emission reduction effects of industrial robot applications: Heterogeneity characteristics and influencing mechanisms [23]	2022	161	40
Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China [24]	2023	100	33
Current technological innovation and development direction of the 14th Five-Year Plan period in China coal industry [25]	2021	159	32
Towards low-carbon development: The role of industrial robots in decarbonization in Chinese cities [26]	2023	91	30
Optimization of energy consumption in industrial robots, a review [27]	2023	82	27
Industrial robots and air environment: A moderated mediation model of population density and energy consumption [28]	2022	109	27
Is artificial intelligence a curse or a blessing for enterprise energy intensity? Evidence from China [29]	2024	54	27
Resource Allocation and Service Provisioning in Multi-Agent Cloud Robotics: A Comprehensive Survey [30]	2021	130	26

The study with the highest GCS [21] analyzes the role of digital technologies in emissions in China from 2006 to 2021. The results show that the use of modern technologies, particularly the widespread adoption of industrial robots, significantly contributes to improving the energy efficiency of emissions. According to the researchers, the effect is strongest in urban agglomerations, especially when the government supports carbon regulation in addition to the construction of digital infrastructure.

The following research [22] examines the impact of industrial robots on emissions in 30 Chinese provinces using panel data analysis. The time series examined is based on the analysis of panel data from 2010 to 2019. According to the article, the use of industrial robots greatly contributes to reducing pollution intensity through the development of energy efficiency and green technologies, while not reducing industrial production. The results of the first two studies largely support each other from the perspective of China, which is the world's largest emitter of pollutants today. The two studies show that it is possible to maintain economic development and reduce emissions of pollutants. The first two publications are well complemented by the third strongest GCS study [23], whose research topic is very similar. However, not only was China examined here, but data from 35 countries between 1993 and 2017. The results here are also very similar to the results of the previous two articles, with the only difference being that they were able to show that the harmful emissions effect of industrial robots is more pronounced in economically more developed countries, and within them, this positive effect can be demonstrated in certain industrial sectors. Such industrial segments are applications related to agriculture or the electrical industry, while in other areas, this correlation cannot be demonstrated clearly. Another strength of the research is that it not only examines the effects but also examines the heterogeneity and mediation mechanisms (e.g., absorption capacities) in depth, thereby providing a more detailed picture of the real significance of industrial robots in climate protection.

The work of Wang et al. [24] also examines China with the difference that it examines data from 256 cities. The results converge with the conclusions of the previous articles, but point to the phenomenon of energy rebound (rebound effect), which partially shades the positive results. The research highlights that the reduction in harmful emissions is strongest in the western region; however, the large-scale use of industrial robots simultaneously significantly increases energy consumption. In contrast to the previous ones, this article focuses on the mechanisms (energy efficiency, rebound effect, etc.), complementing the results of the previously analyzed articles. The following article also examines China from the perspective of the coal industry, with a particular focus on green and smart mining, whose main objective is to develop low-carbon coal mining [25].

The sixth article [26], which has the strongest GCS, also analyzes data from Chinese cities, similar to the previous research, confirming that the use of industrial robots contributes to carbon dioxide emissions, as well as through improvements in energy efficiency. Based on the results, these positive effects are most significant in developed industrial centers, where there is also strong political support for climate goals. In line with the first two analyzed articles, the role of energy efficiency and innovation is also emphasized here, and decarbonization opportunities are confirmed; however, potential mitigating factors are not taken into account.

While previous articles have mainly used macroeconomic and regional data to investigate the impact of industrial robotization on emissions, the research by Soori et al. [27] focuses on optimizing the energy consumption of industrial robots. They consider various engineering solutions (e.g., the use of energy-efficient motors, reducing the weight of robot arms, intelligent programming, etc.), which can be used to reduce the energy consumption of robots, thereby providing a solution to the rebound effect that emerged in the research of Wang et al. [24]. The article also highlights that in addition to reducing the environmental load, the lifespan of robots is also increased, and the sustainability of production processes is improved.

