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Cognitive Computing—Will It Be the Future "Smart Power" for the Energy Enterprises?

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Abstract: Nowadays, cognitive computing has become the popular solution to many problems arising in the energy industry, such as the creation of renewable technologies, energy saving, and searching for new sources. Last decade, a substantial number of scientific papers aiming to support these tasks were published. On the other hand, some years ago, the "cognitive enterprise" (CE) concept was introduced by the IBM company, which assumes, among others, the cognitive technologies used to increase enterprise intelligence. On the road to obtaining the status of a "cognitive enterprise", it should overcome many challenges. Thus, the aim of the paper was to analyze the current state of research on the application of cognitive computing in the energy industry and to define the trends, challenges, milestones, and perspectives in scientific work's development. The aim has been achieved using the bibliometric approach. The preliminary analysis was made by Web of Science data sources; 4182 records were retrieved. The results comprise the research field, geographic distribution of research, time analysis, and affiliation analysis. Additionally, descriptive statistics, as well as simple forecasting, were provided to present the research results. As a result of the research, the publication history road was created as well as the milestone framework on the path toward "cognitive enterprise". The findings of this research can contribute to literature and practice by applying them to the process of cognitive enterprise models' development as well as by adapting the education programs and training courses for enterprises and universities to market requirements.

Keywords: cognitive computing; cognitive enterprise; energy; bibliometric analysis

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1. Introduction

Nowadays, digital transformation is driving the development of modern organizations in many industries. In particular, especially meaningful is the increasing adoption of cognitive technologies, which enable organizations to generate new value by improving their reactivity and resilience, situational awareness, agility, and operational excellence [1].

Cognitive computing (CC) is a new type of computing whose goal is to create "more accurate models of how the human brain/mind senses, reasons, and response to stimulus" [2]. Cognitive computing combines different technologies to develop cognitive models. "Cognitive computing (CC) refers to technology platforms that, broadly speaking, are based on the scientific disciplines of artificial intelligence and signal processing. These platforms encompass machine learning, reasoning, natural language processing, speech recognition and vision (object recognition), human–computer interaction, dialog, and narrative generation, among other technologies" [2].

According to Furbach et al., a cognitive computer system may contain big data, machine learning, Internet of Things, natural processing language, probabilistic reasoning, computer vision, and casual induction [3]. It should have the capability to remember, analyze, learn, provoke, and resolve similarly to the human user. Some authors mention optical character recognition and decision making with cognitive reasoning as cognitive computing technologies [4]. Consequently, the implementation of three concepts helps to make a system cognitive. They are deep contextual insight, hypothesis generation, and continuous learning.

According to [5], cognitive computing also enables the acquiring and processing of huge volumes and diverse types of data, their examination and interpretation, as well as insights to recommend the appropriate actions.

In more detail, cognitive computer systems should include the following capabilities: learn from experience with data, generate or evaluate conflicting hypotheses, report on findings, discover patterns in data, emulate processes or structures found in natural learning systems, use natural language processing (NLP) to extract meaning from textual data and use deep learning tools to extract features from images, video, voice, and sensors, use the predictive analytics algorithms and advanced statistics.

NLP is the primary tool to interpret textual information. On the other hand, deep learning tools help to acquire information from video and sensor data. Visualization tools are required to make this data understandable by pattern recognition in large volumes of data [4].

Moreover, in work [6] by Tarafdar, the author highlights the significant meaning of the relationship between business processes and cognitive computing and argue thatenterprise cognitive computing applications enable an organization's business processes [6]. The author underlined that the goal of CC "is to make business processes more efficient, accurate, relevant and reliable" [6].

The above-mentioned opinion is in line with the "cognitive enterprise concept", which has its increasing popularity in recent years. The cognitive enterprise is, in simple words, the application of cognitive technologies to enterprise-level business needs defined by IBM company [7,8]. In an article by Nicole Laskowski for TechTarget, author cites one explanation care of Rick Davidson, founder and CEO at Cimphoni, who calls "the cognitive enterprise" the next wave, where technology systems that have the ability to understand, learn, and even reason will be able to meet customer expectations before customers know they have an expectation that needs to be met [7].

However, neither cognitive technology nor emerging technologies such as big data, edge computing, and Internet of Things (IoT) alone make the organization cognitive [8]. This process is more complicated. Intelligence requires a rethinking of many enterprise areas, as well as culture changing "that is not hesitant to deviate from traditional hierarchical silos of operation and corporate ownership" [9].

Moreover, one of the core elements of cognitive enterprise is cognitive workflow. Customer-oriented workflows have become humanized and automated [9]. Workflows enabled by cognitive technologies and, consequently, cognitive Business Process Management (BPM) provide the opportunity to humanize business value and deliver to customers.

It should be underlined that according to Elia and Margherita's findings, "although the idea of cognitive enterprise is rapidly emerging in the practitioner discussion, a theoretical framing of the concept is still not widely present in scientific literature" [1].

Furthermore, a previous literature study revealed the relationship between cognitive enterprise and cognitive computing and their fundamentality for cognitive city structure [10,11]. Recent research informs that cognitive computing establishes the basic platform for cognitive city building. Cognitive cities pursue improved information exchange for the development of knowledge and the analysis of human experiences and perceptions. In order to achieve these goals, the city, among other technologies, applies cognitive computing [12]. According to Finger and Portmann, "cognitive cities build on learning cities, which in turn build on smart cities" [10].

The CC is also the subject of sustainable cities theory. Sustainable cities address the efficiency challenges of optimizing the use of limited energy resources [13]. Cognitive technologies can help to overcome these challenges.

To sum up, building a cognitive enterprise in the energy industry is of high importance, especially in light of the United Nations SDG concept.

While the aim of this paper is to present the current state of research in using cognitive computing technologies in the energy industry to show the trends, milestones, and perspectives, they also should be considered in terms of cognitive enterprise and cognitive BPM concepts.

The paper consists of the following parts. First, the literature review is provided. After that, the materials and selected methods are described. In the third part, the results of the research using bibliometric studies and graphical and descriptive statistical methods are analyzed. In the discussion part, the most significant trends, milestones, and forecasts are presented. The history time chart mirrors the main historical events in cognitive computing research development in the energy industry is provided as well. In conclusion, the research limitations and future directions are defined.

Literature Review

Cognitive computing is widely related to the artificial intelligence (AI) concept.

According to current research, the several areas for cognitive computing and AI can be narrowed down in the energy industry.

First, AI and cognitive computing in power grids. With time, the power grids have become more digitalized and more difficult to manage. The increase in the number of grid participants requires evaluating and analyzing a large amount of data. This led to difficulties in keeping the grid in balance. AI and big data technologies support such a problem. Moreover, using AI, companies can evaluate, analyze, and control participants connected via smart grids. Furthermore, by combining renewable energy with AI-powered storage, enterprises improve energy storage management, increase business value, and minimize power losses.

The most current research areas on this topic are described further.

