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Review

Cognitive Systems for the Energy Efficiency Industry

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Abstract: This review underscores the pivotal role of Cognitive Systems (CS) in enhancing energy efficiency within the industrial sector, exploring the application of sophisticated algorithms, data analytics, and machine learning techniques to the real-time optimization of energy consumption. This methodology has the potential to reduce operational expenses and further diminish environmental repercussions; however, it also leverages data-driven insights and predictive maintenance to foresee equipment malfunctions and modulate energy utilization accordingly. The viability of integrating renewable energy sources is emphasized, supporting a transition towards sustainability. Furthermore, this research includes a bibliometric literature analysis from the past decade on the deployment of CS and Artificial Intelligence in enhancing industrial energy efficiency.

Keywords: cognitive systems; energy efficiency industry; cognitive computing applications; artificial consciousness

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Citation: Arevalo, J.; Latorre-Biel, J.-I.; Flor-Montalvo, F.-J.; Perez-Parte, M.; Blanco, J. Cognitive Systems for the Energy Efficiency Industry. *Energies* **2024**, *17*, 1860. https://doi.org/10.3390/en17081860

Academic Editor: David Borge-Diez

Received: 6 March 2024
Revised: 27 March 2024
Accepted: 10 April 2024
Published: 13 April 2024

1. Introduction

In the continuously evolving landscape of industrial technology, the quest for energy efficiency has emerged as a cornerstone for sustainable and responsible operational practices. As various sectors confront the dual challenges of accommodating increasing demands while concurrently striving to reduce environmental impacts, the incorporation of avant-garde technologies has been recognized as a hallmark of innovation. Cognitive Systems (CS) are leading this technological advancement and stand at the cusp of transforming how industrial entities manage and refine their energy consumption strategies. By harnessing the potential of Artificial Intelligence (AI) and Machine Learning (ML), these systems offer a promising path for enhancing energy utilization efficiency, thereby contributing significantly to the global trend toward sustainability.

According to the European Parliament, energy efficiency involves minimizing energy consumption for equivalent activities or results, thereby enhancing the efficiency of energy use. Achieving this requires adopting more efficient technologies, improving consumption processes and practices, and optimizing energy systems. Crucially, energy efficiency plays a fundamental role in reducing greenhouse gas emissions, decreasing energy expenditures, and promoting sustainable development. This concept underscores the importance of strategic investments in technology and process optimization to achieve broader environmental and economic benefits.

A Cognitive System is engineered to simulate the operational dynamics of the human brain, aiming to achieve objectives that include learning, reasoning, perception, and inference. It is designed to facilitate decision-making processes and, in specific scenarios, to execute those decisions autonomously. Furthermore, such systems are able to interact with their environment in ways that are considered intelligent. CS can be embodied in various forms, including applications, agents, services, and Application Programming Interfaces (APIs), thereby offering a versatile framework for enhancing computational intelligence across diverse sectors.

The multifaceted capabilities of these systems enable them to process vast amounts of data, recognize patterns, and make informed decisions, thus serving as a pivotal technology in advancing energy efficiency and operational optimization in industrial settings. CS allow for cooperation between humans and computers in decision-making and controlling complex situations without an inflexible reliance on predetermined programs. From the beginning of this research field, studies suggest that this symbiotic partnership performs intellectual operations much more effectively than any human could without a performance enhancer [1].

In this line of argument, according to Kelly and Hamm [2], a new frontier has been crossed in the evolution of computing over the last decade, entering the era of CS. These systems promise to navigate complexity and assist individuals and organizations in making better decisions. Christensen et al. [3] observed that to achieve this objective, information from multiple sensory modalities must be used for decision-making, including simple haptics, vision, proprioception, and speech. The tasks related to speech and Natural Language Recognition (NLR), as well as vision and haptic senses, are addressed through ML systems, based on Deep Learning Networks (DLNs), which are able to provide the necessary features for the proper performance of these tasks.

Despite the aforementioned, Elnagar and Thomas [4] argue that Cognitive Computing (COC) seeks to integrate human cognition into computerized models. However, there are currently no scientific classifications to accurately outline the essence of COC. They argue that the absence of a unified interpretation of what constitutes COC has resulted in subpar COC research within information systems. Consequently, it is imperative to initially establish a clear identification of COC as a phenomenon to guide and pinpoint potential research areas within information systems, before starting to generate a programming code capable of solving certain problems. This is what Visvizi [5] highlights in his brief definition of AI, offering a nuanced perspective on the terminology of computational intelligence. When coded in Python, it is termed ML; conversely, when conceptualized in PowerPoint, it is designated as AI, to which the term Cognitive System can also be added for a broader interpretation.

Gamez [6] propels the conversation on CS and COC forward by devising approaches and methodologies aimed at delineating the phenomenology of Machine Consciousness: a machine endowed with the capability to perform processes akin to consciousness, by integrating various data sources to deduce outcomes, possesses the capacity to analyze and comprehend industrial processes, thereby pinpointing areas for enhancement and boosting operational efficiency. Equipped with an awareness of energy consumption and an insight into system operations, such a machine could devise strategies to diminish energy usage without compromising efficiency. Simultaneously, it could foresee potential failures in equipment and systems, facilitating the adoption of predictive maintenance strategies to forestall unforeseen interruptions. These disruptions detrimentally impact the energy consumption, as the initiation and cessation phases of industrial machinery are highly energy-intensive. A conscious machine could foresee these scenarios and proactively adjust to shifts in operational conditions or energy requirements, thereby optimizing performance. Furthermore, it could effectively interact with other systems and machines, encouraging collaboration and coordination in intricate industrial settings.