The following study also analyzes panel data for 74 countries between 1993 and 2019 [28]. Here, too, it is confirmed at a global level that the use of industrial robots has a positive impact on carbon dioxide emissions and energy efficiency. This article is a particularly important support for the results of Li et al., which also examined data from several countries with similar conclusions. Zhang et al. [29] also focus on China, but unlike previous studies, they examine companies in detail and find that the combined use of industrial robots and artificial intelligence reduces the energy intensity of companies by 2.5% for every 100 robots employed. The results show that the positive emission effect is stronger in non-labor-intensive companies with high energy intensity. Afrin et al. [30] provide an overview of the field of cloud robotics, focusing on the challenges of resource allocation and service provision, and presenting areas of application, existing technological solutions, and future research directions.

Research suggests that industrial robotization reduces emissions at both the micro and macro levels, contributing to improved energy efficiency. A significant portion of the research is China-centric; however, several global studies have also been conducted. However, factors that nuance these positive effects have also emerged, highlighting regional differences and the role of the regulatory environment, which are extremely important in relation to emission potential.

3.2. Result of Co-Coupling Network Analysis

The Co-Coupling Network (CCN) Analysis is a scientific bibliometric method for analyzing different citation systems. The analysis was carried out using the VOSviewer (version 1.6.18) program. With this program, we were able to create a linkage network that shows how different research papers refer to each other, thus creating clusters [31]. Visualisation uses nodes and links to represent relationships. The nodes contain authors and publications, while the links present the connections between research papers. The different colours indicate clusters, and the thickness of the links suggests the strength of the connections. Using this visualisation technique, the most relevant authors and articles in the field of robotics and automation from the last four years can be identified. Furthermore, the structure of Figure 2 can help to determine the most relevant research directions and trends, indicated by the size of the nodes.

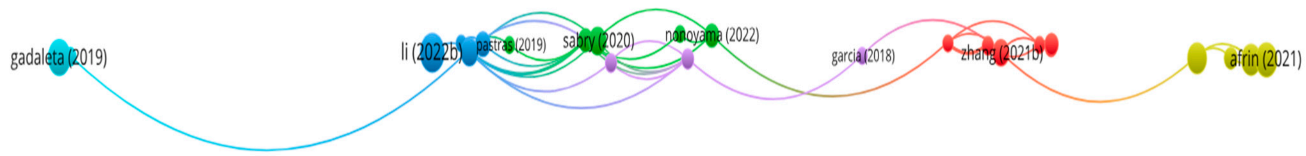

Figure 2. Bibliometric Co-Coupling Network (CCN) Analysis.

The most influential research papers identified through the Co-Coupling Network (CCN) analysis are summarized in Table 2, grouped into clusters based on thematic similarities.

Table 2. TOP 4 cited research based on CCN analysis.

Clusters	Authors	References	Citations	Publish Year
1	Zhang, Yan	[32]	76	2021
	Liu, Iacoponi, Laschi, Wen, Calistio	[33]	49	2020
	Wang, Yan, Gu	[34]	42	2019
	Carabin, Scalera	[35]	33	2020
2	Sabry, Nordin, Sabry, Kadir	[36]	83	2020
	Nonoyama, Liu, Fujiwara, Alam, Nishi	[37]	62	2022
	Liu, Liu, Yao, Xu, Yang	[38]	60	2018
	Pastra, Fysikopoulos, Chryssolouris	[39]	35	2019
3	Li, Zhang, Pan, Han; Veglianti	[23]	161	2022
	Soori, Arezoo, Dastres	[27]	82	2023
	Jiang, Wang, Li, Wang, Yang, Zheng	[40]	66	2023
	Li, Lan, Jiang, Cao, Zhou	[41]	35	2022
4	Afrin, Jin, Rahman, Rahman, Wan, Hossain	[30]	130	2021
	Afrin, Jin, Rahman, Tian, Kulkarni	[42]	105	2019
	Wang, Wang, Liu, Wu	[24]	100	2023
	Yao, Zhou, Wang, Xu, Yan, Liu	[43]	49	2018
5	Yin, Ji, Wang	[44]	46	2019
	Stan, Florin, Pupăză, Jiga	[45]	36	2023
	Bukata, Šůcha, Hanzalek	[46]	34	2019
	Garcia, Bittencourt, Villani	[47]	33	2018