AI is used in smart grids to control the balance of the grid as well as monitor the conditions of power assets. In the paper by Feng et al., a taxonomical review of AI applications in this area is provided, as well as current challenges and trends [13]. In work [14], Chai et al. describe the artificial intelligence approaches to fault diagnosis in power grids. They also discuss the advantages and disadvantages of these technologies as well as future trends and outlooks. Tang et al. propose a new framework for AI analysis in large-scale power grids [15]. Zhang et al. analyze cognitive machine-to-machine communications and their potential [16]. Kottas proposes a smart grid control scheme using fuzzy cognitive networks [17]. Moreover, the cognitive sensor networks for smart grids have become popular. In 2012, Bicen et al. reviewed different energy harvesting techniques for SCSN-based smart grid applications [18]. Under the impact of the sustainable development concept, in 2014, Shengrong and Richard proposed green cognitive mobile networks for multimedia communications [19].

AI solutions for power trading can help improve forecasting, cost-cutting, and power saving. With AI, the suppliers can have optimal utilization of their resources, hence increasing efficiency. Many works have been created in the intelligent energy storage and optimization area [12,20–23]. Hu et al. proposed a hybrid energy storage system created by applying an intelligent energy management strategy [20]. In research by Fleming et al., the authors argue that AI could "enable new methods of cells characterization and monitoring for optimum electrochemical and thermal performance while improving system safety" [12].

In the area of resource management, the works currently could be divided into two main, often interrelated groups: AI in resource management [24–27] and sustainable resource management [28,29].

AI solutions can help in different predictions: predicting system overload, breakdowns, as well as corrosion, cracks, faults, etc., can be a cause of future disasters. The cost of mistakes in the energy industry is exceedingly high. Thus, the decision making and forecasting precision of the highest level is required. With the help of deep learning, it is possible to bring forecasting to the next level.

As artificial intelligence has plenty of applications in the energy sector, cognitive computing has similarly become very popular. In the area of disaster management, cognitive technologies are used to create cognitive Internet of vehicles, cognitive routing protocols, D2D communication, and public perception analysis on AI tools for disaster management [30–33].

From the enterprise management point of view, the new concept proposed by IBM company "cognitive enterprise" has already been discussed just in one scientific work [34]. The number of publications describing the common concept is also unsatisfactory, just works [1,35] occurs last years.

In the area of visualization, the cognitive technologies are represented by "cognitive visualizations" software solutions [36]. "Cognitive visualization tools and image analytics are driving novel solutions to detect risks, spark innovation and solve difficult problems, especially in operation areas. Being able to pull actionable insights from smart meters and IoT devices enables utility companies to better understand usage and demand, and also enables customers to easily monitor and control their monthly energy consumption, particularly during peak demand" [36]. Cognitive computer graphics could be used in tasks aimed to provide monitoring and optimization of energy infrastructure as well as decision making [37]. It is useful for cognitive dashboard creation.

Cognitive digital assistants or virtual agents improve productivity, agility, speed, and understanding. Chatbots can generate personalized, contextual recommendations and interact naturally and contextually with customers to improve customer satisfaction and lower service costs" [36]. These technologies also have been applied for predictive equipment maintenance, more accurate outage predictions, and the application of more advanced weather analytics. It allows companies from the energy sector "to ensure optimal uptime for the grid and reduce maintenance and service costs" [36].

Cognitive computing is increasingly being used in the domain of risk management, often mining large amounts of uncertain data to find indicators of known and unknown risks [38–40]. It is also widely used for security applications in the energy sector [41–43].

Cognitive computing is also a popular tool in supporting human–computer or human–robot interactions [44].

Currently, the world energy sector is under multiple transformations. This fact makes it difficult to implement novel solutions and technologies. Furthermore, in works [45,46], the authors describe the major challenges in AI application in the energy sector. They have mentioned the following challenges: lack of expertise and finances-economic pressure, decentralization and diversification, data privacy and security, and data consumption by AI [45,46].

The application of AI in the energy sector requires employing specialists with sufficient technical expertise in these technologies [46]. Moreover, according to the authors, "the conservative approach of some organizations and huge risks associated with data compels many companies not to join this AI revolution" [45]. Furthermore, the application of advanced technologies in the energy sector would require developing, adjusting, and monitoring software that engages many resources and finances [45].

Energy supply and the entire energy system are prone to cyber-attacks and data theft. Being an integral part of a country's infrastructure, cybersecurity needs to be ensured before completely managing the data to technology.

Above all, risks arise from the nature of AI technologies. According to [45], it is hard to explain how the data is processed and how the conclusions are made. Consumers will expect an enterprise's AI to be explainable, especially as its decisions are related to compliance and financial inclusion. They do not recognize the internal functions of AI technologies [46]. So contaminated data, or data of questionable provenance or reliability, could result in limited trust—"black boxes". Preventing the potential unintended consequences will help organizations incorporate the right risk mitigation strategies in building the cognitive enterprise [45].

So, the path to cognitive enterprise is long and challenging. Many changes in enterprise processes should be made, including cognitive technologies implementation. According to Deloitte company, bots can automate routine tasks [39]. However, the processes requiring judgment and perception analysis should be supported by cognitive technologies, including machine learning and speech recognition. These technologies give the bots new power.

Elia and Margherita argue that "although the idea of cognitive enterprise is rapidly emerging in practitioner discussion, a theoretical framing of the concept is still not present in the literature" concisely [1]. In work [1], the authors conduct a systematic review of extant contributions. They "extract elements related to two key dimensions represented by the cognitive technological infrastructure (i.e., technologies and data) and the cognitive organizational architecture (i.e., processes and capabilities)" [1]. They also define the pillars of the cognitive enterprise, a framework of cognitive maturity stages, and, finally, the enhanced value creation capabilities of the cognitive enterprise [1]. The authors also provide the guidelines to support managers in the cognitive transformation of their organizations [1].

According to IBM company [47,48], the convergence of several emerging technologies such as AI, cloud computing, automation, IoT, blockchain, and 5G "have the power to change business models, reinvent processes, and reimagine the way of work". The IBM company names them "the emergence of the Cognitive Enterprise" [47].

Nevertheless, neither artificial intelligence nor machine learning alone makes the organization cognitive [49]. In the opinion of Ramadoss B., "the intelligence conveyed from AI requires a culture that is not hesitant to deviate from traditional hierarchical silos of operation and corporate ownership" [49].

Moreover, the "cognitive enterprise" concept implementation could require reinventing the core management concepts, especially the Business Process Management concept.

Elia and Margherita state that human-centered design is becoming an ever more important aspect of business platforms and workflows, as well as the systems that underpin them [1,35]. Furthermore, "the cognitive enterprise will demand a new kind of management, supported with deep technology insights, and require new skills and culture" [47]. The greatest challenge could be the capacity to make the necessary changes in the area of expertise, mindsets, and ways of working to bring this vision to life.

The second significant concept that is empowering modern companies in the energy sector is the sustainability concept. For example, Suncor Energy, one of Canada's leading energy companies, recognized two issues as it embarked on a technology-enabled transformation building the layers of a Cognitive Enterprise Suncor Energy [48]. The trends supporting the emergence of the cognitive enterprise presented an opportunity for Suncor to drive a step change, including the use of business platforms that straddle organization and industry boundaries, as well as the maturity of AI, IoT, automation, edge computing, and other exponential technologies, described as "Industry 4.0." To bring the transformation to life, Suncor focused on its culture and new ways of working for its people [48].