The component of the systems that oversee AI, alongside COC, must conform to a specific framework referred to as Cognitive Architecture (CA). Therefore, a prerequisite for achieving Machine Consciousness, also known as Artificial Consciousness, is to use a CA that is capable of COC as a basis.

The subsequent diagram (Figure 1) illustrates the interrelationship among Artificial Consciousness, COC, AI, and additional pertinent disciplines within the scope of this research.

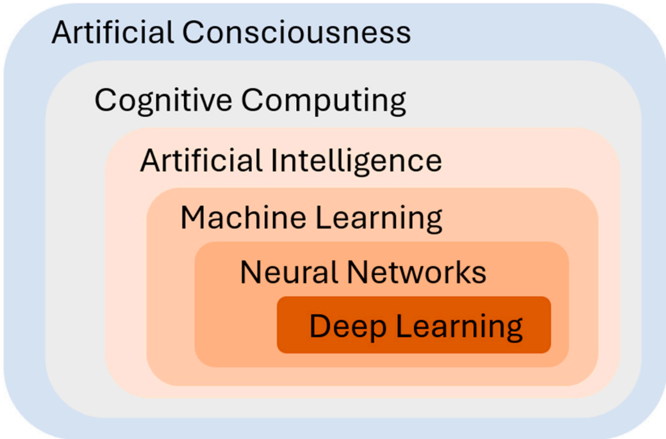

Figure 1. Artificial Consciousness and COC layers.

A series of technological layers that progressively approximate the outcomes of processes inherent to human cognition can be observed therein.

2. State of the Art

2.1. Cognitive Computing

Regarding COC, this research is confronted with the challenge of achieving a COC capable of leading to CS and, ultimately, what is termed Artificial Consciousness. For this purpose, a foundational CA, capable of facilitating the desired COC, is needed.

Christensen et al. [3] adds evidence concerning the structure and nature of COC, highlighting that researchers engaged in the CoSy project did not set long-term objectives for their project, or even a significant subset thereof to cover the scope of their work. Nonetheless, they emphatically asserted that unless researchers focus on synthesizing the disparate elements of the puzzle they have been examining in isolation, they will fail to effectively grasp the broader context, akin to missing the forest for the trees. They acknowledged that the challenges are so formidable that some may even look futile. The approach recommended in addressing this conundrum involves a meticulous analysis of the long-term goal, using it as a cornerstone to establish attainable objectives. This strategy facilitates establishing short- and medium-term goals that are both realistic and directional, guiding us towards the correct trajectory. Consequently, the following question arises: what CA are currently available with the capability of supporting such a comprehensive integration of COC?

Scarcello and Mastroianni [7] highlight that one of the earliest systems designed for controlling energy consumption through temperature regulation is the Heating, Ventilation, and Air Conditioning (HVAC) system. In contemporary settings, climate control is managed via the Internet, utilizing equipment such as temperature sensors and actuators for air conditioner activation. These components are interconnected through Internet of Things (IoT) gateway hardware, employing Wi-Fi and Bluetooth for internal communications. This configuration leverages cloud computing architecture and IoT support to enhance the traditional HVAC system, contributing to the development of cognitive buildings. Furthermore, the traditional HVAC system's capabilities can be expanded with IoT integration. By combining HVAC systems with sensors and AI, more sophisticated HVAC solutions can be created. In this context, Amadeo et al. [8] demonstrate the efficacy of the COGITO platform in managing temperature and, consequently, reducing energy consumption in smart buildings. Similarly, Cicirelli et al. [9] explores thermal comfort management within buildings, which also contributes to reducing energy consumption by addressing various environmental factors.

Likewise, CS within the industry, particularly those focused on enhancing energy efficiency, hold a transformative potential. Leveraging data-driven insights and advanced analytics, these systems have the capability to optimize energy consumption in real-time, thereby significantly reducing operational costs and minimizing environmental impact. Moreover, predictive maintenance capabilities facilitate the early detection of potential equipment failures, allowing for timely repairs during off-peak hours, which further contributes to energy savings.

Overall, the adoption of CS in industrial settings heralds a future where energy efficiency is markedly improved, contributing to sustainability goals and fostering smarter, more responsive environments. In our background research, we have identified and analyzed numerous CA. These architectures, while initially specialized on energy consumption optimization related to maintaining stable temperatures in domestic environments, can be adapted for industrial use, indicating broad applicability across sectors. These CA and more are delineated across a wide range of papers and publications analyzed, among which notable for their adaptability to various scenarios are "*4CAPS: An Adaptive Architecture for Human Information Processing*" [10], "*ACT-R: A cognitive architecture for modeling cognition*" [11], "*ADAPT: A Cognitive Architecture for Robots*" [12], "*Incremental Object Perception in an Attention-Driven Cognitive Architecture*" [13], "*Attention in the ASMO Cognitive Architecture*" [14], "*Consciousness: The science of subjectivity*" [15], "*Realistic Behavior Variation in a BDI-based Cognitive Architecture*" [16], "*A Unified Architecture for Cognition and Motor Control Based on Neuroanatomy Psychophysical Experiments and Cognitive Behaviors*" [17], "*Attention Mechanisms in the CHREST Cognitive Architecture*" [18], "*The CLARION Cognitive Architecture*" [19], "*Introduction to the Soar Cognitive Architecture*" [20], "*Companion Cognitive Systems: A step towards human-level AI*" [21], "*Narrating System Intentionality: Copycat and the Artificial Intelligence Hermeneutic Network*" [22], "*Dual Cognitive Architecture*" [23], and "*A Minimal Architecture for General Cognition*" [24]. These, along with a wide range of additional CA delineated by Elnagar et al. [25], constitute a pyramidal structure comprising four distinct sections: at the bottom, the representation of intelligence followed by brain-like hardware, cognitive algorithms and software, and finally CS at the top of the pyramid.