All articles in Cluster 1 examine the optimization of robot movements and manipulations in various industrial environments. The research focuses on energy efficiency, optimal path planning, and the application of intelligent programming methods. In their research [32], Zhang and Yan present a data-driven method for reducing the energy consumption of industrial robots. To achieve their goal, they used artificial neural networks and genetic algorithms to determine the optimal operating parameters. The study used an Epson C4 robot to demonstrate the accuracy and practical applicability of the model. The inclusion of machine learning in the article complements the other studies in the volume well. The following article presents path planning for spot welding robots using intelligent algorithms with to the aim of improving energy consumption and responding more flexibly to manufacturing requirements [34]. Carabin and Scalera also examine the path planning of industrial robots in their work [35], developing a mathematical method that allows them to determine the motion profile that requires the least amount of energy. They support their theoretical results with experimental data and emphasize that significant energy savings can be achieved with proper path planning without any hardware changes. The fourth article in the cluster presents an underwater robot that uses a legged motion platform and a soft manipulator. Although its area of application is different from the previous ones, it is linked to the other research in the cluster through adaptive motion strategies, path planning, and energy efficiency [33].

Cluster 2 research focuses on the energy efficiency of industrial robots, but with different emphases: fault detection [36], theoretical framework development [37], algorithmic optimization [38], and energy consumption modeling [39]. The elements of the cluster provide insight into how the operation of robots can be understood, modeled, and optimized in a way that simultaneously meets sustainability and industrial goals.

While the articles in Cluster 1 focused primarily on motion strategy methods, Cluster 2 studied system-level energy efficiency, and the studies in Cluster 3 applied a sustainability and predictive approach, with an emphasis on global sustainability frameworks and the introduction of intelligent methods. The first and second articles of the cluster [23,27] have already been reviewed by GCS, where researchers primarily discussed the environmental impacts of robot use. Jiang et al. [40] use a deep learning-based (LSTM) neural network in their publication. LSMTa is able to predict the energy consumption of robots based on their movement parameters, and then optimize their trajectory using an adaptive genetic algorithm. The extraordinary benefits of using artificial intelligence are demonstrated by the fact that the research succeeded in reducing the energy consumption of robots by 22%. The fourth article in the cluster [41] also presents a more efficient energy optimization method, but unlike the previous article, it improves the efficiency of classical optimization algorithms. The fourth article in the cluster [41] also presents ways to make energy optimization more efficient, but unlike the previous article, it improves the efficiency of classical optimization algorithms. Together, these two studies suggest that combining predictive models and efficient computational frameworks may be the best solution for increasing the energy efficiency of robots. In their study, Yao et al. [43] present a cyber-physical production system (CPPS) framework based on function blocks that enables human–robot collaboration and real-time monitoring of energy consumption in a modular, flexible, and energy-efficient industrial assembly environment.

The publications in Cluster 4 represent a system-level approach and a network perspective. In these studies, robots are not examined individually, as in the articles in the first and third clusters, but operate in cloud-based, edge computing, and cyber-physical environments. Similar to the previous ones, the goal is to increase energy efficiency and sustainability, but here it is complemented by robot-human interaction, i.e., the authors examine industrial robots as part of integrated and flexible manufacturing ecosystems. In their article, Afrin et al. [42] examine the resource allocation of industrial robots in an edge cloud environment, where energy consumption and costs must be taken into account in addition to minimizing execution time. The authors present an advanced NSGA-II algorithm that outperforms its competitors by up to 18%. Among the results, they highlight the potential applications in smart factories, particularly solutions related to emergency management tasks.