Nevertheless, Ye and Pang state that "recent advances in artificial intelligence (AI), edge computing, big data, and cognitive computational theory show that multidisciplinary cognitive-inspired computing still struggles with fundamental, long-standing problems building computational models and decision-making mechanisms based on the neurobiological processes of the brain, cognitive sciences, and psychology" [50]. From this it follows that more research should be done. That is why, to provide a more detailed literature study, the bibliometric method has been used, and the results are presented in the next part of this paper.

2. Materials and Methods

To provide quantitative literature review analysis, the bibliometric method was used. Bibliometrics is considered an interdisciplinary science focused on the quantitative analysis of bibliographic data using statistical and mathematical tools [51]. It allows to establish the theoretical frameworks as well as to set up the hypotheses that will lead the way for the research area.

The core features of the bibliometric method are the possibility to draw valuable conclusions [52], using easy-to-manage and objective information [53], with the aim of facilitating decision making and channeling the researcher's efforts [54].

To map the state of the art of a scientific theme, the characterization of bibliometric parameters should be analyzed.

The bibliometric parameters have great availability in scientific research platforms. Due to this, the method has universal application in different fields of knowledge.

Research platforms present different tools for mining scientific data.

In addition to these, there are extensive numbers of platforms specific to the different fields of knowledge. The combination of one or more platforms for mining scientific data can result in a more consistent bibliometric analysis [55]. "On the other hand, it will be more difficult to integrate information from platforms with different structures, and although there are computational tools that support the integration of this data, they still require great improvements" [55].

In the work [55], the authors mentioned the following difficulties in mining the data using various databases:

(a) "Besides the structural differences between the platforms, there are also differences in the classification of the information adopted by each of them. For example, if the same search criteria were applied to different platforms, the results returned may not be the same.
(b) The variation in the number of articles is explained by the different search parameters adopted and also by the particular coverage of each platform. The difference in the results generated by the platforms is approached in the works conducted by" [56–59].

For the above-mentioned reasons, the bibliometric study presented in this paper is focused only on the Web of Science database.

The bibliometric study was successfully applied to energy research topics [60]. For example, in work [61], the entry analysis of the state of the art and publication trends on the topic of integrated solar combined cycles from 1990 to July 2020 using the Web of Science (WOS) database was presented.

Reviewing two decades of energy system analysis with bibliometrics, different topics were discussed [62–71]. Despite a substantial number of works presenting the bibliometric analysis in the energy sector, there is a lack of studies on advances in cognitive technologies, especially in terms of the cognitive enterprise concept.

The research procedure was planned as presented in Figure 1. After the research field identification, the research database was selected. For the above-mentioned reasons in this part, the bibliometric study presented was focused only on the Web of Science database. The following keywords were used: "cognitive computing" AND "energy", "cognitive technology" AND "energy". The following bibliometric parameters were analyzed: research fields, years, countries, and affiliations.

After that, based on the literature review, the selected cognitive technologies were studied separately. The data extracted from the WoS database was used for further graphical analysis with different software tools. Statistical analysis was provided as well.

Moreover, to continue the data analysis, the VOSviewer and Jamovi 2 software was used. This tool is often recommended for bibliometric studies since it automatically counts the different parameters, such as number of occurrences and citations of each country or institution in a portfolio of documents [55]. The software is also capable of creating several types of networks, such as co-citation and co-authorship, citation of articles, institutions, and countries, co-occurrence of keywords, etc. [55]. For the purposes of this research, the co-occurrence of keywords was used.

The VOSviewer software provides several visualization types, for example, the "network visualization". This is the simplest display mode, which shows the iterations of co-authorship and formation of some clusters, or "overlay visualization", a network that brings iterations of co-authorship and formation of clusters and also brings the information of chronological type [55]. It also allows verifying the different densities of the information shown on the network.

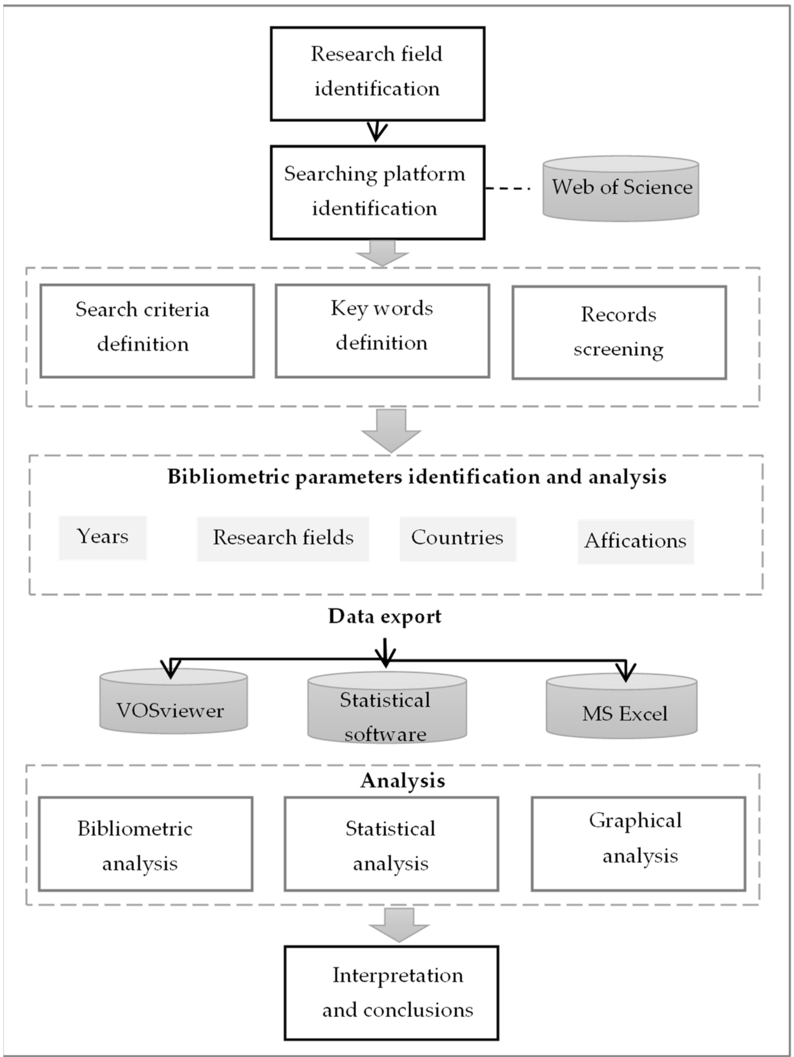

Figure 1. Methodological framework of publication analysis.

3. Results

In the first stage, the common results for the holistic concept were studied. The largest number of studies were made in the fields of engineering, computer science, and transportation fields (Figure 2). Just 53 of paper were associated to management science.

It was noticed that the number of papers has been significantly reduced in the last two years (Figure 3).

Analyzing the publications on cognitive computing in the energy industry by country, it was noticed that the largest number of publications were developed in the USA-1219, China-948, Canada-494, and India-486. In Europe, England was at the leading position in this area, with 281 papers (Figures 4 and 5).