Based on our background research, seven pertinent criteria were identified regarding energy efficiency in the industry, where cognitive systems can provide significant value, detailed as follows:

1. Enhancing production processes through data analysis to pinpoint and correct inefficiencies.
2. Implementing energy management systems for real-time monitoring and optimization of energy use.
3. Applying heat recovery technologies with predictive adjustments tailored to production demands.
4. Utilizing predictive analytics for efficient machinery and equipment scheduling and maintenance.
5. Assessing new, high-efficiency machinery investments based on energy performance.
6. Proactively identifying maintenance issues impacting energy efficiency.
7. Tailoring energy-saving training programs using behavioral analysis.

Nearly all the CA analyzed place significant emphasis on the concept of attention, a concept that the discipline of Deep Learning (DL), particularly through the Transformers model [26] has begun to explore and capitalize on with notable success. The attention mechanism, which enables the model to assess the relative importance of different features within a sequence, mirrors the human ability to focus our attention on specific aspects of our environment while disregarding others. This process, utilizing our cognitive capacities in a manner suggestive of consciousness, is an area of growing interest and application [27].

2.2. The Importance of Energy Efficiency in Industry

The World Energy Outlook [28] offers a thorough analysis and strategic perspectives on the global energy scenario. The analysis for 2023 studied the consequences of structural shifts in economies and energy consumption, illuminating the developing strategies for addressing worldwide energy needs, including industrial energy usage.

The industrial sector is highlighted in this report as the most energy-consuming and CO_2-emitting end-use sector, representing 38% of the total final energy consumption, and 47% of CO_2 emissions, including those from electricity and heat. Energy-intensive industries, such as iron and steel, chemicals, nonmetallic minerals, nonferrous metals, and the paper sector, are responsible for nearly 90% of the coal demand in the industry, over 70% of oil, and almost 55% for natural gas [28]. These industries share needs for high temperatures and long-duration assets.

On the other hand, non-energy-intensive industries, including light industries such as food and textiles, encompass small and medium enterprises (SME) and have lower temperature requirements. These industries account for the remaining 30% of the industrial sector's demand, with an energy mix primarily composed of electricity (37%), natural gas (20%), oil (15%), and bioenergy (14%) as shown in Figure 2 [28].

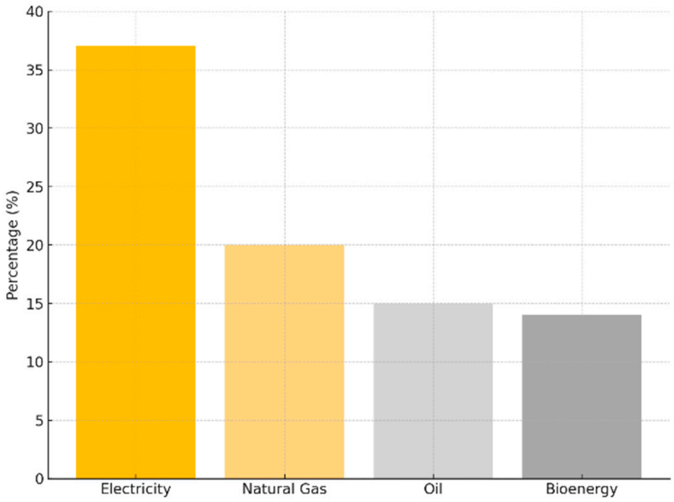

Figure 2. Energy mix and SME.

According to the IEA report [28], 65% of the electricity used by the light industry today powers motorized systems, which have been the largest source of electricity demand in these industries over the past decade and are expected to continue to be so. The report notes that 62 countries have implemented energy performance standards for industrial electric motors as of 2022, covering more than half of the global industrial motor fleet. It also highlights the potential for improving energy efficiency not just through motor upgrades but also via system enhancements, such as adjusting electrical capacity to match service requirements. This can be automated through the use of CS, as reported in this research work.

Furthermore, electrification plays a crucial role in providing heating and cooling systems, across a broad range of temperature levels, including the use of heat pumps for low- temperature applications and electric arc furnaces for high-temperature applications. This is an aspect where CS can also play a crucial role. Moreover, by relying on low-emission energy sources, electrification additionally reduces the CO_2 emissions of the industrial sector, a goal of vital importance in the current operational framework seeking the smallest possible ecological footprint in industrial activity.

Various international statutes mandate the implementation of measures to enhance energy efficiency. DSIRE (Database of State Incentives for Renewables & Efficiency) serves as a comprehensive repository of information on incentives and policies supporting renewable energy and energy efficiency across the United States, making it a key resource for understanding state-specific financial incentives and policy details.