The common theme of the articles in Cluster 5 is data-driven and modeling-based energy optimization. Compared to the previous ones, this is the most integrated and complex part. The articles cover the entire cycle of prediction-optimization-monitoring-validation using a model- and data-driven approach. The first article in the cluster [44] uses machine learning methods to predict energy consumption in industrial robots. The models are capable of accurately reproducing the energy requirements of robots during operation, which provides a solid basis for subsequent optimization. The cluster's next study [45] presents the development of a digital twin-based, energy-efficient robotic deburring work cell that combines real-time monitoring, web-based control, and optimized robot programming in line with Industry 4.0 principles to achieve smart manufacturing. Bukata et al. [46] introduce a new, parallelized Bransh & Bound algorithm to reduce the energy consumption of robot cells, i.e., robots are no longer examined individually, but in cells. The method achieves energy savings of up to 20% by optimizing the speed, positions, energy-saving modes, and sequence of operations of the robots without reducing productivity. The experimental results confirm the effectiveness of the method in an industrial environment. The final study examines the energy consumption of industrial robots in the automotive industry, identifying the most important influencing factors and best practices for increasing energy efficiency based on three experiments [47].

The relationships between the clusters are illustrated in Table 3, where Cluster 5 is considered the most integrated, and deviations from it were analyzed.

Table 3. Clusters based on Co-Coupling Network (CCN).

Cluster	Main Focus	Typical Methods	Common Point	Difference from Cluster 5
1. Path Planning	Energy optimization of robot motions and trajectories	Intelligent algorithms, analytical path planning, data-driven models, special applications (e.g., underwater robots)	Energy-efficient motion	Cluster 5 examines not only path planning but also full systems and prediction
2. Modeling & Diagnostics	System-level energy efficiency and fault handling	Fault detection, theoretical frameworks, energy consumption models, configuration optimization	Accurate modeling of energy consumption	Cluster 5 extends these with machine learning and digital twin approaches
3. Sustainability & Prediction	Carbon footprint reduction, AI-based energy consumption prediction	LSTM, genetic algorithms, dynamic time scaling	Sustainability + AI	Cluster 5 complements prediction with real-time monitoring and industrial validation
4. Integrated Systems	Cloud/edge, cyber-physical systems, human–robot collaboration	Resource allocation, edge computing, function blocks	System-level energy optimization	Cluster 5 places stronger data-driven emphasis on prediction and factor analysis
5. Data-driven Optimization	Full cycle of prediction–optimization–monitoring–validation	Machine learning, digital twin, Branch & Bound, factor analysis	Reducing energy consumption in a complex, integrated manner	This cluster integrates the results of the previous ones into an industry-applicable framework

3.3. Burst Analysis

In our research, we used CiteSpace to perform the Burst Analysis step. CiteSpace is a bibliometric analysis software that enables the mapping of trends in scientific research [48]. The program can create visualisations that help to show clearly the most relevant elements of different scientific research over time. This method is particularly suitable for systematic literature analyses, as it can not only identify current research trends, but also provide predictions of what research topics may be dominant in the future [49].

The Burst Analysis method, carried out using the CiteSpace app, provides a visual representation of the keywords that were very common in scientific research during a given period and how long this period lasted. The size of the nodes indicates how popular they were at that point in time, while their position on the timeline shows the popularity of the keyword over time. The different research keywords are grouped into clusters, which are indicated by different colours, making it easier to identify the relationships between keywords [50]. The result of the Burst Analysis run on the Scopus database we created is shown in Figure 3.

Top 7 Keywords with the Strongest Citation Bursts

Keywords	Year	Strength	Begin	End	2018 - 2025
energy utilization	2018	39.88	**2018**	2023	
robotics	2018	16	**2018**	2021	
industrial manipulators	2018	8.03	**2018**	2021	
manufacture	2018	7.22	**2018**	2021	
energy efficiency	2018	7.93	**2019**	2020	
agricultural robots	2020	10.97	**2020**	2021	
microrobots	2024	11.85	**2024**	2025	

Figure 3. Burst Analysis by CiteSpace app.