The following universities and organizations were in the leading position: University of California System—with a great advantage, University of British Columbia, and Arizona State University (Figure 6).

The analysis of publications using concrete IT cognitive computing tools based on Trafadar's research [6] reveals that there is a lack of papers in this area. Most of them (7 publications) were based on IBM Watson software (Armonk, NY, USA).

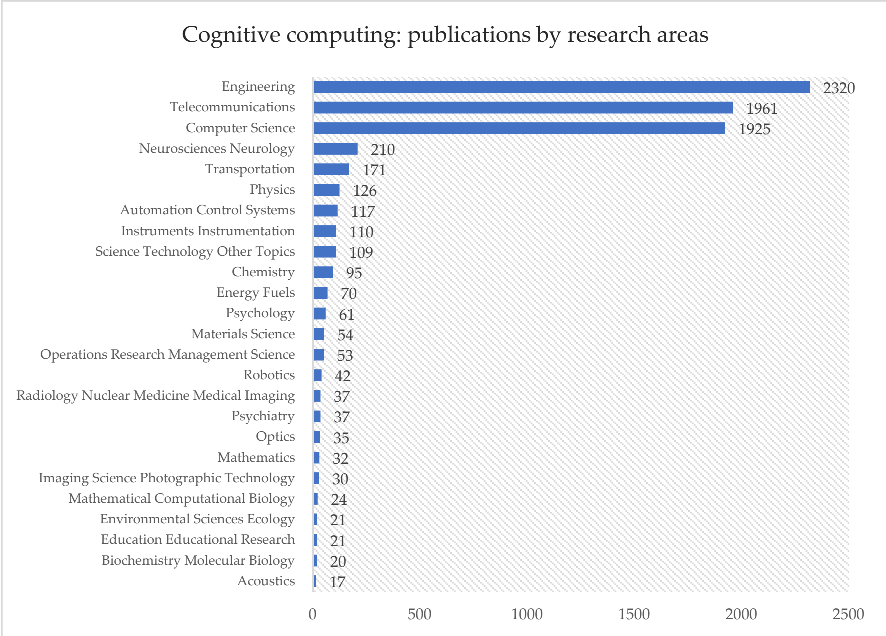

Figure 2. Publications analysis on cognitive computing in energy industry by research areas.

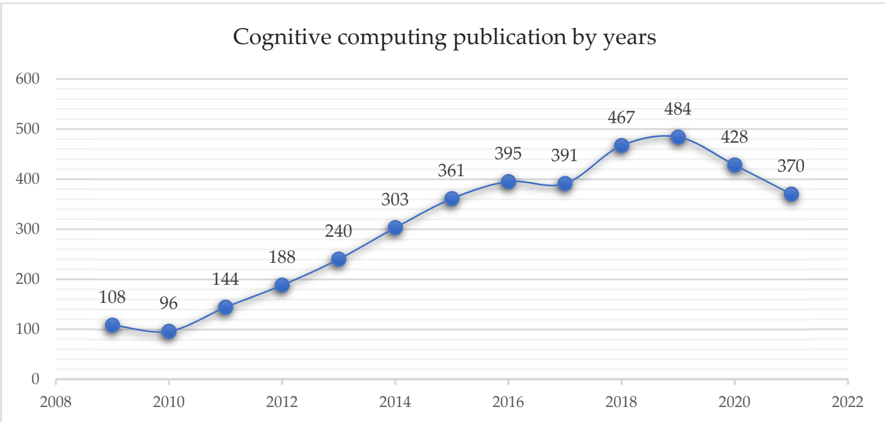

Figure 3. Publications analysis on cognitive computing in the energy industry by years.

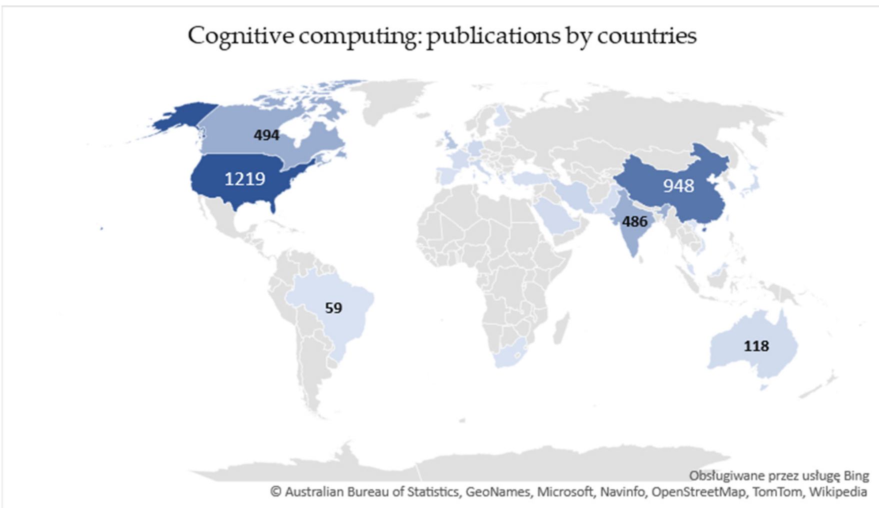

Figure 4. Cognitive computing publications in energy industry by countries (map view).

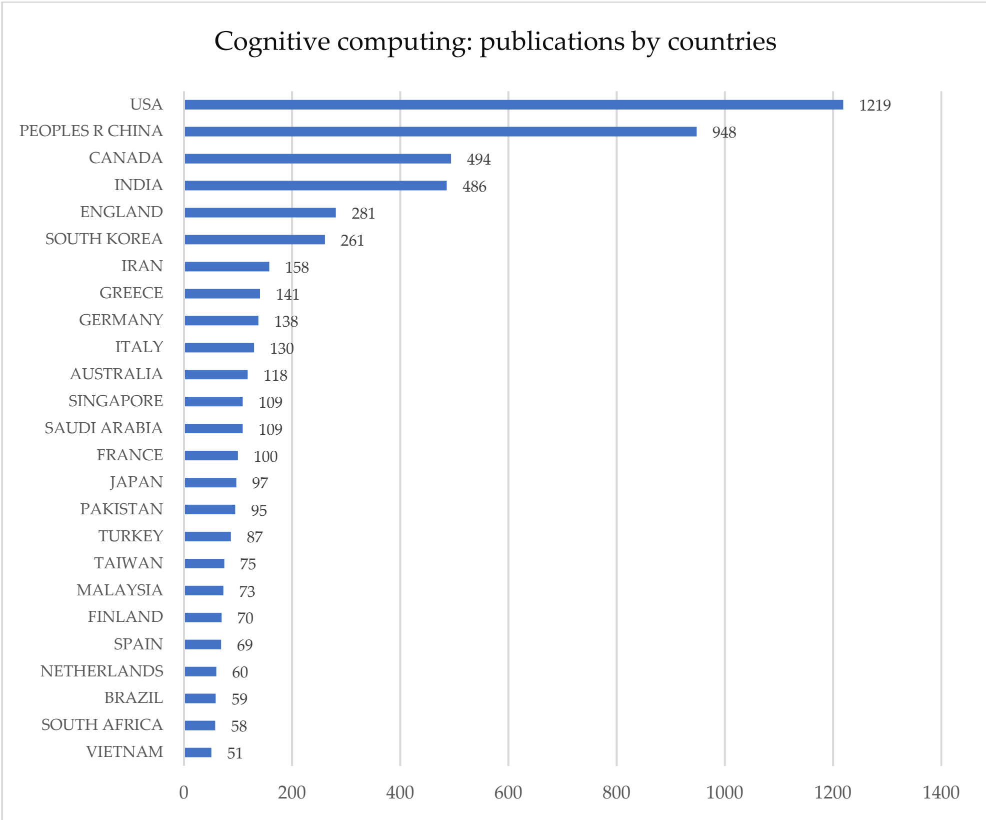

Figure 5. Cognitive computing publications in energy industry by countries.