Furthermore, it is important to highlight Directive (EU) 2023/1791 of the European Parliament and of the Council, dated 13 September 2023, which sets a compulsory goal for the EU to reduce its final energy consumption by 11.7% by 2030. This directive also introduces several strategies to boost energy efficiency within the industry. These strategies can effectively utilize the unique capabilities of Cognitive Systems (CS) under discussion. Generally, these strategies are categorized into two main groups aimed at enhancing industrial energy efficiency, thereby contributing to global emission reduction and energy sustainability goals:

It should also be emphasized that Directive (EU) 2023/1791 of the European Parliament and of the Council, dated 13 September 2023 [29] outlines several measures aimed at enhancing energy efficiency within the industry. These measures can effectively leverage the unique capabilities of CS discussed throughout the study. Broadly, these measures fall into two major categories designed to improve energy efficiency in the industry, thereby supporting the global goals for emission reduction and energy sustainability:

1. Development of programs that encourage and support SMEs to conduct energy audits and implement the recommendations derived from such audits. These energy audits, based on the massive and intelligent collection of data, should be mandatory and regular for companies with an average annual energy consumption above a certain threshold, as the energy savings can be significant.
2. Implementation of energy management systems promoting high-efficiency cogeneration, allowing the simultaneous production of electric energy and useful heat in an efficient manner, thereby saving costs. Furthermore, efficient heating and cooling should be prioritized, evaluating the potential of high-efficiency cogeneration and efficient heating and cooling in long-term renovation strategies.

Given the potential effectiveness of CS in enhancing industrial energy efficiency, this raises the question of our research focus on their applications in this sector over recent years.

3. Materials and Methods

This research focuses on identifying documents from the past ten years in the Scopus database that are related to the use of CS or general AI systems and their applications in improving energy efficiency within the industry. Titles, common keywords, and abstracts are utilized in the research as criteria to gain a clear perspective on the trends and directions of studies in this field.

3.1. ETL-like Methodology

The use of the ETL (Extract, Transform, Load) methodology as a reference in scientific research provides the necessary tools for data integration, cleaning, and analysis. In our study, we have outlined the three phases of this methodology according to the following steps.

3.1.1. Data Extraction

Given the purpose of the proposed research, the approach involves conducting a bibliometric analysis, which includes a descriptive examination of publications over a specific period. To this end, the query options in Scopus Advanced Search were used. A ten-year period, from 2013 to 2023, was considered, with data beyond this range excluded in some analyses, since only one month of 2024 had passed when the query was made, rendering the data not sufficiently significant for these analyses. The search formula and filters used in Scopus are based on the following parameters:

TITLE-ABS-KEY ((cognitive AND systems) OR (artificial AND intelligence));
AND TITLE-ABS-KEY (energy AND efficiency AND industry);
AND PUBYEAR > 2013 AND PUBYEAR < 2025;
AND LIMIT-TO (LANGUAGE, “English”);
AND (LIMIT-TO (DOCTYPE, “ar”));
AND (LIMIT-TO (SRCTYPE, “j”));
AND (LIMIT-TO (PUBSTAGE, “final”)).

This is equivalent to requesting all publications from January 2013 until the time of the query, which was conducted on 31 January 2024. The keywords ‘cognitive systems’, 'artificial intelligence', and 'energy efficiency industry' were used. After executing the search, the metadata were exported in CSV format.

Regarding the quality of the obtained CSV data, Tim Berners-Lee, the father of the Web, devised a 5-star development scheme for Open Data [30]. This scheme serves as a benchmark for assessing the quality level of data publication, where more stars indicate higher compliance with the scheme, and each level encompasses the qualities of the preceding one. Although Scopus is a bibliographic database of abstracts and citations for the academic literature and is not typically offered as Open Data—being owned and managed by Elsevier, an academic publishing company—the data that has been utilized in this academic field are freely accessible. Consequently, the principles of Open Data quality can be applied to assess the quality of the data used in this bibliometric study.

Thus, to achieve one star, it is necessary to publish data on the Web in any format. Scopus not only meets this criterion but also goes further by facilitating the linking to specific articles through their unique identifiers (such as DOI or Scopus ID), thereby enhancing integration with other web resources and earning it the second star for linkability. Furthermore, Scopus provides data in CSV (Comma-Separated Values) format, an open format not owned by any company, which supports its accessibility. For the third criterion, Scopus's use of URIs (Uniform Resource Identifiers) to denote distinct entities (articles, authors, etc.) provides precise identification and referencing, aligning with the four-star requirement of using non-proprietary open formats. Finally, Scopus achieves the fifth star by facilitating data interconnection and contextual understanding through its citation-linking features. This allows users to trace citations forward and backward, offering insights into the context of an article within the broader research landscape. This includes detailing the scientific output of each author, their articles, and collaborations and allows for integration with other platforms and services using standardized identifiers, such as linking with ORCID (Open Researcher and Contributor ID) to connect an author's work across various databases and platforms. With all this in mind, it can be concluded that, although the five Open Data stars cannot be strictly attributed to the quality of the data used for this bibliometric study—since Scopus data are not Open Data in the strict sense—the high quality and characteristics of the data justify an analogous assignment of these five stars.

3.1.2. Data Transformation and Loading

The data were initially processed using a spreadsheet to identify and remove records with incorrect or incomplete information. Subsequently, a preliminary descriptive analysis was conducted, focusing on countries, authors, and collaborators. The metadata were further analyzed using VOSviewer software, version 1.6.20. VOSviewer, in addition to processing numerical data, provides a graphical representation that closely aligns with human cognitive processes, an alignment we aim to emulate with CS. Additionally, an analysis of research collaborations between countries was conducted, requiring a minimum of 10 publications and 25 references for inclusion. For keywords, a threshold of 15 citations was established.

4. Results

The search in the Scopus database for articles related to CS and AI in energy efficiency within the industry yielded a total of 814 articles. This indicates a growing trend in research in this field, in line with the heightened focus on environmental concerns and the increased use of AI technologies. Notably, in 2024, the number of articles published in just one month has already surpassed the total for the entire year of 2014. As of 31 January, there were 22 articles published this year compared to 18 in 2014.