The program identified seven clusters related to the topic of robotisation. The most the results of the Burst Analysis clearly demonstrate the dynamic shift in research focus related to industrial robots over recent years. The keyword “energy utilization” showed the highest burst value (39.88) between 2018 and 2023, indicating that scientific interest in energy consumption has increased [21]. The articles in the clusters created in the previous section, using the CCN method, are also related to this topic through the energy efficiency optimization of robot trajectories [44]. The separate appearance of the keyword “robotics” suggests that digitalization and sustainability goals are strongly linked, as confirmed by the research of Luan et al. [28].

The increase in the term “industrial manipulators” between 2018 and 2021 also shows the importance of optimizing the energy efficiency of robotic arms [38,51]. The burst of the keyword “manufacture” (2018–2021) refers to the widespread use of robots in manufacturing applications, particularly in the automotive industry [25], showing a strong connection to digital twins [45]. The appearance of the keyword “energy efficiency” between 2019 and 2020 shows that energy efficiency has become an integral part of robotics research [37,41].

The strengthening of the keyword “agricultural robots” in 2020–2021 indicates that robotization is increasingly appearing beyond industry [52]. The future trend is indicated by “microrobots” (2024–2025), which points towards miniaturization and precision applications [53,54].

3.4. Co-Occurrence Network of Keywords

Figure 4 shows the analysis of keywords related to industrial robots. The central and largest node in the figure is “industrial robots”, which is directly connected to almost all other clusters, indicating that this is the most dominant theme in the research field. Closely linked keywords include “energy utilization” and “energy efficiency”, both of which highlight the strong focus on sustainability and optimisation in robotics. Other important groups are related to “trajectory planning,” “robot programming,” and “multi-robot systems,” reflecting the technical aspects of motion control and system integration. In addition, the appearance of “microrobots” and “nanobots” suggests an emerging trend of miniaturisation and novel applications. The clusters illustrate that the research landscape is divided into several interconnected themes: energy and efficiency (red cluster), programming and planning (blue cluster), and multi-robot or intelligent systems (green/yellow clusters). This indicates that the study of industrial robots is increasingly multifaceted, covering both macro-level sustainability issues and micro-level technical solutions.