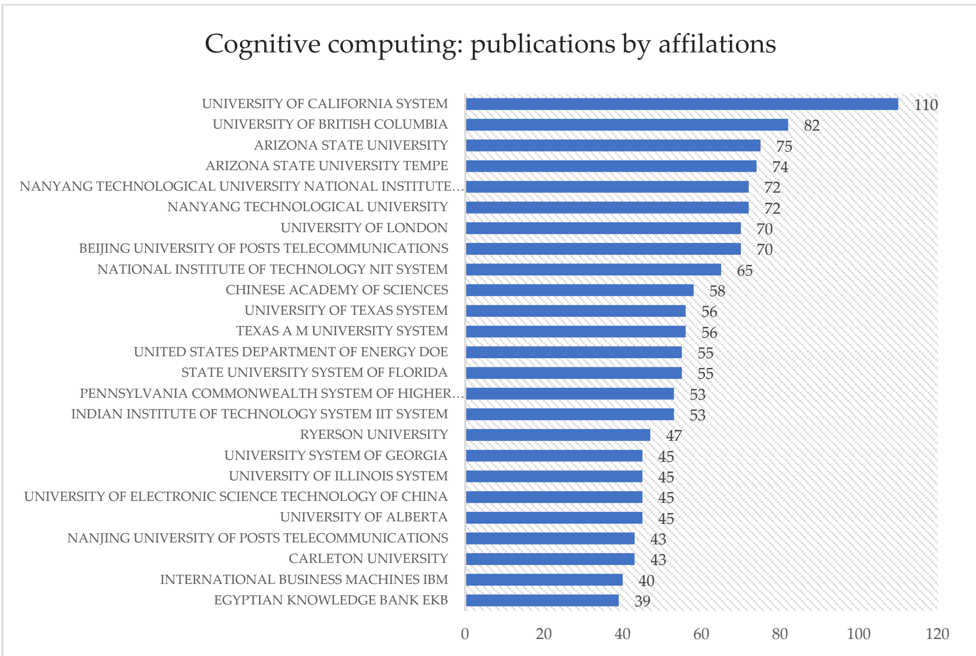

Figure 6. Cognitive computing publications in energy industry by affiliations.

The topic of the application of the "cognitive enterprise" concept to the energy industry also has not been included in publications in the Web of Science database yet.

After the literature analysis on "cognitive computing", the literature on "cognitive technology" research in the WOS database was studied. Most of the works were published in engineering, telecommunications, and computer science areas. These results are similar to "cognitive computing" analysis results (Figure 7). It was noticed more works in area of economics and management. 53 of paper were associated to management science, 73 of papers associated to business economics area.

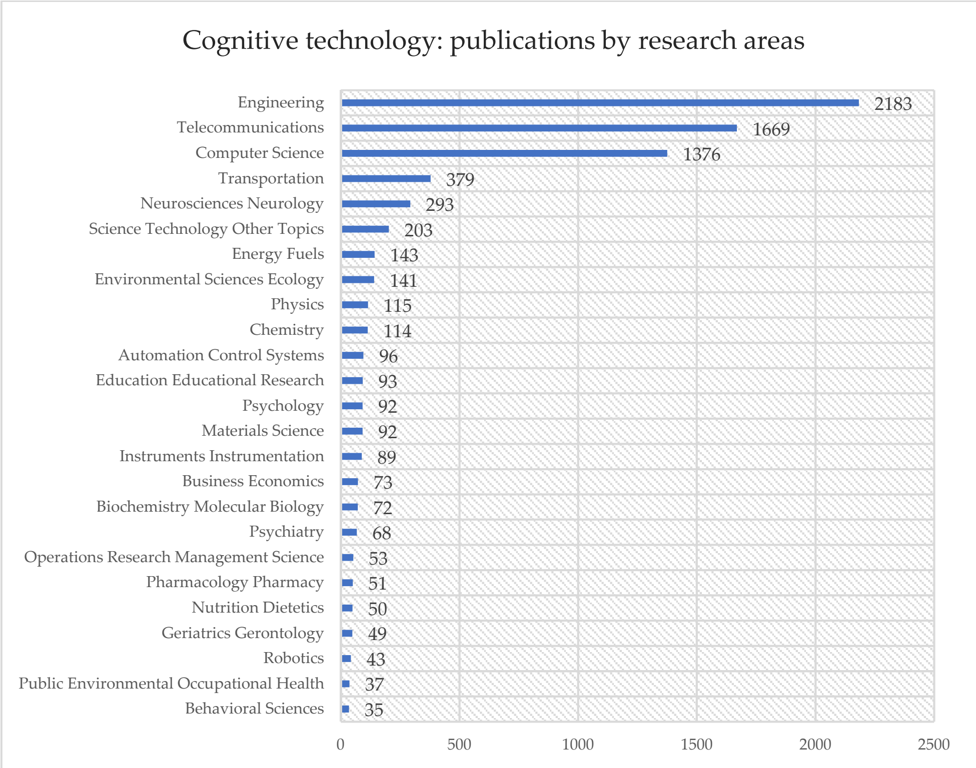

Figure 7. Publications on cognitive technology in energy industry by research areas.

At the next stage of analysis, the Web of Science publications on cognitive technologies based on main AI components were studied in detail. The results of the bibliometric analysis of publications on cognitive technologies number are presented in Table 1. The following technologies were selected: computer vision, deep learning, human-computer interactions, natural language processing (NLP), neural networks (NN), real-time decision-making, sentiment analysis, and reasoning.

Table 1. The results of bibliometric analysis of publication number on cognitive technologies in energy sector.

Publication Years	Computer Vision	Deep Learning	Human–Computer Interactions	NL Processing	Neural Networks	Real-Time Decision Making	Sentiment Analysis	Reasoning
2021	553	3552	74	294	103	357	68	1610
2020	611	3130	76	300	141	413	58	2050
2019	659	2227	68	307	109	382	37	2046
2018	619	1260	105	277	76	326	39	1920
2017	602	607	88	186	75	273	32	1783
2016	469	275	79	134	50	241	33	1661
2015	511	137	76	104	38	182	20	1435
2014	370	82	52	84	37	169	8	1337
2013	305	67	31	77	30	130	4	1172
2012	248	40	29	39	17	102	5	1089
2011	273	32	23	40	13	81	2	822
2010	218	32	18	33	18	57	3	767

The descriptive statistics presented in Table 2 show that the highest median and mean value has the reasoning technologies. On the other hand, deep learning technologies obtain the highest SD and maximum position. A detailed analysis of publications on cognitive technologies applications in the energy domain is presented in Appendix A. The forecasting of publication number is presented as well. Table A1 shows the correlation results.