In the following graph (Figure 3), the data for 2024 have not been included, despite surpassing the total number of articles produced in all of 2014 within just a single month. This omission is due to its comparative insignificance relative to the results observed over the past decade.

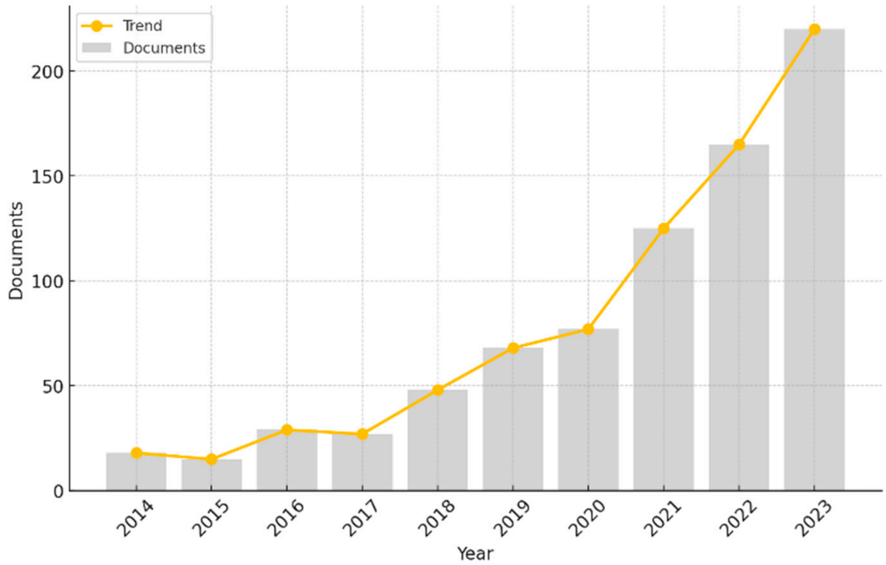

Figure 3. Number of documents published by year (2013–2023).

The main research areas, cited in at least 35 articles, are presented in the table below (Table 1). It is important to note that the sum of the articles from the listed areas exceeds 100% of the total selected articles in Scopus (814), because an article can be categorized under more than one research area. For instance, an article might be classified as belonging to both the Engineering and Mathematics fields.

Table 1. Documents by area.

Area	Documents
Engineering	443
Computer Science	402
Energy	189
Mathematics	133
Environmental Science	94
Physics	84
Materials Science	74
Decision Sciences	66
Social Sciences	55
Business, Management and Accounting	53
Earth and Planetary Sciences	37

Among the 814 articles analyzed, participants from 49 countries were identified in international scientific publications within the field of study. Of these countries, 17 had 20 or more publications each. The graph below (Figure 4) displays the top ten countries ranked by the number of publications.

China, with 175 documents, has been the most prolific country in producing academic material over the last two decades, followed by India with a total of 130 documents, and the USA with 88. However, although the number of documents produced by the USA amounts to nearly a quarter (28.95%) of those generated by China and India combined, less than half of the citations (47.52%) to articles from these three countries, which total approximately 10,000 (10,034), are attributed to China and India combined. The remainder pertains to citations of articles from the USA. This underscores two significant considerations: the quality of the articles produced and the influence of publications depending on their country of origin, as can be seen in Figure 5.

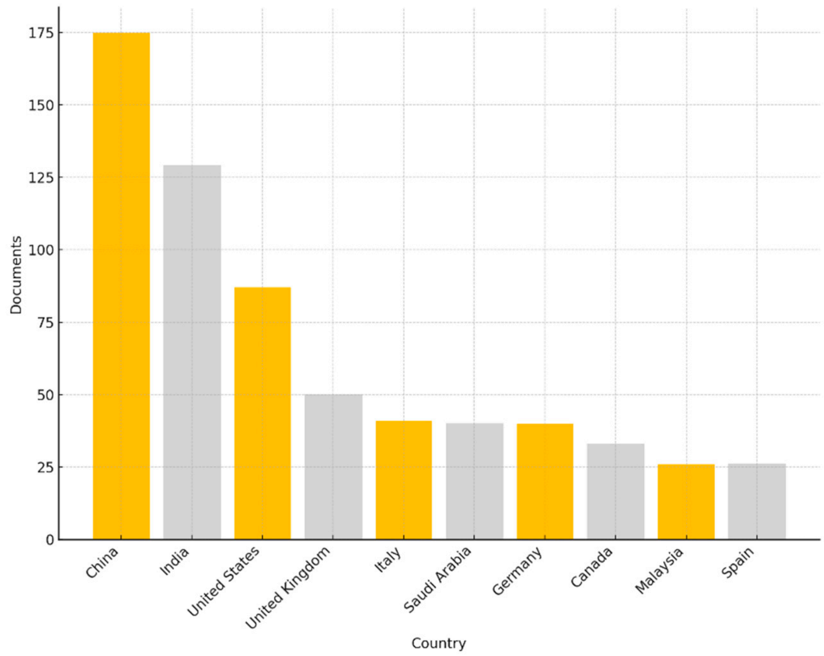

Figure 4. Number of documents by country.