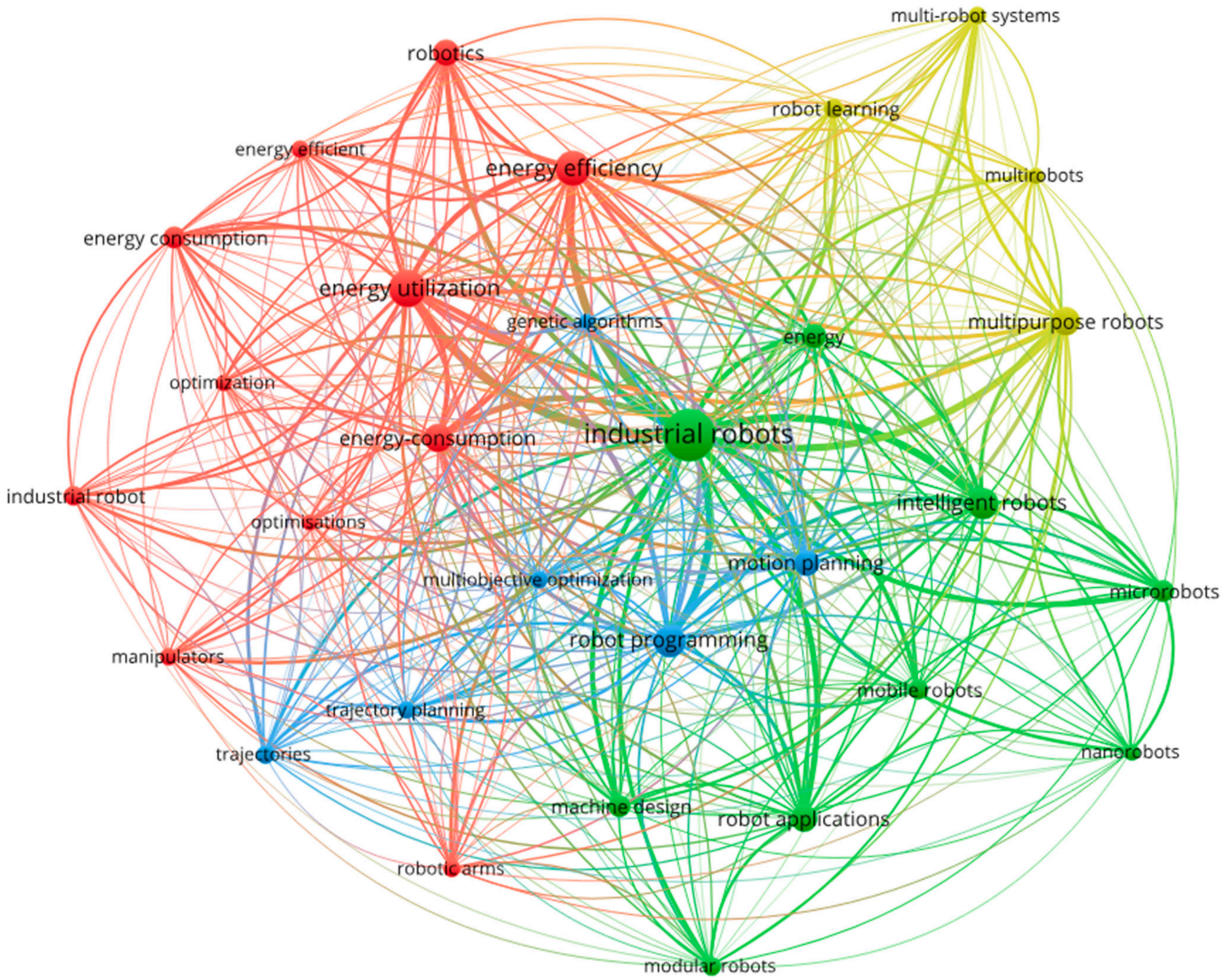

Figure 4. Co-Occurrence Network of Keywords by VOSViewer.

In the research, the Co-Occurrence Network of Keywords (CONK) method was used to map the relationships between keywords. CONK was run using the VOSviewer (version 1.6.20) program. The essence of the method is that it displays the relationships between keywords in the publications under study in a network format. Based on the networks created, the program can automatically generate clusters, which can be analysed to infer key research themes and trends. The advantages of this method are its speed, the automatic creation of clusters, and the easy-to-understand visualisation. Within clusters, sub-systems or groups of themes can be created. The CONK method is beneficial for systematic literature analyses because it is an objective and data-driven tool for reviewing research areas.

The keyword "industrial robots" is at the heart of the green cluster, which integrates a wide range of technical and application-oriented research topics. Within this cluster, the keywords' robot programming', 'motion planning', 'microrobots', and 'nanobots' highlight both classical control aspects and emerging directions, such as miniaturisation and novel robot applications. The yellow cluster is dominated by multi-robot systems, multipurpose robots, and robot learning, which are closely linked to system-level integration and collaborative robotics. In contrast, the red cluster focuses on energy utilization, energy efficiency, and optimization, emphasizing the sustainability perspective of robotics. The blue cluster groups together trajectory planning, manipulators, and robotic arms, reflecting the engineering foundation of robot motion and design.

The network visualisation shows that research on robotisation is multifaceted: it is simultaneously concerned with technical optimisation, energy and sustainability issues, and collaborative applications. Keywords such as optimization and multiobjective optimization act as bridges between the clusters, connecting energy-related topics with motion planning and programming. The presence of terms like genetic algorithms and intelligent robots suggests that artificial intelligence and data-driven methods are increasingly embedded across different themes. The clusters can therefore be divided into two broad types (Table 4): (1) technological, covering engineering, energy, and system integration aspects; and (2) application-oriented, focusing on specific use cases such as multi-robot coordination and microrobotics.

Table 4. Clusters based on Co-Occurrence Network of Keywords (CONK).