Table 2. The descriptive statistics of publication number on cognitive technologies (group size (N), mean, median, minimum and maximum value, standard deviation (SD)).

	N	Missing	Mean	Median	SD	Minimum	Maximum
Computer vision	12	0	453.2	490.0	162.2	218	659
Deep learning	12	0	953.4	206.0	1297.9	32	3552
Human–computer iteractions	12	0	59.9	71.0	28.5	18	105
NL processing	12	0	156.3	119.0	110.8	33	307
Neural networks	12	0	58.9	44.0	41.7	13	141
Real-time decision making	12	0	226.1	211.5	123.7	57	413
Sentiment analysis	12	0	25.8	26.0	22.5	2	68
Reasoning	12	0	1474.3	1522.5	446.3	767	2050

Analyzing all the publications on different cognitive technologies simultaneously, it could be noticed that their number was mostly reduced from the year 2020 (Figure 8).

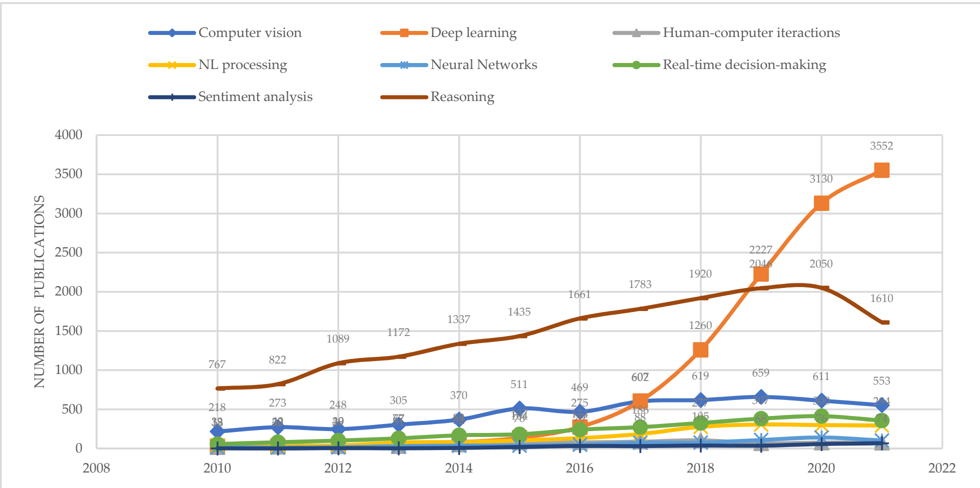

Figure 8. Publications on cognitive technologies in energy industry by years.

After the WoS bibliometric analysis, the VOSviewer tool was used to identify the most popular keywords related to cognitive technology research in the energy sector. According to VOSviewer analysis, the most popular words in the energy industry were used the following: band-structure, total energy calculations, initio-molecular dynamics, absorption, and organic-inorganic hybrid systems (Figure 9).

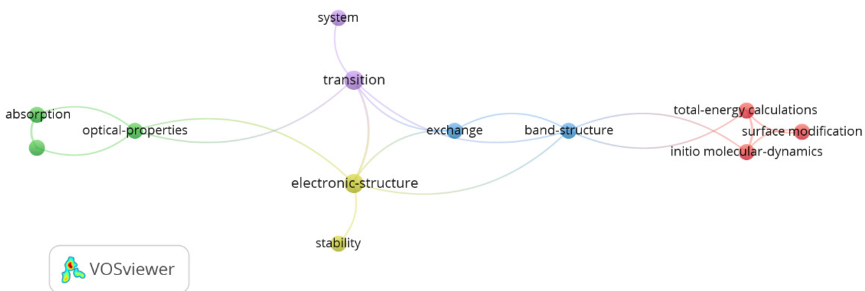

Figure 9. VOSviewer keywords analysis related to application of cognitive technologies in energy industry.

4. Discussion

Comparing the number of publications associated with common terms such as "cognitive computing" and "cognitive technology" applied in the energy sector with the number of papers on separate technologies, it could be concluded that the number of publications on the application of concrete technologies is significantly larger than the papers with common discussion on this topic. The small number of paper related to economics and management field was noticed.

Figure 10 presents an image that shows the results of the analysis of the publications in the energy industry. Among years the largest number of papers were published on reasoning and deep learning technology (Figure 10). However, the percentage of work on reasoning and computer vision has decreased over time. The popularity of deep learning technology has increased sharply from 2016 to take a leading position until 2021. In deep learning, the algorithm learns rules based on correlations between inputs and outputs. In symbolic reasoning, the rules are created through human intervention [72]. These results show the increasing intensity of research on deep learning algorithms and solutions and, taking into consideration the forecast and the analysis from Table A, the continuous popularity of symbolic reasoning solutions.

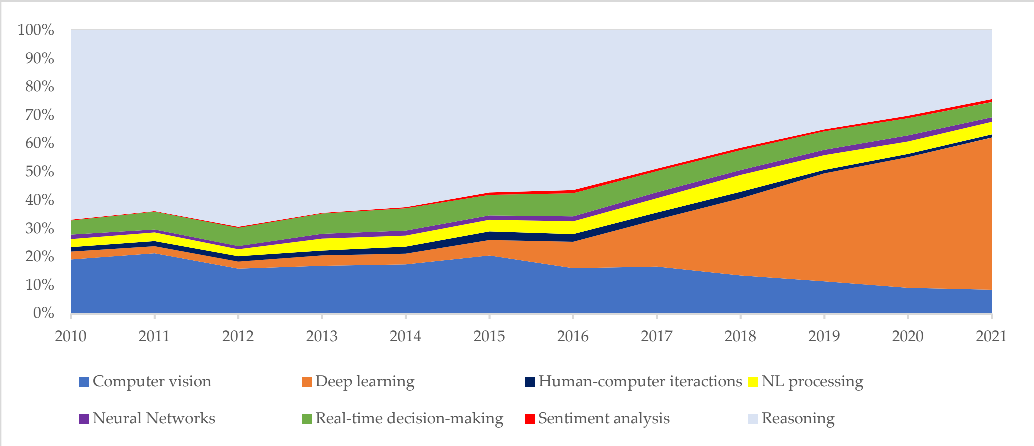

Figure 10. Publications on cognitive technologies in energy industry by years—percentage view.

The technologies based on sentiment analysis have rarely been used for energy industry research over the years. However, their number has slowly increased. The development of human–computer interactions was uneven. The human–computer interactions have been studied with various popularity.

The above-mentioned results (Figures 8 and 9 and Table 1) allows us to create Figure 11, which presents the most significant changes in research on cognitive technologies from 2010 to 2021. It has been noticed that in 2020 the number of publications decreased significantly in some areas, such as computer vision and NLP. In 2021, this observation was repeated, this time with a higher level of intensity. In six of eight areas, a decreasing tendency was noticed. Very probably, it occurred due to the COVID-19 pandemic and the consequences related to it.