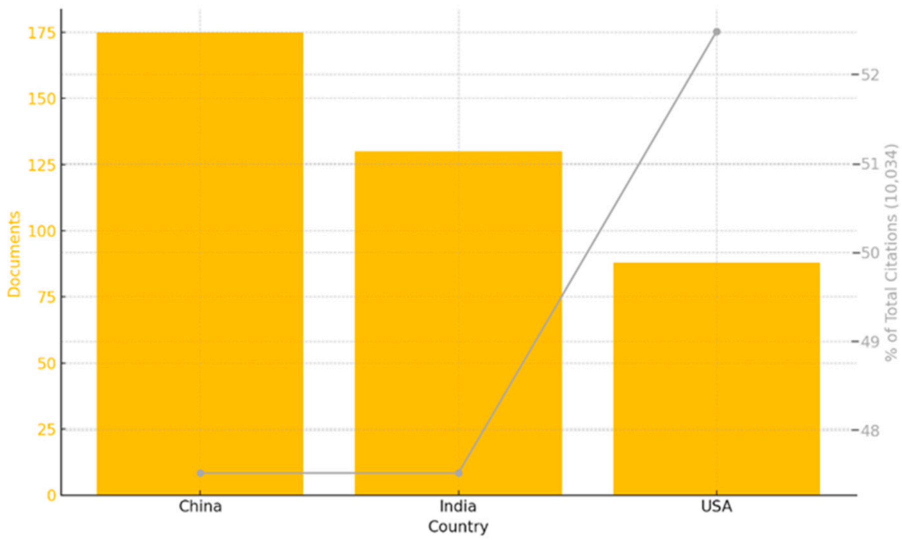

Figure 5. Document production and citation percentage by country.

A bibliometric map, based on published articles and illustrating cooperation between participating countries in this analysis, is depicted in Figure 6. This map is derived from citations of articles from one country to another, specifically among those countries that have published at least 20 articles. It reveals a cluster indicating a strong association between articles published in the USA. Conversely, despite China's significant number of published articles—a trend observed across numerous scientific disciplines—it appears to remain proportionally somewhat isolated in terms of its global influence on scientific production.

In addition, an analysis of the total number of keyword occurrences within the articles reveals that, out of 7157, only 5 exceed the threshold of 100 occurrences (Table 2).

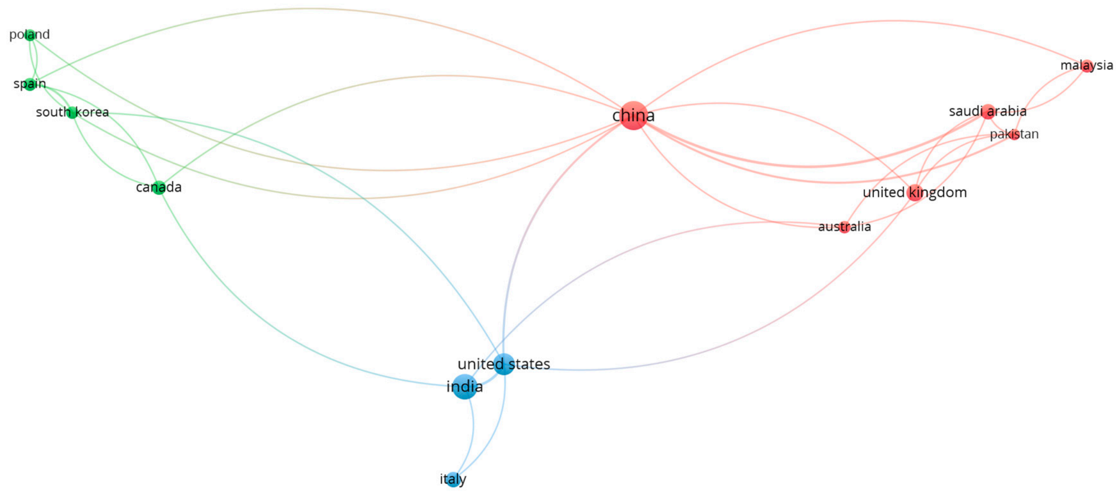

Figure 6. Cooperating between countries.

Table 2. Keywords occurrences.

Keywords	Occurrences
Artificial Intelligence	438
Energy Efficiency	380
Energy Utilization	162
Machine Learning	129
Internet of things	106

This is understandable because, as Elnagar and Thomas [4] have indicated, there lacks a clear and precise scientific classification that unequivocally delineates the functionalities and characteristics of CS. Consequently, other prevalent technologies such as ML and IoT are identified as keywords that have a greater impact compared to CS.

Regarding the sources of publication (Table 3), an analysis was conducted on those with at least ten publications, which identified six main sources.

Table 3. Sources and number of publications.

Source	Number of Publications
Energies (MDPI)	23
IEEE Access	16
Advances in intelligent systems and computing	15
Sustainability (Switzerland)	12
IFIP advances in information and communications	11

Notably, the top two sources of documents contribute to less than 5% of the total publications (4.79%), despite the existence of a total of 552 sources. The 10 most cited documents out of the 814 analyzed account for a total of 4802 citations, representing 37.66% of the overall total of 12,752 citations. This indicates that just over 1% of the articles are responsible for nearly 40% of the citations (Table 4).

It is noteworthy that the articles in question are not recent, all dating from 2021 and earlier. Between 2014 and 2021, a total of 407 articles were published, and an identical number, another 407 articles, have been published from 2022 to the present day. However, none of the articles released in the last two years rank among the top 10 most cited. Furthermore, this study reveals that among the 814 articles analyzed, only 12 authors have published 3 or more articles, out of a total of 3193 authors, suggesting a lack of strong specialization among authors in the field of energy efficiency research.

Table 4. Articles and citations.

Document	Citations
Sze (2017) [31]	2136
Wang (2019) [32]	741
Peng (2016) [33]	326
Touzani (2018) [34]	255
Yuan (2020) [35]	247
Yang (2020) [36]	237
Mondejar (2021) [35]	233
Ahmad (2021) [37]	219
Sodhro (2019) [38]	209
Ni (2019) [39]	199

The authors with the highest number of published documents are shown in Table 5.