Main Type	Cluster	Main Keywords
Technological	Green	industrial robots, robot programming, motion planning, microrobots, nanobots, modular robots
Technological	Yellow	multi-robot systems, multipurpose robots, robot learning, mobile robots, intelligent robots
Technological	Red	energy utilization, energy efficiency, energy consumption, optimization, genetic algorithms
Technological	Blue	trajectory planning, manipulators, robotic arms, robot applications, machine design

The first study [23] in *Cluster 1* examines the impact of industrial robot use on carbon intensity. The results show that industrial robots contribute to reducing carbon emissions, but the extent of the effect varies by industry and level of economic development. The authors emphasize that increasing green total factor productivity and reducing energy intensity are key mechanisms for mitigating carbon impact. In their work [55], Pham and Ahn examine the role of high-precision reducers in industrial robots, which are essential for the reliability and efficiency of robotic arms. Precision drives ensure accurate positioning and contribute to the energy-efficient operation of processes, thereby indirectly improving the overall sustainability performance of robots. The next study [56] presents context-aware cloud robotics in the field of industrial material handling. Through cloud-based decision support and real-time context data processing, automated material handling processes can become more energy-efficient and cost-effective. According to simulation results, cloud robotics solutions significantly reduce the energy consumption of automated vehicles compared to traditional systems.

Overall, the common thread among the three articles is that they all address the energy efficiency and sustainability impacts of industrial robots, albeit at different levels. From macro-level analysis of carbon emissions to the examination of key mechanical subsystems of robots, and from system-level to cloud-based optimization, the articles together provide a comprehensive picture of how industrial robotization can contribute to economic and environmental sustainability.

Cluster 2 explores the energy-saving and carbon-reducing potential of artificial intelligence, robotics, and IoT technologies in diverse contexts, including industrial production, urban environments, and agriculture [22,26,57]. This connection clearly shows that digitalization and robotization play a central role in sustainable development. While cluster 1 focuses on the technical and systemic impacts of robotics, such as macro-level analysis of carbon reduction, the role of precision mechanical subsystems, and the energy efficiency potential of cloud robotics, cluster 2 examines macro-level sustainability processes, highlighting the role of industrial robots, artificial intelligence, and the IoT in decarbonization and energy efficiency.

The articles in Cluster 3 share a common focus on the design and experimental energy optimization of industrial robots, including the efficiency of path planning [58], the improvement of modular robot performance [59], and the energy consumption factors revealed through experimental methodology [60]. These works therefore seek energy efficiency at the micro and engineering levels, as opposed to the system-level and macro effects seen in the first cluster and the AI-IoT-decarbonization relationships examined in the second cluster. Thus, the third cluster is unique in that it shows how energy savings can be achieved through engineering parameters, trajectory planning decisions, and experimental validations, while the previous two clusters examined the same issue at a more strategic, economic, and system integration level.

Cluster 4 studies are all based on data-driven and algorithmic optimization of industrial robots: energy consumption reduction through automatic code generation [61], multi-product, multi-robot station partial disassembly processes supported by mixed-integer programming and hybrid algorithms [62], and data-driven energy optimization methods [32]. What they have in common is that they approach energy efficiency through advanced mathematical models and intelligent algorithms. Unlike the first two clusters, they do not examine macroeconomic or system-level sustainability impacts, and unlike the third cluster, they do not rely on experimental or trajectory design parameters, but rather use formal optimization models and data-driven algorithms to find solutions that can be applied at the industrial level.

4. Discussion and Conclusions

The results of the research confirm that industrial robots are playing an increasingly key role in technological development and sustainability in manufacturing. The bibliometric analysis showed that different research clusters represent different but complementary perspectives: engineering-level trajectory planning, subsystem optimization, macro-level sustainability analysis, and advanced data-driven optimization. These results are consistent with studies that emphasize the importance of predictive modeling and algorithmic approaches in reducing the energy consumption of industrial robots [40]. The literature also highlights that the performance of modular robotic systems is an increasingly important factor in achieving energy-efficient and flexible automation, as supported by the work of Liu and Althoff [59]. Experimental methods, such as design of experiments (DOE), have also proven to be an effective tool for identifying the parameters that most influence energy consumption, providing a practical basis for industrial applications [60].