The publication analysis by counties reveals that the largest number of works was published in 2010–2021 by scientists from the United States of America and the Republic People of China. In third place were Canada and India, with remarkably similar results.

The affiliations analysis gave mixed results. Referring to cognitive computing common analysis, the University of California obtained the highest result, with a great advantage. Nevertheless, referring to separate cognitive technologies, the leading positions were the following United States Department of Energy DOE, Chinese Academy of Science, and third position for California State University, as presented in Table 3.

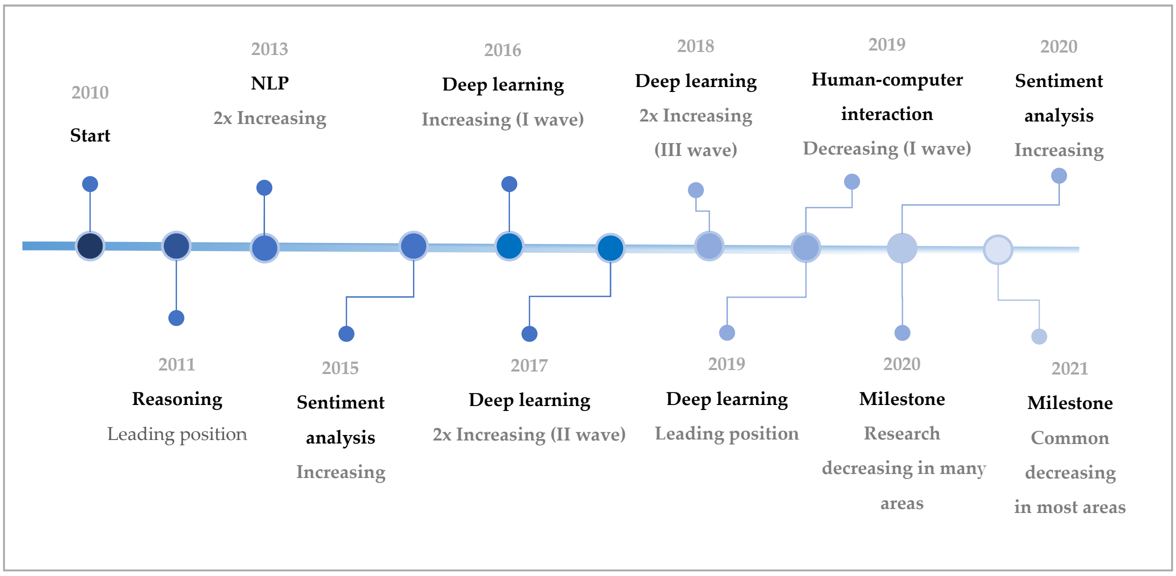

Figure 11. The history of research on cognitive technologies in the energy industry.

Table 3. The results of publications analysis by country and affiliation.

Technology	Affiliation	Country
Deep learning	DOE	USA, China
Computer vision	California State University	China, Germany
Sentiment analysis	UPES	USA, China
NLP	Chinese Academy of Science	China, USA
NN	DOE, Chinese Academy of Science	China, USA
Reasoning	DOE	China, Germany
Human–computer interaction	DOE	China, Germany
Real-time decision making	DOE	USA, United Kingdom

It could be concluded that the leading countries conducting research on cognitive computing in the energy sector area are China, the USA, and Germany. In contrast, the leading organizations in this area are: the United States Department of Energy DOE, the Chinese Academy of Science, California State University, and the University of Petroleum and Energy Studies.

Summarizing the above research results as well as literature review, core milestones were defined and structured in the path from traditional to cognitive enterprise (Figure 12). The milestones were created from down to the top direction, from more detailed to more common, and divided into nine sections according to three areas: milestones in publications on cognitive technologies, milestones in publications on cognitive enterprise core elements, and, finally, milestones focused on global challenges related to CE topic.

First, "multidisciplinary cognitive-inspired computing still struggles with fundamental, long-standing problems building computational models and decision-making mechanisms based on the neurobiological processes of the brain, cognitive sciences, and psychology" [50]. Second is the need for reinventing core management areas such as BPM, knowledge management, human resources management, etc. Next, the small number of scientific publications with a high impact in core areas such as cognitive enterprise, cognitive BPM, and competencies transformation [47,73]. Finally, the noticeable research geographical concentration with a leader position of certain countries such as the USA, China, and Germany (Table 3).

It should be mentioned that this research has several limitations. First, the data were analyzed by means of WoS database analyses tool are restricted to WoS capabilities of analysis. Although the WoS database is very comprehensive and valid, it is better to analyze additionally other databases, including Scopus or Google Scholar [63].On the other hand, it allows us to avoid several difficulties and challenges mentioned in the Materials and Methods section. Another limitation is that the research includes publications in English, and it is recommended that future research include documents published in other languages.

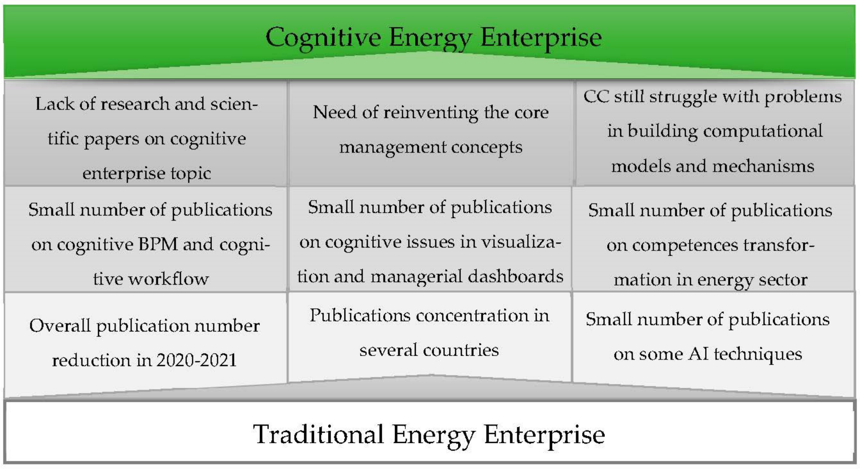

Figure 12. Research milestones in transformation of energy enterprises into cognitive enterprise.

5. Conclusions

Digital technologies are driving the transformation of modern organizations. In particular, the increasing adoption of cognitive technologies, such as artificial intelligence, advanced analytics, high-performing computing, and cyber-physical systems, allows organizations to create new value based on increased reactivity and resilience, situational awareness, agility, and operational excellence [6]. Hence, they have the ability to scale quickly, implement innovative processes, and, consequently, lead industries and markets. The AI technologies "can help improve power management, efficiency, and transparency, and increase the use of renewable energy sources" [74] (p. 1).

Thus, energy enterprises could receive "smart power". However, on the other hand, the extensive list of challenges increases the risks related to the implementation of cognitive technologies. They are financial risks, organizational risks, and human resource risks.