Table 5. Citations and documents by author.

Autor	Document	Citations
eftekhari-zadeh, ehsan	5	92
alizadeh, seyed mehdi	4	63
chochliouros, ioannis p.	4	24
ahmad, iftikhar	3	9
chebak, ahmed	3	38
cho, keonhee	3	2
colla, valentina	3	27
fatahi, rasoul	3	42
nazemi, ehsan	3	84
perera, lokukaluge p.	3	40
rezgui, yacine	3	82
yoon, guwon	3	2

Upon conducting a thorough examination of the findings delineated within the scholarly articles listed in Table 5, it becomes evident that there is a distinct lack of pertinent and accurate information regarding the deployment of CS within particularized processes of the industrial sector. Nonetheless, it is worth noting that certain foundational principles related to data management and analytical methodologies exhibit a degree of universal applicability. Five principal dimensions were delineated, pivotal to the enhancement and integration of cognitive systems for energy efficiency in industrial operations:

1. Data Collection and Cleansing: Highlights the direct impact of data quality and quantity on the performance of cognitive systems.
2. Predictive Analysis: Emphasizes the application of Machine Learning and Deep Learning to anticipate consumption patterns and identify inefficiencies.
3. Process Optimization: Focuses on algorithmic strategies to achieve optimal operational efficiency.
4. Supervised and Unsupervised Learning: Addresses the role of these learning paradigms in classifying data and revealing hidden consumption patterns.
5. Deep Neural Networks: Stresses their significance in simulating complex processes for energy efficiency improvement.

These categories reflect a comprehensive strategy necessary for the effective deployment of cognitive systems in industrial energy management.

However, a notable exception is a single article titled "*Efficient Processing of Deep Neural Networks*" [31] which has garnered 2151 citations. This publication represents the authors' sole contribution to this line of research. It discusses the pervasive adoption of Deep Neural Networks (DNNs) in AI applications and explores strategies for optimizing their design to enhance performance and energy efficiency. It is noteworthy that the articles in question are not recent, all dating from 2021 and earlier.

5. Discussion

This research delineates the foundational principles of CS and their value in extending the efficiency of energy consumption within the industrial sector. A comprehensive exploration has revealed a diverse array of CA. From this array, two primary functions have been pinpointed where CS exhibit optimal performance: the regulation of energy usage in climate control systems and the execution of preventive maintenance on industrial machinery. To address the imperative of optimizing energy consumption, this review has included global datasets sourced from the International Energy Agency and the European Commission, both of which emphatically underscore the critical nature of this requirement. It becomes evident that leveraging international cooperation presents a more feasible approach to fulfilling this demand. The analysis further discerns that in the realm of scholarly article production pertinent to this topic, such collaborative efforts are indeed flourishing, thereby fostering the essential synergies needed to advance in this area.

There are pronounced collaborative clusters demonstrating a robust link between research outputs, particularly from research originating in the USA. This interconnection underscores the synergistic academic efforts between nations in advancing the field of energy efficiency and CS. In contrast, despite China's substantial contribution to the body of literature, as evidenced by its high volume of publications—a phenomenon consistent across a broad spectrum of scientific disciplines—it exhibits a relative degree of isolation concerning its impact on global scientific collaboration. This observation suggests a potential area for further research into the dynamics of international research networks and their influence on the dissemination and development of scientific knowledge.

In this research, the content of the first 10 referenced articles has also been analyzed to gather specific data on the use of CS or AI in general for optimizing energy consumption in industry, as well as references to any of the main CA.

The most cited article [31], receiving 2136 citations, explores the optimization of DNN designs for improved performance and energy efficiency. It emphasizes techniques for efficient DNN processing, aiming to enhance energy efficiency without sacrificing accuracy or incurring additional hardware costs. This aspect is vital for the widespread application of DNN in AI systems, highlighting the potential alignment with CS or AI in optimizing energy consumption, especially in sectors where efficiency is paramount. However, it does not explicitly mention CS. The second top-rated article [32], with 741 citations, delves into smart meter data analytics, concentrating on its applications, methodologies, and challenges in boosting power grid efficiency and sustainability. This research indirectly contributes to advancements in industrial energy efficiency through smart meter data for load management, yet it does not directly refer to energy efficiency in the industry or CS.

The remaining articles, despite collectively garnering fewer citations than the first two, subtly contribute to the research objective of this work regarding the role of CS in industrial energy efficiency. One article [33] examines Cloud Radio Access Networks (C-RANs) and their potential in improving spectral and energy efficiency within wireless networks. Although it primarily focuses on C-RAN architecture and its implications for telecommunication networks' efficiency, it indirectly hints at broader energy efficiency considerations without delving into industrial applications or CS explicitly. Another article introduces a baseline modeling approach using the Gradient Boosting Machine (GBM) algorithm to analyze commercial building energy consumption data. This study, comparing the GBM models performance against the Time-of-Week-and-Temperature (TOWT) and Random Forest (RF) models, demonstrates the GBM model's superior predictive accuracy. It underscores the potential for refining energy savings estimation in buildings, suggesting implications for broader energy efficiency efforts. Notably, it explores the feasibility of shorter training periods for such models, which could impact measurement and verification

(M&V) practices in energy management without explicitly addressing industrial contexts or CS application.

In one of the analyzed articles [35], authors examine the development of all-organic composites for high-temperature dielectric energy storage, aiming to enhance energy density and efficiency up to 200 °C. Although the focus lies on technological advancements in materials science for energy storage devices, there is no direct mention of applications in industrial energy efficiency or CS. The article delves into the electrical properties, fabrication, and potential uses of these materials in high-temperature environments, suggesting implications for energy storage and management but not explicitly within the industrial sector.