Beyond technical approaches, the results also highlight the broader sustainability impacts of robotization. Industrial robots directly contribute to carbon emission reduction and low-carbon development by reducing energy consumption and supporting the integration of renewable energy sources and green technologies. They also indirectly enhance competitiveness, innovation, and productivity growth, aligning with the Industry 4.0 and 5.0 paradigms. Based on the research questions, we were able to draw the following conclusions:

RQ1. How do different dimensions of industrial robot research (engineering design, system-level modeling, macroeconomic analysis, and data-driven optimization) complement each other in shaping a comprehensive understanding of energy efficiency and sustainability?

The various dimensions of industrial robot research complement each other to form a comprehensive picture of energy efficiency and sustainability. Engineering-level studies, such as Energy-efficient design of multipoint trajectories for Cartesian robots [58], directly show how energy consumption can be reduced through path planning and motion optimization. System-level modeling reveals the key factors that influence consumption and provides a basis for efficient configuration decisions [60]. Macro-level analyses that examine the impact of robotization on carbon intensity and economic sustainability [23]. Data-driven methods, such as optimization based on machine learning or digital twins, bridge the gap between engineering and system-level results, as well as macroeconomic conclusions. Thus, the interconnection of different dimensions allows us to interpret industrial robots not only as technical tools, but also as key players in the sustainability transition.

RQ2. How can data-driven optimization approaches (e.g., machine learning, digital twins, genetic algorithms) be integrated with engineering-level design and macro-level sustainability assessments to create holistic models of energy-efficient robotisation?

The examination of the energy efficiency and sustainability impacts of industrial robots is based on several methodological approaches. Engineering-level research often uses experimental methods, which identify the most important influencing factors through DOE (Design of Experiment)-based studies [47]. Macro-level analyses are based on panel data, such as which explains the relationship between robotization and carbon reduction through the rebound effect [24]. Data-driven and artificial intelligence-based methods are also gaining ground, using predictive modeling to help forecast and optimize consumption [40]. Together, these methods enable us to assess the impact of robotization on multiple levels, from engineering parameters to economic sustainability, thereby providing a comprehensive understanding of the role of technology.

Although the research offers valuable insights into the role of industrial robots in enhancing energy efficiency and sustainability, several limitations must be considered. First, the analysis was based exclusively on studies published in English, so literature published in other languages—which may contain additional relevant findings—was not included. Second, data collection was limited to the Scopus database, while the inclusion of Web of Science and other indexes could have provided a broader and deeper overview in some cases. Third, the chosen bibliometric methods (e.g., co-occurrence analysis, burst analysis, cluster mapping) have limitations in themselves, as they primarily highlight the structure of networks but do not necessarily reflect the depth of content or qualitative relationships. In addition, the interpretation of the results is linked to research decisions, such as keyword filtering and cluster interpretation, and thus involves a certain degree of subjectivity.

Furthermore, it is evident that the number of studies related to industrial robotization is increasing; however, several significant gaps remain. The articles analyzed are primarily based on data from China or the Far East, whereas global comparisons are relatively rare. Additionally, we can observe a lack of integrated frameworks that combine engineering-level optimization approaches with socio-economic sustainability outcomes.

The multi-level nature of the identified clusters shows that one of the most promising directions for future research is to link micro-level engineering optimization with macro-level sustainability assessments. For example, combining trajectory planning and experimental analysis with machine learning-based predictive models could offer more integrated solutions to energy efficiency challenges.

Future research directions could include integrating different methodological approaches, combining engineering-level optimization (e.g., track design, subsystem development) with data-driven predictive modeling and macro-level sustainability analyses. This would facilitate the development of complex and industrially applicable frameworks for energy efficiency. A promising direction could be to examine the policy and industry implications in greater depth, particularly exploring how companies and decision-makers can integrate the energy efficiency and carbon reduction opportunities offered by robotization into their strategies. This could help ensure that robotization promotes sustainable development not only at the technical level, but also at the economic and social levels.

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