Moreover, according to an IMF report, there is a tendency toward global data policy framework construction. "It should clarify the rules of the digital economy, while ensuring that it is competitive and resilient" [75] (p. 5). Key elements of the common minimum international principle should be used, such as principles of data protection, principles on interoperability and data portability, and principles on data sharing for regulatory purposes [75]. These principles should be taken into consideration to address increasingly complex problems in the energy sector by means of emerging technologies such as AI and big data.

Understanding the skills has a significant meaning for energy enterprises, especially in the renewable energy sector. Building the cognitive enterprise, the skills transformation phenomenon should be taken into consideration [1]. According to IBM, company skills inference technology is powered by AI [47]. Thus, human resource management has become a core element of the energy enterprise.

Moreover, the rise of AI and other information technologies may also lead to greater concentrations of market power [76].

Despite many advantages of AI and cognitive technologies application in the energy sector, there is a lack of scientific research in this area toward building a cognitive enterprise. Thus, this research attempts to fill the gap in the literature study and provide an analysis of trends and advances in cognitive technologies research.

The author's main findings are the historical analysis of the research on cognitive technologies in the energy sector, the tendencies and anomalies identification during the publication history analysis, and the milestones of the cognitive enterprise implementation definition. The findings of this research can contribute to literature and practice by applying them to the process of cognitive enterprise model development as well as by adapting the education programs and training courses for enterprises and universities to market requirements.

Moreover, the energy enterprise path toward cognitive enterprise could be easy if all the areas were appropriately analyzed and discussed by the scientific community, and the milestones and changes will be wading through. Remembering the challenges in implementing the Business Process Reengineering concept, enterprise transformation, especially in such a core industry, should be carefully thought out, and the risk should be minimized on the road to becoming the "smart power" for energy enterprises.

Thus, this research takes a look at cognitive computing from the cognitive enterprise perspective. The research will be continued in order to support the cognitive enterprise concept implementation in the energy domain. Taking into consideration the limitations of this research, future work should be focused on several areas. First, more databases could be studied, including other languages. The 2020 and 2021 milestones should be analyzed, and hypotheses about the COVID-19 impact should be proved. Second, the deeper cognitive technologies and other emerging technologies analysis could be performed to connect them on the way of transformation toward building the "cognitive enterprise".

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Appendix A

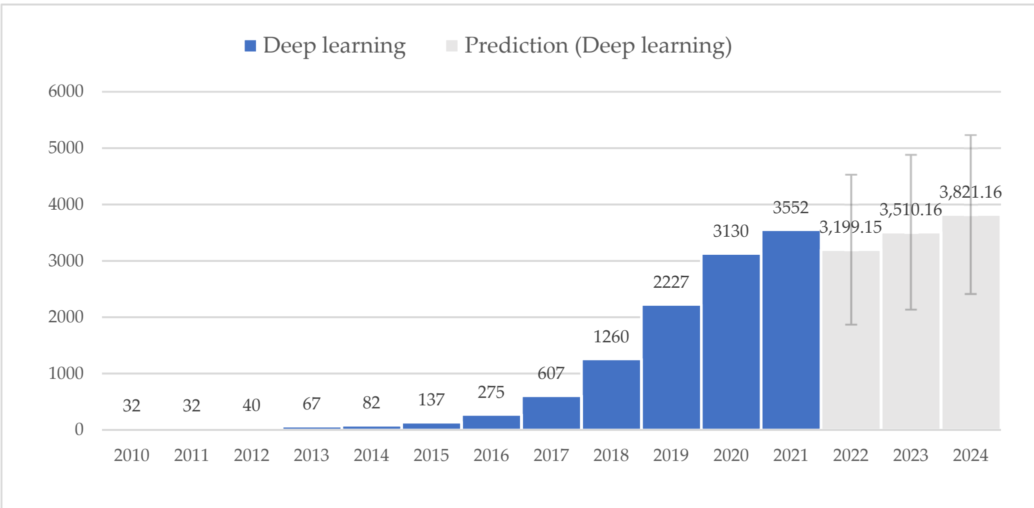

Figure A1. Prediction of number of publications on deep learning in energy sector.

Table A1. Correlation matrix.

		Computer Vision		Deep Learning		Human–Computer Interactions		NL Processing		Neural Networks		Real-Time Decision Making		Sentiment Analysis		Reasoning
Computer vision	Pearson's r	—														
	p-value	—														
Deep learning	Pearson's r	0.683	*	—												
	p-value	0.014		—												
Human–computer interactions	Pearson's r	0.910	***	0.475		—										
	p-value	<0.001		0.119		—										
NL processing	Pearson's r	0.912	***	0.890	***	0.761	**	—								
	p-value	<0.001		<0.001		0.004		—								
Neural Networks	Pearson's r	0.863	***	0.912	***	0.671	*	0.953	***	—						
	p-value	<0.001		<0.001		0.017		<0.001		—						
Real-time decision making	Pearson's r	0.935	***	0.863	***	0.800	**	0.981	***	0.970	***	—				
	p-value	<0.001		<0.001		0.002		<0.001		<0.001		—				
Sentiment analysis	Pearson's r	0.826	***	0.912	***	0.747	**	0.916	***	0.909	***	0.925	***	—		
	p-value	<0.001		<0.001		0.005		<0.001		<0.001		<0.001		—		
Reasoning	Pearson's r	0.957	***	0.669	*	0.878	***	0.902	***	0.881	***	0.950	***	0.804	**	—
	p-value	<0.001		0.017		<0.001		<0.001		<0.001		<0.001		0.002		—

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

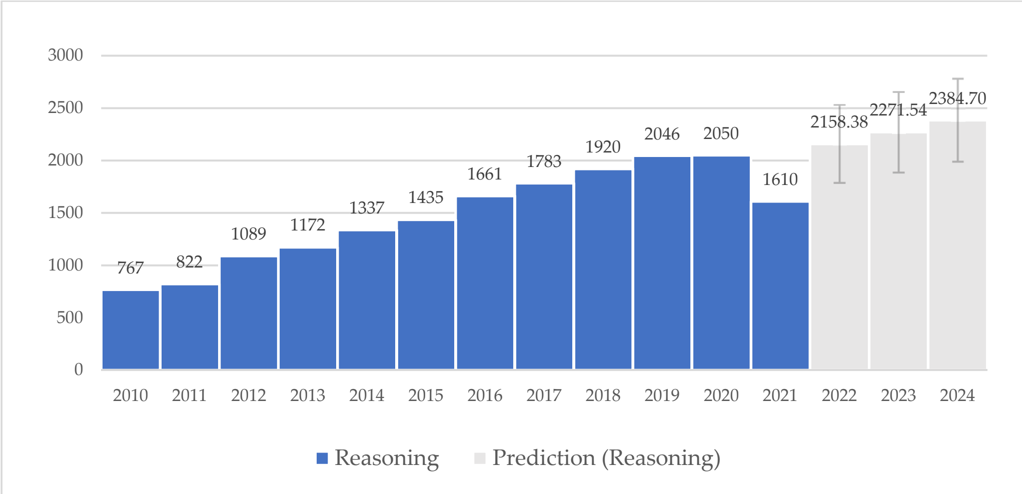

Figure A2. Prediction of number of publications on reasoning research in energy sector.

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