Another highly cited article [40] explores digitization's impact on sustainable development goals, with a particular focus on addressing energy challenges. It thoroughly examines energy efficiency in industrial and transportation sectors, highlighting the critical role of distributed generation and smart grids in fostering a more sustainable energy supply. The article points out the substantial energy consumption within these sectors and notes that a significant portion of this energy is lost as residual heat due to process inefficiencies, especially those requiring high temperatures commonly produced by burning fossil fuels. Such inefficiencies lead to wasting precious energy resources and exacerbating global warming. Additionally, the article discusses how IoT can revolutionize industry by optimizing processes. This optimization is facilitated through the adoption of standardized inline sensors for process metering and the widespread use of logging systems and connectivity.

Discussions on the development of AI-enabled intelligent 6G networks [36] have been found, highlighting high energy efficiency as a crucial requirement for these future networks, and the application of AI in the sustainable energy industry, highlighting its role in enhancing energy efficiency in various sectors including industry and transportation. There are several discussions [37,38] about AI potential to optimize processes such as solar and hydrogen power generation, supply and demand management, and predictive maintenance, which indirectly contribute to energy efficiency in industrial settings. The emphasis is on AI capability to improve operational performance and efficiency across the energy sector, including industrial applications, by leveraging big data, ML models, and smart grid technologies.

6. Conclusions

Advancing towards intricate cognitive models capable of emulating human decision-making processes and improving energy efficiency represents a formidable and intricate endeavor. The optimization of CS heralds a paradigm shift in industrial energy management, promising to usher in an era of operations that are not only more sustainable but also significantly more efficient, thereby offering mutual benefits to the corporate sector and the environmental landscape alike. This prospective scenario underscores the pivotal role of CS in mediating the confluence of technological progress and ecological stewardship. Upgrading CS's latent capacity to revolutionize industrial energy efficiency requires a concerted effort involving synergistic collaborations among the corporate sphere, academic institutions, and governmental bodies. Such cooperative engagements are crucial for the rapid formulation and adoption of uniform standards and optimal practices concerning the application of CS, ensuring their deployment is both efficacious and adheres to ethical guidelines. Furthermore, substantial investments in educational initiatives and training programs are imperative to equip the labor force with the requisite skills for interacting with and administering these sophisticated systems, thus facilitating their seamless integration into pre-existing frameworks. Consequently, it becomes imperative to develop novel theoretical constructs and at the same time implement pragmatic applications thereof. These pragmatic applications are precisely the main deficiency in current cognitive systems.

Expanding on the need for ongoing research into developing more sophisticated cognitive models, it has been argued that the future of industrial energy efficiency relies heavily on the ability to enhance and refine these systems. Current advancements in IA and ML provide a solid foundation; although, there is a significant gap between the decision-making capabilities of these systems and the nuanced context-aware decisions made by humans. To bridge this gap, research must focus on creating cognitive models that not only process information more efficiently but also understand and interpret complex patterns and contexts in ways that mimic human cognitive processes. General-purpose CA represent a promising direction in this endeavor. These systems, designed to be flexible and adaptable, can potentially be applied across a variety of industrial settings, each with their unique challenges and requirements. By developing architectures that can learn from and adapt to their environment, researchers move closer to creating systems that can independently identify areas for energy optimization, predict future trends, and make informed decisions to enhance operational efficiency.

Furthermore, the integration of these CS with IoT and big data analytics amplifies their potential, providing a wealth of real-time data from sensors and devices across industrial operations and offering a detailed view of energy usage patterns. When combined with CS capable of analyzing this data in real-time, it becomes possible to not only react to current conditions but also predict and prepare for future energy needs, thereby ensuring more sustainable and efficient energy use. However, the path to achieving these advanced CS is fraught with challenges. One of the primary obstacles is the complexity of human cognition itself. Developing systems that can truly understand and replicate the depth of human decision-making requires a multidisciplinary approach, combining insights from psychology, neuroscience, computer science, and engineering. Additionally, ethical considerations and the need for transparency in AI decision-making processes must be addressed to ensure these systems are trusted and widely accepted.

The journey towards more sophisticated cognitive models that can mimic human decision-making and enhance energy efficiency is complex and challenging. The full potential of CS can be unlocked to transform industrial energy management, leading to more sustainable and efficient operations that benefit both businesses and the environment. This vision for the future emphasizes the critical role of CS in achieving a balance between technological advancement and sustainable development. To realize the full potential of CS in industrial energy efficiency, collaboration across industries, academia, and government is essential. Such a collaboration can accelerate the development of standardized frameworks and best practices for implementing CS, ensuring they are both effective and ethical. Moreover, investment in education and training is necessary to prepare the workforce to interact with and manage these advanced systems, ensuring they can be integrated smoothly into existing operations. In such a way, it is necessary to have not only new theoretical models but also practical implementations.

Author Contributions: Conceptualization, J.A. and J.B.; methodology, J.A. and F.-J.F.-M.; software, J.A.; validation, M.P.-P. and J.-I.L.-B.; formal analysis, J.-I.L.-B.; investigation, J.A. and F.-J.F.-M.; resources, M.P.-P.; data curation, J.A.; writing—original draft preparation, J.A., F.-J.F.-M. and J.B.; writing—review and editing, J.B. and J.-I.L.-B.; visualization, M.P.-P.; supervision, J.B.; project administration, M.P.-P. All authors have read and agreed to the published version of the manuscript version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflicts of interest.

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